Agile Tools for Real-World Data

Python for Data Analysis

O'REILLY®

Wes McKinney

Python for Data Analysis

Wes McKinney

O'REILLY®
Beijing • Cambridge • Farnham • Köln • Sebastopol • Tokyo

Python for Data Analysis
by Wes McKinney

Copyright © 2013 Wes McKinney. All rights reserved.
Printed in the United States of America.

Published by O'Reilly Media, Inc., 1005 Gravenstein Highway North, Sebastopol, CA 95472.

O'Reilly books may be purchased for educational, business, or sales promotional use. Online editions are also available for most titles (*http://my.safaribooksonline.com*). For more information, contact our corporate/institutional sales department: 800-998-9938 or *corporate@oreilly.com*.

Editors: Julie Steele and Meghan Blanchette
Production Editor: Melanie Yarbrough
Copyeditor: Teresa Exley
Proofreader: BIM Publishing Services
Indexer: BIM Publishing Services
Cover Designer: Karen Montgomery
Interior Designer: David Futato
Illustrator: Rebecca Demarest

October 2012: First Edition.

Revision History for the First Edition:
2012-10-05 First release
See *http://oreilly.com/catalog/errata.csp?isbn=9781449319793* for release details.

Nutshell Handbook, the Nutshell Handbook logo, and the O'Reilly logo are registered trademarks of O'Reilly Media, Inc. *Python for Data Analysis*, the cover image of a golden-tailed tree shrew, and related trade dress are trademarks of O'Reilly Media, Inc.

Many of the designations used by manufacturers and sellers to distinguish their products are claimed as trademarks. Where those designations appear in this book, and O'Reilly Media, Inc., was aware of a trademark claim, the designations have been printed in caps or initial caps.

While every precaution has been taken in the preparation of this book, the publisher and author assume no responsibility for errors or omissions, or for damages resulting from the use of the information contained herein.

ISBN: 978-1-449-31979-3

[LSI]

1349356084

Table of Contents

Preface ..... **xi**

1. Preliminaries **1**
What Is This Book About? 1
Why Python for Data Analysis? 2
Python as Glue 2
Solving the "Two-Language" Problem 2
Why Not Python? 3
Essential Python Libraries 3
NumPy 4
pandas 4
matplotlib 5
IPython 5
SciPy 6
Installation and Setup 6
Windows 7
Apple OS X 9
GNU/Linux 10
Python 2 and Python 3 11
Integrated Development Environments (IDEs) 11
Community and Conferences 12
Navigating This Book 12
Code Examples 13
Data for Examples 13
Import Conventions 13
Jargon 13
Acknowledgements 14

2. Introductory Examples **17**
1.usa.gov data from bit.ly 17
Counting Time Zones in Pure Python 19

Counting Time Zones with pandas 21
MovieLens 1M Data Set 26
Measuring rating disagreement 30
US Baby Names 1880-2010 32
Analyzing Naming Trends 36
Conclusions and The Path Ahead 43

3. IPython: An Interactive Computing and Development Environment 45
IPython Basics 46
Tab Completion 47
Introspection 48
The %run Command 49
Executing Code from the Clipboard 50
Keyboard Shortcuts 52
Exceptions and Tracebacks 53
Magic Commands 54
Qt-based Rich GUI Console 55
Matplotlib Integration and Pylab Mode 56
Using the Command History 58
Searching and Reusing the Command History 58
Input and Output Variables 58
Logging the Input and Output 59
Interacting with the Operating System 60
Shell Commands and Aliases 60
Directory Bookmark System 62
Software Development Tools 62
Interactive Debugger 62
Timing Code: %time and %timeit 67
Basic Profiling: %prun and %run -p 68
Profiling a Function Line-by-Line 70
IPython HTML Notebook 72
Tips for Productive Code Development Using IPython 72
Reloading Module Dependencies 74
Code Design Tips 74
Advanced IPython Features 76
Making Your Own Classes IPython-friendly 76
Profiles and Configuration 77
Credits 78

4. NumPy Basics: Arrays and Vectorized Computation 79
The NumPy ndarray: A Multidimensional Array Object 80
Creating ndarrays 81
Data Types for ndarrays 83

Operations between Arrays and Scalars 85
Basic Indexing and Slicing 86
Boolean Indexing 89
Fancy Indexing 92
Transposing Arrays and Swapping Axes 93
Universal Functions: Fast Element-wise Array Functions 95
Data Processing Using Arrays 97
Expressing Conditional Logic as Array Operations 98
Mathematical and Statistical Methods 100
Methods for Boolean Arrays 101
Sorting 101
Unique and Other Set Logic 102
File Input and Output with Arrays 103
Storing Arrays on Disk in Binary Format 103
Saving and Loading Text Files 104
Linear Algebra 105
Random Number Generation 106
Example: Random Walks 108
Simulating Many Random Walks at Once 109

5. Getting Started with pandas 111
Introduction to pandas Data Structures 112
Series 112
DataFrame 115
Index Objects 120
Essential Functionality 122
Reindexing 122
Dropping entries from an axis 125
Indexing, selection, and filtering 125
Arithmetic and data alignment 128
Function application and mapping 132
Sorting and ranking 133
Axis indexes with duplicate values 136
Summarizing and Computing Descriptive Statistics 137
Correlation and Covariance 139
Unique Values, Value Counts, and Membership 141
Handling Missing Data 142
Filtering Out Missing Data 143
Filling in Missing Data 145
Hierarchical Indexing 147
Reordering and Sorting Levels 149
Summary Statistics by Level 150
Using a DataFrame's Columns 150

Other pandas Topics 151
Integer Indexing 151
Panel Data 152

6. Data Loading, Storage, and File Formats 155
Reading and Writing Data in Text Format 155
Reading Text Files in Pieces 160
Writing Data Out to Text Format 162
Manually Working with Delimited Formats 163
JSON Data 165
XML and HTML: Web Scraping 166
Binary Data Formats 171
Using HDF5 Format 171
Reading Microsoft Excel Files 172
Interacting with HTML and Web APIs 173
Interacting with Databases 174
Storing and Loading Data in MongoDB 176

7. Data Wrangling: Clean, Transform, Merge, Reshape 177
Combining and Merging Data Sets 177
Database-style DataFrame Merges 178
Merging on Index 182
Concatenating Along an Axis 185
Combining Data with Overlap 188
Reshaping and Pivoting 189
Reshaping with Hierarchical Indexing 190
Pivoting “long” to “wide” Format 192
Data Transformation 194
Removing Duplicates 194
Transforming Data Using a Function or Mapping 195
Replacing Values 196
Renaming Axis Indexes 197
Discretization and Binning 199
Detecting and Filtering Outliers 201
Permutation and Random Sampling 202
Computing Indicator/Dummy Variables 203
String Manipulation 205
String Object Methods 206
Regular expressions 207
Vectorized string functions in pandas 210
Example: USDA Food Database 212

8. Plotting and Visualization 219
A Brief matplotlib API Primer 219
Figures and Subplots 220
Colors, Markers, and Line Styles 224
Ticks, Labels, and Legends 225
Annotations and Drawing on a Subplot 228
Saving Plots to File 231
matplotlib Configuration 231
Plotting Functions in pandas 232
Line Plots 232
Bar Plots 235
Histograms and Density Plots 238
Scatter Plots 239
Plotting Maps: Visualizing Haiti Earthquake Crisis Data 241
Python Visualization Tool Ecosystem 247
Chaco 248
mayavi 248
Other Packages 248
The Future of Visualization Tools? 249

9. Data Aggregation and Group Operations 251
GroupBy Mechanics 252
Iterating Over Groups 255
Selecting a Column or Subset of Columns 256
Grouping with Dicts and Series 257
Grouping with Functions 258
Grouping by Index Levels 259
Data Aggregation 259
Column-wise and Multiple Function Application 262
Returning Aggregated Data in “unindexed” Form 264
Group-wise Operations and Transformations 264
Apply: General split-apply-combine 266
Quantile and Bucket Analysis 268
Example: Filling Missing Values with Group-specific Values 270
Example: Random Sampling and Permutation 271
Example: Group Weighted Average and Correlation 273
Example: Group-wise Linear Regression 274
Pivot Tables and Cross-Tabulation 275
Cross-Tabulations: Crosstab 277
Example: 2012 Federal Election Commission Database 278
Donation Statistics by Occupation and Employer 280
Bucketing Donation Amounts 283
Donation Statistics by State 285

10. Time Series 289
Date and Time Data Types and Tools 290
Converting between string and datetime 291
Time Series Basics 293
Indexing, Selection, Subsetting 294
Time Series with Duplicate Indices 296
Date Ranges, Frequencies, and Shifting 297
Generating Date Ranges 298
Frequencies and Date Offsets 299
Shifting (Leading and Lagging) Data 301
Time Zone Handling 303
Localization and Conversion 304
Operations with Time Zone–aware Timestamp Objects 305
Operations between Different Time Zones 306
Periods and Period Arithmetic 307
Period Frequency Conversion 308
Quarterly Period Frequencies 309
Converting Timestamps to Periods (and Back) 311
Creating a PeriodIndex from Arrays 312
Resampling and Frequency Conversion 312
Downsampling 314
Upsampling and Interpolation 316
Resampling with Periods 318
Time Series Plotting 319
Moving Window Functions 320
Exponentially-weighted functions 324
Binary Moving Window Functions 324
User-Defined Moving Window Functions 326
Performance and Memory Usage Notes 327

11. Financial and Economic Data Applications 329
Data Munging Topics 329
Time Series and Cross-Section Alignment 330
Operations with Time Series of Different Frequencies 332
Time of Day and "as of" Data Selection 334
Splicing Together Data Sources 336
Return Indexes and Cumulative Returns 338
Group Transforms and Analysis 340
Group Factor Exposures 342
Decile and Quartile Analysis 343
More Example Applications 345
Signal Frontier Analysis 345
Future Contract Rolling 347

Rolling Correlation and Linear Regression 350

12. Advanced NumPy 353
ndarray Object Internals 353
NumPy dtype Hierarchy 354
Advanced Array Manipulation 355
Reshaping Arrays 355
C versus Fortran Order 356
Concatenating and Splitting Arrays 357
Repeating Elements: Tile and Repeat 360
Fancy Indexing Equivalents: Take and Put 361
Broadcasting 362
Broadcasting Over Other Axes 364
Setting Array Values by Broadcasting 367
Advanced ufunc Usage 367
ufunc Instance Methods 368
Custom ufuncs 370
Structured and Record Arrays 370
Nested dtypes and Multidimensional Fields 371
Why Use Structured Arrays? 372
Structured Array Manipulations: numpy.lib.recfunctions 372
More About Sorting 373
Indirect Sorts: argsort and lexsort 374
Alternate Sort Algorithms 375
numpy.searchsorted: Finding elements in a Sorted Array 376
NumPy Matrix Class 377
Advanced Array Input and Output 379
Memory-mapped Files 379
HDF5 and Other Array Storage Options 380
Performance Tips 380
The Importance of Contiguous Memory 381
Other Speed Options: Cython, f2py, C 382

Appendix: Python Language Essentials 385

Index 433

Preface

The scientific Python ecosystem of open source libraries has grown substantially over the last 10 years. By late 2011, I had long felt that the lack of centralized learning resources for data analysis and statistical applications was a stumbling block for new Python programmers engaged in such work. Key projects for data analysis (especially NumPy, IPython, matplotlib, and pandas) had also matured enough that a book written about them would likely not go out-of-date very quickly. Thus, I mustered the nerve to embark on this writing project. This is the book that I wish existed when I started using Python for data analysis in 2007. I hope you find it useful and are able to apply these tools productively in your work.

Conventions Used in This Book

The following typographical conventions are used in this book:

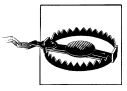
Italic
: Indicates new terms, URLs, email addresses, filenames, and file extensions.

`Constant width`
: Used for program listings, as well as within paragraphs to refer to program elements such as variable or function names, databases, data types, environment variables, statements, and keywords.

`Constant width bold`
: Shows commands or other text that should be typed literally by the user.

`Constant width italic`
: Shows text that should be replaced with user-supplied values or by values determined by context.

This icon signifies a tip, suggestion, or general note.



This icon indicates a warning or caution.

Using Code Examples

This book is here to help you get your job done. In general, you may use the code in this book in your programs and documentation. You do not need to contact us for permission unless you're reproducing a significant portion of the code. For example, writing a program that uses several chunks of code from this book does not require permission. Selling or distributing a CD-ROM of examples from O'Reilly books does require permission. Answering a question by citing this book and quoting example code does not require permission. Incorporating a significant amount of example code from this book into your product's documentation does require permission.

We appreciate, but do not require, attribution. An attribution usually includes the title, author, publisher, and ISBN. For example: "*Python for Data Analysis* by William Wesley McKinney (O'Reilly). Copyright 2012 William McKinney, 978-1-449-31979-3."

If you feel your use of code examples falls outside fair use or the permission given above, feel free to contact us at *permissions@oreilly.com*.

Safari® Books Online

Safari Books Online (*www.safaribooksonline.com*) is an on-demand digital library that delivers expert content in both book and video form from the world's leading authors in technology and business.

Technology professionals, software developers, web designers, and business and creative professionals use Safari Books Online as their primary resource for research, problem solving, learning, and certification training.

Safari Books Online offers a range of product mixes and pricing programs for organizations, government agencies, and individuals. Subscribers have access to thousands of books, training videos, and prepublication manuscripts in one fully searchable database from publishers like O'Reilly Media, Prentice Hall Professional, Addison-Wesley Professional, Microsoft Press, Sams, Que, Peachpit Press, Focal Press, Cisco Press, John Wiley & Sons, Syngress, Morgan Kaufmann, IBM Redbooks, Packt, Adobe Press, FT Press, Apress, Manning, New Riders, McGraw-Hill, Jones & Bartlett, Course Technology, and dozens more. For more information about Safari Books Online, please visit us online.

How to Contact Us

Please address comments and questions concerning this book to the publisher:

O'Reilly Media, Inc.
1005 Gravenstein Highway North
Sebastopol, CA 95472
800-998-9938 (in the United States or Canada)
707-829-0515 (international or local)
707-829-0104 (fax)

We have a web page for this book, where we list errata, examples, and any additional information. You can access this page at *http://oreil.ly/python_for_data_analysis*.

To comment or ask technical questions about this book, send email to *bookquestions@oreilly.com*.

For more information about our books, courses, conferences, and news, see our website at *http://www.oreilly.com*.

Find us on Facebook: *http://facebook.com/oreilly*

Follow us on Twitter: *http://twitter.com/oreillymedia*

Watch us on YouTube: *http://www.youtube.com/oreillymedia*

CHAPTER 1
Preliminaries

What Is This Book About?

This book is concerned with the nuts and bolts of manipulating, processing, cleaning, and crunching data in Python. It is also a practical, modern introduction to scientific computing in Python, tailored for data-intensive applications. This is a book about the parts of the Python language and libraries you'll need to effectively solve a broad set of data analysis problems. This book is *not* an exposition on analytical methods using Python as the implementation language.

When I say "data", what am I referring to exactly? The primary focus is on *structured data*, a deliberately vague term that encompasses many different common forms of data, such as

- Multidimensional arrays (matrices)
- Tabular or spreadsheet-like data in which each column may be a different type (string, numeric, date, or otherwise). This includes most kinds of data commonly stored in relational databases or tab- or comma-delimited text files
- Multiple tables of data interrelated by key columns (what would be primary or foreign keys for a SQL user)
- Evenly or unevenly spaced time series

This is by no means a complete list. Even though it may not always be obvious, a large percentage of data sets can be transformed into a structured form that is more suitable for analysis and modeling. If not, it may be possible to extract features from a data set into a structured form. As an example, a collection of news articles could be processed into a word frequency table which could then be used to perform sentiment analysis.

Most users of spreadsheet programs like Microsoft Excel, perhaps the most widely used data analysis tool in the world, will not be strangers to these kinds of data.

Why Python for Data Analysis?

For many people (myself among them), the Python language is easy to fall in love with. Since its first appearance in 1991, Python has become one of the most popular dynamic, programming languages, along with Perl, Ruby, and others. Python and Ruby have become especially popular in recent years for building websites using their numerous web frameworks, like Rails (Ruby) and Django (Python). Such languages are often called *scripting* languages as they can be used to write quick-and-dirty small programs, or *scripts*. I don't like the term "scripting language" as it carries a connotation that they cannot be used for building mission-critical software. Among interpreted languages Python is distinguished by its large and active *scientific computing* community. Adoption of Python for scientific computing in both industry applications and academic research has increased significantly since the early 2000s.

For data analysis and interactive, exploratory computing and data visualization, Python will inevitably draw comparisons with the many other domain-specific open source and commercial programming languages and tools in wide use, such as R, MATLAB, SAS, Stata, and others. In recent years, Python's improved library support (primarily pandas) has made it a strong alternative for data manipulation tasks. Combined with Python's strength in general purpose programming, it is an excellent choice as a single language for building data-centric applications.

Python as Glue

Part of Python's success as a scientific computing platform is the ease of integrating C, C++, and FORTRAN code. Most modern computing environments share a similar set of legacy FORTRAN and C libraries for doing linear algebra, optimization, integration, fast fourier transforms, and other such algorithms. The same story has held true for many companies and national labs that have used Python to glue together 30 years' worth of legacy software.

Most programs consist of small portions of code where most of the time is spent, with large amounts of "glue code" that doesn't run often. In many cases, the execution time of the glue code is insignificant; effort is most fruitfully invested in optimizing the computational bottlenecks, sometimes by moving the code to a lower-level language like C.

In the last few years, the Cython project (*http://cython.org*) has become one of the preferred ways of both creating fast compiled extensions for Python and also interfacing with C and C++ code.

Solving the "Two-Language" Problem

In many organizations, it is common to research, prototype, and test new ideas using a more domain-specific computing language like MATLAB or R then later port those

ideas to be part of a larger production system written in, say, Java, C#, or C++. What people are increasingly finding is that Python is a suitable language not only for doing research and prototyping but also building the production systems, too. I believe that more and more companies will go down this path as there are often significant organizational benefits to having both scientists and technologists using the same set of programmatic tools.

Why Not Python?

While Python is an excellent environment for building computationally-intensive scientific applications and building most kinds of general purpose systems, there are a number of uses for which Python may be less suitable.

As Python is an interpreted programming language, in general most Python code will run substantially slower than code written in a compiled language like Java or C++. As *programmer time* is typically more valuable than *CPU time*, many are happy to make this tradeoff. However, in an application with very low latency requirements (for example, a high frequency trading system), the time spent programming in a lower-level, lower-productivity language like C++ to achieve the maximum possible performance might be time well spent.

Python is not an ideal language for highly concurrent, multithreaded applications, particularly applications with many CPU-bound threads. The reason for this is that it has what is known as the *global interpreter lock* (GIL), a mechanism which prevents the interpreter from executing more than one Python bytecode instruction at a time. The technical reasons for why the GIL exists are beyond the scope of this book, but as of this writing it does not seem likely that the GIL will disappear anytime soon. While it is true that in many big data processing applications, a cluster of computers may be required to process a data set in a reasonable amount of time, there are still situations where a single-process, multithreaded system is desirable.

This is not to say that Python cannot execute truly multithreaded, parallel code; that code just cannot be executed in a single Python process. As an example, the Cython project features easy integration with OpenMP, a C framework for parallel computing, in order to to parallelize loops and thus significantly speed up numerical algorithms.

Essential Python Libraries

For those who are less familiar with the scientific Python ecosystem and the libraries used throughout the book, I present the following overview of each library.

NumPy

NumPy, short for Numerical Python, is the foundational package for scientific computing in Python. The majority of this book will be based on NumPy and libraries built on top of NumPy. It provides, among other things:

- A fast and efficient multidimensional array object *ndarray*
- Functions for performing element-wise computations with arrays or mathematical operations between arrays
- Tools for reading and writing array-based data sets to disk
- Linear algebra operations, Fourier transform, and random number generation
- Tools for integrating connecting C, C++, and Fortran code to Python

Beyond the fast array-processing capabilities that NumPy adds to Python, one of its primary purposes with regards to data analysis is as the primary container for data to be passed between algorithms. For numerical data, NumPy arrays are a much more efficient way of storing and manipulating data than the other built-in Python data structures. Also, libraries written in a lower-level language, such as C or Fortran, can operate on the data stored in a NumPy array without copying any data.

pandas

pandas provides rich data structures and functions designed to make working with structured data fast, easy, and expressive. It is, as you will see, one of the critical ingredients enabling Python to be a powerful and productive data analysis environment. The primary object in pandas that will be used in this book is the `DataFrame`, a two-dimensional tabular, column-oriented data structure with both row and column labels:

```
>>> frame
    total_bill  tip   sex     smoker  day  time    size
1   16.99       1.01  Female  No      Sun  Dinner  2
2   10.34       1.66  Male    No      Sun  Dinner  3
3   21.01       3.5   Male    No      Sun  Dinner  3
4   23.68       3.31  Male    No      Sun  Dinner  2
5   24.59       3.61  Female  No      Sun  Dinner  4
6   25.29       4.71  Male    No      Sun  Dinner  4
7   8.77        2     Male    No      Sun  Dinner  2
8   26.88       3.12  Male    No      Sun  Dinner  4
9   15.04       1.96  Male    No      Sun  Dinner  2
10  14.78       3.23  Male    No      Sun  Dinner  2
```

pandas combines the high performance array-computing features of NumPy with the flexible data manipulation capabilities of spreadsheets and relational databases (such as SQL). It provides sophisticated indexing functionality to make it easy to reshape, slice and dice, perform aggregations, and select subsets of data. pandas is the primary tool that we will use in this book.

For financial users, pandas features rich, high-performance time series functionality and tools well-suited for working with financial data. In fact, I initially designed pandas as an ideal tool for financial data analysis applications.

For users of the R language for statistical computing, the DataFrame name will be familiar, as the object was named after the similar R `data.frame` object. They are not the same, however; the functionality provided by `data.frame` in R is essentially a strict subset of that provided by the pandas `DataFrame`. While this is a book about Python, I will occasionally draw comparisons with R as it is one of the most widely-used open source data analysis environments and will be familiar to many readers.

The pandas name itself is derived from *panel data*, an econometrics term for multidimensional structured data sets, and *Python data analysis* itself.

matplotlib

matplotlib is the most popular Python library for producing plots and other 2D data visualizations. It was originally created by John D. Hunter (JDH) and is now maintained by a large team of developers. It is well-suited for creating plots suitable for publication. It integrates well with IPython (see below), thus providing a comfortable interactive environment for plotting and exploring data. The plots are also *interactive*; you can zoom in on a section of the plot and pan around the plot using the toolbar in the plot window.

IPython

IPython is the component in the standard scientific Python toolset that ties everything together. It provides a robust and productive environment for interactive and exploratory computing. It is an enhanced Python shell designed to accelerate the writing, testing, and debugging of Python code. It is particularly useful for interactively working with data and visualizing data with matplotlib. IPython is usually involved with the majority of my Python work, including running, debugging, and testing code.

Aside from the standard terminal-based IPython shell, the project also provides

- A Mathematica-like HTML notebook for connecting to IPython through a web browser (more on this later).
- A Qt framework-based GUI console with inline plotting, multiline editing, and syntax highlighting
- An infrastructure for interactive parallel and distributed computing

I will devote a chapter to IPython and how to get the most out of its features. I strongly recommend using it while working through this book.

SciPy

SciPy is a collection of packages addressing a number of different standard problem domains in scientific computing. Here is a sampling of the packages included:

- `scipy.integrate`: numerical integration routines and differential equation solvers
- `scipy.linalg`: linear algebra routines and matrix decompositions extending beyond those provided in `numpy.linalg`.
- `scipy.optimize`: function optimizers (minimizers) and root finding algorithms
- `scipy.signal`: signal processing tools
- `scipy.sparse`: sparse matrices and sparse linear system solvers
- `scipy.special`: wrapper around SPECFUN, a Fortran library implementing many common mathematical functions, such as the gamma function
- `scipy.stats`: standard continuous and discrete probability distributions (density functions, samplers, continuous distribution functions), various statistical tests, and more descriptive statistics
- `scipy.weave`: tool for using inline C++ code to accelerate array computations

Together NumPy and SciPy form a reasonably complete computational replacement for much of MATLAB along with some of its add-on toolboxes.

Installation and Setup

Since everyone uses Python for different applications, there is no single solution for setting up Python and required add-on packages. Many readers will not have a complete scientific Python environment suitable for following along with this book, so here I will give detailed instructions to get set up on each operating system. I recommend using one of the following base Python distributions:

- Enthought Python Distribution: a scientific-oriented Python distribution from Enthought (*http://www.enthought.com*). This includes EPDFree, a free base scientific distribution (with NumPy, SciPy, matplotlib, Chaco, and IPython) and EPD Full, a comprehensive suite of more than 100 scientific packages across many domains. EPD Full is free for academic use but has an annual subscription for non-academic users.
- Python(x,y) (*http://pythonxy.googlecode.com*): A free scientific-oriented Python distribution for Windows.

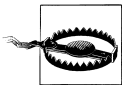
I will be using EPDFree for the installation guides, though you are welcome to take another approach depending on your needs. At the time of this writing, EPD includes Python 2.7, though this might change at some point in the future. After installing, you will have the following packages installed and importable:

- Scientific Python base: NumPy, SciPy, matplotlib, and IPython. These are all included in EPDFree.
- IPython Notebook dependencies: tornado and pyzmq. These are included in EPDFree.
- pandas (version 0.8.2 or higher).

At some point while reading you may wish to install one or more of the following packages: statsmodels, PyTables, PyQt (or equivalently, PySide), xlrd, lxml, basemap, pymongo, and requests. These are used in various examples. Installing these optional libraries is not necessary, and I would would suggest waiting until you need them. For example, installing PyQt or PyTables from source on OS X or Linux can be rather arduous. For now, it's most important to get up and running with the bare minimum: EPDFree and pandas.

For information on each Python package and links to binary installers or other help, see the Python Package Index (PyPI, *http://pypi.python.org*). This is also an excellent resource for finding new Python packages.

To avoid confusion and to keep things simple, I am avoiding discussion of more complex environment management tools like pip and virtualenv. There are many excellent guides available for these tools on the Internet.



Some users may be interested in alternate Python implementations, such as IronPython, Jython, or PyPy. To make use of the tools presented in this book, it is (currently) necessary to use the standard C-based Python interpreter, known as CPython.

Windows

To get started on Windows, download the EPDFree installer from *http://www.enthought.com*, which should be an MSI installer named like `epd_free-7.3-1-win-x86.msi`. Run the installer and accept the default installation location `C:\Python27`. If you had previously installed Python in this location, you may want to delete it manually first (or using Add/Remove Programs).

Next, you need to verify that Python has been successfully added to the system path and that there are no conflicts with any prior-installed Python versions. First, open a command prompt by going to the Start Menu and starting the Command Prompt application, also known as `cmd.exe`. Try starting the Python interpreter by typing `python`. You should see a message that matches the version of EPDFree you installed:

```
C:\Users\Wes>python
Python 2.7.3 |EPD_free 7.3-1 (32-bit)| (default, Apr 12 2012, 14:30:37) on win32
Type "credits", "demo" or "enthought" for more information.
>>>
```

If you see a message for a different version of EPD or it doesn't work at all, you will need to clean up your Windows environment variables. On Windows 7 you can start typing "environment variables" in the programs search field and select `Edit environment variables for your account`. On Windows XP, you will have to go to `Control Panel > System > Advanced > Environment Variables`. On the window that pops up, you are looking for the `Path` variable. It needs to contain the following two directory paths, separated by semicolons:

```
C:\Python27;C:\Python27\Scripts
```

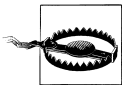
If you installed other versions of Python, be sure to delete any other Python-related directories from both the system and user `Path` variables. After making a path alternation, you have to restart the command prompt for the changes to take effect.

Once you can launch Python successfully from the command prompt, you need to install pandas. The easiest way is to download the appropriate binary installer from *http://pypi.python.org/pypi/pandas*. For EPDFree, this should be `pandas-0.9.0.win32-py2.7.exe`. After you run this, let's launch IPython and check that things are installed correctly by importing pandas and making a simple matplotlib plot:

```
C:\Users\Wes>ipython --pylab
Python 2.7.3 |EPD_free 7.3-1 (32-bit)|
Type "copyright", "credits" or "license" for more information.

IPython 0.12.1 -- An enhanced Interactive Python.
?         -> Introduction and overview of IPython's features.
%quickref -> Quick reference.
help      -> Python's own help system.
object?   -> Details about 'object', use 'object??' for extra details.

Welcome to pylab, a matplotlib-based Python environment [backend: WXAgg].
For more information, type 'help(pylab)'.

In [1]: import pandas

In [2]: plot(arange(10))
```

If successful, there should be no error messages and a plot window will appear. You can also check that the IPython HTML notebook can be successfully run by typing:

```
$ ipython notebook --pylab=inline
```



If you use the IPython notebook application on Windows and normally use Internet Explorer, you will likely need to install and run Mozilla Firefox or Google Chrome instead.

EPDFree on Windows contains only 32-bit executables. If you want or need a 64-bit setup on Windows, using EPD Full is the most painless way to accomplish that. If you would rather install from scratch and not pay for an EPD subscription, Christoph Gohlke at the University of California, Irvine, publishes unofficial binary installers for

all of the book's necessary packages (*http://www.lfd.uci.edu/~gohlke/pythonlibs/*) for 32- and 64-bit Windows.

Apple OS X

To get started on OS X, you must first install Xcode, which includes Apple's suite of software development tools. The necessary component for our purposes is the gcc C and C++ compiler suite. The Xcode installer can be found on the OS X install DVD that came with your computer or downloaded from Apple directly.

Once you've installed Xcode, launch the terminal (Terminal.app) by navigating to `Applications > Utilities`. Type `gcc` and press enter. You should hopefully see something like:

```
$ gcc
i686-apple-darwin10-gcc-4.2.1: no input files
```

Now you need to install EPDFree. Download the installer which should be a disk image named something like `epd_free-7.3-1-macosx-i386.dmg`. Double-click the `.dmg` file to mount it, then double-click the `.mpkg` file inside to run the installer.

When the installer runs, it automatically appends the EPDFree executable path to your `.bash_profile` file. This is located at `/Users/your_uname/.bash_profile`:

```
# Setting PATH for EPD_free-7.3-1
PATH="/Library/Frameworks/Python.framework/Versions/Current/bin:${PATH}"
export PATH
```

Should you encounter any problems in the following steps, you'll want to inspect your `.bash_profile` and potentially add the above directory to your path.

Now, it's time to install pandas. Execute this command in the terminal:

```
$ sudo easy_install pandas
Searching for pandas
Reading http://pypi.python.org/simple/pandas/
Reading http://pandas.pydata.org
Reading http://pandas.sourceforge.net
Best match: pandas 0.9.0
Downloading http://pypi.python.org/packages/source/p/pandas/pandas-0.9.0.zip
Processing pandas-0.9.0.zip
Writing /tmp/easy_install-H5mIX6/pandas-0.9.0/setup.cfg
Running pandas-0.9.0/setup.py -q bdist_egg --dist-dir /tmp/easy_install-H5mIX6/
pandas-0.9.0/egg-dist-tmp-RhLG0z
Adding pandas 0.9.0 to easy-install.pth file

Installed /Library/Frameworks/Python.framework/Versions/7.3/lib/python2.7/
site-packages/pandas-0.9.0-py2.7-macosx-10.5-i386.egg
Processing dependencies for pandas
Finished processing dependencies for pandas
```

To verify everything is working, launch IPython in Pylab mode and test importing pandas then making a plot interactively:

```
$ ipython --pylab
22:29 ~/VirtualBox VMs/WindowsXP $ ipython
Python 2.7.3 |EPD_free 7.3-1 (32-bit)| (default, Apr 12 2012, 11:28:34)
Type "copyright", "credits" or "license" for more information.

IPython 0.12.1 -- An enhanced Interactive Python.
?         -> Introduction and overview of IPython's features.
%quickref -> Quick reference.
help      -> Python's own help system.
object?   -> Details about 'object', use 'object??' for extra details.

Welcome to pylab, a matplotlib-based Python environment [backend: WXAgg].
For more information, type 'help(pylab)'.

In [1]: import pandas

In [2]: plot(arange(10))
```

If this succeeds, a plot window with a straight line should pop up.

GNU/Linux

Some, but not all, Linux distributions include sufficiently up-to-date versions of all the required Python packages and can be installed using the built-in package management tool like `apt`. I detail setup using EPD-Free as it's easily reproducible across distributions.

Linux details will vary a bit depending on your Linux flavor, but here I give details for Debian-based GNU/Linux systems like Ubuntu and Mint. Setup is similar to OS X with the exception of how EPDFree is installed. The installer is a shell script that must be executed in the terminal. Depending on whether you have a 32-bit or 64-bit system, you will either need to install the `x86` (32-bit) or `x86_64` (64-bit) installer. You will then have a file named something similar to `epd_free-7.3-1-rh5-x86_64.sh`. To install it, execute this script with bash:

```
$ bash epd_free-7.3-1-rh5-x86_64.sh
```

After accepting the license, you will be presented with a choice of where to put the EPDFree files. I recommend installing the files in your home directory, say `/home/wesm/epd` (substituting your own username for `wesm`).

Once the installer has finished, you need to add EPDFree's `bin` directory to your `$PATH` variable. If you are using the bash shell (the default in Ubuntu, for example), this means adding the following path addition in your `.bashrc`:

```
export PATH=/home/wesm/epd/bin:$PATH
```

Obviously, substitute the installation directory you used for `/home/wesm/epd/`. After doing this you can either start a new terminal process or execute your `.bashrc` again with `source ~/.bashrc`.

You need a C compiler such as gcc to move forward; many Linux distributions include gcc, but others may not. On Debian systems, you can install gcc by executing:

```
sudo apt-get install gcc
```

If you type `gcc` on the command line it should say something like:

```
$ gcc
gcc: no input files
```

Now, time to install pandas:

```
$ easy_install pandas
```

If you installed EPDFree as root, you may need to add `sudo` to the command and enter the sudo or root password. To verify things are working, perform the same checks as in the OS X section.

Python 2 and Python 3

The Python community is currently undergoing a drawn-out transition from the Python 2 series of interpreters to the Python 3 series. Until the appearance of Python 3.0, all Python code was backwards compatible. The community decided that in order to move the language forward, certain backwards incompatible changes were necessary.

I am writing this book with Python 2.7 as its basis, as the majority of the scientific Python community has not yet transitioned to Python 3. The good news is that, with a few exceptions, you should have no trouble following along with the book if you happen to be using Python 3.2.

Integrated Development Environments (IDEs)

When asked about my standard development environment, I almost always say "IPython plus a text editor". I typically write a program and iteratively test and debug each piece of it in IPython. It is also useful to be able to play around with data interactively and visually verify that a particular set of data manipulations are doing the right thing. Libraries like pandas and NumPy are designed to be easy-to-use in the shell.

However, some will still prefer to work in an IDE instead of a text editor. They do provide many nice "code intelligence" features like completion or quickly pulling up the documentation associated with functions and classes. Here are some that you can explore:

- Eclipse with PyDev Plugin
- Python Tools for Visual Studio (for Windows users)
- PyCharm
- Spyder
- Komodo IDE

Community and Conferences

Outside of an Internet search, the scientific Python mailing lists are generally helpful and responsive to questions. Some ones to take a look at are:

- pydata: a Google Group list for questions related to Python for data analysis and pandas
- pystatsmodels: for statsmodels or pandas-related questions
- numpy-discussion: for NumPy-related questions
- scipy-user: for general SciPy or scientific Python questions

I deliberately did not post URLs for these in case they change. They can be easily located via Internet search.

Each year many conferences are held all over the world for Python programmers. PyCon and EuroPython are the two main general Python conferences in the United States and Europe, respectively. SciPy and EuroSciPy are scientific-oriented Python conferences where you will likely find many "birds of a feather" if you become more involved with using Python for data analysis after reading this book.

Navigating This Book

If you have never programmed in Python before, you may actually want to start at the *end* of the book, where I have placed a condensed tutorial on Python syntax, language features, and built-in data structures like tuples, lists, and dicts. These things are considered prerequisite knowledge for the remainder of the book.

The book starts by introducing you to the IPython environment. Next, I give a short introduction to the key features of NumPy, leaving more advanced NumPy use for another chapter at the end of the book. Then, I introduce pandas and devote the rest of the book to data analysis topics applying pandas, NumPy, and matplotlib (for visualization). I have structured the material in the most incremental way possible, though there is occasionally some minor cross-over between chapters.

Data files and related material for each chapter are hosted as a git repository on GitHub:

```
http://github.com/pydata/pydata-book
```

I encourage you to download the data and use it to replicate the book's code examples and experiment with the tools presented in each chapter. I will happily accept contributions, scripts, IPython notebooks, or any other materials you wish to contribute to the book's repository for all to enjoy.

Code Examples

Most of the code examples in the book are shown with input and output as it would appear executed in the IPython shell.

```
In [5]: code
Out[5]: output
```

At times, for clarity, multiple code examples will be shown side by side. These should be read left to right and executed separately.

```
In [5]: code          In [6]: code2
Out[5]: output        Out[6]: output2
```

Data for Examples

Data sets for the examples in each chapter are hosted in a repository on GitHub: *http://github.com/pydata/pydata-book*. You can download this data either by using the git revision control command-line program or by downloading a zip file of the repository from the website.

I have made every effort to ensure that it contains everything necessary to reproduce the examples, but I may have made some mistakes or omissions. If so, please send me an e-mail: `wesmckinn@gmail.com`.

Import Conventions

The Python community has adopted a number of naming conventions for commonly-used modules:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

This means that when you see `np.arange`, this is a reference to the `arange` function in NumPy. This is done as it's considered bad practice in Python software development to import everything (`from numpy import *`) from a large package like NumPy.

Jargon

I'll use some terms common both to programming and data science that you may not be familiar with. Thus, here are some brief definitions:

Munge/Munging/Wrangling
: Describes the overall process of manipulating unstructured and/or messy data into a structured or clean form. The word has snuck its way into the jargon of many modern day data hackers. Munge rhymes with "lunge".

Pseudocode
: A description of an algorithm or process that takes a code-like form while likely not being actual valid source code.

Syntactic sugar
: Programming syntax which does not add new features, but makes something more convenient or easier to type.

Acknowledgements

It would have been difficult for me to write this book without the support of a large number of people.

On the O'Reilly staff, I'm very grateful for my editors Meghan Blanchette and Julie Steele who guided me through the process. Mike Loukides also worked with me in the proposal stages and helped make the book a reality.

I received a wealth of technical review from a large cast of characters. In particular, Martin Blais and Hugh White were incredibly helpful in improving the book's examples, clarity, and organization from cover to cover. James Long, Drew Conway, Fernando Pérez, Brian Granger, Thomas Kluyver, Adam Klein, Josh Klein, Chang She, and Stéfan van der Walt each reviewed one or more chapters, providing pointed feedback from many different perspectives.

I got many great ideas for examples and data sets from friends and colleagues in the data community, among them: Mike Dewar, Jeff Hammerbacher, James Johndrow, Kristian Lum, Adam Klein, Hilary Mason, Chang She, and Ashley Williams.

I am of course indebted to the many leaders in the open source scientific Python community who've built the foundation for my development work and gave encouragement while I was writing this book: the IPython core team (Fernando Pérez, Brian Granger, Min Ragan-Kelly, Thomas Kluyver, and others), John Hunter, Skipper Seabold, Travis Oliphant, Peter Wang, Eric Jones, Robert Kern, Josef Perktold, Francesc Alted, Chris Fonnesbeck, and too many others to mention. Several other people provided a great deal of support, ideas, and encouragement along the way: Drew Conway, Sean Taylor, Giuseppe Paleologo, Jared Lander, David Epstein, John Krowas, Joshua Bloom, Den Pilsworth, John Myles-White, and many others I've forgotten.

I'd also like to thank a number of people from my formative years. First, my former AQR colleagues who've cheered me on in my pandas work over the years: Alex Reyfman, Michael Wong, Tim Sargen, Oktay Kurbanov, Matthew Tschantz, Roni Israelov, Michael Katz, Chris Uga, Prasad Ramanan, Ted Square, and Hoon Kim. Lastly, my academic advisors Haynes Miller (MIT) and Mike West (Duke).

On the personal side, Casey Dinkin provided invaluable day-to-day support during the writing process, tolerating my highs and lows as I hacked together the final draft on

top of an already overcommitted schedule. Lastly, my parents, Bill and Kim, taught me to always follow my dreams and to never settle for less.

CHAPTER 2

Introductory Examples

This book teaches you the Python tools to work productively with data. While readers may have many different end goals for their work, the tasks required generally fall into a number of different broad groups:

Interacting with the outside world
: Reading and writing with a variety of file formats and databases.

Preparation
: Cleaning, munging, combining, normalizing, reshaping, slicing and dicing, and transforming data for analysis.

Transformation
: Applying mathematical and statistical operations to groups of data sets to derive new data sets. For example, aggregating a large table by group variables.

Modeling and computation
: Connecting your data to statistical models, machine learning algorithms, or other computational tools

Presentation
: Creating interactive or static graphical visualizations or textual summaries

In this chapter I will show you a few data sets and some things we can do with them. These examples are just intended to pique your interest and thus will only be explained at a high level. Don't worry if you have no experience with any of these tools; they will be discussed in great detail throughout the rest of the book. In the code examples you'll see input and output prompts like `In [15]:`; these are from the IPython shell.

1.usa.gov data from bit.ly

In 2011, URL shortening service bit.ly partnered with the United States government website `usa.gov` to provide a feed of anonymous data gathered from users who shorten links ending with `.gov` or `.mil`. As of this writing, in addition to providing a live feed, hourly snapshots are available as downloadable text files.[1]

In the case of the hourly snapshots, each line in each file contains a common form of web data known as JSON, which stands for JavaScript Object Notation. For example, if we read just the first line of a file you may see something like

```
In [15]: path = 'ch02/usagov_bitly_data2012-03-16-1331923249.txt'

In [16]: open(path).readline()
Out[16]: '{ "a": "Mozilla\\/5.0 (Windows NT 6.1; WOW64) AppleWebKit\\/535.11
(KHTML, like Gecko) Chrome\\/17.0.963.78 Safari\\/535.11", "c": "US", "nk": 1,
"tz": "America\\/New_York", "gr": "MA", "g": "A6qOVH", "h": "wfLQtf", "l":
"orofrog", "al": "en-US,en;q=0.8", "hh": "1.usa.gov", "r":
"http:\\/\\/www.facebook.com\\/l\\/7AQEFzjSi\\/1.usa.gov\\/wfLQtf", "u":
"http:\\/\\/www.ncbi.nlm.nih.gov\\/pubmed\\/22415991", "t": 1331923247, "hc":
1331822918, "cy": "Danvers", "ll": [ 42.576698, -70.954903 ] }\n'
```

Python has numerous built-in and 3rd party modules for converting a JSON string into a Python dictionary object. Here I'll use the `json` module and its `loads` function invoked on each line in the sample file I downloaded:

```
import json
path = 'ch02/usagov_bitly_data2012-03-16-1331923249.txt'
records = [json.loads(line) for line in open(path)]
```

If you've never programmed in Python before, the last expression here is called a *list comprehension*, which is a concise way of applying an operation (like `json.loads`) to a collection of strings or other objects. Conveniently, iterating over an open file handle gives you a sequence of its lines. The resulting object `records` is now a list of Python dicts:

```
In [18]: records[0]
Out[18]:
{u'a': u'Mozilla/5.0 (Windows NT 6.1; WOW64) AppleWebKit/535.11 (KHTML, like
Gecko) Chrome/17.0.963.78 Safari/535.11',
 u'al': u'en-US,en;q=0.8',
 u'c': u'US',
 u'cy': u'Danvers',
 u'g': u'A6qOVH',
 u'gr': u'MA',
 u'h': u'wfLQtf',
 u'hc': 1331822918,
 u'hh': u'1.usa.gov',
 u'l': u'orofrog',
 u'll': [42.576698, -70.954903],
 u'nk': 1,
 u'r': u'http://www.facebook.com/l/7AQEFzjSi/1.usa.gov/wfLQtf',
 u't': 1331923247,
 u'tz': u'America/New_York',
 u'u': u'http://www.ncbi.nlm.nih.gov/pubmed/22415991'}
```

1. *http://www.usa.gov/About/developer-resources/1usagov.shtml*

Note that Python indices start at 0 and not 1 like some other languages (like R). It's now easy to access individual values within records by passing a string for the key you wish to access:

```
In [19]: records[0]['tz']
Out[19]: u'America/New_York'
```

The `u` here in front of the quotation stands for *unicode*, a standard form of string encoding. Note that IPython shows the time zone string object *representation* here rather than its print equivalent:

```
In [20]: print records[0]['tz']
America/New_York
```

Counting Time Zones in Pure Python

Suppose we were interested in the most often-occurring time zones in the data set (the `tz` field). There are many ways we could do this. First, let's extract a list of time zones again using a list comprehension:

```
In [25]: time_zones = [rec['tz'] for rec in records]
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
/home/wesm/book_scripts/whetting/<ipython> in <module>()
----> 1 time_zones = [rec['tz'] for rec in records]

KeyError: 'tz'
```

Oops! Turns out that not all of the records have a time zone field. This is easy to handle as we can add the check `if 'tz' in rec` at the end of the list comprehension:

```
In [26]: time_zones = [rec['tz'] for rec in records if 'tz' in rec]

In [27]: time_zones[:10]
Out[27]:
[u'America/New_York',
 u'America/Denver',
 u'America/New_York',
 u'America/Sao_Paulo',
 u'America/New_York',
 u'America/New_York',
 u'Europe/Warsaw',
 u'',
 u'',
 u'']
```

Just looking at the first 10 time zones we see that some of them are unknown (empty). You can filter these out also but I'll leave them in for now. Now, to produce counts by time zone I'll show two approaches: the harder way (using just the Python standard library) and the easier way (using pandas). One way to do the counting is to use a dict to store counts while we iterate through the time zones:

```
def get_counts(sequence):
    counts = {}
```

```
    for x in sequence:
        if x in counts:
            counts[x] += 1
        else:
            counts[x] = 1
    return counts
```

If you know a bit more about the Python standard library, you might prefer to write the same thing more briefly:

```
from collections import defaultdict

def get_counts2(sequence):
    counts = defaultdict(int) # values will initialize to 0
    for x in sequence:
        counts[x] += 1
    return counts
```

I put this logic in a function just to make it more reusable. To use it on the time zones, just pass the `time_zones` list:

```
In [31]: counts = get_counts(time_zones)

In [32]: counts['America/New_York']
Out[32]: 1251

In [33]: len(time_zones)
Out[33]: 3440
```

If we wanted the top 10 time zones and their counts, we have to do a little bit of dictionary acrobatics:

```
def top_counts(count_dict, n=10):
    value_key_pairs = [(count, tz) for tz, count in count_dict.items()]
    value_key_pairs.sort()
    return value_key_pairs[-n:]
```

We have then:

```
In [35]: top_counts(counts)
Out[35]:
[(33, u'America/Sao_Paulo'),
 (35, u'Europe/Madrid'),
 (36, u'Pacific/Honolulu'),
 (37, u'Asia/Tokyo'),
 (74, u'Europe/London'),
 (191, u'America/Denver'),
 (382, u'America/Los_Angeles'),
 (400, u'America/Chicago'),
 (521, u''),
 (1251, u'America/New_York')]
```

If you search the Python standard library, you may find the `collections.Counter` class, which makes this task a lot easier:

```
In [49]: from collections import Counter

In [50]: counts = Counter(time_zones)

In [51]: counts.most_common(10)
Out[51]:
[(u'America/New_York', 1251),
 (u'', 521),
 (u'America/Chicago', 400),
 (u'America/Los_Angeles', 382),
 (u'America/Denver', 191),
 (u'Europe/London', 74),
 (u'Asia/Tokyo', 37),
 (u'Pacific/Honolulu', 36),
 (u'Europe/Madrid', 35),
 (u'America/Sao_Paulo', 33)]
```

Counting Time Zones with pandas

The main pandas data structure is the *DataFrame*, which you can think of as representing a table or spreadsheet of data. Creating a DataFrame from the original set of records is simple:

```
In [289]: from pandas import DataFrame, Series

In [290]: import pandas as pd

In [291]: frame = DataFrame(records)

In [292]: frame
Out[292]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3560 entries, 0 to 3559
Data columns:
_heartbeat_    120  non-null values
a              3440  non-null values
al             3094  non-null values
c              2919  non-null values
cy             2919  non-null values
g              3440  non-null values
gr             2919  non-null values
h              3440  non-null values
hc             3440  non-null values
hh             3440  non-null values
kw             93  non-null values
l              3440  non-null values
ll             2919  non-null values
nk             3440  non-null values
r              3440  non-null values
t              3440  non-null values
tz             3440  non-null values
```

```
u              3440  non-null values
dtypes: float64(4), object(14)

In [293]: frame['tz'][:10]
Out[293]:
0     America/New_York
1       America/Denver
2     America/New_York
3    America/Sao_Paulo
4     America/New_York
5     America/New_York
6        Europe/Warsaw
7
8
9
Name: tz
```

The output shown for the `frame` is the *summary view*, shown for large DataFrame objects. The Series object returned by `frame['tz']` has a method `value_counts` that gives us what we're looking for:

```
In [294]: tz_counts = frame['tz'].value_counts()

In [295]: tz_counts[:10]
Out[295]:
America/New_York       1251
                        521
America/Chicago         400
America/Los_Angeles     382
America/Denver          191
Europe/London            74
Asia/Tokyo               37
Pacific/Honolulu         36
Europe/Madrid            35
America/Sao_Paulo        33
```

Then, we might want to make a plot of this data using plotting library, matplotlib. You can do a bit of munging to fill in a substitute value for unknown and missing time zone data in the records. The `fillna` function can replace missing (NA) values and unknown (empty strings) values can be replaced by boolean array indexing:

```
In [296]: clean_tz = frame['tz'].fillna('Missing')

In [297]: clean_tz[clean_tz == ''] = 'Unknown'

In [298]: tz_counts = clean_tz.value_counts()

In [299]: tz_counts[:10]
Out[299]:
America/New_York       1251
Unknown                 521
America/Chicago         400
America/Los_Angeles     382
America/Denver          191
Missing                 120
```

```
Europe/London          74
Asia/Tokyo             37
Pacific/Honolulu       36
Europe/Madrid          35
```

Making a horizontal bar plot can be accomplished using the `plot` method on the `counts` objects:

```
In [301]: tz_counts[:10].plot(kind='barh', rot=0)
```

See Figure 2-1 for the resulting figure. We'll explore more tools for working with this kind of data. For example, the `a` field contains information about the browser, device, or application used to perform the URL shortening:

```
In [302]: frame['a'][1]
Out[302]: u'GoogleMaps/RochesterNY'

In [303]: frame['a'][50]
Out[303]: u'Mozilla/5.0 (Windows NT 5.1; rv:10.0.2) Gecko/20100101 Firefox/10.0.2'

In [304]: frame['a'][51]
Out[304]: u'Mozilla/5.0 (Linux; U; Android 2.2.2; en-us; LG-P925/V10e Build/FRG83G) AppleWebKit/533.1 (K
```

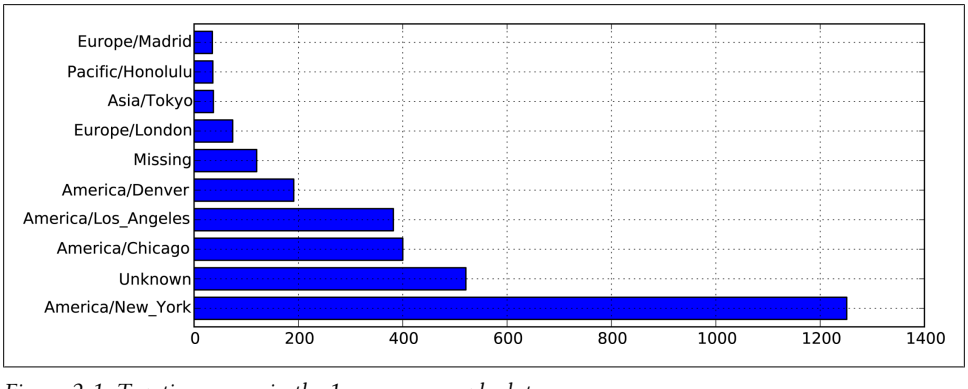


Figure 2-1. Top time zones in the 1.usa.gov sample data

Parsing all of the interesting information in these "agent" strings may seem like a daunting task. Luckily, once you have mastered Python's built-in string functions and regular expression capabilities, it is really not so bad. For example, we could split off the first token in the string (corresponding roughly to the browser capability) and make another summary of the user behavior:

```
In [305]: results = Series([x.split()[0] for x in frame.a.dropna()])

In [306]: results[:5]
Out[306]:
0               Mozilla/5.0
1    GoogleMaps/RochesterNY
2               Mozilla/4.0
3               Mozilla/5.0
4               Mozilla/5.0
```

```
In [307]: results.value_counts()[:8]
Out[307]:
Mozilla/5.0                 2594
Mozilla/4.0                  601
GoogleMaps/RochesterNY       121
Opera/9.80                    34
TEST_INTERNET_AGENT           24
GoogleProducer                21
Mozilla/6.0                    5
BlackBerry8520/5.0.0.681       4
```

Now, suppose you wanted to decompose the top time zones into Windows and non-Windows users. As a simplification, let's say that a user is on Windows if the string `'Windows'` is in the agent string. Since some of the agents are missing, I'll exclude these from the data:

```
In [308]: cframe = frame[frame.a.notnull()]
```

We want to then compute a value whether each row is Windows or not:

```
In [309]: operating_system = np.where(cframe['a'].str.contains('Windows'),
   .....:                             'Windows', 'Not Windows')

In [310]: operating_system[:5]
Out[310]:
0        Windows
1    Not Windows
2        Windows
3    Not Windows
4        Windows
Name: a
```

Then, you can group the data by its time zone column and this new list of operating systems:

```
In [311]: by_tz_os = cframe.groupby(['tz', operating_system])
```

The group counts, analogous to the `value_counts` function above, can be computed using `size`. This result is then reshaped into a table with `unstack`:

```
In [312]: agg_counts = by_tz_os.size().unstack().fillna(0)

In [313]: agg_counts[:10]
Out[313]:
a                               Not Windows  Windows
tz
                                        245      276
Africa/Cairo                              0        3
Africa/Casablanca                         0        1
Africa/Ceuta                              0        2
Africa/Johannesburg                       0        1
Africa/Lusaka                             0        1
America/Anchorage                         4        1
America/Argentina/Buenos_Aires            1        0
```

```
America/Argentina/Cordoba                0        1
America/Argentina/Mendoza                0        1
```

Finally, let's select the top overall time zones. To do so, I construct an indirect index array from the row counts in `agg_counts`:

```
# Use to sort in ascending order
In [314]: indexer = agg_counts.sum(1).argsort()

In [315]: indexer[:10]
Out[315]:
tz
                                  24
Africa/Cairo                      20
Africa/Casablanca                 21
Africa/Ceuta                      92
Africa/Johannesburg               87
Africa/Lusaka                     53
America/Anchorage                 54
America/Argentina/Buenos_Aires    57
America/Argentina/Cordoba         26
America/Argentina/Mendoza         55
```

I then use `take` to select the rows in that order, then slice off the last 10 rows:

```
In [316]: count_subset = agg_counts.take(indexer)[-10:]

In [317]: count_subset
Out[317]:
a                    Not Windows  Windows
tz
America/Sao_Paulo             13       20
Europe/Madrid                 16       19
Pacific/Honolulu               0       36
Asia/Tokyo                     2       35
Europe/London                 43       31
America/Denver               132       59
America/Los_Angeles          130      252
America/Chicago              115      285
                             245      276
America/New_York             339      912
```

Then, as shown in the preceding code block, this can be plotted in a bar plot; I'll make it a stacked bar plot by passing `stacked=True` (see Figure 2-2) :

```
In [319]: count_subset.plot(kind='barh', stacked=True)
```

The plot doesn't make it easy to see the relative percentage of Windows users in the smaller groups, but the rows can easily be normalized to sum to 1 then plotted again (see Figure 2-3):

```
In [321]: normed_subset = count_subset.div(count_subset.sum(1), axis=0)

In [322]: normed_subset.plot(kind='barh', stacked=True)
```

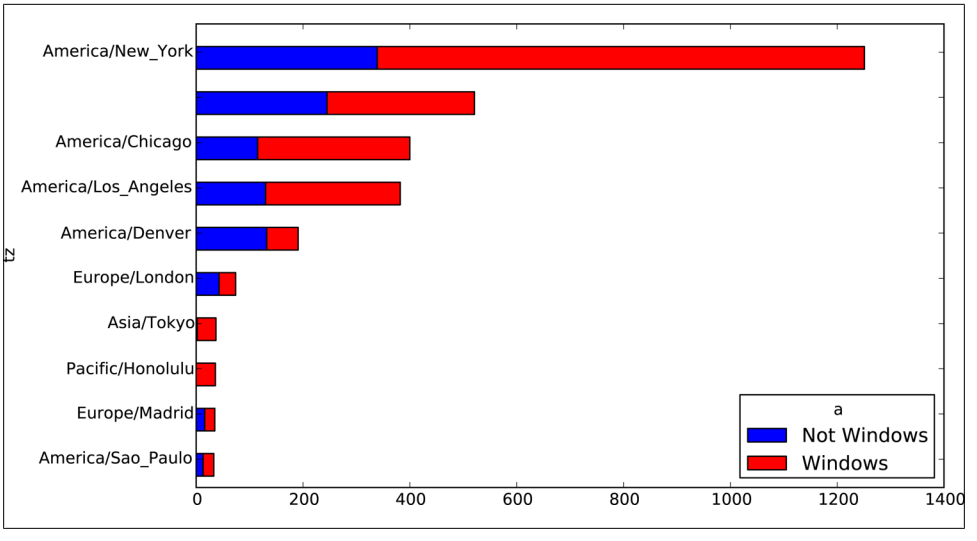


Figure 2-2. Top time zones by Windows and non-Windows users

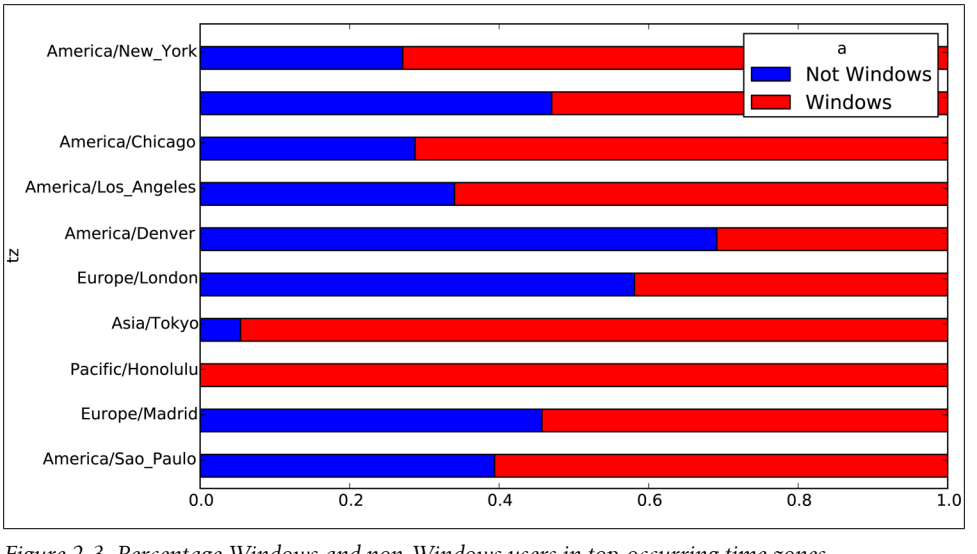


Figure 2-3. Percentage Windows and non-Windows users in top-occurring time zones

All of the methods employed here will be examined in great detail throughout the rest of the book.

MovieLens 1M Data Set

GroupLens Research (*http://www.grouplens.org/node/73*) provides a number of collections of movie ratings data collected from users of MovieLens in the late 1990s and

early 2000s. The data provide movie ratings, movie metadata (genres and year), and demographic data about the users (age, zip code, gender, and occupation). Such data is often of interest in the development of recommendation systems based on machine learning algorithms. While I will not be exploring machine learning techniques in great detail in this book, I will show you how to slice and dice data sets like these into the exact form you need.

The MovieLens 1M data set contains 1 million ratings collected from 6000 users on 4000 movies. It's spread across 3 tables: ratings, user information, and movie information. After extracting the data from the zip file, each table can be loaded into a pandas DataFrame object using `pandas.read_table`:

```
import pandas as pd

unames = ['user_id', 'gender', 'age', 'occupation', 'zip']
users = pd.read_table('ml-1m/users.dat', sep='::', header=None,
                      names=unames)

rnames = ['user_id', 'movie_id', 'rating', 'timestamp']
ratings = pd.read_table('ml-1m/ratings.dat', sep='::', header=None,
                        names=rnames)

mnames = ['movie_id', 'title', 'genres']
movies = pd.read_table('ml-1m/movies.dat', sep='::', header=None,
                        names=mnames)
```

You can verify that everything succeeded by looking at the first few rows of each DataFrame with Python's slice syntax:

```
In [334]: users[:5]
Out[334]:
   user_id gender  age  occupation    zip
0        1      F    1          10  48067
1        2      M   56          16  70072
2        3      M   25          15  55117
3        4      M   45           7  02460
4        5      M   25          20  55455

In [335]: ratings[:5]
Out[335]:
   user_id  movie_id  rating  timestamp
0        1      1193       5  978300760
1        1       661       3  978302109
2        1       914       3  978301968
3        1      3408       4  978300275
4        1      2355       5  978824291

In [336]: movies[:5]
Out[336]:
   movie_id                               title                        genres
0         1                    Toy Story (1995)   Animation|Children's|Comedy
1         2                      Jumanji (1995)  Adventure|Children's|Fantasy
2         3             Grumpier Old Men (1995)                Comedy|Romance
3         4            Waiting to Exhale (1995)                  Comedy|Drama
```

```
4         5  Father of the Bride Part II (1995)                    Comedy

In [337]: ratings
Out[337]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns:
user_id      1000209  non-null values
movie_id     1000209  non-null values
rating       1000209  non-null values
timestamp    1000209  non-null values
dtypes: int64(4)
```

Note that ages and occupations are coded as integers indicating groups described in the data set's `README` file. Analyzing the data spread across three tables is not a simple task; for example, suppose you wanted to compute mean ratings for a particular movie by sex and age. As you will see, this is much easier to do with all of the data merged together into a single table. Using pandas's `merge` function, we first merge `ratings` with `users` then merging that result with the `movies` data. pandas infers which columns to use as the merge (or *join*) keys based on overlapping names:

```
In [338]: data = pd.merge(pd.merge(ratings, users), movies)

In [339]: data
Out[339]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000209 entries, 0 to 1000208
Data columns:
user_id       1000209  non-null values
movie_id      1000209  non-null values
rating        1000209  non-null values
timestamp     1000209  non-null values
gender        1000209  non-null values
age           1000209  non-null values
occupation    1000209  non-null values
zip           1000209  non-null values
title         1000209  non-null values
genres        1000209  non-null values
dtypes: int64(6), object(4)

In [340]: data.ix[0]
Out[340]:
user_id                                  1
movie_id                                 1
rating                                   5
timestamp                        978824268
gender                                   F
age                                      1
occupation                              10
zip                                  48067
title                     Toy Story (1995)
genres        Animation|Children's|Comedy
Name: 0
```

In this form, aggregating the ratings grouped by one or more user or movie attributes is straightforward once you build some familiarity with pandas. To get mean movie ratings for each film grouped by gender, we can use the `pivot_table` method:

```
In [341]: mean_ratings = data.pivot_table('rating', rows='title',
   .....:                                  cols='gender', aggfunc='mean')

In [342]: mean_ratings[:5]
Out[342]:
gender                                F         M
title
$1,000,000 Duck (1971)         3.375000  2.761905
'Night Mother (1986)           3.388889  3.352941
'Til There Was You (1997)      2.675676  2.733333
'burbs, The (1989)             2.793478  2.962085
...And Justice for All (1979)  3.828571  3.689024
```

This produced another DataFrame containing mean ratings with movie totals as row labels and gender as column labels. First, I'm going to filter down to movies that received at least 250 ratings (a completely arbitrary number); to do this, I group the data by title and use `size()` to get a Series of group sizes for each title:

```
In [343]: ratings_by_title = data.groupby('title').size()

In [344]: ratings_by_title[:10]
Out[344]:
title
$1,000,000 Duck (1971)                37
'Night Mother (1986)                  70
'Til There Was You (1997)             52
'burbs, The (1989)                   303
...And Justice for All (1979)        199
1-900 (1994)                           2
10 Things I Hate About You (1999)    700
101 Dalmatians (1961)                565
101 Dalmatians (1996)                364
12 Angry Men (1957)                  616

In [345]: active_titles = ratings_by_title.index[ratings_by_title >= 250]

In [346]: active_titles
Out[346]:
Index(['burbs, The (1989), 10 Things I Hate About You (1999),
       101 Dalmatians (1961), ..., Young Sherlock Holmes (1985),
       Zero Effect (1998), eXistenZ (1999)], dtype=object)
```

The index of titles receiving at least 250 ratings can then be used to select rows from `mean_ratings` above:

```
In [347]: mean_ratings = mean_ratings.ix[active_titles]

In [348]: mean_ratings
Out[348]:
<class 'pandas.core.frame.DataFrame'>
Index: 1216 entries, 'burbs, The (1989) to eXistenZ (1999)
```

```
Data columns:
F    1216  non-null values
M    1216  non-null values
dtypes: float64(2)
```

To see the top films among female viewers, we can sort by the `F` column in descending order:

```
In [350]: top_female_ratings = mean_ratings.sort_index(by='F', ascending=False)

In [351]: top_female_ratings[:10]
Out[351]:
gender                                                    F         M
Close Shave, A (1995)                              4.644444  4.473795
Wrong Trousers, The (1993)                         4.588235  4.478261
Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)      4.572650  4.464589
Wallace & Gromit: The Best of Aardman Animation (1996)  4.563107  4.385075
Schindler's List (1993)                            4.562602  4.491415
Shawshank Redemption, The (1994)                   4.539075  4.560625
Grand Day Out, A (1992)                            4.537879  4.293255
To Kill a Mockingbird (1962)                       4.536667  4.372611
Creature Comforts (1990)                           4.513889  4.272277
Usual Suspects, The (1995)                         4.513317  4.518248
```

Measuring rating disagreement

Suppose you wanted to find the movies that are most divisive between male and female viewers. One way is to add a column to `mean_ratings` containing the difference in means, then sort by that:

```
In [352]: mean_ratings['diff'] = mean_ratings['M'] - mean_ratings['F']
```

Sorting by `'diff'` gives us the movies with the greatest rating difference and which were preferred by women:

```
In [353]: sorted_by_diff = mean_ratings.sort_index(by='diff')

In [354]: sorted_by_diff[:15]
Out[354]:
gender                                        F         M      diff
Dirty Dancing (1987)                   3.790378  2.959596 -0.830782
Jumpin' Jack Flash (1986)              3.254717  2.578358 -0.676359
Grease (1978)                          3.975265  3.367041 -0.608224
Little Women (1994)                    3.870588  3.321739 -0.548849
Steel Magnolias (1989)                 3.901734  3.365957 -0.535777
Anastasia (1997)                       3.800000  3.281609 -0.518391
Rocky Horror Picture Show, The (1975)  3.673016  3.160131 -0.512885
Color Purple, The (1985)               4.158192  3.659341 -0.498851
Age of Innocence, The (1993)           3.827068  3.339506 -0.487561
Free Willy (1993)                      2.921348  2.438776 -0.482573
French Kiss (1995)                     3.535714  3.056962 -0.478752
Little Shop of Horrors, The (1960)     3.650000  3.179688 -0.470312
Guys and Dolls (1955)                  4.051724  3.583333 -0.468391
Mary Poppins (1964)                    4.197740  3.730594 -0.467147
Patch Adams (1998)                     3.473282  3.008746 -0.464536
```

Reversing the order of the rows and again slicing off the top 15 rows, we get the movies preferred by men that women didn't rate as highly:

```
# Reverse order of rows, take first 15 rows
In [355]: sorted_by_diff[::-1][:15]
Out[355]:
gender                                          F         M      diff
Good, The Bad and The Ugly, The (1966)  3.494949  4.221300  0.726351
Kentucky Fried Movie, The (1977)        2.878788  3.555147  0.676359
Dumb & Dumber (1994)                    2.697987  3.336595  0.638608
Longest Day, The (1962)                 3.411765  4.031447  0.619682
Cable Guy, The (1996)                   2.250000  2.863787  0.613787
Evil Dead II (Dead By Dawn) (1987)      3.297297  3.909283  0.611985
Hidden, The (1987)                      3.137931  3.745098  0.607167
Rocky III (1982)                        2.361702  2.943503  0.581801
Caddyshack (1980)                       3.396135  3.969737  0.573602
For a Few Dollars More (1965)           3.409091  3.953795  0.544704
Porky's (1981)                          2.296875  2.836364  0.539489
Animal House (1978)                     3.628906  4.167192  0.538286
Exorcist, The (1973)                    3.537634  4.067239  0.529605
Fright Night (1985)                     2.973684  3.500000  0.526316
Barb Wire (1996)                        1.585366  2.100386  0.515020
```

Suppose instead you wanted the movies that elicited the most disagreement among viewers, independent of gender. Disagreement can be measured by the variance or standard deviation of the ratings:

```
# Standard deviation of rating grouped by title
In [356]: rating_std_by_title = data.groupby('title')['rating'].std()

# Filter down to active_titles
In [357]: rating_std_by_title = rating_std_by_title.ix[active_titles]

# Order Series by value in descending order
In [358]: rating_std_by_title.order(ascending=False)[:10]
Out[358]:
title
Dumb & Dumber (1994)                    1.321333
Blair Witch Project, The (1999)         1.316368
Natural Born Killers (1994)             1.307198
Tank Girl (1995)                        1.277695
Rocky Horror Picture Show, The (1975)   1.260177
Eyes Wide Shut (1999)                   1.259624
Evita (1996)                            1.253631
Billy Madison (1995)                    1.249970
Fear and Loathing in Las Vegas (1998)   1.246408
Bicentennial Man (1999)                 1.245533
Name: rating
```

You may have noticed that movie genres are given as a pipe-separated (|) string. If you wanted to do some analysis by genre, more work would be required to transform the genre information into a more usable form. I will revisit this data later in the book to illustrate such a transformation.

US Baby Names 1880-2010

The United States Social Security Administration (SSA) has made available data on the frequency of baby names from 1880 through the present. Hadley Wickham, an author of several popular R packages, has often made use of this data set in illustrating data manipulation in R.

```
In [4]: names.head(10)
Out[4]:
        name sex  births  year
0       Mary   F    7065  1880
1       Anna   F    2604  1880
2       Emma   F    2003  1880
3  Elizabeth   F    1939  1880
4     Minnie   F    1746  1880
5   Margaret   F    1578  1880
6        Ida   F    1472  1880
7      Alice   F    1414  1880
8     Bertha   F    1320  1880
9      Sarah   F    1288  1880
```

There are many things you might want to do with the data set:

- Visualize the proportion of babies given a particular name (your own, or another name) over time.
- Determine the relative rank of a name.
- Determine the most popular names in each year or the names with largest increases or decreases.
- Analyze trends in names: vowels, consonants, length, overall diversity, changes in spelling, first and last letters
- Analyze external sources of trends: biblical names, celebrities, demographic changes

Using the tools we've looked at so far, most of these kinds of analyses are very straightforward, so I will walk you through many of them. I encourage you to download and explore the data yourself. If you find an interesting pattern in the data, I would love to hear about it.

As of this writing, the US Social Security Administration makes available data files, one per year, containing the total number of births for each sex/name combination. The raw archive of these files can be obtained here:

```
http://www.ssa.gov/oact/babynames/limits.html
```

In the event that this page has been moved by the time you're reading this, it can most likely be located again by Internet search. After downloading the "National data" file `names.zip` and unzipping it, you will have a directory containing a series of files like `yob1880.txt`. I use the UNIX `head` command to look at the first 10 lines of one of the files (on Windows, you can use the `more` command or open it in a text editor):

```
In [367]: !head -n 10 names/yob1880.txt
Mary,F,7065
Anna,F,2604
Emma,F,2003
Elizabeth,F,1939
Minnie,F,1746
Margaret,F,1578
Ida,F,1472
Alice,F,1414
Bertha,F,1320
Sarah,F,1288
```

As this is a nicely comma-separated form, it can be loaded into a DataFrame with `pandas.read_csv`:

```
In [368]: import pandas as pd

In [369]: names1880 = pd.read_csv('names/yob1880.txt', names=['name', 'sex', 'births'])

In [370]: names1880
Out[370]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2000 entries, 0 to 1999
Data columns:
name      2000  non-null values
sex       2000  non-null values
births    2000  non-null values
dtypes: int64(1), object(2)
```

These files only contain names with at least 5 occurrences in each year, so for simplicity's sake we can use the sum of the births column by sex as the total number of births in that year:

```
In [371]: names1880.groupby('sex').births.sum()
Out[371]:
sex
F       90993
M      110493
Name: births
```

Since the data set is split into files by year, one of the first things to do is to assemble all of the data into a single DataFrame and further to add a `year` field. This is easy to do using `pandas.concat`:

```
# 2010 is the last available year right now
years = range(1880, 2011)

pieces = []
columns = ['name', 'sex', 'births']

for year in years:
    path = 'names/yob%d.txt' % year
    frame = pd.read_csv(path, names=columns)

    frame['year'] = year
    pieces.append(frame)
```

```
# Concatenate everything into a single DataFrame
names = pd.concat(pieces, ignore_index=True)
```

There are a couple things to note here. First, remember that `concat` glues the DataFrame objects together row-wise by default. Secondly, you have to pass `ignore_index=True` because we're not interested in preserving the original row numbers returned from `read_csv`. So we now have a very large DataFrame containing all of the names data:

Now the `names` DataFrame looks like:

```
In [373]: names
Out[373]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1690784 entries, 0 to 1690783
Data columns:
name      1690784  non-null values
sex       1690784  non-null values
births    1690784  non-null values
year      1690784  non-null values
dtypes: int64(2), object(2)
```

With this data in hand, we can already start aggregating the data at the year and sex level using `groupby` or `pivot_table`, see Figure 2-4:

```
In [374]: total_births = names.pivot_table('births', rows='year',
   .....:                                  cols='sex', aggfunc=sum)

In [375]: total_births.tail()
Out[375]:
sex         F        M
year
2006  1896468  2050234
2007  1916888  2069242
2008  1883645  2032310
2009  1827643  1973359
2010  1759010  1898382

In [376]: total_births.plot(title='Total births by sex and year')
```

Next, let's insert a column `prop` with the fraction of babies given each name relative to the total number of births. A `prop` value of `0.02` would indicate that 2 out of every 100 babies was given a particular name. Thus, we group the data by year and sex, then add the new column to each group:

```
def add_prop(group):
    # Integer division floors
    births = group.births.astype(float)

    group['prop'] = births / births.sum()
    return group
names = names.groupby(['year', 'sex']).apply(add_prop)
```

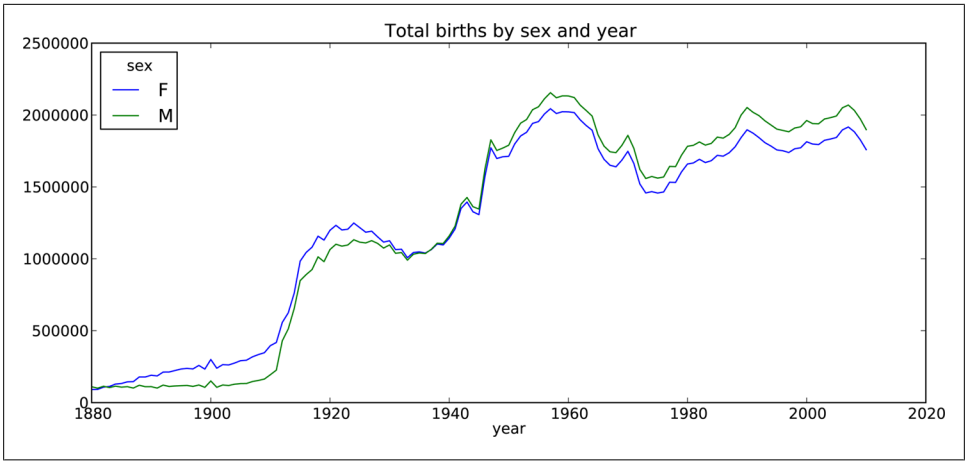


Figure 2-4. Total births by sex and year

Remember that because `births` is of integer type, we have to cast either the numerator or denominator to floating point to compute a fraction (unless you are using Python 3!).

The resulting complete data set now has the following columns:

```
In [378]: names
Out[378]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1690784 entries, 0 to 1690783
Data columns:
name      1690784  non-null values
sex       1690784  non-null values
births    1690784  non-null values
year      1690784  non-null values
prop      1690784  non-null values
dtypes: float64(1), int64(2), object(2)
```

When performing a group operation like this, it's often valuable to do a sanity check, like verifying that the `prop` column sums to 1 within all the groups. Since this is floating point data, use `np.allclose` to check that the group sums are sufficiently close to (but perhaps not exactly equal to) 1:

```
In [379]: np.allclose(names.groupby(['year', 'sex']).prop.sum(), 1)
Out[379]: True
```

Now that this is done, I'm going to extract a subset of the data to facilitate further analysis: the top 1000 names for each sex/year combination. This is yet another group operation:

```
def get_top1000(group):
    return group.sort_index(by='births', ascending=False)[:1000]
```

```
grouped = names.groupby(['year', 'sex'])
top1000 = grouped.apply(get_top1000)
```

If you prefer a do-it-yourself approach, you could also do:

```
pieces = []
for year, group in names.groupby(['year', 'sex']):
    pieces.append(group.sort_index(by='births', ascending=False)[:1000])
top1000 = pd.concat(pieces, ignore_index=True)
```

The resulting data set is now quite a bit smaller:

```
In [382]: top1000
Out[382]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 261877 entries, 0 to 261876
Data columns:
name      261877  non-null values
sex       261877  non-null values
births    261877  non-null values
year      261877  non-null values
prop      261877  non-null values
dtypes: float64(1), int64(2), object(2)
```

We'll use this Top 1,000 data set in the following investigations into the data.

Analyzing Naming Trends

With the full data set and Top 1,000 data set in hand, we can start analyzing various naming trends of interest. Splitting the Top 1,000 names into the boy and girl portions is easy to do first:

```
In [383]: boys = top1000[top1000.sex == 'M']

In [384]: girls = top1000[top1000.sex == 'F']
```

Simple time series, like the number of Johns or Marys for each year can be plotted but require a bit of munging to be a bit more useful. Let's form a pivot table of the total number of births by year and name:

```
In [385]: total_births = top1000.pivot_table('births', rows='year', cols='name',
   .....:                                    aggfunc=sum)
```

Now, this can be plotted for a handful of names using DataFrame's `plot` method:

```
In [386]: total_births
Out[386]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 131 entries, 1880 to 2010
Columns: 6865 entries, Aaden to Zuri
dtypes: float64(6865)

In [387]: subset = total_births[['John', 'Harry', 'Mary', 'Marilyn']]

In [388]: subset.plot(subplots=True, figsize=(12, 10), grid=False,
   .....:             title="Number of births per year")
```

See Figure 2-5 for the result. On looking at this, you might conclude that these names have grown out of favor with the American population. But the story is actually more complicated than that, as will be explored in the next section.

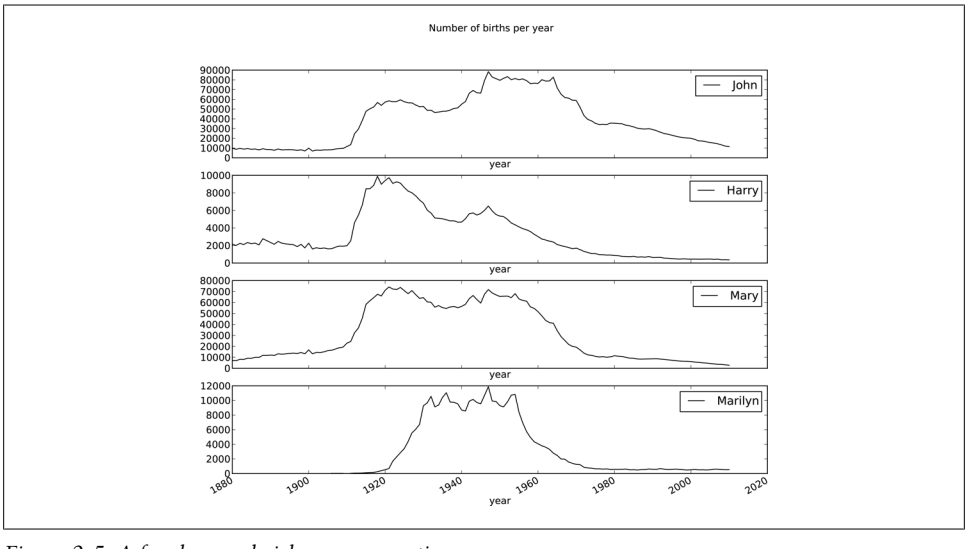


Figure 2-5. A few boy and girl names over time

Measuring the increase in naming diversity

One explanation for the decrease in plots above is that fewer parents are choosing common names for their children. This hypothesis can be explored and confirmed in the data. One measure is the proportion of births represented by the top 1000 most popular names, which I aggregate and plot by year and sex:

```
In [390]: table = top1000.pivot_table('prop', rows='year',
   .....:                             cols='sex', aggfunc=sum)

In [391]: table.plot(title='Sum of table1000.prop by year and sex',
   .....:            yticks=np.linspace(0, 1.2, 13), xticks=range(1880, 2020, 10))
```

See Figure 2-6 for this plot. So you can see that, indeed, there appears to be increasing name diversity (decreasing total proportion in the top 1,000). Another interesting metric is the number of distinct names, taken in order of popularity from highest to lowest, in the top 50% of births. This number is a bit more tricky to compute. Let's consider just the boy names from 2010:

```
In [392]: df = boys[boys.year == 2010]

In [393]: df
Out[393]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000 entries, 260877 to 261876
Data columns:
```

```
name      1000  non-null values
sex       1000  non-null values
births    1000  non-null values
year      1000  non-null values
prop      1000  non-null values
dtypes: float64(1), int64(2), object(2)
```

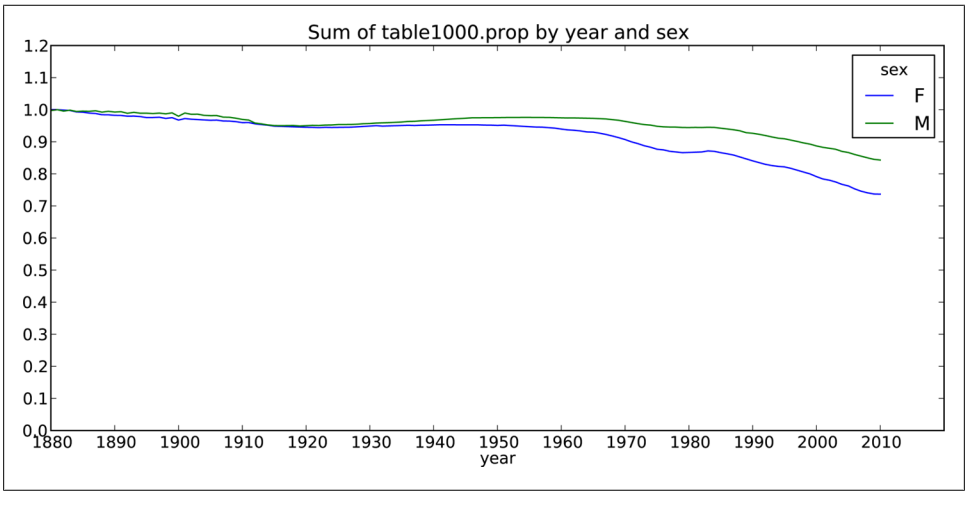


Figure 2-6. Proportion of births represented in top 1000 names by sex

After sorting `prop` in descending order, we want to know how many of the most popular names it takes to reach 50%. You could write a `for` loop to do this, but a vectorized NumPy way is a bit more clever. Taking the cumulative sum, `cumsum`, of `prop` then calling the method `searchsorted` returns the position in the cumulative sum at which `0.5` would need to be inserted to keep it in sorted order:

```
In [394]: prop_cumsum = df.sort_index(by='prop', ascending=False).prop.cumsum()

In [395]: prop_cumsum[:10]
Out[395]:
260877    0.011523
260878    0.020934
260879    0.029959
260880    0.038930
260881    0.047817
260882    0.056579
260883    0.065155
260884    0.073414
260885    0.081528
260886    0.089621

In [396]: prop_cumsum.searchsorted(0.5)
Out[396]: 116
```

Since arrays are zero-indexed, adding 1 to this result gives you a result of 117. By contrast, in 1900 this number was much smaller:

```
In [397]: df = boys[boys.year == 1900]

In [398]: in1900 = df.sort_index(by='prop', ascending=False).prop.cumsum()

In [399]: in1900.searchsorted(0.5) + 1
Out[399]: 25
```

It should now be fairly straightforward to apply this operation to each year/sex combination; `groupby` those fields and `apply` a function returning the count for each group:

```
def get_quantile_count(group, q=0.5):
    group = group.sort_index(by='prop', ascending=False)
    return group.prop.cumsum().searchsorted(q) + 1

diversity = top1000.groupby(['year', 'sex']).apply(get_quantile_count)
diversity = diversity.unstack('sex')
```

This resulting DataFrame `diversity` now has two time series, one for each sex, indexed by year. This can be inspected in IPython and plotted as before (see Figure 2-7):

```
In [401]: diversity.head()
Out[401]:
sex     F   M
year
1880   38  14
1881   38  14
1882   38  15
1883   39  15
1884   39  16

In [402]: diversity.plot(title="Number of popular names in top 50%")
```

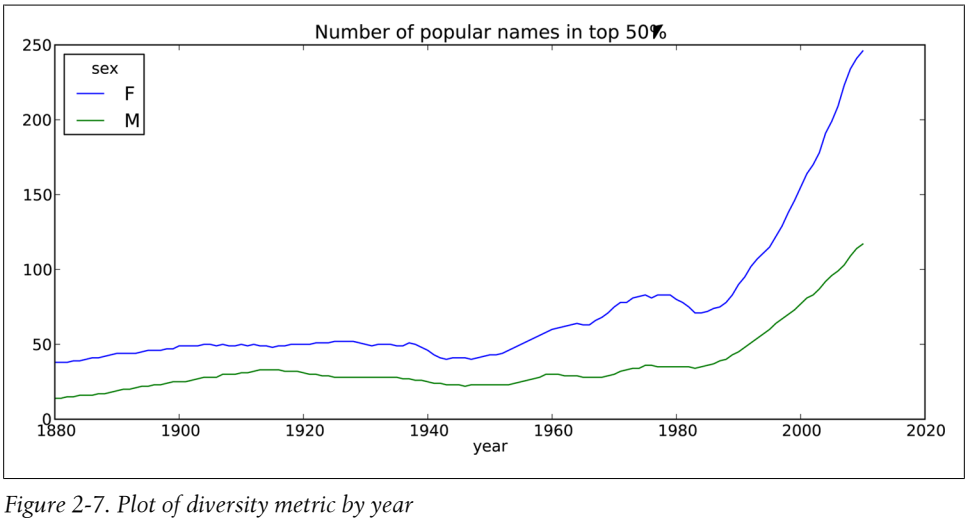


Figure 2-7. Plot of diversity metric by year

As you can see, girl names have always been more diverse than boy names, and they have only become more so over time. Further analysis of what exactly is driving the diversity, like the increase of alternate spellings, is left to the reader.

The "Last letter" Revolution

In 2007, a baby name researcher Laura Wattenberg pointed out on her website (*http://www.babynamewizard.com*) that the distribution of boy names by final letter has changed significantly over the last 100 years. To see this, I first aggregate all of the births in the full data set by year, sex, and final letter:

```
# extract last letter from name column
get_last_letter = lambda x: x[-1]
last_letters = names.name.map(get_last_letter)
last_letters.name = 'last_letter'

table = names.pivot_table('births', rows=last_letters,
                          cols=['sex', 'year'], aggfunc=sum)
```

Then, I select out three representative years spanning the history and print the first few rows:

```
In [404]: subtable = table.reindex(columns=[1910, 1960, 2010], level='year')

In [405]: subtable.head()
Out[405]:
sex                F                     M
year            1910    1960    2010   1910    1960    2010
last_letter
a             108376  691247  670605    977    5204   28438
b                NaN     694     450    411    3912   38859
c                  5      49     946    482   15476   23125
d               6750    3729    2607  22111  262112   44398
e             133569  435013  313833  28655  178823  129012
```

Next, normalize the table by total births to compute a new table containing proportion of total births for each sex ending in each letter:

```
In [406]: subtable.sum()
Out[406]:
sex  year
F    1910     396416
     1960    2022062
     2010    1759010
M    1910     194198
     1960    2132588
     2010    1898382

In [407]: letter_prop = subtable / subtable.sum().astype(float)
```

With the letter proportions now in hand, I can make bar plots for each sex broken down by year. See Figure 2-8:

```
import matplotlib.pyplot as plt
```

```
fig, axes = plt.subplots(2, 1, figsize=(10, 8))
letter_prop['M'].plot(kind='bar', rot=0, ax=axes[0], title='Male')
letter_prop['F'].plot(kind='bar', rot=0, ax=axes[1], title='Female',
                      legend=False)
```

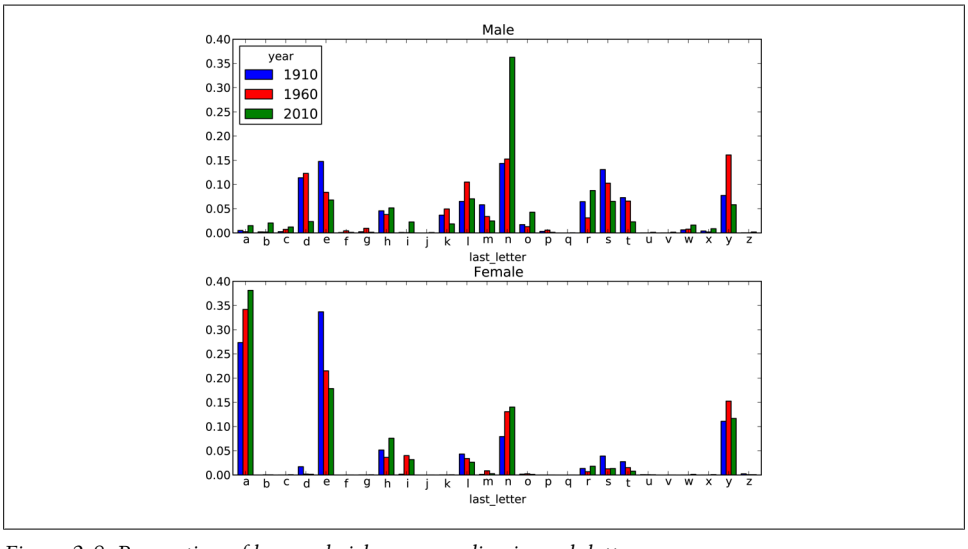


Figure 2-8. Proportion of boy and girl names ending in each letter

As you can see, boy names ending in "n" have experienced significant growth since the 1960s. Going back to the full table created above, I again normalize by year and sex and select a subset of letters for the boy names, finally transposing to make each column a time series:

```
In [410]: letter_prop = table / table.sum().astype(float)

In [411]: dny_ts = letter_prop.ix[['d', 'n', 'y'], 'M'].T

In [412]: dny_ts.head()
Out[412]:
             d         n         y
year
1880  0.083055  0.153213  0.075760
1881  0.083247  0.153214  0.077451
1882  0.085340  0.149560  0.077537
1883  0.084066  0.151646  0.079144
1884  0.086120  0.149915  0.080405
```

With this DataFrame of time series in hand, I can make a plot of the trends over time again with its `plot` method (see Figure 2-9):

```
In [414]: dny_ts.plot()
```

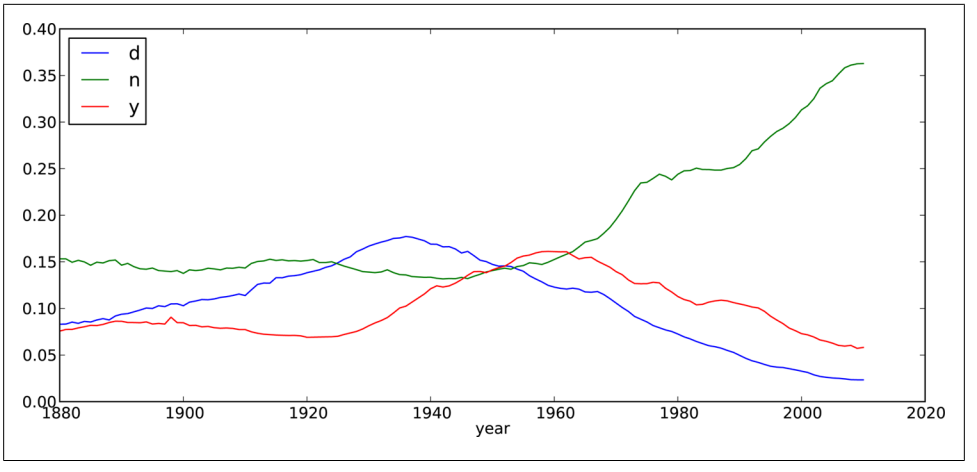


Figure 2-9. Proportion of boys born with names ending in d/n/y over time

Boy names that became girl names (and vice versa)

Another fun trend is looking at boy names that were more popular with one sex earlier in the sample but have "changed sexes" in the present. One example is the name Lesley or Leslie. Going back to the `top1000` dataset, I compute a list of names occurring in the dataset starting with `'lesl'`:

```
In [415]: all_names = top1000.name.unique()

In [416]: mask = np.array(['lesl' in x.lower() for x in all_names])

In [417]: lesley_like = all_names[mask]

In [418]: lesley_like
Out[418]: array([Leslie, Lesley, Leslee, Lesli, Lesly], dtype=object)
```

From there, we can filter down to just those names and sum births grouped by name to see the relative frequencies:

```
In [419]: filtered = top1000[top1000.name.isin(lesley_like)]

In [420]: filtered.groupby('name').births.sum()
Out[420]:
name
Leslee      1082
Lesley     35022
Lesli        929
Leslie    370429
Lesly      10067
Name: births
```

Next, let's aggregate by sex and year and normalize within year:

```
In [421]: table = filtered.pivot_table('births', rows='year',
   .....:                              cols='sex', aggfunc='sum')

In [422]: table = table.div(table.sum(1), axis=0)

In [423]: table.tail()
Out[423]:
sex   F   M
year
2006  1 NaN
2007  1 NaN
2008  1 NaN
2009  1 NaN
2010  1 NaN
```

Lastly, it's now easy to make a plot of the breakdown by sex over time (Figure 2-10):

```
In [425]: table.plot(style={'M': 'k-', 'F': 'k--'})
```

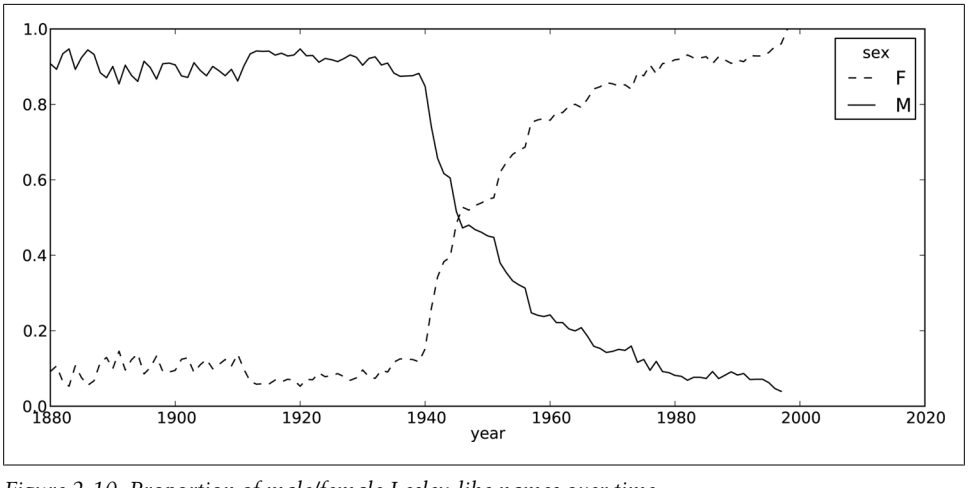


Figure 2-10. Proportion of male/female Lesley-like names over time

Conclusions and The Path Ahead

The examples in this chapter are rather simple, but they're here to give you a bit of a flavor of what sorts of things you can expect in the upcoming chapters. The focus of this book is on *tools* as opposed to presenting more sophisticated analytical methods. Mastering the techniques in this book will enable you to implement your own analyses (assuming you know what you want to do!) in short order.

CHAPTER 3

IPython: An Interactive Computing and Development Environment

> Act without doing; work without effort. Think of the small as large and the few as many. Confront the difficult while it is still easy; accomplish the great task by a series of small acts.
>
> —Laozi

People often ask me, "What is your Python development environment?" My answer is almost always the same, "IPython and a text editor". You may choose to substitute an Integrated Development Environment (IDE) for a text editor in order to take advantage of more advanced graphical tools and code completion capabilities. Even if so, I strongly recommend making IPython an important part of your workflow. Some IDEs even provide IPython integration, so it's possible to get the best of both worlds.

The *IPython* project began in 2001 as Fernando Pérez's side project to make a better interactive Python interpreter. In the subsequent 11 years it has grown into what's widely considered one of the most important tools in the modern scientific Python computing stack. While it does not provide any computational or data analytical tools by itself, IPython is designed from the ground up to maximize your productivity in both interactive computing and software development. It encourages an *execute-explore* workflow instead of the typical *edit-compile-run* workflow of many other programming languages. It also provides very tight integration with the operating system's shell and file system. Since much of data analysis coding involves exploration, trial and error, and iteration, IPython will, in almost all cases, help you get the job done faster.

Of course, the IPython project now encompasses a great deal more than just an enhanced, interactive Python shell. It also includes a rich GUI console with inline plotting, a web-based interactive notebook format, and a lightweight, fast parallel computing engine. And, as with so many other tools designed for and by programmers, it is highly customizable. I'll discuss some of these features later in the chapter.

Since IPython has interactivity at its core, some of the features in this chapter are difficult to fully illustrate without a live console. If this is your first time learning about IPython, I recommend that you follow along with the examples to get a feel for how things work. As with any keyboard-driven console-like environment, developing muscle-memory for the common commands is part of the learning curve.

Many parts of this chapter (for example: profiling and debugging) can be safely omitted on a first reading as they are not necessary for understanding the rest of the book. This chapter is intended to provide a standalone, rich overview of the functionality provided by IPython.

IPython Basics

You can launch IPython on the command line just like launching the regular Python interpreter except with the `ipython` command:

```
$ ipython
Python 2.7.2 (default, May 27 2012, 21:26:12)
Type "copyright", "credits" or "license" for more information.

IPython 0.12 -- An enhanced Interactive Python.
?         -> Introduction and overview of IPython's features.
%quickref -> Quick reference.
help      -> Python's own help system.
object?   -> Details about 'object', use 'object??' for extra details.

In [1]: a = 5

In [2]: a
Out[2]: 5
```

You can execute arbitrary Python statements by typing them in and pressing `<return>`. When typing just a variable into IPython, it renders a string representation of the object:

```
In [542]: data = {i : randn() for i in range(7)}

In [543]: data
Out[543]:
{0: 0.6900018528091594,
 1: 1.0015434424937888,
 2: -0.5030873913603446,
 3: -0.6222742250596455,
 4: -0.9211686080130108,
 5: -0.726213492660829,
 6: 0.2228955458351768}
```

Many kinds of Python objects are formatted to be more readable, or *pretty-printed*, which is distinct from normal printing with `print`. If you printed a dict like the above in the standard Python interpreter, it would be much less readable:

```
>>> from numpy.random import randn
>>> data = {i : randn() for i in range(7)}
>>> print data
{0: -1.5948255432744511, 1: 0.10569006472787983, 2: 1.972367135977295,
3: 0.15455217573074576, 4: -0.24058577449429575, 5: -1.2904897053651216,
6: 0.3308507317325902}
```

IPython also provides facilities to make it easy to execute arbitrary blocks of code (via somewhat glorified copy-and-pasting) and whole Python scripts. These will be discussed shortly.

Tab Completion

On the surface, the IPython shell looks like a cosmetically slightly-different interactive Python interpreter. Users of Mathematica may find the enumerated input and output prompts familiar. One of the major improvements over the standard Python shell is *tab completion*, a feature common to most interactive data analysis environments. While entering expressions in the shell, pressing `<Tab>` will search the namespace for any variables (objects, functions, etc.) matching the characters you have typed so far:

```
In [1]: an_apple = 27

In [2]: an_example = 42

In [3]: an<Tab>
an_apple    and         an_example  any
```

In this example, note that IPython displayed both the two variables I defined as well as the Python keyword `and` and built-in function `any`. Naturally, you can also complete methods and attributes on any object after typing a period:

```
In [3]: b = [1, 2, 3]

In [4]: b.<Tab>
b.append   b.extend   b.insert   b.remove   b.sort
b.count    b.index    b.pop      b.reverse
```

The same goes for modules:

```
In [1]: import datetime

In [2]: datetime.<Tab>
datetime.date           datetime.MAXYEAR        datetime.timedelta
datetime.datetime       datetime.MINYEAR        datetime.tzinfo
datetime.datetime_CAPI  datetime.time
```

Note that IPython by default hides methods and attributes starting with underscores, such as magic methods and internal "private" methods and attributes, in order to avoid cluttering the display (and confusing new Python users!). These, too, can be tab-completed but you must first type an underscore to see them. If you prefer to always see such methods in tab completion, you can change this setting in the IPython configuration.

Tab completion works in many contexts outside of searching the interactive namespace and completing object or module attributes. When typing anything that looks like a file path (even in a Python string), pressing `<Tab>` will complete anything on your computer's file system matching what you've typed:

```
In [3]: book_scripts/<Tab>
book_scripts/cprof_example.py        book_scripts/ipython_script_test.py
book_scripts/ipython_bug.py          book_scripts/prof_mod.py

In [3]: path = 'book_scripts/<Tab>
book_scripts/cprof_example.py        book_scripts/ipython_script_test.py
book_scripts/ipython_bug.py          book_scripts/prof_mod.py
```

Combined with the `%run` command (see later section), this functionality will undoubtedly save you many keystrokes.

Another area where tab completion saves time is in the completion of function keyword arguments (including the `=` sign!).

Introspection

Using a question mark (`?`) before or after a variable will display some general information about the object:

```
In [545]: b?
Type:       list
String Form:[1, 2, 3]
Length:     3
Docstring:
list() -> new empty list
list(iterable) -> new list initialized from iterable's items
```

This is referred to as *object introspection*. If the object is a function or instance method, the docstring, if defined, will also be shown. Suppose we'd written the following function:

```
def add_numbers(a, b):
    """
    Add two numbers together

    Returns
    -------
    the_sum : type of arguments
```

```
    """
    return a + b
```

Then using ? shows us the docstring:

```
In [547]: add_numbers?
Type:       function
String Form:<function add_numbers at 0x5fad848>
File:       book_scripts/<ipython-input-546-5473012eeb65>
Definition: add_numbers(a, b)
Docstring:
Add two numbers together
Returns
-------
the_sum : type of arguments
```

Using ?? will also show the function's source code if possible:

```
In [548]: add_numbers??
Type:       function
String Form:<function add_numbers at 0x5fad848>
File:       book_scripts/<ipython-input-546-5473012eeb65>
Definition: add_numbers(a, b)
Source:
def add_numbers(a, b):
    """
    Add two numbers together
    Returns
    -------
    the_sum : type of arguments
    """
    return a + b
```

? has a final usage, which is for searching the IPython namespace in a manner similar to the standard UNIX or Windows command line. A number of characters combined with the wildcard (*) will show all names matching the wildcard expression. For example, we could get a list of all functions in the top level NumPy namespace containing `load`:

```
In [549]: np.*load*?
np.load
np.loads
np.loadtxt
np.pkgload
```

The %run Command

Any file can be run as a Python program inside the environment of your IPython session using the `%run` command. Suppose you had the following simple script stored in `ipython_script_test.py`:

```
def f(x, y, z):
    return (x + y) / z

a = 5
```

```
b = 6
c = 7.5

result = f(a, b, c)
```

This can be executed by passing the file name to `%run`:

```
In [550]: %run ipython_script_test.py
```

The script is run in an *empty namespace* (with no imports or other variables defined) so that the behavior should be identical to running the program on the command line using `python script.py`. All of the variables (imports, functions, and globals) defined in the file (up until an exception, if any, is raised) will then be accessible in the IPython shell:

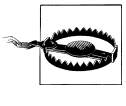
```
In [551]: c
Out[551]: 7.5

In [552]: result
Out[552]: 1.4666666666666666
```

If a Python script expects command line arguments (to be found in `sys.argv`), these can be passed after the file path as though run on the command line.

Should you wish to give a script access to variables already defined in the interactive IPython namespace, use `%run -i` instead of plain `%run`.

Interrupting running code

Pressing `<Ctrl-C>` while any code is running, whether a script through `%run` or a long-running command, will cause a `KeyboardInterrupt` to be raised. This will cause nearly all Python programs to stop immediately except in very exceptional cases.



When a piece of Python code has called into some compiled extension modules, pressing `<Ctrl-C>` will not cause the program execution to stop immediately in all cases. In such cases, you will have to either wait until control is returned to the Python interpreter, or, in more dire circumstances, forcibly terminate the Python process via the OS task manager.

Executing Code from the Clipboard

A quick-and-dirty way to execute code in IPython is via pasting from the clipboard. This might seem fairly crude, but in practice it is very useful. For example, while developing a complex or time-consuming application, you may wish to execute a script piece by piece, pausing at each stage to examine the currently loaded data and results. Or, you might find a code snippet on the Internet that you want to run and play around with, but you'd rather not create a new `.py` file for it.

Code snippets can be pasted from the clipboard in many cases by pressing `<Ctrl-Shift-V>`. Note that it is not completely robust as this mode of pasting mimics typing each line into IPython, and line breaks are treated as `<return>`. This means that if you paste code with an indented block and there is a blank line, IPython will think that the indented block is over. Once the next line in the block is executed, an `IndentationError` will be raised. For example the following code:

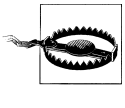
```
x = 5
y = 7
if x > 5:
    x += 1

    y = 8
```

will not work if simply pasted:

```
In [1]: x = 5

In [2]: y = 7

In [3]: if x > 5:
   ...:         x += 1
   ...:

In [4]:     y = 8
IndentationError: unexpected indent

If you want to paste code into IPython, try the %paste and %cpaste
magic functions.
```

As the error message suggests, we should instead use the `%paste` and `%cpaste` magic functions. `%paste` takes whatever text is in the clipboard and executes it as a single block in the shell:

```
In [6]: %paste
x = 5
y = 7
if x > 5:
    x += 1

    y = 8
## -- End pasted text --
```



Depending on your platform and how you installed Python, there's a small chance that `%paste` will not work. Packaged distributions like EPDFree (as described in in the intro) should not be a problem.

`%cpaste` is similar, except that it gives you a special prompt for pasting code into:

```
In [7]: %cpaste
Pasting code; enter '--' alone on the line to stop or use Ctrl-D.
:x = 5
:y = 7
:if x > 5:
```

```
:    x += 1
:
:    y = 8
:--
```

With the `%cpaste` block, you have the freedom to paste as much code as you like before executing it. You might decide to use `%cpaste` in order to look at the pasted code before executing it. If you accidentally paste the wrong code, you can break out of the `%cpaste` prompt by pressing `<Ctrl-C>`.

Later, I'll introduce the IPython HTML Notebook which brings a new level of sophistication for developing analyses block-by-block in a browser-based notebook format with executable code cells.

IPython interaction with editors and IDEs

Some text editors, such as Emacs and vim, have 3rd party extensions enabling blocks of code to be sent directly from the editor to a running IPython shell. Refer to the IPython website or do an Internet search to find out more.

Some IDEs, such as the PyDev plugin for Eclipse and Python Tools for Visual Studio from Microsoft (and possibly others), have integration with the IPython terminal application. If you want to work in an IDE but don't want to give up the IPython console features, this may be a good option for you.

Keyboard Shortcuts

IPython has many keyboard shortcuts for navigating the prompt (which will be familiar to users of the Emacs text editor or the UNIX bash shell) and interacting with the shell's command history (see later section). Table 3-1 summarizes some of the most commonly used shortcuts. See Figure 3-1 for an illustration of a few of these, such as cursor movement.

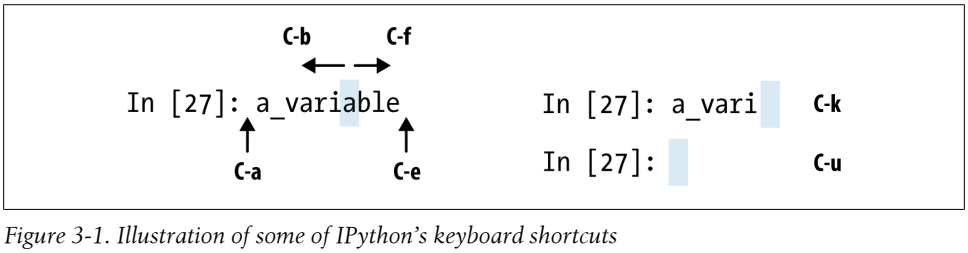


Figure 3-1. Illustration of some of IPython's keyboard shortcuts

Table 3-1. Standard IPython Keyboard Shortcuts

Command	Description
`Ctrl-P` or `up-arrow`	Search backward in command history for commands starting with currently-entered text
`Ctrl-N` or `down-arrow`	Search forward in command history for commands starting with currently-entered text
`Ctrl-R`	Readline-style reverse history search (partial matching)
`Ctrl-Shift-V`	Paste text from clipboard
`Ctrl-C`	Interrupt currently-executing code
`Ctrl-A`	Move cursor to beginning of line
`Ctrl-E`	Move cursor to end of line
`Ctrl-K`	Delete text from cursor until end of line
`Ctrl-U`	Discard all text on current line
`Ctrl-F`	Move cursor forward one character
`Ctrl-B`	Move cursor back one character
`Ctrl-L`	Clear screen

Exceptions and Tracebacks

If an exception is raised while `%run`-ing a script or executing any statement, IPython will by default print a full call stack trace (traceback) with a few lines of context around the position at each point in the stack.

```
In [553]: %run ch03/ipython_bug.py
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
/home/wesm/code/ipython/IPython/utils/py3compat.pyc in execfile(fname, *where)
    176             else:
    177                 filename = fname
--> 178             __builtin__.execfile(filename, *where)
book_scripts/ch03/ipython_bug.py in <module>()
     13     throws_an_exception()
     14
---> 15 calling_things()
book_scripts/ch03/ipython_bug.py in calling_things()
     11 def calling_things():
     12     works_fine()
---> 13     throws_an_exception()
     14
     15 calling_things()
book_scripts/ch03/ipython_bug.py in throws_an_exception()
      7     a = 5
      8     b = 6
----> 9     assert(a + b == 10)
     10
     11 def calling_things():
AssertionError:
```

Having additional context by itself is a big advantage over the standard Python interpreter (which does not provide any additional context). The amount of context shown can be controlled using the `%xmode` magic command, from minimal (same as the standard Python interpreter) to verbose (which inlines function argument values and more). As you will see later in the chapter, you can step *into the stack* (using the `%debug` or `%pdb` magics) after an error has occurred for interactive post-mortem debugging.

Magic Commands

IPython has many special commands, known as "magic" commands, which are designed to faciliate common tasks and enable you to easily control the behavior of the IPython system. A magic command is any command prefixed by the the percent symbol `%`. For example, you can check the execution time of any Python statement, such as a matrix multiplication, using the `%timeit` magic function (which will be discussed in more detail later):

```
In [554]: a = np.random.randn(100, 100)

In [555]: %timeit np.dot(a, a)
10000 loops, best of 3: 69.1 us per loop
```

Magic commands can be viewed as command line programs to be run within the IPython system. Many of them have additional "command line" options, which can all be viewed (as you might expect) using `?`:

```
In [1]: %reset?
Resets the namespace by removing all names defined by the user.

Parameters
----------
  -f : force reset without asking for confirmation.

  -s : 'Soft' reset: Only clears your namespace, leaving history intact.
  References to objects may be kept. By default (without this option),
  we do a 'hard' reset, giving you a new session and removing all
  references to objects from the current session.

Examples
--------
In [6]: a = 1

In [7]: a
Out[7]: 1

In [8]: 'a' in _ip.user_ns
Out[8]: True

In [9]: %reset -f

In [1]: 'a' in _ip.user_ns
Out[1]: False
```

Magic functions can be used by default without the percent sign, as long as no variable is defined with the same name as the magic function in question. This feature is called *automagic* and can be enabled or disabled using `%automagic`.

Since IPython's documentation is easily accessible from within the system, I encourage you to explore all of the special commands available by typing `%quickref` or `%magic`. I will highlight a few more of the most critical ones for being productive in interactive computing and Python development in IPython.

Table 3-2. Frequently-used IPython Magic Commands

Command	Description
`%quickref`	Display the IPython Quick Reference Card
`%magic`	Display detailed documentation for all of the available magic commands
`%debug`	Enter the interactive debugger at the bottom of the last exception traceback
`%hist`	Print command input (and optionally output) history
`%pdb`	Automatically enter debugger after any exception
`%paste`	Execute pre-formatted Python code from clipboard
`%cpaste`	Open a special prompt for manually pasting Python code to be executed
`%reset`	Delete all variables / names defined in interactive namespace
`%page` *`OBJECT`*	Pretty print the object and display it through a pager
`%run` *`script.py`*	Run a Python script inside IPython
`%prun` *`statement`*	Execute *`statement`* with `cProfile` and report the profiler output
`%time` *`statement`*	Report the execution time of single statement
`%timeit` *`statement`*	Run a statement multiple times to compute an emsemble average execution time. Useful for timing code with very short execution time
`%who, %who_ls, %whos`	Display variables defined in interactive namespace, with varying levels of information / verbosity
`%xdel` *`variable`*	Delete a variable and attempt to clear any references to the object in the IPython internals

Qt-based Rich GUI Console

The IPython team has developed a Qt framework-based GUI console, designed to wed the features of the terminal-only applications with the features provided by a rich text widget, like embedded images, multiline editing, and syntax highlighting. If you have either PyQt or PySide installed, the application can be launched with inline plotting by running this on the command line:

```
ipython qtconsole --pylab=inline
```

The Qt console can launch multiple IPython processes in tabs, enabling you to switch between tasks. It can also share a process with the IPython HTML Notebook application, which I'll highlight later.

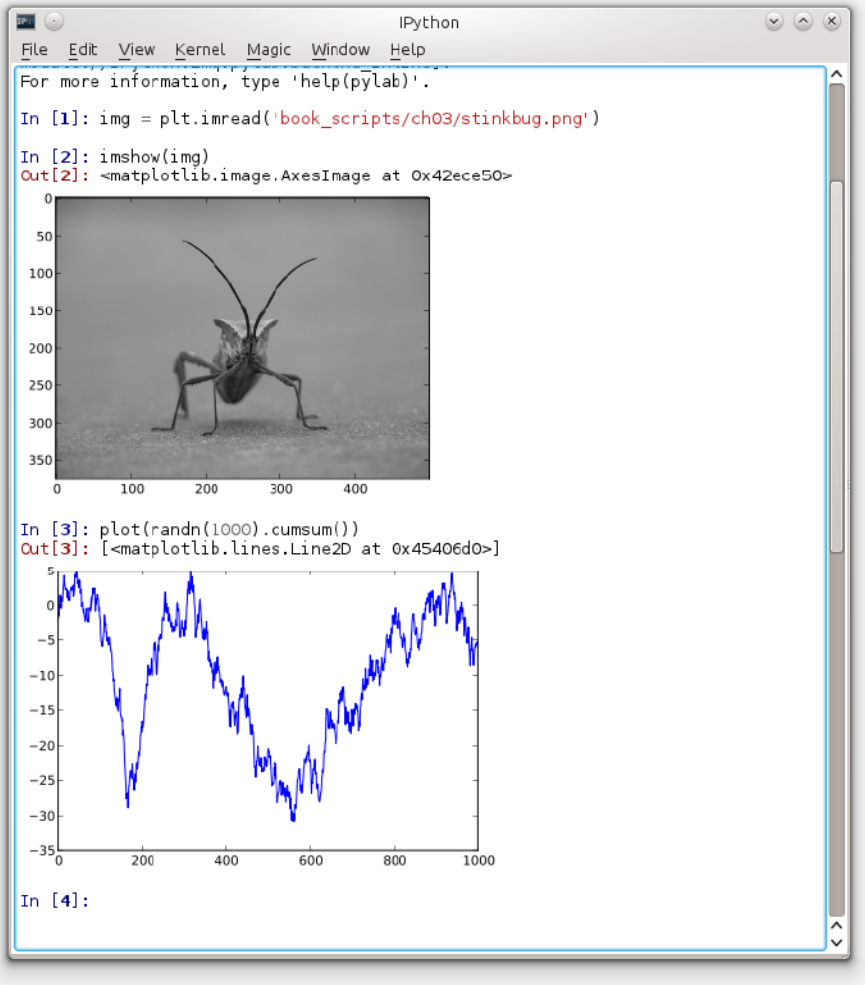


Figure 3-2. IPython Qt Console

Matplotlib Integration and Pylab Mode

Part of why IPython is so widely used in scientific computing is that it is designed as a companion to libraries like matplotlib and other GUI toolkits. Don't worry if you have never used matplotlib before; it will be discussed in much more detail later in this book. If you create a matplotlib plot window in the regular Python shell, you'll be sad to find that the GUI event loop "takes control" of the Python session until the plot window is closed. That won't work for interactive data analysis and visualization, so IPython has

implemented special handling for each GUI framework so that it will work seamlessly with the shell.

The typical way to launch IPython with matplotlib integration is by adding the `--pylab` flag (two dashes).

```
$ ipython --pylab
```

This will cause several things to happen. First IPython will launch with the default GUI backend integration enabled so that matplotlib plot windows can be created with no issues. Secondly, most of NumPy and matplotlib will be imported into the top level interactive namespace to produce an interactive computing environment reminiscent of MATLAB and other domain-specific scientific computing environments. It's possible to do this setup by hand by using `%gui`, too (try running `%gui?` to find out how).

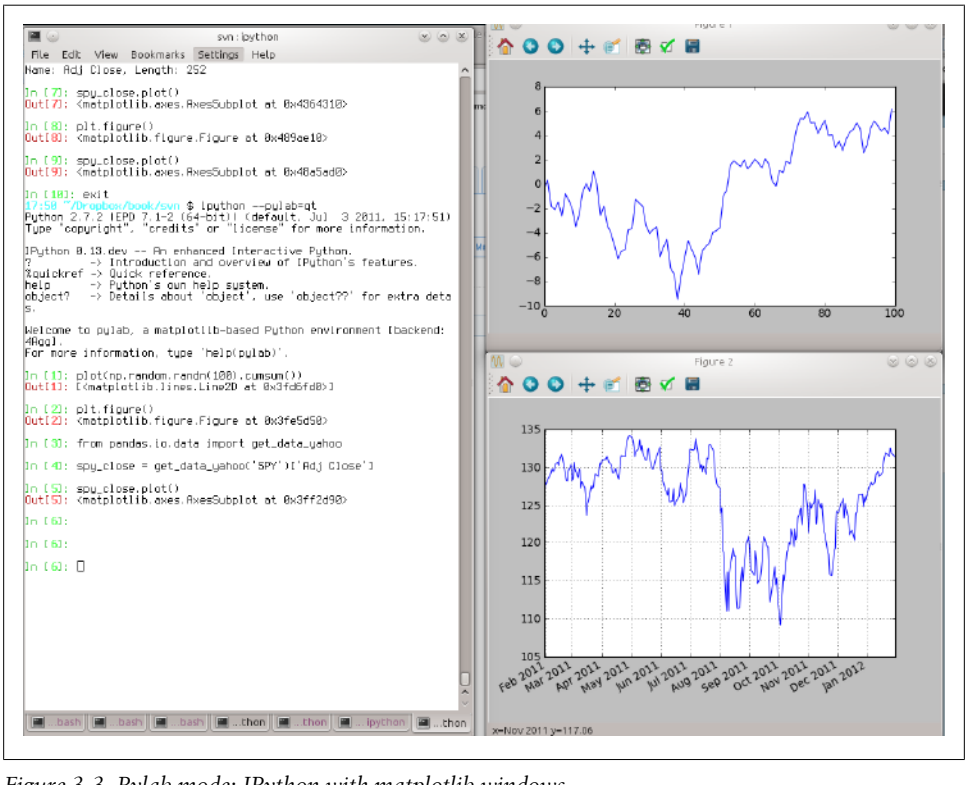


Figure 3-3. Pylab mode: IPython with matplotlib windows

Using the Command History

IPython maintains a small on-disk database containing the text of each command that you execute. This serves various purposes:

- Searching, completing, and executing previously-executed commands with minimal typing
- Persisting the command history between sessions.
- Logging the input/output history to a file

Searching and Reusing the Command History

Being able to search and execute previous commands is, for many people, the most useful feature. Since IPython encourages an iterative, interactive code development workflow, you may often find yourself repeating the same commands, such as a `%run` command or some other code snippet. Suppose you had run:

```
In[7]: %run first/second/third/data_script.py
```

and then explored the results of the script (assuming it ran successfully), only to find that you made an incorrect calculation. After figuring out the problem and modifying `data_script.py`, you can start typing a few letters of the `%run` command then press either the `<Ctrl-P>` key combination or the `<up arrow>` key. This will search the command history for the first prior command matching the letters you typed. Pressing either `<Ctrl-P>` or `<up arrow>` multiple times will continue to search through the history. If you pass over the command you wish to execute, fear not. You can move *forward* through the command history by pressing either `<Ctrl-N>` or `<down arrow>`. After doing this a few times you may start pressing these keys without thinking!

Using `<Ctrl-R>` gives you the same partial incremental searching capability provided by the `readline` used in UNIX-style shells, such as the bash shell. On Windows, `read line` functionality is emulated by IPython. To use this, press `<Ctrl-R>` then type a few characters contained in the input line you want to search for:

```
In [1]: a_command = foo(x, y, z)

(reverse-i-search)`com': a_command = foo(x, y, z)
```

Pressing `<Ctrl-R>` will cycle through the history for each line matching the characters you've typed.

Input and Output Variables

Forgetting to assign the result of a function call to a variable can be very annoying. Fortunately, IPython stores references to *both* the input (the text that you type) and output (the object that is returned) in special variables. The previous two outputs are stored in the _ (one underscore) and __ (two underscores) variables, respectively:

```
In [556]: 2 ** 27
Out[556]: 134217728

In [557]: _
Out[557]: 134217728
```

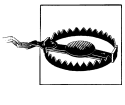
Input variables are stored in variables named like `_iX`, where `X` is the input line number. For each such input variables there is a corresponding output variable `_X`. So after input line 27, say, there will be two new variables `_27` (for the output) and `_i27` for the input.

```
In [26]: foo = 'bar'

In [27]: foo
Out[27]: 'bar'

In [28]: _i27
Out[28]: u'foo'

In [29]: _27
Out[29]: 'bar'
```

Since the input variables are strings, that can be executed again using the Python `exec` keyword:

```
In [30]: exec _i27
```

Several magic functions allow you to work with the input and output history. `%hist` is capable of printing all or part of the input history, with or without line numbers. `%reset` is for clearing the interactive namespace and optionally the input and output caches. The `%xdel` magic function is intended for removing all references to a *particular* object from the IPython machinery. See the documentation for both of these magics for more details.



When working with very large data sets, keep in mind that IPython's input and output history causes any object referenced there to not be garbage collected (freeing up the memory), even if you delete the variables from the interactive namespace using the `del` keyword. In such cases, careful usage of `%xdel` and `%reset` can help you avoid running into memory problems.

Logging the Input and Output

IPython is capable of logging the entire console session including input and output. Logging is turned on by typing `%logstart`:

```
In [3]: %logstart
Activating auto-logging. Current session state plus future input saved.
Filename       : ipython_log.py
Mode           : rotate
Output logging : False
Raw input log  : False
```

```
Timestamping   : False
State          : active
```

IPython logging can be enabled at any time and it will record your entire session (including previous commands). Thus, if you are working on something and you decide you want to save everything you did, you can simply enable logging. See the docstring of `%logstart` for more options (including changing the output file path), as well as the companion functions `%logoff, %logon, %logstate,` and `%logstop`.

Interacting with the Operating System

Another important feature of IPython is that it provides very strong integration with the operating system shell. This means, among other things, that you can perform most standard command line actions as you would in the Windows or UNIX (Linux, OS X) shell without having to exit IPython. This includes executing shell commands, changing directories, and storing the results of a command in a Python object (list or string). There are also simple shell command aliasing and directory bookmarking features.

See Table 3-3 for a summary of magic functions and syntax for calling shell commands. I'll briefly visit these features in the next few sections.

Table 3-3. IPython system-related commands

Command	Description
`!cmd`	Execute cmd in the system shell
`output = !cmd args`	Run cmd and store the stdout in `output`
`%alias` *`alias_name cmd`*	Define an alias for a system (shell) command
`%bookmark`	Utilize IPython's directory bookmarking system
`%cd` *`directory`*	Change system working directory to passed directory
`%pwd`	Return the current system working directory
`%pushd` *`directory`*	Place current directory on stack and change to target directory
`%popd`	Change to directory popped off the top of the stack
`%dirs`	Return a list containing the current directory stack
`%dhist`	Print the history of visited directories
`%env`	Return the system environment variables as a dict

Shell Commands and Aliases

Starting a line in IPython with an exclamation point `!`, or bang, tells IPython to execute everything after the bang in the system shell. This means that you can delete files (using `rm` or `del`, depending on your OS), change directories, or execute any other process. It's even possible to start processes that take control away from IPython, even another Python interpreter:

```
In [2]: !python
Python 2.7.2 |EPD 7.1-2 (64-bit)| (default, Jul  3 2011, 15:17:51)
[GCC 4.1.2 20080704 (Red Hat 4.1.2-44)] on linux2
Type "packages", "demo" or "enthought" for more information.
>>>
```

The console output of a shell command can be stored in a variable by assigning the `!`-escaped expression to a variable. For example, on my Linux-based machine connected to the Internet via ethernet, I can get my IP address as a Python variable:

```
In [1]: ip_info = !ifconfig eth0 | grep "inet "

In [2]: ip_info[0].strip()
Out[2]: 'inet addr:192.168.1.137  Bcast:192.168.1.255  Mask:255.255.255.0'
```

The returned Python object `ip_info` is actually a custom list type containing various versions of the console output.

IPython can also substitute in Python values defined in the current environment when using `!`. To do this, preface the variable name by the dollar sign `$`:

```
In [3]: foo = 'test*'

In [4]: !ls $foo
test4.py  test.py  test.xml
```

The `%alias` magic function can define custom shortcuts for shell commands. As a simple example:

```
In [1]: %alias ll ls -l

In [2]: ll /usr
total 332
drwxr-xr-x   2 root root  69632 2012-01-29 20:36 bin/
drwxr-xr-x   2 root root   4096 2010-08-23 12:05 games/
drwxr-xr-x 123 root root  20480 2011-12-26 18:08 include/
drwxr-xr-x 265 root root 126976 2012-01-29 20:36 lib/
drwxr-xr-x  44 root root  69632 2011-12-26 18:08 lib32/
lrwxrwxrwx   1 root root      3 2010-08-23 16:02 lib64 -> lib/
drwxr-xr-x  15 root root   4096 2011-10-13 19:03 local/
drwxr-xr-x   2 root root  12288 2012-01-12 09:32 sbin/
drwxr-xr-x 387 root root  12288 2011-11-04 22:53 share/
drwxrwsr-x  24 root src    4096 2011-07-17 18:38 src/
```

Multiple commands can be executed just as on the command line by separating them with semicolons:

```
In [558]: %alias test_alias (cd ch08; ls; cd ..)

In [559]: test_alias
macrodata.csv  spx.csv    tips.csv
```

You'll notice that IPython "forgets" any aliases you define interactively as soon as the session is closed. To create permanent aliases, you will need to use the configuration system. See later in the chapter.

Directory Bookmark System

IPython has a simple directory bookmarking system to enable you to save aliases for common directories so that you can jump around very easily. For example, I'm an avid user of Dropbox, so I can define a bookmark to make it easy to change directories to my Dropbox:

```
In [6]: %bookmark db /home/wesm/Dropbox/
```

Once I've done this, when I use the `%cd` magic, I can use any bookmarks I've defined

```
In [7]: cd db
(bookmark:db) -> /home/wesm/Dropbox/
/home/wesm/Dropbox
```

If a bookmark name conflicts with a directory name in your current working directory, you can use the `-b` flag to override and use the bookmark location. Using the `-l` option with `%bookmark` lists all of your bookmarks:

```
In [8]: %bookmark -l
Current bookmarks:
db -> /home/wesm/Dropbox/
```

Bookmarks, unlike aliases, are automatically persisted between IPython sessions.

Software Development Tools

In addition to being a comfortable environment for interactive computing and data exploration, IPython is well suited as a software development environment. In data analysis applications, it's important first to have *correct* code. Fortunately, IPython has closely integrated and enhanced the built-in Python `pdb` debugger. Secondly you want your code to be *fast*. For this IPython has easy-to-use code timing and profiling tools. I will give an overview of these tools in detail here.

Interactive Debugger

IPython's debugger enhances `pdb` with tab completion, syntax highlighting, and context for each line in exception tracebacks. One of the best times to debug code is right after an error has occurred. The `%debug` command, when entered immediately after an exception, invokes the "post-mortem" debugger and drops you into the stack frame where the exception was raised:

```
In [2]: run ch03/ipython_bug.py
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
/home/wesm/book_scripts/ch03/ipython_bug.py in <module>()
     13     throws_an_exception()
     14
---> 15 calling_things()

/home/wesm/book_scripts/ch03/ipython_bug.py in calling_things()
```

```
     11 def calling_things():
     12     works_fine()
---> 13     throws_an_exception()
     14
     15 calling_things()

/home/wesm/book_scripts/ch03/ipython_bug.py in throws_an_exception()
      7     a = 5
      8     b = 6
----> 9     assert(a + b == 10)
     10
     11 def calling_things():

AssertionError:

In [3]: %debug
> /home/wesm/book_scripts/ch03/ipython_bug.py(9)throws_an_exception()
      8     b = 6
----> 9     assert(a + b == 10)
     10

ipdb>
```

Once inside the debugger, you can execute arbitrary Python code and explore all of the objects and data (which have been "kept alive" by the interpreter) inside each stack frame. By default you start in the lowest level, where the error occurred. By pressing `u` (up) and `d` (down), you can switch between the levels of the stack trace:

```
ipdb> u
> /home/wesm/book_scripts/ch03/ipython_bug.py(13)calling_things()
     12     works_fine()
---> 13     throws_an_exception()
     14
```

Executing the `%pdb` command makes it so that IPython automatically invokes the debugger after any exception, a mode that many users will find especially useful.

It's also easy to use the debugger to help develop code, especially when you wish to set breakpoints or step through the execution of a function or script to examine the state at each stage. There are several ways to accomplish this. The first is by using `%run` with the `-d` flag, which invokes the debugger before executing any code in the passed script. You must immediately press `s` (step) to enter the script:

```
In [5]: run -d ch03/ipython_bug.py
Breakpoint 1 at /home/wesm/book_scripts/ch03/ipython_bug.py:1
NOTE: Enter 'c' at the ipdb>  prompt to start your script.
> <string>(1)<module>()

ipdb> s
--Call--
> /home/wesm/book_scripts/ch03/ipython_bug.py(1)<module>()
1---> 1 def works_fine():
      2     a = 5
      3     b = 6
```

After this point, it's up to you how you want to work your way through the file. For example, in the above exception, we could set a breakpoint right before calling the `works_fine` method and run the script until we reach the breakpoint by pressing `c` (continue):

```
ipdb> b 12
ipdb> c
> /home/wesm/book_scripts/ch03/ipython_bug.py(12)calling_things()
     11 def calling_things():
2--> 12     works_fine()
     13     throws_an_exception()
```

At this point, you can `step` into `works_fine()` or execute `works_fine()` by pressing `n` (next) to advance to the next line:

```
ipdb> n
> /home/wesm/book_scripts/ch03/ipython_bug.py(13)calling_things()
2    12     works_fine()
---> 13     throws_an_exception()
     14
```

Then, we could step into `throws_an_exception` and advance to the line where the error occurs and look at the variables in the scope. Note that debugger commands take precedence over variable names; in such cases preface the variables with `!` to examine their contents.

```
ipdb> s
--Call--
> /home/wesm/book_scripts/ch03/ipython_bug.py(6)throws_an_exception()
      5
----> 6 def throws_an_exception():
      7     a = 5

ipdb> n
> /home/wesm/book_scripts/ch03/ipython_bug.py(7)throws_an_exception()
      6 def throws_an_exception():
----> 7     a = 5
      8     b = 6

ipdb> n
> /home/wesm/book_scripts/ch03/ipython_bug.py(8)throws_an_exception()
      7     a = 5
----> 8     b = 6
      9     assert(a + b == 10)

ipdb> n
> /home/wesm/book_scripts/ch03/ipython_bug.py(9)throws_an_exception()
      8     b = 6
----> 9     assert(a + b == 10)
     10

ipdb> !a
5
ipdb> !b
6
```

Becoming proficient in the interactive debugger is largely a matter of practice and experience. See Table 3-3 for a full catalogue of the debugger commands. If you are used to an IDE, you might find the terminal-driven debugger to be a bit bewildering at first, but that will improve in time. Most of the Python IDEs have excellent GUI debuggers, but it is usually a significant productivity gain to remain in IPython for your debugging.

Table 3-4. (I)Python debugger commands

Command	Action
`h(elp)`	Display command list
`help` *`command`*	Show documentation for *`command`*
`c(ontinue)`	Resume program execution
`q(uit)`	Exit debugger without executing any more code
`b(reak)` *`number`*	Set breakpoint at *`number`* in current file
`b` *`path/to/file.py:number`*	Set breakpoint at line *`number`* in specified file
`s(tep)`	Step *into* function call
`n(ext)`	Execute current line and advance to next line at current level
`u(p) / d(own)`	Move up/down in function call stack
`a(rgs)`	Show arguments for current function
`debug` *`statement`*	Invoke statement *`statement`* in new (recursive) debugger
`l(ist)` *`statement`*	Show current position and context at current level of stack
`w(here)`	Print full stack trace with context at current position

Other ways to make use of the debugger

There are a couple of other useful ways to invoke the debugger. The first is by using a special `set_trace` function (named after `pdb.set_trace`), which is basically a "poor man's breakpoint". Here are two small recipes you might want to put somewhere for your general use (potentially adding them to your IPython profile as I do):

```
def set_trace():
    from IPython.core.debugger import Pdb
    Pdb(color_scheme='Linux').set_trace(sys._getframe().f_back)

def debug(f, *args, **kwargs):
    from IPython.core.debugger import Pdb
    pdb = Pdb(color_scheme='Linux')
    return pdb.runcall(f, *args, **kwargs)
```

The first function, `set_trace`, is very simple. Put `set_trace()` anywhere in your code that you want to stop and take a look around (for example, right before an exception occurs):

```
In [7]: run ch03/ipython_bug.py
> /home/wesm/book_scripts/ch03/ipython_bug.py(16)calling_things()
     15     set_trace()
```

```
---> 16     throws_an_exception()
     17
```

Pressing `c` (continue) will cause the code to resume normally with no harm done.

The `debug` function above enables you to invoke the interactive debugger easily on an arbitrary function call. Suppose we had written a function like

```
def f(x, y, z=1):
    tmp = x + y
    return tmp / z
```

and we wished to step through its logic. Ordinarily using `f` would look like `f(1, 2, z=3)`. To instead step into `f`, pass `f` as the first argument to `debug` followed by the positional and keyword arguments to be passed to `f`:

```
In [6]: debug(f, 1, 2, z=3)
> <ipython-input>(2)f()
      1 def f(x, y, z):
----> 2     tmp = x + y
      3     return tmp / z

ipdb>
```

I find that these two simple recipes save me a lot of time on a day-to-day basis.

Lastly, the debugger can be used in conjunction with `%run`. By running a script with `%run -d`, you will be dropped directly into the debugger, ready to set any breakpoints and start the script:

```
In [1]: %run -d ch03/ipython_bug.py
Breakpoint 1 at /home/wesm/book_scripts/ch03/ipython_bug.py:1
NOTE: Enter 'c' at the ipdb>  prompt to start your script.
> <string>(1)<module>()

ipdb>
```

Adding `-b` with a line number starts the debugger with a breakpoint set already:

```
In [2]: %run -d -b2 ch03/ipython_bug.py
Breakpoint 1 at /home/wesm/book_scripts/ch03/ipython_bug.py:2
NOTE: Enter 'c' at the ipdb>  prompt to start your script.
> <string>(1)<module>()

ipdb> c
> /home/wesm/book_scripts/ch03/ipython_bug.py(2)works_fine()
      1 def works_fine():
1---> 2     a = 5
      3     b = 6

ipdb>
```

Timing Code: %time and %timeit

For larger-scale or longer-running data analysis applications, you may wish to measure the execution time of various components or of individual statements or function calls. You may want a report of which functions are taking up the most time in a complex process. Fortunately, IPython enables you to get this information very easily while you are developing and testing your code.

Timing code by hand using the built-in `time` module and its functions `time.clock` and `time.time` is often tedious and repetitive, as you must write the same uninteresting boilerplate code:

```
import time
start = time.time()
for i in range(iterations):
    # some code to run here
elapsed_per = (time.time() - start) / iterations
```

Since this is such a common operation, IPython has two magic functions `%time` and `%timeit` to automate this process for you. `%time` runs a statement once, reporting the total execution time. Suppose we had a large list of strings and we wanted to compare different methods of selecting all strings starting with a particular prefix. Here is a simple list of 700,000 strings and two identical methods of selecting only the ones that start with `'foo'`:

```
# a very large list of strings
strings = ['foo', 'foobar', 'baz', 'qux',
           'python', 'Guido Van Rossum'] * 100000

method1 = [x for x in strings if x.startswith('foo')]

method2 = [x for x in strings if x[:3] == 'foo']
```

It looks like they should be about the same performance-wise, right? We can check for sure using `%time`:

```
In [561]: %time method1 = [x for x in strings if x.startswith('foo')]
CPU times: user 0.19 s, sys: 0.00 s, total: 0.19 s
Wall time: 0.19 s

In [562]: %time method2 = [x for x in strings if x[:3] == 'foo']
CPU times: user 0.09 s, sys: 0.00 s, total: 0.09 s
Wall time: 0.09 s
```

The `Wall time` is the main number of interest. So, it looks like the first method takes more than twice as long, but it's not a very precise measurement. If you try `%time`-ing those statements multiple times yourself, you'll find that the results are somewhat variable. To get a more precise measurement, use the `%timeit` magic function. Given an arbitrary statement, it has a heuristic to run a statement multiple times to produce a fairly accurate average runtime.

```
In [563]: %timeit [x for x in strings if x.startswith('foo')]
10 loops, best of 3: 159 ms per loop
```

```
In [564]: %timeit [x for x in strings if x[:3] == 'foo']
10 loops, best of 3: 59.3 ms per loop
```

This seemingly innocuous example illustrates that it is worth understanding the performance characteristics of the Python standard library, NumPy, pandas, and other libraries used in this book. In larger-scale data analysis applications, those milliseconds will start to add up!

`%timeit` is especially useful for analyzing statements and functions with very short execution times, even at the level of microseconds (1e-6 seconds) or nanoseconds (1e-9 seconds). These may seem like insignificant amounts of time, but of course a 20 microsecond function invoked 1 million times takes 15 seconds longer than a 5 microsecond function. In the above example, we could very directly compare the two string operations to understand their performance characteristics:

```
In [565]: x = 'foobar'

In [566]: y = 'foo'

In [567]: %timeit x.startswith(y)
1000000 loops, best of 3: 267 ns per loop

In [568]: %timeit x[:3] == y
10000000 loops, best of 3: 147 ns per loop
```

Basic Profiling: %prun and %run -p

Profiling code is closely related to timing code, except it is concerned with determining *where* time is spent. The main Python profiling tool is the `cProfile` module, which is not specific to IPython at all. `cProfile` executes a program or any arbitrary block of code while keeping track of how much time is spent in each function.

A common way to use `cProfile` is on the command line, running an entire program and outputting the aggregated time per function. Suppose we had a simple script which does some linear algebra in a loop (computing the maximum absolute eigenvalues of a series of `100 x 100` matrices):

```
import numpy as np
from numpy.linalg import eigvals

def run_experiment(niter=100):
    K = 100
    results = []
    for _ in xrange(niter):
        mat = np.random.randn(K, K)
        max_eigenvalue = np.abs(eigvals(mat)).max()
        results.append(max_eigenvalue)
    return results
some_results = run_experiment()
print 'Largest one we saw: %s' % np.max(some_results)
```

Don't worry if you are not familiar with NumPy. You can run this script through `cProfile` by running the following in the command line:

```
python -m cProfile cprof_example.py
```

If you try that, you'll find that the results are outputted sorted by function name. This makes it a bit hard to get an idea of where the most time is spent, so it's very common to specify a *sort order* using the `-s` flag:

```
$ python -m cProfile -s cumulative cprof_example.py
Largest one we saw: 11.923204422
    15116 function calls (14927 primitive calls) in 0.720 seconds

Ordered by: cumulative time

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     1    0.001    0.001    0.721    0.721 cprof_example.py:1(<module>)
   100    0.003    0.000    0.586    0.006 linalg.py:702(eigvals)
   200    0.572    0.003    0.572    0.003 {numpy.linalg.lapack_lite.dgeev}
     1    0.002    0.002    0.075    0.075 __init__.py:106(<module>)
   100    0.059    0.001    0.059    0.001 {method 'randn'}
     1    0.000    0.000    0.044    0.044 add_newdocs.py:9(<module>)
     2    0.001    0.001    0.037    0.019 __init__.py:1(<module>)
     2    0.003    0.002    0.030    0.015 __init__.py:2(<module>)
     1    0.000    0.000    0.030    0.030 type_check.py:3(<module>)
     1    0.001    0.001    0.021    0.021 __init__.py:15(<module>)
     1    0.013    0.013    0.013    0.013 numeric.py:1(<module>)
     1    0.000    0.000    0.009    0.009 __init__.py:6(<module>)
     1    0.001    0.001    0.008    0.008 __init__.py:45(<module>)
   262    0.005    0.000    0.007    0.000 function_base.py:3178(add_newdoc)
   100    0.003    0.000    0.005    0.000 linalg.py:162(_assertFinite)
   ...
```

Only the first 15 rows of the output are shown. It's easiest to read by scanning down the `cumtime` column to see how much total time was spent *inside* each function. Note that if a function calls some other function, *the clock does not stop running*. `cProfile` records the start and end time of each function call and uses that to produce the timing.

In addition to the above command-line usage, `cProfile` can also be used programmatically to profile arbitrary blocks of code without having to run a new process. IPython has a convenient interface to this capability using the `%prun` command and the `-p` option to `%run`. `%prun` takes the same "command line options" as `cProfile` but will profile an arbitrary Python statement instead of a while `.py` file:

```
In [4]: %prun -l 7 -s cumulative run_experiment()
         4203 function calls in 0.643 seconds

Ordered by: cumulative time
List reduced from 32 to 7 due to restriction <7>

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     1    0.000    0.000    0.643    0.643 <string>:1(<module>)
     1    0.001    0.001    0.643    0.643 cprof_example.py:4(run_experiment)
   100    0.003    0.000    0.583    0.006 linalg.py:702(eigvals)
```

```
   200    0.569    0.003    0.569    0.003 {numpy.linalg.lapack_lite.dgeev}
   100    0.058    0.001    0.058    0.001 {method 'randn'}
   100    0.003    0.000    0.005    0.000 linalg.py:162(_assertFinite)
   200    0.002    0.000    0.002    0.000 {method 'all' of 'numpy.ndarray' objects}
```

Similarly, calling `%run -p -s cumulative cprof_example.py` has the same effect as the command-line approach above, except you never have to leave IPython.

Profiling a Function Line-by-Line

In some cases the information you obtain from `%prun` (or another `cProfile`-based profile method) may not tell the whole story about a function's execution time, or it may be so complex that the results, aggregated by function name, are hard to interpret. For this case, there is a small library called `line_profiler` (obtainable via PyPI or one of the package management tools). It contains an IPython extension enabling a new magic function `%lprun` that computes a line-by-line-profiling of one or more functions. You can enable this extension by modifying your IPython configuration (see the IPython documentation or the section on configuration later in this chapter) to include the following line:

```
# A list of dotted module names of IPython extensions to load.
c.TerminalIPythonApp.extensions = ['line_profiler']
```

`line_profiler` can be used programmatically (see the full documentation), but it is perhaps most powerful when used interactively in IPython. Suppose you had a module `prof_mod` with the following code doing some NumPy array operations:

```
from numpy.random import randn

def add_and_sum(x, y):
    added = x + y
    summed = added.sum(axis=1)
    return summed

def call_function():
    x = randn(1000, 1000)
    y = randn(1000, 1000)
    return add_and_sum(x, y)
```

If we wanted to understand the performance of the `add_and_sum` function, `%prun` gives us the following:

```
In [569]: %run prof_mod

In [570]: x = randn(3000, 3000)

In [571]: y = randn(3000, 3000)

In [572]: %prun add_and_sum(x, y)
         4 function calls in 0.049 seconds
   Ordered by: internal time
   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
        1    0.036    0.036    0.046    0.046 prof_mod.py:3(add_and_sum)
```

```
     1    0.009    0.009    0.009    0.009 {method 'sum' of 'numpy.ndarray' objects}
     1    0.003    0.003    0.049    0.049 <string>:1(<module>)
     1    0.000    0.000    0.000    0.000 {method 'disable' of '_lsprof.Profiler' objects}
```

This is not especially enlightening. With the `line_profiler` IPython extension activated, a new command `%lprun` is available. The only difference in usage is that we must instruct `%lprun` which function or functions we wish to profile. The general syntax is:

```
%lprun -f func1 -f func2 statement_to_profile
```

In this case, we want to profile `add_and_sum`, so we run:

```
In [573]: %lprun -f add_and_sum add_and_sum(x, y)
Timer unit: 1e-06 s
File: book_scripts/prof_mod.py
Function: add_and_sum at line 3
Total time: 0.045936 s
Line #      Hits         Time  Per Hit   % Time  Line Contents
==============================================================
     3                                           def add_and_sum(x, y):
     4         1        36510  36510.0     79.5      added = x + y
     5         1         9425   9425.0     20.5      summed = added.sum(axis=1)
     6         1            1      1.0      0.0      return summed
```

You'll probably agree this is much easier to interpret. In this case we profiled the same function we used in the statement. Looking at the module code above, we could call `call_function` and profile that as well as `add_and_sum`, thus getting a full picture of the performance of the code:

```
In [574]: %lprun -f add_and_sum -f call_function call_function()
Timer unit: 1e-06 s
File: book_scripts/prof_mod.py
Function: add_and_sum at line 3
Total time: 0.005526 s
Line #      Hits         Time  Per Hit   % Time  Line Contents
==============================================================
     3                                           def add_and_sum(x, y):
     4         1         4375   4375.0     79.2      added = x + y
     5         1         1149   1149.0     20.8      summed = added.sum(axis=1)
     6         1            2      2.0      0.0      return summed
File: book_scripts/prof_mod.py
Function: call_function at line 8
Total time: 0.121016 s
Line #      Hits         Time  Per Hit   % Time  Line Contents
==============================================================
     8                                           def call_function():
     9         1        57169  57169.0     47.2      x = randn(1000, 1000)
    10         1        58304  58304.0     48.2      y = randn(1000, 1000)
    11         1         5543   5543.0      4.6      return add_and_sum(x, y)
```

As a general rule of thumb, I tend to prefer `%prun` (`cProfile`) for "macro" profiling and `%lprun` (`line_profiler`) for "micro" profiling. It's worthwhile to have a good understanding of both tools.

The reason that you have to specify explicitly the names of the functions you want to profile with `%lprun` is that the overhead of "tracing" the execution time of each line is significant. Tracing functions that are not of interest would potentially significantly alter the profile results.

IPython HTML Notebook

Starting in 2011, the IPython team, led by Brian Granger, built a web technology–based interactive computational document format that is commonly known as the IPython Notebook. It has grown into a wonderful tool for interactive computing and an ideal medium for reproducible research and teaching. I've used it while writing most of the examples in the book; I encourage you to make use of it, too.

It has a JSON-based `.ipynb` document format that enables easy sharing of code, output, and figures. Recently in Python conferences, a popular approach for demonstrations has been to use the notebook and post the `.ipynb` files online afterward for everyone to play with.

The notebook application runs as a lightweight server process on the command line. It can be started by running:

```
$ ipython notebook --pylab=inline
[NotebookApp] Using existing profile dir: u'/home/wesm/.config/ipython/profile_default'
[NotebookApp] Serving notebooks from /home/wesm/book_scripts
[NotebookApp] The IPython Notebook is running at: http://127.0.0.1:8888/
[NotebookApp] Use Control-C to stop this server and shut down all kernels.
```

On most platforms, your primary web browser will automatically open up to the notebook dashboard. In some cases you may have to navigate to the listed URL. From there, you can create a new notebook and start exploring.

Since you use the notebook inside a web browser, the server process can run anywhere. You can even securely connect to notebooks running on cloud service providers like Amazon EC2. As of this writing, a new project NotebookCloud (*http://notebookcloud.appspot.com*) makes it easy to launch notebooks on EC2.

Tips for Productive Code Development Using IPython

Writing code in a way that makes it easy to develop, debug, and ultimately *use* interactively may be a paradigm shift for many users. There are procedural details like code reloading that may require some adjustment as well as coding style concerns.

As such, most of this section is more of an art than a science and will require some experimentation on your part to determine a way to write your Python code that is effective and productive for you. Ultimately you want to structure your code in a way that makes it easy to use iteratively and to be able to explore the results of running a program or function as effortlessly as possible. I have found software designed with

127.0.0.1:8888/5a085d6e-d135-447b-869d-a4848ec3f77b

IP[y]: Notebook NotebookEx Last saved: Jul 26 1:06 PM

File Edit View Insert Cell Kernel Help

Code

In [1]:
```
import numpy as np
import pandas as pd
print 'Hello world!'
```

```
Hello world!
```

In [2]:
```
tips = pd.read_csv('book_scripts/ch08/tips.csv')
tips.head()
```

Out[2]:

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

In [4]:
```
img = plt.imread('book_scripts/ch03/stinkbug.png')
figure(figsize=(4, 4))
plt.imshow(img)
```

Out[4]:
```
<matplotlib.image.AxesImage at 0x7f465d34a510>
```

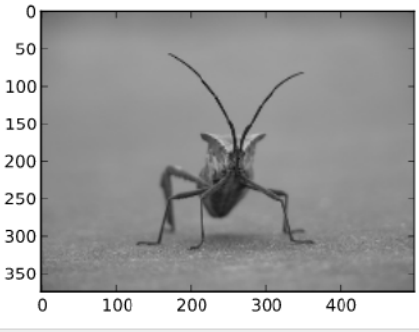


Figure 3-4. IPython Notebook

IPython in mind to be easier to work with than code intended only to be run as as standalone command-line application. This becomes especially important when something goes wrong and you have to diagnose an error in code that you or someone else might have written months or years beforehand.

Reloading Module Dependencies

In Python, when you type `import some_lib`, the code in `some_lib` is executed and all the variables, functions, and imports defined within are stored in the newly created `some_lib` module namespace. The next time you type `import some_lib`, you will get a reference to the existing module namespace. The potential difficulty in interactive code development in IPython comes when you, say, `%run` a script that depends on some other module where you may have made changes. Suppose I had the following code in `test_script.py`:

```
import some_lib

x = 5
y = [1, 2, 3, 4]
result = some_lib.get_answer(x, y)
```

If you were to execute `%run test_script.py` then modify `some_lib.py`, the next time you execute `%run test_script.py` you will still get the *old version* of `some_lib` because of Python's "load-once" module system. This behavior differs from some other data analysis environments, like MATLAB, which automatically propagate code changes.[1] To cope with this, you have a couple of options. The first way is to use Python's built-in `reload` function, altering `test_script.py` to look like the following:

```
import some_lib
reload(some_lib)

x = 5
y = [1, 2, 3, 4]
result = some_lib.get_answer(x, y)
```

This guarantees that you will get a fresh copy of `some_lib` every time you run `test_script.py`. Obviously, if the dependencies go deeper, it might be a bit tricky to be inserting usages of `reload` all over the place. For this problem, IPython has a special `dreload` function (*not* a magic function) for "deep" (recursive) reloading of modules. If I were to run `import some_lib` then type `dreload(some_lib)`, it will attempt to reload `some_lib` as well as all of its dependencies. This will not work in all cases, unfortunately, but when it does it beats having to restart IPython.

Code Design Tips

There's no simple recipe for this, but here are some high-level principles I have found effective in my own work.

1. Since a module or package may be imported in many different places in a particular program, Python caches a module's code the first time it is imported rather than executing the code in the module every time. Otherwise, modularity and good code organization could potentially cause inefficiency in an application.

Keep relevant objects and data alive

It's not unusual to see a program written for the command line with a structure somewhat like the following trivial example:

```
from my_functions import g

def f(x, y):
    return g(x + y)

def main():
    x = 6
    y = 7.5
    result = x + y

if __name__ == '__main__':
    main()
```

Do you see what might be wrong with this program if we were to run it in IPython? After it's done, none of the results or objects defined in the `main` function willl be accessible in the IPython shell. A better way is to have whatever code is in `main` execute directly in the module's global namespace (or in the `if __name__ == '__main__':` block, if you want the module to also be importable). That way, when you `%run` the code, you'll be able to look at all of the variables defined in `main`. It's less meaningful in this simple example, but in this book we'll be looking at some complex data analysis problems involving large data sets that you will want to be able to play with in IPython.

Flat is better than nested

Deeply nested code makes me think about the many layers of an onion. When testing or debugging a function, how many layers of the onion must you peel back in order to reach the code of interest? The idea that "flat is better than nested" is a part of the Zen of Python, and it applies generally to developing code for interactive use as well. Making functions and classes as decoupled and modular as possible makes them easier to test (if you are writing unit tests), debug, and use interactively.

Overcome a fear of longer files

If you come from a Java (or another such language) background, you may have been told to keep files short. In many languages, this is sound advice; long length is usually a bad "code smell", indicating refactoring or reorganization may be necessary. However, while developing code using IPython, working with 10 small, but interconnected files (under, say, 100 lines each) is likely to cause you more headache in general than a single large file or two or three longer files. Fewer files means fewer modules to reload and less jumping between files while editing, too. I have found maintaining larger modules, each with high *internal* cohesion, to be much more useful and pythonic. After iterating toward a solution, it sometimes will make sense to refactor larger files into smaller ones.

Obviously, I don't support taking this argument to the extreme, which would to be to put all of your code in a single monstrous file. Finding a sensible and intuitive module and package structure for a large codebase often takes a bit of work, but it is especially important to get right in teams. Each module should be internally cohesive, and it should be as obvious as possible where to find functions and classes responsible for each area of functionality.

Advanced IPython Features

Making Your Own Classes IPython-friendly

IPython makes every effort to display a console-friendly string representation of any object that you inspect. For many objects, like dicts, lists, and tuples, the built-in `pprint` module is used to do the nice formatting. In user-defined classes, however, you have to generate the desired string output yourself. Suppose we had the following simple class:

```
class Message:
    def __init__(self, msg):
        self.msg = msg
```

If you wrote this, you would be disappointed to discover that the default output for your class isn't very nice:

```
In [576]: x = Message('I have a secret')

In [577]: x
Out[577]: <__main__.Message instance at 0x60ebbd8>
```

IPython takes the string returned by the `__repr__` magic method (by doing `output = repr(obj)`) and prints that to the console. Thus, we can add a simple `__repr__` method to the above class to get a more helpful output:

```
class Message:
    def __init__(self, msg):
        self.msg = msg

    def __repr__(self):
        return 'Message: %s' % self.msg

In [579]: x = Message('I have a secret')

In [580]: x
Out[580]: Message: I have a secret
```

Profiles and Configuration

Most aspects of the appearance (colors, prompt, spacing between lines, etc.) and behavior of the IPython shell are configurable through an extensive configuration system. Here are some of the things you can do via configuration:

- Change the color scheme
- Change how the input and output prompts look, or remove the blank line after `Out` and before the next `In` prompt
- Change how the input and output prompts look
- Execute an arbitrary list of Python statements. These could be imports that you use all the time or anything else you want to happen each time you launch IPython
- Enable IPython extensions, like the `%lprun` magic in `line_profiler`
- Define your own magics or system aliases

All of these configuration options are specified in a special `ipython_config.py` file which will be found in the `~/.config/ipython/` directory on UNIX-like systems and `%HOME %/.ipython/` directory on Windows. Where your home directory is depends on your system. Configuration is performed based on a particular *profile*. When you start IPython normally, you load up, by default, the *default profile*, stored in the `profile_default` directory. Thus, on my Linux OS the full path to my default IPython configuration file is:

```
/home/wesm/.config/ipython/profile_default/ipython_config.py
```

I'll spare you the gory details of what's in this file. Fortunately it has comments describing what each configuration option is for, so I will leave it to the reader to tinker and customize. One additional useful feature is that it's possible to have *multiple profiles*. Suppose you wanted to have an alternate IPython configuration tailored for a particular application or project. Creating a new profile is as simple is typing something like

```
ipython profile create secret_project
```

Once you've done this, edit the config files in the newly-created `profile_secret_project` directory then launch IPython like so

```
$ ipython --profile=secret_project
Python 2.7.2 |EPD 7.1-2 (64-bit)| (default, Jul  3 2011, 15:17:51)
Type "copyright", "credits" or "license" for more information.

IPython 0.13 -- An enhanced Interactive Python.
?         -> Introduction and overview of IPython's features.
%quickref -> Quick reference.
help      -> Python's own help system.
object?   -> Details about 'object', use 'object??' for extra details.

IPython profile: secret_project
```

```
In [1]:
```

As always, the online IPython documentation is an excellent resource for more on profiles and configuration.

Credits

Parts of this chapter were derived from the wonderful documentation put together by the IPython Development Team. I can't thank them enough for all of their work building this amazing set of tools.

CHAPTER 4

NumPy Basics: Arrays and Vectorized Computation

NumPy, short for Numerical Python, is the fundamental package required for high performance scientific computing and data analysis. It is the foundation on which nearly all of the higher-level tools in this book are built. Here are some of the things it provides:

- `ndarray`, a fast and space-efficient multidimensional array providing vectorized arithmetic operations and sophisticated *broadcasting* capabilities
- Standard mathematical functions for fast operations on entire arrays of data without having to write loops
- Tools for reading / writing array data to disk and working with memory-mapped files
- Linear algebra, random number generation, and Fourier transform capabilities
- Tools for integrating code written in C, C++, and Fortran

The last bullet point is also one of the most important ones from an ecosystem point of view. Because NumPy provides an easy-to-use C API, it is very easy to pass data to external libraries written in a low-level language and also for external libraries to return data to Python as NumPy arrays. This feature has made Python a language of choice for wrapping legacy C/C++/Fortran codebases and giving them a dynamic and easy-to-use interface.

While NumPy by itself does not provide very much high-level data analytical functionality, having an understanding of NumPy arrays and array-oriented computing will help you use tools like pandas much more effectively. If you're new to Python and just looking to get your hands dirty working with data using pandas, feel free to give this chapter a skim. For more on advanced NumPy features like broadcasting, see Chapter 12.

For most data analysis applications, the main areas of functionality I'll focus on are:

- Fast vectorized array operations for data munging and cleaning, subsetting and filtering, transformation, and any other kinds of computations
- Common array algorithms like sorting, unique, and set operations
- Efficient descriptive statistics and aggregating/summarizing data
- Data alignment and relational data manipulations for merging and joining together heterogeneous data sets
- Expressing conditional logic as array expressions instead of loops with `if-elif-else` branches
- Group-wise data manipulations (aggregation, transformation, function application). Much more on this in Chapter 5

While NumPy provides the computational foundation for these operations, you will likely want to use pandas as your basis for most kinds of data analysis (especially for structured or tabular data) as it provides a rich, high-level interface making most common data tasks very concise and simple. pandas also provides some more domain-specific functionality like time series manipulation, which is not present in NumPy.

In this chapter and throughout the book, I use the standard NumPy convention of always using `import numpy as np`. You are, of course, welcome to put `from numpy import *` in your code to avoid having to write `np.`, but I would caution you against making a habit of this.

The NumPy ndarray: A Multidimensional Array Object

One of the key features of NumPy is its N-dimensional array object, or ndarray, which is a fast, flexible container for large data sets in Python. Arrays enable you to perform mathematical operations on whole blocks of data using similar syntax to the equivalent operations between scalar elements:

```
In [8]: data
Out[8]:
array([[ 0.9526, -0.246 , -0.8856],
       [ 0.5639,  0.2379,  0.9104]])

In [9]: data * 10
Out[9]:
array([[ 9.5256, -2.4601, -8.8565],
       [ 5.6385,  2.3794,  9.104 ]])

In [10]: data + data
Out[10]:
array([[ 1.9051, -0.492 , -1.7713],
       [ 1.1277,  0.4759,  1.8208]])
```

An ndarray is a generic multidimensional container for homogeneous data; that is, all of the elements must be the same type. Every array has a `shape`, a tuple indicating the size of each dimension, and a `dtype`, an object describing the *data type* of the array:

```
In [11]: data.shape
Out[11]: (2, 3)
```

```
In [12]: data.dtype
Out[12]: dtype('float64')
```

This chapter will introduce you to the basics of using NumPy arrays, and should be sufficient for following along with the rest of the book. While it's not necessary to have a deep understanding of NumPy for many data analytical applications, becoming proficient in array-oriented programming and thinking is a key step along the way to becoming a scientific Python guru.

Whenever you see "array", "NumPy array", or "ndarray" in the text, with few exceptions they all refer to the same thing: the ndarray object.

Creating ndarrays

The easiest way to create an array is to use the `array` function. This accepts any sequence-like object (including other arrays) and produces a new NumPy array containing the passed data. For example, a list is a good candidate for conversion:

```
In [13]: data1 = [6, 7.5, 8, 0, 1]

In [14]: arr1 = np.array(data1)

In [15]: arr1
Out[15]: array([ 6. ,  7.5,  8. ,  0. ,  1. ])
```

Nested sequences, like a list of equal-length lists, will be converted into a multidimensional array:

```
In [16]: data2 = [[1, 2, 3, 4], [5, 6, 7, 8]]

In [17]: arr2 = np.array(data2)

In [18]: arr2
Out[18]:
array([[1, 2, 3, 4],
       [5, 6, 7, 8]])

In [19]: arr2.ndim
Out[19]: 2

In [20]: arr2.shape
Out[20]: (2, 4)
```

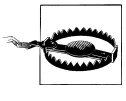
Unless explicitly specified (more on this later), `np.array` tries to infer a good data type for the array that it creates. The data type is stored in a special `dtype` object; for example, in the above two examples we have:

```
In [21]: arr1.dtype
Out[21]: dtype('float64')
```

```
In [22]: arr2.dtype
Out[22]: dtype('int64')
```

In addition to `np.array`, there are a number of other functions for creating new arrays. As examples, `zeros` and `ones` create arrays of 0's or 1's, respectively, with a given length or shape. `empty` creates an array without initializing its values to any particular value. To create a higher dimensional array with these methods, pass a tuple for the shape:

```
In [23]: np.zeros(10)
Out[23]: array([ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.])

In [24]: np.zeros((3, 6))
Out[24]:
array([[ 0.,  0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.,  0.]])

In [25]: np.empty((2, 3, 2))
Out[25]:
array([[[  4.94065646e-324,   4.94065646e-324],
        [  3.87491056e-297,   2.46845796e-130],
        [  4.94065646e-324,   4.94065646e-324]],

       [[  1.90723115e+083,   5.73293533e-053],
        [ -2.33568637e+124,  -6.70608105e-012],
        [  4.42786966e+160,   1.27100354e+025]]])
```



It's not safe to assume that `np.empty` will return an array of all zeros. In many cases, as previously shown, it will return uninitialized garbage values.

`arange` is an array-valued version of the built-in Python `range` function:

```
In [26]: np.arange(15)
Out[26]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14])
```

See Table 4-1 for a short list of standard array creation functions. Since NumPy is focused on numerical computing, the data type, if not specified, will in many cases be `float64` (floating point).

Table 4-1. Array creation functions

Function	Description
`array`	Convert input data (list, tuple, array, or other sequence type) to an ndarray either by inferring a dtype or explicitly specifying a dtype. Copies the input data by default.
`asarray`	Convert input to ndarray, but do not copy if the input is already an ndarray
`arange`	Like the built-in `range` but returns an ndarray instead of a list.
`ones, ones_like`	Produce an array of all 1's with the given shape and dtype. `ones_like` takes another array and produces a ones array of the same shape and dtype.
`zeros, zeros_like`	Like `ones` and `ones_like` but producing arrays of 0's instead

Function	Description
`empty, empty_like`	Create new arrays by allocating new memory, but do not populate with any values like `ones` and `zeros`
`eye, identity`	Create a square N x N identity matrix (1's on the diagonal and 0's elsewhere)

Data Types for ndarrays

The *data type* or `dtype` is a special object containing the information the ndarray needs to interpret a chunk of memory as a particular type of data:

```
In [27]: arr1 = np.array([1, 2, 3], dtype=np.float64)

In [28]: arr2 = np.array([1, 2, 3], dtype=np.int32)

In [29]: arr1.dtype            In [30]: arr2.dtype
Out[29]: dtype('float64')      Out[30]: dtype('int32')
```

Dtypes are part of what make NumPy so powerful and flexible. In most cases they map directly onto an underlying machine representation, which makes it easy to read and write binary streams of data to disk and also to connect to code written in a low-level language like C or Fortran. The numerical dtypes are named the same way: a type name, like `float` or `int`, followed by a number indicating the number of bits per element. A standard double-precision floating point value (what's used under the hood in Python's `float` object) takes up 8 bytes or 64 bits. Thus, this type is known in NumPy as `float64`. See Table 4-2 for a full listing of NumPy's supported data types.

Don't worry about memorizing the NumPy dtypes, especially if you're a new user. It's often only necessary to care about the general *kind* of data you're dealing with, whether floating point, complex, integer, boolean, string, or general Python object. When you need more control over how data are stored in memory and on disk, especially large data sets, it is good to know that you have control over the storage type.

Table 4-2. NumPy data types

Type	Type Code	Description
`int8, uint8`	`i1, u1`	Signed and unsigned 8-bit (1 byte) integer types
`int16, uint16`	`i2, u2`	Signed and unsigned 16-bit integer types
`int32, uint32`	`i4, u4`	Signed and unsigned 32-bit integer types
`int64, uint64`	`i8, u8`	Signed and unsigned 32-bit integer types
`float16`	`f2`	Half-precision floating point
`float32`	`f4 or f`	Standard single-precision floating point. Compatible with C float
`float64, float128`	`f8 or d`	Standard double-precision floating point. Compatible with C double and Python `float` object

Type	Type Code	Description
`float128`	`f16 or g`	Extended-precision floating point
`complex64, complex128, complex256`	`c8, c16, c32`	Complex numbers represented by two 32, 64, or 128 floats, respectively
`bool`	`?`	Boolean type storing `True` and `False` values
`object`	`O`	Python object type
`string_`	`S`	Fixed-length string type (1 byte per character). For example, to create a string dtype with length 10, use `'S10'`.
`unicode_`	`U`	Fixed-length unicode type (number of bytes platform specific). Same specification semantics as `string_` (e.g. `'U10'`).

You can explicitly convert or *cast* an array from one dtype to another using ndarray's `astype` method:

```
In [31]: arr = np.array([1, 2, 3, 4, 5])

In [32]: arr.dtype
Out[32]: dtype('int64')

In [33]: float_arr = arr.astype(np.float64)

In [34]: float_arr.dtype
Out[34]: dtype('float64')
```

In this example, integers were cast to floating point. If I cast some floating point numbers to be of integer dtype, the decimal part will be truncated:

```
In [35]: arr = np.array([3.7, -1.2, -2.6, 0.5, 12.9, 10.1])

In [36]: arr
Out[36]: array([  3.7,  -1.2,  -2.6,   0.5,  12.9,  10.1])

In [37]: arr.astype(np.int32)
Out[37]: array([ 3, -1, -2,  0, 12, 10], dtype=int32)
```

Should you have an array of strings representing numbers, you can use `astype` to convert them to numeric form:

```
In [38]: numeric_strings = np.array(['1.25', '-9.6', '42'], dtype=np.string_)

In [39]: numeric_strings.astype(float)
Out[39]: array([  1.25,  -9.6 ,  42.  ])
```

If casting were to fail for some reason (like a string that cannot be converted to `float64`), a `TypeError` will be raised. See that I was a bit lazy and wrote `float` instead of `np.float64`; NumPy is smart enough to alias the Python types to the equivalent dtypes.

You can also use another array's dtype attribute:

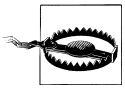
```
In [40]: int_array = np.arange(10)
```

```
In [41]: calibers = np.array([.22, .270, .357, .380, .44, .50], dtype=np.float64)

In [42]: int_array.astype(calibers.dtype)
Out[42]: array([ 0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9.])
```

There are shorthand type code strings you can also use to refer to a dtype:

```
In [43]: empty_uint32 = np.empty(8, dtype='u4')

In [44]: empty_uint32
Out[44]:
array([       0,        0, 65904672,        0, 64856792,        0,
       39438163,        0], dtype=uint32)
```

Calling `astype` *always* creates a new array (a copy of the data), even if the new dtype is the same as the old dtype.



It's worth keeping in mind that floating point numbers, such as those in `float64` and `float32` arrays, are only capable of approximating fractional quantities. In complex computations, you may accrue some *floating point error*, making comparisons only valid up to a certain number of decimal places.

Operations between Arrays and Scalars

Arrays are important because they enable you to express batch operations on data without writing any `for` loops. This is usually called *vectorization*. Any arithmetic operations between equal-size arrays applies the operation elementwise:

```
In [45]: arr = np.array([[1., 2., 3.], [4., 5., 6.]])

In [46]: arr
Out[46]:
array([[ 1.,  2.,  3.],
       [ 4.,  5.,  6.]])

In [47]: arr * arr                In [48]: arr - arr
Out[47]:                          Out[48]:
array([[  1.,   4.,   9.],        array([[ 0.,  0.,  0.],
       [ 16.,  25.,  36.]])              [ 0.,  0.,  0.]])
```

Arithmetic operations with scalars are as you would expect, propagating the value to each element:

```
In [49]: 1 / arr                          In [50]: arr ** 0.5
Out[49]:                                  Out[50]:
array([[ 1.    ,  0.5   ,  0.3333],        array([[ 1.    ,  1.4142,  1.7321],
       [ 0.25  ,  0.2   ,  0.1667]])              [ 2.    ,  2.2361,  2.4495]])
```

Operations between differently sized arrays is called *broadcasting* and will be discussed in more detail in Chapter 12. Having a deep understanding of broadcasting is not necessary for most of this book.

Basic Indexing and Slicing

NumPy array indexing is a rich topic, as there are many ways you may want to select a subset of your data or individual elements. One-dimensional arrays are simple; on the surface they act similarly to Python lists:

```
In [51]: arr = np.arange(10)

In [52]: arr
Out[52]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [53]: arr[5]
Out[53]: 5

In [54]: arr[5:8]
Out[54]: array([5, 6, 7])

In [55]: arr[5:8] = 12

In [56]: arr
Out[56]: array([ 0,  1,  2,  3,  4, 12, 12, 12,  8,  9])
```

As you can see, if you assign a scalar value to a slice, as in `arr[5:8] = 12`, the value is propagated (or *broadcasted* henceforth) to the entire selection. An important first distinction from lists is that array slices are *views* on the original array. This means that the data is not copied, and any modifications to the view will be reflected in the source array:

```
In [57]: arr_slice = arr[5:8]

In [58]: arr_slice[1] = 12345

In [59]: arr
Out[59]: array([    0,     1,     2,     3,     4,    12, 12345,    12,     8,     9])

In [60]: arr_slice[:] = 64

In [61]: arr
Out[61]: array([ 0,  1,  2,  3,  4, 64, 64, 64,  8,  9])
```

If you are new to NumPy, you might be surprised by this, especially if they have used other array programming languages which copy data more zealously. As NumPy has been designed with large data use cases in mind, you could imagine performance and memory problems if NumPy insisted on copying data left and right.

If you want a copy of a slice of an ndarray instead of a view, you will need to explicitly copy the array; for example `arr[5:8].copy()`.

With higher dimensional arrays, you have many more options. In a two-dimensional array, the elements at each index are no longer scalars but rather one-dimensional arrays:

```
In [62]: arr2d = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])

In [63]: arr2d[2]
Out[63]: array([7, 8, 9])
```

Thus, individual elements can be accessed recursively. But that is a bit too much work, so you can pass a comma-separated list of indices to select individual elements. So these are equivalent:

```
In [64]: arr2d[0][2]
Out[64]: 3

In [65]: arr2d[0, 2]
Out[65]: 3
```

See Figure 4-1 for an illustration of indexing on a 2D array.

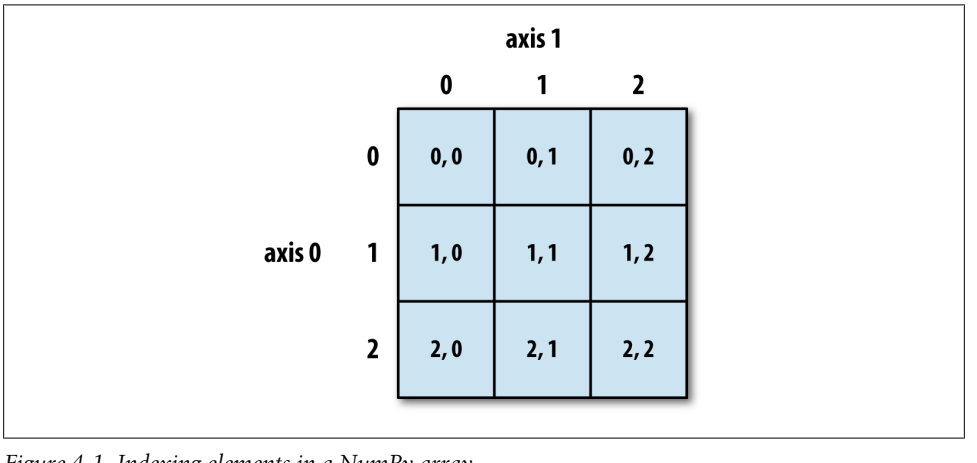


Figure 4-1. Indexing elements in a NumPy array

In multidimensional arrays, if you omit later indices, the returned object will be a lower-dimensional ndarray consisting of all the data along the higher dimensions. So in the 2 × 2 × 3 array `arr3d`

```
In [66]: arr3d = np.array([[[1, 2, 3], [4, 5, 6]], [[7, 8, 9], [10, 11, 12]]])

In [67]: arr3d
Out[67]:
array([[[ 1,  2,  3],
```

```
        [ 4,  5,  6]],
       [[ 7,  8,  9],
        [10, 11, 12]]])
```

`arr3d[0]` is a 2 × 3 array:

```
In [68]: arr3d[0]
Out[68]:
array([[1, 2, 3],
       [4, 5, 6]])
```

Both scalar values and arrays can be assigned to `arr3d[0]`:

```
In [69]: old_values = arr3d[0].copy()

In [70]: arr3d[0] = 42

In [71]: arr3d
Out[71]:
array([[[42, 42, 42],
        [42, 42, 42]],
       [[ 7,  8,  9],
        [10, 11, 12]]])

In [72]: arr3d[0] = old_values

In [73]: arr3d
Out[73]:
array([[[ 1,  2,  3],
        [ 4,  5,  6]],
       [[ 7,  8,  9],
        [10, 11, 12]]])
```

Similarly, `arr3d[1, 0]` gives you all of the values whose indices start with `(1, 0)`, forming a 1-dimensional array:

```
In [74]: arr3d[1, 0]
Out[74]: array([7, 8, 9])
```

Note that in all of these cases where subsections of the array have been selected, the returned arrays are views.

Indexing with slices

Like one-dimensional objects such as Python lists, ndarrays can be sliced using the familiar syntax:

```
In [75]: arr[1:6]
Out[75]: array([ 1,  2,  3,  4, 64])
```

Higher dimensional objects give you more options as you can slice one or more axes and also mix integers. Consider the 2D array above, `arr2d`. Slicing this array is a bit different:

```
In [76]: arr2d            In [77]: arr2d[:2]
Out[76]:                  Out[77]:
```

```
array([[1, 2, 3],         array([[1, 2, 3],
       [4, 5, 6],                [4, 5, 6]])
       [7, 8, 9]])
```

As you can see, it has sliced along axis 0, the first axis. A slice, therefore, selects a range of elements along an axis. You can pass multiple slices just like you can pass multiple indexes:

```
In [78]: arr2d[:2, 1:]
Out[78]:
array([[2, 3],
       [5, 6]])
```

When slicing like this, you always obtain array views of the same number of dimensions. By mixing integer indexes and slices, you get lower dimensional slices:

```
In [79]: arr2d[1, :2]        In [80]: arr2d[2, :1]
Out[79]: array([4, 5])       Out[80]: array([7])
```

See Figure 4-2 for an illustration. Note that a colon by itself means to take the entire axis, so you can slice only higher dimensional axes by doing:

```
In [81]: arr2d[:, :1]
Out[81]:
array([[1],
       [4],
       [7]])
```

Of course, assigning to a slice expression assigns to the whole selection:

```
In [82]: arr2d[:2, 1:] = 0
```

Boolean Indexing

Let's consider an example where we have some data in an array and an array of names with duplicates. I'm going to use here the `randn` function in `numpy.random` to generate some random normally distributed data:

```
In [83]: names = np.array(['Bob', 'Joe', 'Will', 'Bob', 'Will', 'Joe', 'Joe'])

In [84]: data = randn(7, 4)

In [85]: names
Out[85]:
array(['Bob', 'Joe', 'Will', 'Bob', 'Will', 'Joe', 'Joe'],
      dtype='|S4')

In [86]: data
Out[86]:
array([[-0.048 ,  0.5433, -0.2349,  1.2792],
       [-0.268 ,  0.5465,  0.0939, -2.0445],
       [-0.047 , -2.026 ,  0.7719,  0.3103],
       [ 2.1452,  0.8799, -0.0523,  0.0672],
       [-1.0023, -0.1698,  1.1503,  1.7289],
```

```
       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174, -0.9297, -1.2564]])
```

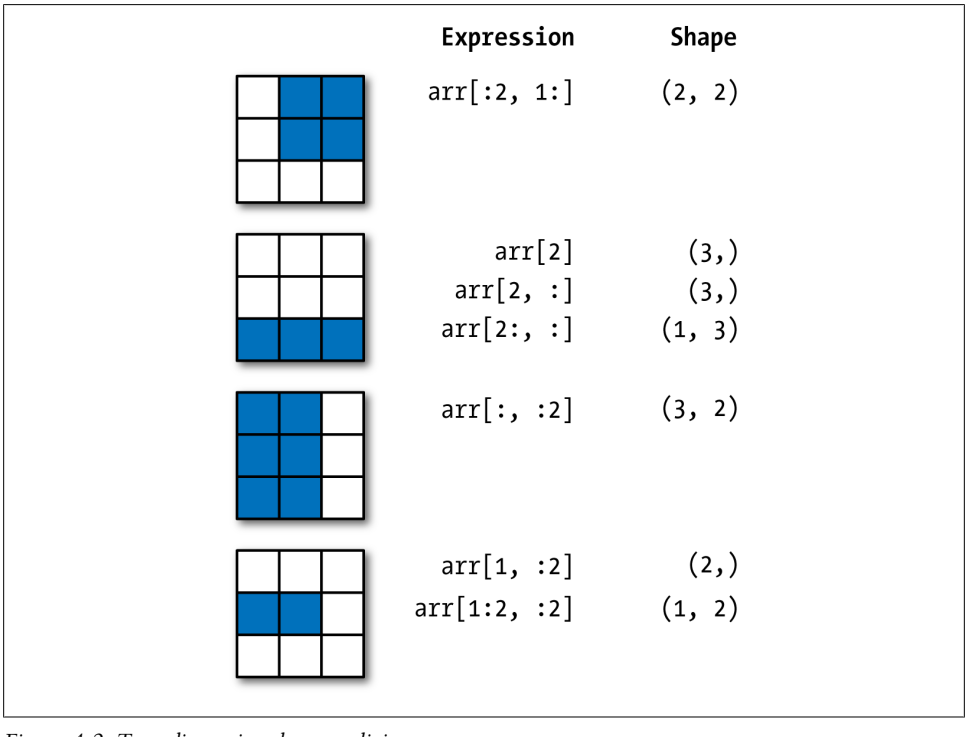


Figure 4-2. Two-dimensional array slicing

Suppose each name corresponds to a row in the `data` array. If we wanted to select all the rows with corresponding name `'Bob'`. Like arithmetic operations, comparisons (such as `==`) with arrays are also vectorized. Thus, comparing `names` with the string `'Bob'` yields a boolean array:

```
In [87]: names == 'Bob'
Out[87]: array([ True, False, False, True, False, False, False], dtype=bool)
```

This boolean array can be passed when indexing the array:

```
In [88]: data[names == 'Bob']
Out[88]:
array([[-0.048 ,  0.5433, -0.2349,  1.2792],
       [ 2.1452,  0.8799, -0.0523,  0.0672]])
```

The boolean array must be of the same length as the axis it's indexing. You can even mix and match boolean arrays with slices or integers (or sequences of integers, more on this later):

```
In [89]: data[names == 'Bob', 2:]
Out[89]:
array([[-0.2349,  1.2792],
```

```
       [-0.0523,  0.0672]])

In [90]: data[names == 'Bob', 3]
Out[90]: array([ 1.2792,  0.0672])
```

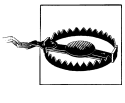
To select everything but `'Bob'`, you can either use `!=` or negate the condition using `-`:

```
In [91]: names != 'Bob'
Out[91]: array([False, True, True, False, True, True, True], dtype=bool)

In [92]: data[-(names == 'Bob')]
Out[92]:
array([[-0.268 ,  0.5465,  0.0939, -2.0445],
       [-0.047 , -2.026 ,  0.7719,  0.3103],
       [-1.0023, -0.1698,  1.1503,  1.7289],
       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174, -0.9297, -1.2564]])
```

Selecting two of the three names to combine multiple boolean conditions, use boolean arithmetic operators like `&` (and) and `|` (or):

```
In [93]: mask = (names == 'Bob') | (names == 'Will')

In [94]: mask
Out[94]: array([True, False, True, True, True, False, False], dtype=bool)

In [95]: data[mask]
Out[95]:
array([[-0.048 ,  0.5433, -0.2349,  1.2792],
       [-0.047 , -2.026 ,  0.7719,  0.3103],
       [ 2.1452,  0.8799, -0.0523,  0.0672],
       [-1.0023, -0.1698,  1.1503,  1.7289]])
```

Selecting data from an array by boolean indexing *always* creates a copy of the data, even if the returned array is unchanged.



The Python keywords `and` and `or` do not work with boolean arrays.

Setting values with boolean arrays works in a common-sense way. To set all of the negative values in `data` to 0 we need only do:

```
In [96]: data[data < 0] = 0

In [97]: data
Out[97]:
array([[ 0.    ,  0.5433,  0.    ,  1.2792],
       [ 0.    ,  0.5465,  0.0939,  0.    ],
       [ 0.    ,  0.    ,  0.7719,  0.3103],
       [ 2.1452,  0.8799,  0.    ,  0.0672],
       [ 0.    ,  0.    ,  1.1503,  1.7289],
       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174,  0.    ,  0.    ]])
```

Setting whole rows or columns using a 1D boolean array is also easy:

```
In [98]: data[names != 'Joe'] = 7

In [99]: data
Out[99]:
array([[ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 0.    ,  0.5465,  0.0939,  0.    ],
       [ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174,  0.    ,  0.    ]])
```

Fancy Indexing

Fancy indexing is a term adopted by NumPy to describe indexing using integer arrays. Suppose we had a 8 × 4 array:

```
In [100]: arr = np.empty((8, 4))

In [101]: for i in range(8):
   .....:     arr[i] = i

In [102]: arr
Out[102]:
array([[ 0.,  0.,  0.,  0.],
       [ 1.,  1.,  1.,  1.],
       [ 2.,  2.,  2.,  2.],
       [ 3.,  3.,  3.,  3.],
       [ 4.,  4.,  4.,  4.],
       [ 5.,  5.,  5.,  5.],
       [ 6.,  6.,  6.,  6.],
       [ 7.,  7.,  7.,  7.]])
```

To select out a subset of the rows in a particular order, you can simply pass a list or ndarray of integers specifying the desired order:

```
In [103]: arr[[4, 3, 0, 6]]
Out[103]:
array([[ 4.,  4.,  4.,  4.],
       [ 3.,  3.,  3.,  3.],
       [ 0.,  0.,  0.,  0.],
       [ 6.,  6.,  6.,  6.]])
```

Hopefully this code did what you expected! Using negative indices select rows from the end:

```
In [104]: arr[[-3, -5, -7]]
Out[104]:
array([[ 5.,  5.,  5.,  5.],
       [ 3.,  3.,  3.,  3.],
       [ 1.,  1.,  1.,  1.]])
```

Passing multiple index arrays does something slightly different; it selects a 1D array of elements corresponding to each tuple of indices:

```
# more on reshape in Chapter 12
In [105]: arr = np.arange(32).reshape((8, 4))

In [106]: arr
Out[106]:
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23],
       [24, 25, 26, 27],
       [28, 29, 30, 31]])

In [107]: arr[[1, 5, 7, 2], [0, 3, 1, 2]]
Out[107]: array([ 4, 23, 29, 10])
```

Take a moment to understand what just happened: the elements `(1, 0)`, `(5, 3)`, `(7, 1)`, and `(2, 2)` were selected. The behavior of fancy indexing in this case is a bit different from what some users might have expected (myself included), which is the rectangular region formed by selecting a subset of the matrix's rows and columns. Here is one way to get that:

```
In [108]: arr[[1, 5, 7, 2]][:, [0, 3, 1, 2]]
Out[108]:
array([[ 4,  7,  5,  6],
       [20, 23, 21, 22],
       [28, 31, 29, 30],
       [ 8, 11,  9, 10]])
```

Another way is to use the `np.ix_` function, which converts two 1D integer arrays to an indexer that selects the square region:

```
In [109]: arr[np.ix_([1, 5, 7, 2], [0, 3, 1, 2])]
Out[109]:
array([[ 4,  7,  5,  6],
       [20, 23, 21, 22],
       [28, 31, 29, 30],
       [ 8, 11,  9, 10]])
```

Keep in mind that fancy indexing, unlike slicing, always copies the data into a new array.

Transposing Arrays and Swapping Axes

Transposing is a special form of reshaping which similarly returns a view on the underlying data without copying anything. Arrays have the `transpose` method and also the special `T` attribute:

```
In [110]: arr = np.arange(15).reshape((3, 5))

In [111]: arr                        In [112]: arr.T
```

```
Out[111]:
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14]])
```

```
Out[112]:
array([[ 0,  5, 10],
       [ 1,  6, 11],
       [ 2,  7, 12],
       [ 3,  8, 13],
       [ 4,  9, 14]])
```

When doing matrix computations, you will do this very often, like for example computing the inner matrix product X^TX using `np.dot`:

```
In [113]: arr = np.random.randn(6, 3)

In [114]: np.dot(arr.T, arr)
Out[114]:
array([[ 2.584 ,  1.8753,  0.8888],
       [ 1.8753,  6.6636,  0.3884],
       [ 0.8888,  0.3884,  3.9781]])
```

For higher dimensional arrays, `transpose` will accept a tuple of axis numbers to permute the axes (for extra mind bending):

```
In [115]: arr = np.arange(16).reshape((2, 2, 4))

In [116]: arr
Out[116]:
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7]],
       [[ 8,  9, 10, 11],
        [12, 13, 14, 15]]])

In [117]: arr.transpose((1, 0, 2))
Out[117]:
array([[[ 0,  1,  2,  3],
        [ 8,  9, 10, 11]],
       [[ 4,  5,  6,  7],
        [12, 13, 14, 15]]])
```

Simple transposing with `.T` is just a special case of swapping axes. ndarray has the method `swapaxes` which takes a pair of axis numbers:

```
In [118]: arr
Out[118]:
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7]],

       [[ 8,  9, 10, 11],
        [12, 13, 14, 15]]])
```

```
In [119]: arr.swapaxes(1, 2)
Out[119]:
array([[[ 0,  4],
        [ 1,  5],
        [ 2,  6],
        [ 3,  7]],

       [[ 8, 12],
        [ 9, 13],
        [10, 14],
        [11, 15]]])
```

`swapaxes` similarly returns a view on the data without making a copy.

Universal Functions: Fast Element-wise Array Functions

A universal function, or *ufunc*, is a function that performs elementwise operations on data in ndarrays. You can think of them as fast vectorized wrappers for simple functions that take one or more scalar values and produce one or more scalar results.

Many ufuncs are simple elementwise transformations, like `sqrt` or `exp`:

```
In [120]: arr = np.arange(10)

In [121]: np.sqrt(arr)
Out[121]:
array([ 0.    ,  1.    ,  1.4142,  1.7321,  2.    ,  2.2361,  2.4495,
        2.6458,  2.8284,  3.    ])

In [122]: np.exp(arr)
Out[122]:
array([    1.    ,     2.7183,     7.3891,    20.0855,    54.5982,
         148.4132,   403.4288,  1096.6332,  2980.958 ,  8103.0839])
```

These are referred to as *unary* ufuncs. Others, such as `add` or `maximum`, take 2 arrays (thus, *binary* ufuncs) and return a single array as the result:

```
In [123]: x = randn(8)

In [124]: y = randn(8)

In [125]: x
Out[125]:
array([ 0.0749,  0.0974,  0.2002, -0.2551,  0.4655,  0.9222,  0.446 ,
       -0.9337])

In [126]: y
Out[126]:
array([ 0.267 , -1.1131, -0.3361,  0.6117, -1.2323,  0.4788,  0.4315,
       -0.7147])

In [127]: np.maximum(x, y) # element-wise maximum
Out[127]:
array([ 0.267 ,  0.0974,  0.2002,  0.6117,  0.4655,  0.9222,  0.446 ,
       -0.7147])
```

While not common, a ufunc can return multiple arrays. `modf` is one example, a vectorized version of the built-in Python `divmod`: it returns the fractional and integral parts of a floating point array:

```
In [128]: arr = randn(7) * 5

In [129]: np.modf(arr)
Out[129]:
(array([-0.6808,  0.0636, -0.386 ,  0.1393, -0.8806,  0.9363, -0.883 ]),
 array([-2.,  4., -3.,  5., -3.,  3., -6.]))
```

See Table 4-3 and Table 4-4 for a listing of available ufuncs.

Table 4-3. Unary ufuncs

Function	Description
`abs, fabs`	Compute the absolute value element-wise for integer, floating point, or complex values. Use `fabs` as a faster alternative for non-complex-valued data
`sqrt`	Compute the square root of each element. Equivalent to `arr ** 0.5`
`square`	Compute the square of each element. Equivalent to `arr ** 2`
`exp`	Compute the exponent e^x of each element
`log, log10, log2, log1p`	Natural logarithm (base *e*), log base 10, log base 2, and log(1 + x), respectively
`sign`	Compute the sign of each element: 1 (positive), 0 (zero), or -1 (negative)
`ceil`	Compute the ceiling of each element, i.e. the smallest integer greater than or equal to each element
`floor`	Compute the floor of each element, i.e. the largest integer less than or equal to each element
`rint`	Round elements to the nearest integer, preserving the `dtype`
`modf`	Return fractional and integral parts of array as separate array
`isnan`	Return boolean array indicating whether each value is `NaN` (Not a Number)
`isfinite, isinf`	Return boolean array indicating whether each element is finite (non-`inf`, non-`NaN`) or infinite, respectively
`cos, cosh, sin, sinh, tan, tanh`	Regular and hyperbolic trigonometric functions
`arccos, arccosh, arcsin, arcsinh, arctan, arctanh`	Inverse trigonometric functions
`logical_not`	Compute truth value of `not x` element-wise. Equivalent to `-arr`.

Table 4-4. Binary universal functions

Function	Description
`add`	Add corresponding elements in arrays
`subtract`	Subtract elements in second array from first array
`multiply`	Multiply array elements
`divide, floor_divide`	Divide or floor divide (truncating the remainder)
`power`	Raise elements in first array to powers indicated in second array
`maximum, fmax`	Element-wise maximum. `fmax` ignores `NaN`
`minimum, fmin`	Element-wise minimum. `fmin` ignores `NaN`
`mod`	Element-wise modulus (remainder of division)
`copysign`	Copy sign of values in second argument to values in first argument

Function	Description
`greater, greater_equal, less, less_equal, equal, not_equal`	Perform element-wise comparison, yielding boolean array. Equivalent to infix operators `>, >=, <, <=, ==, !=`
`logical_and, logical_or, logical_xor`	Compute element-wise truth value of logical operation. Equivalent to infix operators `&, |, ^`

Data Processing Using Arrays

Using NumPy arrays enables you to express many kinds of data processing tasks as concise array expressions that might otherwise require writing loops. This practice of replacing explicit loops with array expressions is commonly referred to as *vectorization*. In general, vectorized array operations will often be one or two (or more) orders of magnitude faster than their pure Python equivalents, with the biggest impact in any kind of numerical computations. Later, in Chapter 12, I will explain *broadcasting*, a powerful method for vectorizing computations.

As a simple example, suppose we wished to evaluate the function `sqrt(x^2 + y^2)` across a regular grid of values. The `np.meshgrid` function takes two 1D arrays and produces two 2D matrices corresponding to all pairs of `(x, y)` in the two arrays:

```
In [130]: points = np.arange(-5, 5, 0.01) # 1000 equally spaced points

In [131]: xs, ys = np.meshgrid(points, points)

In [132]: ys
Out[132]:
array([[-5.  , -5.  , -5.  , ..., -5.  , -5.  , -5.  ],
       [-4.99, -4.99, -4.99, ..., -4.99, -4.99, -4.99],
       [-4.98, -4.98, -4.98, ..., -4.98, -4.98, -4.98],
       ...,
       [ 4.97,  4.97,  4.97, ...,  4.97,  4.97,  4.97],
       [ 4.98,  4.98,  4.98, ...,  4.98,  4.98,  4.98],
       [ 4.99,  4.99,  4.99, ...,  4.99,  4.99,  4.99]])
```

Now, evaluating the function is a simple matter of writing the same expression you would write with two points:

```
In [134]: import matplotlib.pyplot as plt

In [135]: z = np.sqrt(xs ** 2 + ys ** 2)

In [136]: z
Out[136]:
array([[ 7.0711,  7.064 ,  7.0569, ...,  7.0499,  7.0569,  7.064 ],
       [ 7.064 ,  7.0569,  7.0499, ...,  7.0428,  7.0499,  7.0569],
       [ 7.0569,  7.0499,  7.0428, ...,  7.0357,  7.0428,  7.0499],
       ...,
       [ 7.0499,  7.0428,  7.0357, ...,  7.0286,  7.0357,  7.0428],
       [ 7.0569,  7.0499,  7.0428, ...,  7.0357,  7.0428,  7.0499],
       [ 7.064 ,  7.0569,  7.0499, ...,  7.0428,  7.0499,  7.0569]])
```

```
In [137]: plt.imshow(z, cmap=plt.cm.gray); plt.colorbar()
Out[137]: <matplotlib.colorbar.Colorbar instance at 0x4e46d40>

In [138]: plt.title("Image plot of $\sqrt{x^2 + y^2}$ for a grid of values")
Out[138]: <matplotlib.text.Text at 0x4565790>
```

See Figure 4-3. Here I used the matplotlib function `imshow` to create an image plot from a 2D array of function values.

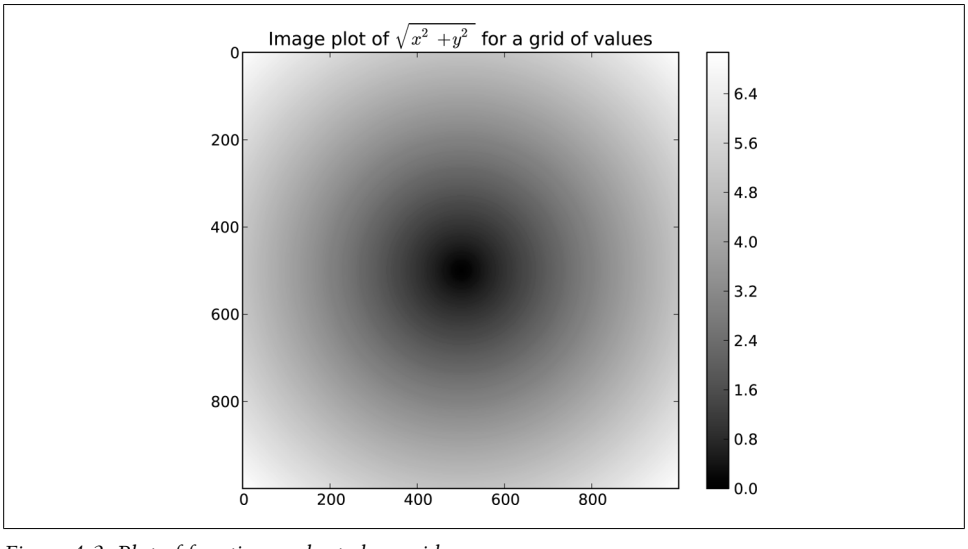


Figure 4-3. Plot of function evaluated on grid

Expressing Conditional Logic as Array Operations

The `numpy.where` function is a vectorized version of the ternary expression `x if condition else y`. Suppose we had a boolean array and two arrays of values:

```
In [140]: xarr = np.array([1.1, 1.2, 1.3, 1.4, 1.5])

In [141]: yarr = np.array([2.1, 2.2, 2.3, 2.4, 2.5])

In [142]: cond = np.array([True, False, True, True, False])
```

Suppose we wanted to take a value from `xarr` whenever the corresponding value in `cond` is `True` otherwise take the value from `yarr`. A list comprehension doing this might look like:

```
In [143]: result = [(x if c else y)
   .....:           for x, y, c in zip(xarr, yarr, cond)]

In [144]: result
Out[144]: [1.1000000000000001, 2.2000000000000002, 1.3, 1.3999999999999999, 2.5]
```

This has multiple problems. First, it will not be very fast for large arrays (because all the work is being done in pure Python). Secondly, it will not work with multidimensional arrays. With `np.where` you can write this very concisely:

```
In [145]: result = np.where(cond, xarr, yarr)

In [146]: result
Out[146]: array([ 1.1,  2.2,  1.3,  1.4,  2.5])
```

The second and third arguments to `np.where` don't need to be arrays; one or both of them can be scalars. A typical use of `where` in data analysis is to produce a new array of values based on another array. Suppose you had a matrix of randomly generated data and you wanted to replace all positive values with 2 and all negative values with -2. This is very easy to do with `np.where`:

```
In [147]: arr = randn(4, 4)

In [148]: arr
Out[148]:
array([[ 0.6372,  2.2043,  1.7904,  0.0752],
       [-1.5926, -1.1536,  0.4413,  0.3483],
       [-0.1798,  0.3299,  0.7827, -0.7585],
       [ 0.5857,  0.1619,  1.3583, -1.3865]])

In [149]: np.where(arr > 0, 2, -2)
Out[149]:
array([[ 2,  2,  2,  2],
       [-2, -2,  2,  2],
       [-2,  2,  2, -2],
       [ 2,  2,  2, -2]])

In [150]: np.where(arr > 0, 2, arr) # set only positive values to 2
Out[150]:
array([[ 2.    ,  2.    ,  2.    ,  2.    ],
       [-1.5926, -1.1536,  2.    ,  2.    ],
       [-0.1798,  2.    ,  2.    , -0.7585],
       [ 2.    ,  2.    ,  2.    , -1.3865]])
```

The arrays passed to `where` can be more than just equal sizes array or scalers.

With some cleverness you can use `where` to express more complicated logic; consider this example where I have two boolean arrays, `cond1` and `cond2`, and wish to assign a different value for each of the 4 possible pairs of boolean values:

```
result = []
for i in range(n):
    if cond1[i] and cond2[i]:
        result.append(0)
    elif cond1[i]:
        result.append(1)
    elif cond2[i]:
        result.append(2)
    else:
        result.append(3)
```

While perhaps not immediately obvious, this `for` loop can be converted into a nested `where` expression:

```
np.where(cond1 & cond2, 0,
         np.where(cond1, 1,
                  np.where(cond2, 2, 3)))
```

In this particular example, we can also take advantage of the fact that boolean values are treated as 0 or 1 in calculations, so this could alternatively be expressed (though a bit more cryptically) as an arithmetic operation:

```
result = 1 * cond1 + 2 * cond2 + 3 * -(cond1 | cond2)
```

Mathematical and Statistical Methods

A set of mathematical functions which compute statistics about an entire array or about the data along an axis are accessible as array methods. Aggregations (often called *reductions*) like `sum`, `mean`, and standard deviation `std` can either be used by calling the array instance method or using the top level NumPy function:

```
In [151]: arr = np.random.randn(5, 4) # normally-distributed data

In [152]: arr.mean()
Out[152]: 0.062814911084854597

In [153]: np.mean(arr)
Out[153]: 0.062814911084854597

In [154]: arr.sum()
Out[154]: 1.2562982216970919
```

Functions like `mean` and `sum` take an optional `axis` argument which computes the statistic over the given axis, resulting in an array with one fewer dimension:

```
In [155]: arr.mean(axis=1)
Out[155]: array([-1.2833,  0.2844,  0.6574,  0.6743, -0.0187])

In [156]: arr.sum(0)
Out[156]: array([-3.1003, -1.6189,  1.4044,  4.5712])
```

Other methods like `cumsum` and `cumprod` do not aggregate, instead producing an array of the intermediate results:

```
In [157]: arr = np.array([[0, 1, 2], [3, 4, 5], [6, 7, 8]])

In [158]: arr.cumsum(0)
Out[158]:
array([[ 0,  1,  2],
       [ 3,  5,  7],
       [ 9, 12, 15]])

In [159]: arr.cumprod(1)
Out[159]:
array([[  0,   0,   0],
       [  3,  12,  60],
       [  6,  42, 336]])
```

See Table 4-5 for a full listing. We'll see many examples of these methods in action in later chapters.

Table 4-5. Basic array statistical methods

Method	Description
`sum`	Sum of all the elements in the array or along an axis. Zero-length arrays have sum 0.
`mean`	Arithmetic mean. Zero-length arrays have NaN mean.
`std, var`	Standard deviation and variance, respectively, with optional degrees of freedom adjustment (default denominator n).
`min, max`	Minimum and maximum.
`argmin, argmax`	Indices of minimum and maximum elements, respectively.
`cumsum`	Cumulative sum of elements starting from 0
`cumprod`	Cumulative product of elements starting from 1

Methods for Boolean Arrays

Boolean values are coerced to 1 (`True`) and 0 (`False`) in the above methods. Thus, `sum` is often used as a means of counting `True` values in a boolean array:

```
In [160]: arr = randn(100)

In [161]: (arr > 0).sum() # Number of positive values
Out[161]: 44
```

There are two additional methods, `any` and `all`, useful especially for boolean arrays. `any` tests whether one or more values in an array is `True`, while `all` checks if every value is `True`:

```
In [162]: bools = np.array([False, False, True, False])

In [163]: bools.any()
Out[163]: True

In [164]: bools.all()
Out[164]: False
```

These methods also work with non-boolean arrays, where non-zero elements evaluate to `True`.

Sorting

Like Python's built-in list type, NumPy arrays can be sorted in-place using the `sort` method:

```
In [165]: arr = randn(8)

In [166]: arr
Out[166]:
array([ 0.6903,  0.4678,  0.0968, -0.1349,  0.9879,  0.0185, -1.3147,
       -0.5425])

In [167]: arr.sort()
```

```
In [168]: arr
Out[168]:
array([-1.3147, -0.5425, -0.1349,  0.0185,  0.0968,  0.4678,  0.6903,
        0.9879])
```

Multidimensional arrays can have each 1D section of values sorted in-place along an axis by passing the axis number to `sort`:

```
In [169]: arr = randn(5, 3)

In [170]: arr
Out[170]:
array([[-0.7139, -1.6331, -0.4959],
       [ 0.8236, -1.3132, -0.1935],
       [-1.6748,  3.0336, -0.863 ],
       [-0.3161,  0.5362, -2.468 ],
       [ 0.9058,  1.1184, -1.0516]])

In [171]: arr.sort(1)

In [172]: arr
Out[172]:
array([[-1.6331, -0.7139, -0.4959],
       [-1.3132, -0.1935,  0.8236],
       [-1.6748, -0.863 ,  3.0336],
       [-2.468 , -0.3161,  0.5362],
       [-1.0516,  0.9058,  1.1184]])
```

The top level method `np.sort` returns a sorted copy of an array instead of modifying the array in place. A quick-and-dirty way to compute the quantiles of an array is to sort it and select the value at a particular rank:

```
In [173]: large_arr = randn(1000)

In [174]: large_arr.sort()

In [175]: large_arr[int(0.05 * len(large_arr))] # 5% quantile
Out[175]: -1.5791023260896004
```

For more details on using NumPy's sorting methods, and more advanced techniques like indirect sorts, see Chapter 12. Several other kinds of data manipulations related to sorting (for example, sorting a table of data by one or more columns) are also to be found in pandas.

Unique and Other Set Logic

NumPy has some basic set operations for one-dimensional ndarrays. Probably the most commonly used one is `np.unique`, which returns the sorted unique values in an array:

```
In [176]: names = np.array(['Bob', 'Joe', 'Will', 'Bob', 'Will', 'Joe', 'Joe'])

In [177]: np.unique(names)
Out[177]:
```

```
array(['Bob', 'Joe', 'Will'],
      dtype='|S4')

In [178]: ints = np.array([3, 3, 3, 2, 2, 1, 1, 4, 4])

In [179]: np.unique(ints)
Out[179]: array([1, 2, 3, 4])
```

Contrast `np.unique` with the pure Python alternative:

```
In [180]: sorted(set(names))
Out[180]: ['Bob', 'Joe', 'Will']
```

Another function, `np.in1d`, tests membership of the values in one array in another, returning a boolean array:

```
In [181]: values = np.array([6, 0, 0, 3, 2, 5, 6])

In [182]: np.in1d(values, [2, 3, 6])
Out[182]: array([ True, False, False,  True,  True, False,  True], dtype=bool)
```

See Table 4-6 for a listing of set functions in NumPy.

Table 4-6. Array set operations

Method	Description
`unique(x)`	Compute the sorted, unique elements in x
`intersect1d(x, y)`	Compute the sorted, common elements in x and y
`union1d(x, y)`	Compute the sorted union of elements
`in1d(x, y)`	Compute a boolean array indicating whether each element of x is contained in y
`setdiff1d(x, y)`	Set difference, elements in x that are not in y
`setxor1d(x, y)`	Set symmetric differences; elements that are in either of the arrays, but not both

File Input and Output with Arrays

NumPy is able to save and load data to and from disk either in text or binary format. In later chapters you will learn about tools in pandas for reading tabular data into memory.

Storing Arrays on Disk in Binary Format

`np.save` and `np.load` are the two workhorse functions for efficiently saving and loading array data on disk. Arrays are saved by default in an uncompressed raw binary format with file extension `.npy`.

```
In [183]: arr = np.arange(10)

In [184]: np.save('some_array', arr)
```

If the file path does not already end in `.npy`, the extension will be appended. The array on disk can then be loaded using `np.load`:

```
In [185]: np.load('some_array.npy')
Out[185]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

You save multiple arrays in a zip archive using `np.savez` and passing the arrays as keyword arguments:

```
In [186]: np.savez('array_archive.npz', a=arr, b=arr)
```

When loading an `.npz` file, you get back a dict-like object which loads the individual arrays lazily:

```
In [187]: arch = np.load('array_archive.npz')

In [188]: arch['b']
Out[188]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

Saving and Loading Text Files

Loading text from files is a fairly standard task. The landscape of file reading and writing functions in Python can be a bit confusing for a newcomer, so I will focus mainly on the `read_csv` and `read_table` functions in pandas. It will at times be useful to load data into vanilla NumPy arrays using `np.loadtxt` or the more specialized `np.genfromtxt`.

These functions have many options allowing you to specify different delimiters, converter functions for certain columns, skipping rows, and other things. Take a simple case of a comma-separated file (CSV) like this:

```
In [191]: !cat array_ex.txt
0.580052,0.186730,1.040717,1.134411
0.194163,-0.636917,-0.938659,0.124094
-0.126410,0.268607,-0.695724,0.047428
-1.484413,0.004176,-0.744203,0.005487
2.302869,0.200131,1.670238,-1.881090
-0.193230,1.047233,0.482803,0.960334
```

This can be loaded into a 2D array like so:

```
In [192]: arr = np.loadtxt('array_ex.txt', delimiter=',')

In [193]: arr
Out[193]:
array([[ 0.5801,  0.1867,  1.0407,  1.1344],
       [ 0.1942, -0.6369, -0.9387,  0.1241],
       [-0.1264,  0.2686, -0.6957,  0.0474],
       [-1.4844,  0.0042, -0.7442,  0.0055],
       [ 2.3029,  0.2001,  1.6702, -1.8811],
       [-0.1932,  1.0472,  0.4828,  0.9603]])
```

`np.savetxt` performs the inverse operation: writing an array to a delimited text file. `genfromtxt` is similar to `loadtxt` but is geared for structured arrays and missing data handling; see Chapter 12 for more on structured arrays.

For more on file reading and writing, especially tabular or spreadsheet-like data, see the later chapters involving pandas and DataFrame objects.

Linear Algebra

Linear algebra, like matrix multiplication, decompositions, determinants, and other square matrix math, is an important part of any array library. Unlike some languages like MATLAB, multiplying two two-dimensional arrays with * is an element-wise product instead of a matrix dot product. As such, there is a function `dot`, both an array method, and a function in the `numpy` namespace, for matrix multiplication:

```
In [194]: x = np.array([[1., 2., 3.], [4., 5., 6.]])

In [195]: y = np.array([[6., 23.], [-1, 7], [8, 9]])

In [196]: x                  In [197]: y
Out[196]:                    Out[197]:
array([[ 1.,  2.,  3.],      array([[  6.,  23.],
       [ 4.,  5.,  6.]])             [ -1.,   7.],
                                     [  8.,   9.]])

In [198]: x.dot(y)  # equivalently np.dot(x, y)
Out[198]:
array([[  28.,   64.],
       [  67.,  181.]])
```

A matrix product between a 2D array and a suitably sized 1D array results in a 1D array:

```
In [199]: np.dot(x, np.ones(3))
Out[199]: array([  6.,  15.])
```

`numpy.linalg` has a standard set of matrix decompositions and things like inverse and determinant. These are implemented under the hood using the same industry-standard Fortran libraries used in other languages like MATLAB and R, such as like BLAS, LAPACK, or possibly (depending on your NumPy build) the Intel MKL:

```
In [201]: from numpy.linalg import inv, qr

In [202]: X = randn(5, 5)

In [203]: mat = X.T.dot(X)

In [204]: inv(mat)
Out[204]:
array([[ 3.0361, -0.1808, -0.6878, -2.8285, -1.1911],
       [-0.1808,  0.5035,  0.1215,  0.6702,  0.0956],
       [-0.6878,  0.1215,  0.2904,  0.8081,  0.3049],
       [-2.8285,  0.6702,  0.8081,  3.4152,  1.1557],
       [-1.1911,  0.0956,  0.3049,  1.1557,  0.6051]])

In [205]: mat.dot(inv(mat))
```

```
Out[205]:
array([[ 1.,  0.,  0.,  0., -0.],
       [ 0.,  1., -0.,  0.,  0.],
       [ 0., -0.,  1.,  0.,  0.],
       [ 0., -0., -0.,  1., -0.],
       [ 0.,  0.,  0.,  0.,  1.]])

In [206]: q, r = qr(mat)

In [207]: r
Out[207]:
array([[ -6.9271,   7.389 ,   6.1227,  -7.1163,  -4.9215],
       [  0.    ,  -3.9735,  -0.8671,   2.9747,  -5.7402],
       [  0.    ,   0.    , -10.2681,   1.8909,   1.6079],
       [  0.    ,   0.    ,   0.    ,  -1.2996,   3.3577],
       [  0.    ,   0.    ,   0.    ,   0.    ,   0.5571]])
```

See Table 4-7 for a list of some of the most commonly-used linear algebra functions.

The scientific Python community is hopeful that there may be a matrix multiplication infix operator implemented someday, providing syntactically nicer alternative to using `np.dot`. But for now this is the way.

Table 4-7. Commonly-used numpy.linalg functions

Function	Description
`diag`	Return the diagonal (or off-diagonal) elements of a square matrix as a 1D array, or convert a 1D array into a square matrix with zeros on the off-diagonal
`dot`	Matrix multiplication
`trace`	Compute the sum of the diagonal elements
`det`	Compute the matrix determinant
`eig`	Compute the eigenvalues and eigenvectors of a square matrix
`inv`	Compute the inverse of a square matrix
`pinv`	Compute the Moore-Penrose pseudo-inverse inverse of a square matrix
`qr`	Compute the QR decomposition
`svd`	Compute the singular value decomposition (SVD)
`solve`	Solve the linear system Ax = b for x, where A is a square matrix
`lstsq`	Compute the least-squares solution to y = Xb

Random Number Generation

The `numpy.random` module supplements the built-in Python `random` with functions for efficiently generating whole arrays of sample values from many kinds of probability

distributions. For example, you can get a 4 by 4 array of samples from the standard normal distribution using `normal`:

```
In [208]: samples = np.random.normal(size=(4, 4))

In [209]: samples
Out[209]:
array([[ 0.1241,  0.3026,  0.5238,  0.0009],
       [ 1.3438, -0.7135, -0.8312, -2.3702],
       [-1.8608, -0.8608,  0.5601, -1.2659],
       [ 0.1198, -1.0635,  0.3329, -2.3594]])
```

Python's built-in `random` module, by contrast, only samples one value at a time. As you can see from this benchmark, `numpy.random` is well over an order of magnitude faster for generating very large samples:

```
In [210]: from random import normalvariate

In [211]: N = 1000000

In [212]: %timeit samples = [normalvariate(0, 1) for _ in xrange(N)]
1 loops, best of 3: 1.33 s per loop

In [213]: %timeit np.random.normal(size=N)
10 loops, best of 3: 57.7 ms per loop
```

See table Table 4-8 for a partial list of functions available in `numpy.random`. I'll give some examples of leveraging these functions' ability to generate large arrays of samples all at once in the next section.

Table 4-8. Partial list of numpy.random functions

Function	Description
`seed`	Seed the random number generator
`permutation`	Return a random permutation of a sequence, or return a permuted range
`shuffle`	Randomly permute a sequence in place
`rand`	Draw samples from a uniform distribution
`randint`	Draw random integers from a given low-to-high range
`randn`	Draw samples from a normal distribution with mean 0 and standard deviation 1 (MATLAB-like interface)
`binomial`	Draw samples a binomial distribution
`normal`	Draw samples from a normal (Gaussian) distribution
`beta`	Draw samples from a beta distribution
`chisquare`	Draw samples from a chi-square distribution
`gamma`	Draw samples from a gamma distribution
`uniform`	Draw samples from a uniform [0, 1) distribution

Example: Random Walks

An illustrative application of utilizing array operations is in the simulation of random walks. Let's first consider a simple random walk starting at 0 with steps of 1 and -1 occurring with equal probability. A pure Python way to implement a single random walk with 1,000 steps using the built-in `random` module:

```
import random
position = 0
walk = [position]
steps = 1000
for i in xrange(steps):
    step = 1 if random.randint(0, 1) else -1
    position += step
    walk.append(position)
```

See Figure 4-4 for an example plot of the first 100 values on one of these random walks.

Figure 4-4. A simple random walk

You might make the observation that `walk` is simply the cumulative sum of the random steps and could be evaluated as an array expression. Thus, I use the `np.random` module to draw 1,000 coin flips at once, set these to 1 and -1, and compute the cumulative sum:

```
In [215]: nsteps = 1000

In [216]: draws = np.random.randint(0, 2, size=nsteps)

In [217]: steps = np.where(draws > 0, 1, -1)

In [218]: walk = steps.cumsum()
```

From this we can begin to extract statistics like the minimum and maximum value along the walk's trajectory:

```
In [219]: walk.min()        In [220]: walk.max()
Out[219]: -3                Out[220]: 31
```

A more complicated statistic is the *first crossing time*, the step at which the random walk reaches a particular value. Here we might want to know how long it took the random walk to get at least 10 steps away from the origin 0 in either direction. `np.abs(walk) >= 10` gives us a boolean array indicating where the walk has reached or exceeded 10, but we want the index of the *first* 10 or -10. Turns out this can be computed using `argmax`, which returns the first index of the maximum value in the boolean array (`True` is the maximum value):

```
In [221]: (np.abs(walk) >= 10).argmax()
Out[221]: 37
```

Note that using `argmax` here is not always efficient because it always makes a full scan of the array. In this special case once a `True` is observed we know it to be the maximum value.

Simulating Many Random Walks at Once

If your goal was to simulate many random walks, say 5,000 of them, you can generate all of the random walks with minor modifications to the above code. The `numpy.random` functions if passed a 2-tuple will generate a 2D array of draws, and we can compute the cumulative sum across the rows to compute all 5,000 random walks in one shot:

```
In [222]: nwalks = 5000

In [223]: nsteps = 1000

In [224]: draws = np.random.randint(0, 2, size=(nwalks, nsteps)) # 0 or 1

In [225]: steps = np.where(draws > 0, 1, -1)

In [226]: walks = steps.cumsum(1)

In [227]: walks
Out[227]:
array([[  1,   0,   1, ...,   8,   7,   8],
       [  1,   0,  -1, ...,  34,  33,  32],
       [  1,   0,  -1, ...,   4,   5,   4],
       ...,
       [  1,   2,   1, ...,  24,  25,  26],
       [  1,   2,   3, ...,  14,  13,  14],
       [ -1,  -2,  -3, ..., -24, -23, -22]])
```

Now, we can compute the maximum and minimum values obtained over all of the walks:

```
In [228]: walks.max()        In [229]: walks.min()
Out[228]: 138                Out[229]: -133
```

Out of these walks, let's compute the minimum crossing time to 30 or -30. This is slightly tricky because not all 5,000 of them reach 30. We can check this using the `any` method:

```
In [230]: hits30 = (np.abs(walks) >= 30).any(1)

In [231]: hits30
Out[231]: array([False, True, False, ..., False, True, False], dtype=bool)

In [232]: hits30.sum() # Number that hit 30 or -30
Out[232]: 3410
```

We can use this boolean array to select out the rows of `walks` that actually cross the absolute 30 level and call `argmax` across axis 1 to get the crossing times:

```
In [233]: crossing_times = (np.abs(walks[hits30]) >= 30).argmax(1)

In [234]: crossing_times.mean()
Out[234]: 498.88973607038122
```

Feel free to experiment with other distributions for the steps other than equal sized coin flips. You need only use a different random number generation function, like `normal` to generate normally distributed steps with some mean and standard deviation:

```
In [235]: steps = np.random.normal(loc=0, scale=0.25,
   .....:                          size=(nwalks, nsteps))
```

CHAPTER 5

Getting Started with pandas

pandas will be the primary library of interest throughout much of the rest of the book. It contains high-level data structures and manipulation tools designed to make data analysis fast and easy in Python. pandas is built on top of NumPy and makes it easy to use in NumPy-centric applications.

As a bit of background, I started building pandas in early 2008 during my tenure at AQR, a quantitative investment management firm. At the time, I had a distinct set of requirements that were not well-addressed by any single tool at my disposal:

- Data structures with labeled axes supporting automatic or explicit data alignment. This prevents common errors resulting from misaligned data and working with differently-indexed data coming from different sources.
- Integrated time series functionality.
- The same data structures handle both time series data and non-time series data.
- Arithmetic operations and reductions (like summing across an axis) would pass on the metadata (axis labels).
- Flexible handling of missing data.
- Merge and other relational operations found in popular database databases (SQL-based, for example).

I wanted to be able to do all of these things in one place, preferably in a language well-suited to general purpose software development. Python was a good candidate language for this, but at that time there was not an integrated set of data structures and tools providing this functionality.

Over the last four years, pandas has matured into a quite large library capable of solving a much broader set of data handling problems than I ever anticipated, but it has expanded in its scope without compromising the simplicity and ease-of-use that I desired from the very beginning. I hope that after reading this book, you will find it to be just as much of an indispensable tool as I do.

Throughout the rest of the book, I use the following import conventions for pandas:

```
In [1]: from pandas import Series, DataFrame

In [2]: import pandas as pd
```

Thus, whenever you see `pd.` in code, it's referring to pandas. Series and DataFrame are used so much that I find it easier to import them into the local namespace.

Introduction to pandas Data Structures

To get started with pandas, you will need to get comfortable with its two workhorse data structures: *Series* and *DataFrame*. While they are not a universal solution for every problem, they provide a solid, easy-to-use basis for most applications.

Series

A Series is a one-dimensional array-like object containing an array of data (of any NumPy data type) and an associated array of data labels, called its *index*. The simplest Series is formed from only an array of data:

```
In [4]: obj = Series([4, 7, -5, 3])

In [5]: obj
Out[5]:
0    4
1    7
2   -5
3    3
```

The string representation of a Series displayed interactively shows the index on the left and the values on the right. Since we did not specify an index for the data, a default one consisting of the integers 0 through N - 1 (where N is the length of the data) is created. You can get the array representation and index object of the Series via its values and index attributes, respectively:

```
In [6]: obj.values
Out[6]: array([ 4,  7, -5,  3])

In [7]: obj.index
Out[7]: Int64Index([0, 1, 2, 3])
```

Often it will be desirable to create a Series with an index identifying each data point:

```
In [8]: obj2 = Series([4, 7, -5, 3], index=['d', 'b', 'a', 'c'])

In [9]: obj2
Out[9]:
d    4
b    7
a   -5
c    3
```

```
In [10]: obj2.index
Out[10]: Index([d, b, a, c], dtype=object)
```

Compared with a regular NumPy array, you can use values in the index when selecting single values or a set of values:

```
In [11]: obj2['a']
Out[11]: -5

In [12]: obj2['d'] = 6

In [13]: obj2[['c', 'a', 'd']]
Out[13]:
c    3
a   -5
d    6
```

NumPy array operations, such as filtering with a boolean array, scalar multiplication, or applying math functions, will preserve the index-value link:

```
In [14]: obj2
Out[14]:
d    6
b    7
a   -5
c    3

In [15]: obj2[obj2 > 0]      In [16]: obj2 * 2      In [17]: np.exp(obj2)
Out[15]:                     Out[16]:               Out[17]:
d    6                       d    12                d     403.428793
b    7                       b    14                b    1096.633158
c    3                       a   -10                a       0.006738
                             c     6                c      20.085537
```

Another way to think about a Series is as a fixed-length, ordered dict, as it is a mapping of index values to data values. It can be substituted into many functions that expect a dict:

```
In [18]: 'b' in obj2
Out[18]: True

In [19]: 'e' in obj2
Out[19]: False
```

Should you have data contained in a Python dict, you can create a Series from it by passing the dict:

```
In [20]: sdata = {'Ohio': 35000, 'Texas': 71000, 'Oregon': 16000, 'Utah': 5000}

In [21]: obj3 = Series(sdata)

In [22]: obj3
Out[22]:
Ohio      35000
Oregon    16000
```

```
Texas     71000
Utah       5000
```

When only passing a dict, the index in the resulting Series will have the dict's keys in sorted order.

```
In [23]: states = ['California', 'Ohio', 'Oregon', 'Texas']

In [24]: obj4 = Series(sdata, index=states)

In [25]: obj4
Out[25]:
California      NaN
Ohio          35000
Oregon        16000
Texas         71000
```

In this case, 3 values found in `sdata` were placed in the appropriate locations, but since no value for `'California'` was found, it appears as `NaN` (not a number) which is considered in pandas to mark missing or *NA* values. I will use the terms "missing" or "NA" to refer to missing data. The `isnull` and `notnull` functions in pandas should be used to detect missing data:

```
In [26]: pd.isnull(obj4)      In [27]: pd.notnull(obj4)
Out[26]:                      Out[27]:
California     True           California    False
Ohio          False           Ohio           True
Oregon        False           Oregon         True
Texas         False           Texas          True
```

Series also has these as instance methods:

```
In [28]: obj4.isnull()
Out[28]:
California     True
Ohio          False
Oregon        False
Texas         False
```

I discuss working with missing data in more detail later in this chapter.

A critical Series feature for many applications is that it automatically aligns differently-indexed data in arithmetic operations:

```
In [29]: obj3          In [30]: obj4
Out[29]:               Out[30]:
Ohio      35000        California      NaN
Oregon    16000        Ohio          35000
Texas     71000        Oregon        16000
Utah       5000        Texas         71000

In [31]: obj3 + obj4
Out[31]:
California       NaN
Ohio           70000
Oregon         32000
```

```
Texas         142000
Utah             NaN
```

Data alignment features are addressed as a separate topic.

Both the Series object itself and its index have a `name` attribute, which integrates with other key areas of pandas functionality:

```
In [32]: obj4.name = 'population'

In [33]: obj4.index.name = 'state'

In [34]: obj4
Out[34]:
state
California      NaN
Ohio          35000
Oregon        16000
Texas         71000
Name: population
```

A Series's index can be altered in place by assignment:

```
In [35]: obj.index = ['Bob', 'Steve', 'Jeff', 'Ryan']

In [36]: obj
Out[36]:
Bob      4
Steve    7
Jeff    -5
Ryan     3
```

DataFrame

A DataFrame represents a tabular, spreadsheet-like data structure containing an ordered collection of columns, each of which can be a different value type (numeric, string, boolean, etc.). The DataFrame has both a row and column index; it can be thought of as a dict of Series (one for all sharing the same index). Compared with other such DataFrame-like structures you may have used before (like R's `data.frame`), row-oriented and column-oriented operations in DataFrame are treated roughly symmetrically. Under the hood, the data is stored as one or more two-dimensional blocks rather than a list, dict, or some other collection of one-dimensional arrays. The exact details of DataFrame's internals are far outside the scope of this book.

While DataFrame stores the data internally in a two-dimensional format, you can easily represent much higher-dimensional data in a tabular format using hierarchical indexing, a subject of a later section and a key ingredient in many of the more advanced data-handling features in pandas.

There are numerous ways to construct a DataFrame, though one of the most common is from a dict of equal-length lists or NumPy arrays

```
data = {'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9]}
frame = DataFrame(data)
```

The resulting DataFrame will have its index assigned automatically as with Series, and the columns are placed in sorted order:

```
In [38]: frame
Out[38]:
   pop   state  year
0  1.5    Ohio  2000
1  1.7    Ohio  2001
2  3.6    Ohio  2002
3  2.4  Nevada  2001
4  2.9  Nevada  2002
```

If you specify a sequence of columns, the DataFrame's columns will be exactly what you pass:

```
In [39]: DataFrame(data, columns=['year', 'state', 'pop'])
Out[39]:
   year   state  pop
0  2000    Ohio  1.5
1  2001    Ohio  1.7
2  2002    Ohio  3.6
3  2001  Nevada  2.4
4  2002  Nevada  2.9
```

As with Series, if you pass a column that isn't contained in `data`, it will appear with NA values in the result:

```
In [40]: frame2 = DataFrame(data, columns=['year', 'state', 'pop', 'debt'],
   ....:                    index=['one', 'two', 'three', 'four', 'five'])

In [41]: frame2
Out[41]:
       year   state  pop  debt
one    2000    Ohio  1.5   NaN
two    2001    Ohio  1.7   NaN
three  2002    Ohio  3.6   NaN
four   2001  Nevada  2.4   NaN
five   2002  Nevada  2.9   NaN

In [42]: frame2.columns
Out[42]: Index([year, state, pop, debt], dtype=object)
```

A column in a DataFrame can be retrieved as a Series either by dict-like notation or by attribute:

```
In [43]: frame2['state']        In [44]: frame2.year
Out[43]:                        Out[44]:
one        Ohio                 one      2000
```

```
two        Ohio                two      2001
three      Ohio                three    2002
four     Nevada                four     2001
five     Nevada                five     2002
Name: state                    Name: year
```

Note that the returned Series have the same index as the DataFrame, and their `name` attribute has been appropriately set.

Rows can also be retrieved by position or name by a couple of methods, such as the `ix` indexing field (much more on this later):

```
In [45]: frame2.ix['three']
Out[45]:
year     2002
state    Ohio
pop       3.6
debt      NaN
Name: three
```

Columns can be modified by assignment. For example, the empty `'debt'` column could be assigned a scalar value or an array of values:

```
In [46]: frame2['debt'] = 16.5

In [47]: frame2
Out[47]:
       year   state  pop  debt
one    2000    Ohio  1.5  16.5
two    2001    Ohio  1.7  16.5
three  2002    Ohio  3.6  16.5
four   2001  Nevada  2.4  16.5
five   2002  Nevada  2.9  16.5

In [48]: frame2['debt'] = np.arange(5.)

In [49]: frame2
Out[49]:
       year   state  pop  debt
one    2000    Ohio  1.5     0
two    2001    Ohio  1.7     1
three  2002    Ohio  3.6     2
four   2001  Nevada  2.4     3
five   2002  Nevada  2.9     4
```

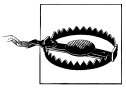
When assigning lists or arrays to a column, the value's length must match the length of the DataFrame. If you assign a Series, it will be instead conformed exactly to the DataFrame's index, inserting missing values in any holes:

```
In [50]: val = Series([-1.2, -1.5, -1.7], index=['two', 'four', 'five'])

In [51]: frame2['debt'] = val

In [52]: frame2
Out[52]:
       year   state  pop  debt
```

```
one    2000    Ohio  1.5   NaN
two    2001    Ohio  1.7  -1.2
three  2002    Ohio  3.6   NaN
four   2001  Nevada  2.4  -1.5
five   2002  Nevada  2.9  -1.7
```

Assigning a column that doesn't exist will create a new column. The `del` keyword will delete columns as with a dict:

```
In [53]: frame2['eastern'] = frame2.state == 'Ohio'

In [54]: frame2
Out[54]:
       year   state  pop  debt eastern
one    2000    Ohio  1.5   NaN    True
two    2001    Ohio  1.7  -1.2    True
three  2002    Ohio  3.6   NaN    True
four   2001  Nevada  2.4  -1.5   False
five   2002  Nevada  2.9  -1.7   False

In [55]: del frame2['eastern']

In [56]: frame2.columns
Out[56]: Index([year, state, pop, debt], dtype=object)
```



The column returned when indexing a DataFrame is a *view* on the underlying data, not a copy. Thus, any in-place modifications to the Series will be reflected in the DataFrame. The column can be explicitly copied using the Series's `copy` method.

Another common form of data is a nested dict of dicts format:

```
In [57]: pop = {'Nevada': {2001: 2.4, 2002: 2.9},
   ....:        'Ohio': {2000: 1.5, 2001: 1.7, 2002: 3.6}}
```

If passed to DataFrame, it will interpret the outer dict keys as the columns and the inner keys as the row indices:

```
In [58]: frame3 = DataFrame(pop)

In [59]: frame3
Out[59]:
      Nevada  Ohio
2000     NaN   1.5
2001     2.4   1.7
2002     2.9   3.6
```

Of course you can always transpose the result:

```
In [60]: frame3.T
Out[60]:
        2000  2001  2002
Nevada   NaN   2.4   2.9
Ohio     1.5   1.7   3.6
```

The keys in the inner dicts are unioned and sorted to form the index in the result. This isn't true if an explicit index is specified:

```
In [61]: DataFrame(pop, index=[2001, 2002, 2003])
Out[61]:
      Nevada  Ohio
2001     2.4   1.7
2002     2.9   3.6
2003     NaN   NaN
```

Dicts of Series are treated much in the same way:

```
In [62]: pdata = {'Ohio': frame3['Ohio'][:-1],
   ....:          'Nevada': frame3['Nevada'][:2]}

In [63]: DataFrame(pdata)
Out[63]:
      Nevada  Ohio
2000     NaN   1.5
2001     2.4   1.7
```

For a complete list of things you can pass the DataFrame constructor, see Table 5-1.

If a DataFrame's `index` and `columns` have their `name` attributes set, these will also be displayed:

```
In [64]: frame3.index.name = 'year'; frame3.columns.name = 'state'

In [65]: frame3
Out[65]:
state  Nevada  Ohio
year
2000      NaN   1.5
2001      2.4   1.7
2002      2.9   3.6
```

Like Series, the `values` attribute returns the data contained in the DataFrame as a 2D ndarray:

```
In [66]: frame3.values
Out[66]:
array([[ nan,  1.5],
       [ 2.4,  1.7],
       [ 2.9,  3.6]])
```

If the DataFrame's columns are different dtypes, the dtype of the values array will be chosen to accomodate all of the columns:

```
In [67]: frame2.values
Out[67]:
array([[2000, Ohio, 1.5, nan],
       [2001, Ohio, 1.7, -1.2],
       [2002, Ohio, 3.6, nan],
       [2001, Nevada, 2.4, -1.5],
       [2002, Nevada, 2.9, -1.7]], dtype=object)
```

Table 5-1. Possible data inputs to DataFrame constructor

Type	Notes
2D ndarray	A matrix of data, passing optional row and column labels
dict of arrays, lists, or tuples	Each sequence becomes a column in the DataFrame. All sequences must be the same length.
NumPy structured/record array	Treated as the "dict of arrays" case
dict of Series	Each value becomes a column. Indexes from each Series are unioned together to form the result's row index if no explicit index is passed.
dict of dicts	Each inner dict becomes a column. Keys are unioned to form the row index as in the "dict of Series" case.
list of dicts or Series	Each item becomes a row in the DataFrame. Union of dict keys or Series indexes become the DataFrame's column labels
List of lists or tuples	Treated as the "2D ndarray" case
Another DataFrame	The DataFrame's indexes are used unless different ones are passed
NumPy MaskedArray	Like the "2D ndarray" case except masked values become NA/missing in the DataFrame result

Index Objects

pandas's Index objects are responsible for holding the axis labels and other metadata (like the axis name or names). Any array or other sequence of labels used when constructing a Series or DataFrame is internally converted to an Index:

```
In [68]: obj = Series(range(3), index=['a', 'b', 'c'])

In [69]: index = obj.index

In [70]: index
Out[70]: Index([a, b, c], dtype=object)

In [71]: index[1:]
Out[71]: Index([b, c], dtype=object)
```

Index objects are immutable and thus can't be modified by the user:

```
In [72]: index[1] = 'd'
---------------------------------------------------------------------------
Exception                                 Traceback (most recent call last)
<ipython-input-72-676fdeb26a68> in <module>()
----> 1 index[1] = 'd'
/Users/wesm/code/pandas/pandas/core/index.pyc in __setitem__(self, key, value)
    302     def __setitem__(self, key, value):
    303         """Disable the setting of values."""
--> 304         raise Exception(str(self.__class__) + ' object is immutable')
    305
    306     def __getitem__(self, key):
Exception: <class 'pandas.core.index.Index'> object is immutable
```

Immutability is important so that Index objects can be safely shared among data structures:

```
In [73]: index = pd.Index(np.arange(3))

In [74]: obj2 = Series([1.5, -2.5, 0], index=index)

In [75]: obj2.index is index
Out[75]: True
```

Table 5-2 has a list of built-in Index classes in the library. With some development effort, Index can even be subclassed to implement specialized axis indexing functionality.

Many users will not need to know much about Index objects, but they're nonetheless an important part of pandas's data model.

Table 5-2. Main Index objects in pandas

Class	Description
`Index`	The most general Index object, representing axis labels in a NumPy array of Python objects.
`Int64Index`	Specialized Index for integer values.
`MultiIndex`	"Hierarchical" index object representing multiple levels of indexing on a single axis. Can be thought of as similar to an array of tuples.
`DatetimeIndex`	Stores nanosecond timestamps (represented using NumPy's `datetime64` dtype).
`PeriodIndex`	Specialized Index for Period data (timespans).

In addition to being array-like, an Index also functions as a fixed-size set:

```
In [76]: frame3
Out[76]:
state  Nevada  Ohio
year
2000      NaN   1.5
2001      2.4   1.7
2002      2.9   3.6

In [77]: 'Ohio' in frame3.columns
Out[77]: True

In [78]: 2003 in frame3.index
Out[78]: False
```

Each Index has a number of methods and properties for set logic and answering other common questions about the data it contains. These are summarized in Table 5-3.

Table 5-3. Index methods and properties

Method	Description
`append`	Concatenate with additional Index objects, producing a new Index
`diff`	Compute set difference as an Index
`intersection`	Compute set intersection
`union`	Compute set union
`isin`	Compute boolean array indicating whether each value is contained in the passed collection
`delete`	Compute new Index with element at index `i` deleted
`drop`	Compute new index by deleting passed values
`insert`	Compute new Index by inserting element at index `i`
`is_monotonic`	Returns `True` if each element is greater than or equal to the previous element
`is_unique`	Returns `True` if the Index has no duplicate values
`unique`	Compute the array of unique values in the Index

Essential Functionality

In this section, I'll walk you through the fundamental mechanics of interacting with the data contained in a Series or DataFrame. Upcoming chapters will delve more deeply into data analysis and manipulation topics using pandas. This book is not intended to serve as exhaustive documentation for the pandas library; I instead focus on the most important features, leaving the less common (that is, more esoteric) things for you to explore on your own.

Reindexing

A critical method on pandas objects is `reindex`, which means to create a new object with the data *conformed* to a new index. Consider a simple example from above:

```
In [79]: obj = Series([4.5, 7.2, -5.3, 3.6], index=['d', 'b', 'a', 'c'])

In [80]: obj
Out[80]:
d    4.5
b    7.2
a   -5.3
c    3.6
```

Calling `reindex` on this Series rearranges the data according to the new index, introducing missing values if any index values were not already present:

```
In [81]: obj2 = obj.reindex(['a', 'b', 'c', 'd', 'e'])

In [82]: obj2
Out[82]:
a   -5.3
```

```
b    7.2
c    3.6
d    4.5
e    NaN
```

```
In [83]: obj.reindex(['a', 'b', 'c', 'd', 'e'], fill_value=0)
Out[83]:
a   -5.3
b    7.2
c    3.6
d    4.5
e    0.0
```

For ordered data like time series, it may be desirable to do some interpolation or filling of values when reindexing. The `method` option allows us to do this, using a method such as `ffill` which forward fills the values:

```
In [84]: obj3 = Series(['blue', 'purple', 'yellow'], index=[0, 2, 4])

In [85]: obj3.reindex(range(6), method='ffill')
Out[85]:
0      blue
1      blue
2    purple
3    purple
4    yellow
5    yellow
```

Table 5-4 lists available `method` options. At this time, interpolation more sophisticated than forward- and backfilling would need to be applied after the fact.

Table 5-4. reindex method (interpolation) options

Argument	Description
`ffill` or `pad`	Fill (or carry) values forward
`bfill` or `backfill`	Fill (or carry) values backward

With DataFrame, `reindex` can alter either the (row) index, columns, or both. When passed just a sequence, the rows are reindexed in the result:

```
In [86]: frame = DataFrame(np.arange(9).reshape((3, 3)), index=['a', 'c', 'd'],
   ....:                   columns=['Ohio', 'Texas', 'California'])

In [87]: frame
Out[87]:
   Ohio  Texas  California
a     0      1           2
c     3      4           5
d     6      7           8

In [88]: frame2 = frame.reindex(['a', 'b', 'c', 'd'])

In [89]: frame2
Out[89]:
```

```
   Ohio  Texas  California
a     0      1           2
b   NaN    NaN         NaN
c     3      4           5
d     6      7           8
```

The columns can be reindexed using the `columns` keyword:

```
In [90]: states = ['Texas', 'Utah', 'California']

In [91]: frame.reindex(columns=states)
Out[91]:
   Texas  Utah  California
a      1   NaN           2
c      4   NaN           5
d      7   NaN           8
```

Both can be reindexed in one shot, though interpolation will only apply row-wise (axis 0):

```
In [92]: frame.reindex(index=['a', 'b', 'c', 'd'], method='ffill',
   ....:               columns=states)
Out[92]:
   Texas  Utah  California
a      1   NaN           2
b      1   NaN           2
c      4   NaN           5
d      7   NaN           8
```

As you'll see soon, reindexing can be done more succinctly by label-indexing with `ix`:

```
In [93]: frame.ix[['a', 'b', 'c', 'd'], states]
Out[93]:
   Texas  Utah  California
a      1   NaN           2
b    NaN   NaN         NaN
c      4   NaN           5
d      7   NaN           8
```

Table 5-5. reindex function arguments

Argument	Description
`index`	New sequence to use as index. Can be `Index` instance or any other sequence-like Python data structure. An `Index` will be used exactly as is without any copying
`method`	Interpolation (fill) method, see Table 5-4 for options.
`fill_value`	Substitute value to use when introducing missing data by reindexing
`limit`	When forward- or backfilling, maximum size gap to fill
`level`	Match simple Index on level of MultiIndex, otherwise select subset of
`copy`	Do not copy underlying data if new index is equivalent to old index. `True` by default (i.e. always copy data).

Dropping entries from an axis

Dropping one or more entries from an axis is easy if you have an index array or list without those entries. As that can require a bit of munging and set logic, the `drop` method will return a new object with the indicated value or values deleted from an axis:

```
In [94]: obj = Series(np.arange(5.), index=['a', 'b', 'c', 'd', 'e'])

In [95]: new_obj = obj.drop('c')

In [96]: new_obj
Out[96]:
a    0
b    1
d    3
e    4

In [97]: obj.drop(['d', 'c'])
Out[97]:
a    0
b    1
e    4
```

With DataFrame, index values can be deleted from either axis:

```
In [98]: data = DataFrame(np.arange(16).reshape((4, 4)),
   ....:                  index=['Ohio', 'Colorado', 'Utah', 'New York'],
   ....:                  columns=['one', 'two', 'three', 'four'])

In [99]: data.drop(['Colorado', 'Ohio'])
Out[99]:
          one  two  three  four
Utah        8    9     10    11
New York   12   13     14    15

In [100]: data.drop('two', axis=1)
Out[100]:
          one  three  four
Ohio        0      2     3
Colorado    4      6     7
Utah        8     10    11
New York   12     14    15

In [101]: data.drop(['two', 'four'], axis=1)
Out[101]:
          one  three
Ohio        0      2
Colorado    4      6
Utah        8     10
New York   12     14
```

Indexing, selection, and filtering

Series indexing (`obj[...]`) works analogously to NumPy array indexing, except you can use the Series's index values instead of only integers. Here are some examples this:

```
In [102]: obj = Series(np.arange(4.), index=['a', 'b', 'c', 'd'])

In [103]: obj['b']
Out[103]: 1.0

In [104]: obj[1]
Out[104]: 1.0

In [105]: obj[2:4]
Out[105]:

In [106]: obj[['b', 'a', 'd']]
Out[106]:
```

```
c    2                      b    1
d    3                      a    0
                            d    3

In [107]: obj[[1, 3]]       In [108]: obj[obj < 2]
Out[107]:                   Out[108]:
b    1                      a    0
d    3                      b    1
```

Slicing with labels behaves differently than normal Python slicing in that the endpoint is inclusive:

```
In [109]: obj['b':'c']
Out[109]:
b    1
c    2
```

Setting using these methods works just as you would expect:

```
In [110]: obj['b':'c'] = 5

In [111]: obj
Out[111]:
a    0
b    5
c    5
d    3
```

As you've seen above, indexing into a DataFrame is for retrieving one or more columns either with a single value or sequence:

```
In [112]: data = DataFrame(np.arange(16).reshape((4, 4)),
   .....:                  index=['Ohio', 'Colorado', 'Utah', 'New York'],
   .....:                  columns=['one', 'two', 'three', 'four'])

In [113]: data
Out[113]:
          one  two  three  four
Ohio        0    1      2     3
Colorado    4    5      6     7
Utah        8    9     10    11
New York   12   13     14    15

In [114]: data['two']        In [115]: data[['three', 'one']]
Out[114]:                    Out[115]:
Ohio         1                         three  one
Colorado     5               Ohio          2    0
Utah         9               Colorado      6    4
New York    13               Utah         10    8
Name: two                    New York     14   12
```

Indexing like this has a few special cases. First selecting rows by slicing or a boolean array:

```
In [116]: data[:2]                     In [117]: data[data['three'] > 5]
Out[116]:                              Out[117]:
          one  two  three  four                   one  two  three  four
```

```
Ohio        0    1      2     3        Colorado    4    5      6     7
Colorado    4    5      6     7        Utah        8    9     10    11
                                        New York   12   13     14    15
```

This might seem inconsistent to some readers, but this syntax arose out of practicality and nothing more. Another use case is in indexing with a boolean DataFrame, such as one produced by a scalar comparison:

```
In [118]: data < 5
Out[118]:
            one    two  three   four
Ohio       True   True   True   True
Colorado   True  False  False  False
Utah      False  False  False  False
New York  False  False  False  False

In [119]: data[data < 5] = 0

In [120]: data
Out[120]:
          one  two  three  four
Ohio        0    0      0     0
Colorado    0    5      6     7
Utah        8    9     10    11
New York   12   13     14    15
```

This is intended to make DataFrame syntactically more like an ndarray in this case.

For DataFrame label-indexing on the rows, I introduce the special indexing field `ix`. It enables you to select a subset of the rows and columns from a DataFrame with NumPy-like notation plus axis labels. As I mentioned earlier, this is also a less verbose way to do reindexing:

```
In [121]: data.ix['Colorado', ['two', 'three']]
Out[121]:
two      5
three    6
Name: Colorado

In [122]: data.ix[['Colorado', 'Utah'], [3, 0, 1]]
Out[122]:
          four  one  two
Colorado     7    0    5
Utah        11    8    9

In [123]: data.ix[2]        In [124]: data.ix[:'Utah', 'two']
Out[123]:                   Out[124]:
one       8                 Ohio        0
two       9                 Colorado    5
three    10                 Utah        9
four     11                 Name: two
Name: Utah

In [125]: data.ix[data.three > 5, :3]
Out[125]:
```

```
          one  two  three
Colorado    0    5      6
Utah        8    9     10
New York   12   13     14
```

So there are many ways to select and rearrange the data contained in a pandas object. For DataFrame, there is a short summary of many of them in Table 5-6. You have a number of additional options when working with hierarchical indexes as you'll later see.

When designing pandas, I felt that having to type `frame[:, col]` to select a column was too verbose (and error-prone), since column selection is one of the most common operations. Thus I made the design trade-off to push all of the rich label-indexing into `ix`.

Table 5-6. Indexing options with DataFrame

Type	Notes
`obj[val]`	Select single column or sequence of columns from the DataFrame. Special case conveniences: boolean array (filter rows), slice (slice rows), or boolean DataFrame (set values based on some criterion).
`obj.ix[val]`	Selects single row of subset of rows from the DataFrame.
`obj.ix[:, val]`	Selects single column of subset of columns.
`obj.ix[val1, val2]`	Select both rows and columns.
`reindex` method	Conform one or more axes to new indexes.
`xs` method	Select single row or column as a Series by label.
`icol, irow` methods	Select single column or row, respectively, as a Series by integer location.
`get_value, set_value` methods	Select single value by row and column label.

Arithmetic and data alignment

One of the most important pandas features is the behavior of arithmetic between objects with different indexes. When adding together objects, if any index pairs are not the same, the respective index in the result will be the union of the index pairs. Let's look at a simple example:

```
In [126]: s1 = Series([7.3, -2.5, 3.4, 1.5], index=['a', 'c', 'd', 'e'])

In [127]: s2 = Series([-2.1, 3.6, -1.5, 4, 3.1], index=['a', 'c', 'e', 'f', 'g'])

In [128]: s1        In [129]: s2
Out[128]:           Out[129]:
a    7.3            a   -2.1
c   -2.5            c    3.6
d    3.4            e   -1.5
```

```
e    1.5            f    4.0
                    g    3.1
```

Adding these together yields:

```
In [130]: s1 + s2
Out[130]:
a    5.2
c    1.1
d    NaN
e    0.0
f    NaN
g    NaN
```

The internal data alignment introduces NA values in the indices that don't overlap. Missing values propagate in arithmetic computations.

In the case of DataFrame, alignment is performed on both the rows and the columns:

```
In [131]: df1 = DataFrame(np.arange(9.).reshape((3, 3)), columns=list('bcd'),
   .....:                 index=['Ohio', 'Texas', 'Colorado'])

In [132]: df2 = DataFrame(np.arange(12.).reshape((4, 3)), columns=list('bde'),
   .....:                 index=['Utah', 'Ohio', 'Texas', 'Oregon'])

In [133]: df1            In [134]: df2
Out[133]:                Out[134]:
          b  c  d                    b   d   e
Ohio      0  1  2        Utah        0   1   2
Texas     3  4  5        Ohio        3   4   5
Colorado  6  7  8        Texas       6   7   8
                         Oregon      9  10  11
```

Adding these together returns a DataFrame whose index and columns are the unions of the ones in each DataFrame:

```
In [135]: df1 + df2
Out[135]:
           b   c   d   e
Colorado NaN NaN NaN NaN
Ohio       3 NaN   6 NaN
Oregon   NaN NaN NaN NaN
Texas      9 NaN  12 NaN
Utah     NaN NaN NaN NaN
```

Arithmetic methods with fill values

In arithmetic operations between differently-indexed objects, you might want to fill with a special value, like 0, when an axis label is found in one object but not the other:

```
In [136]: df1 = DataFrame(np.arange(12.).reshape((3, 4)), columns=list('abcd'))

In [137]: df2 = DataFrame(np.arange(20.).reshape((4, 5)), columns=list('abcde'))

In [138]: df1          In [139]: df2
Out[138]:              Out[139]:
   a  b   c   d           a   b   c   d   e
```

```
0  0  1   2   3        0   0   1   2   3   4
1  4  5   6   7        1   5   6   7   8   9
2  8  9  10  11        2  10  11  12  13  14
                       3  15  16  17  18  19
```

Adding these together results in NA values in the locations that don't overlap:

```
In [140]: df1 + df2
Out[140]:
    a   b   c   d   e
0   0   2   4   6 NaN
1   9  11  13  15 NaN
2  18  20  22  24 NaN
3 NaN NaN NaN NaN NaN
```

Using the `add` method on `df1`, I pass `df2` and an argument to `fill_value`:

```
In [141]: df1.add(df2, fill_value=0)
Out[141]:
    a   b   c   d   e
0   0   2   4   6   4
1   9  11  13  15   9
2  18  20  22  24  14
3  15  16  17  18  19
```

Relatedly, when reindexing a Series or DataFrame, you can also specify a different fill value:

```
In [142]: df1.reindex(columns=df2.columns, fill_value=0)
Out[142]:
   a  b   c   d  e
0  0  1   2   3  0
1  4  5   6   7  0
2  8  9  10  11  0
```

Table 5-7. Flexible arithmetic methods

Method	Description
`add`	Method for addition (+)
`sub`	Method for subtraction (-)
`div`	Method for division (/)
`mul`	Method for multiplication (*)

Operations between DataFrame and Series

As with NumPy arrays, arithmetic between DataFrame and Series is well-defined. First, as a motivating example, consider the difference between a 2D array and one of its rows:

```
In [143]: arr = np.arange(12.).reshape((3, 4))

In [144]: arr
Out[144]:
array([[  0.,   1.,   2.,   3.],
       [  4.,   5.,   6.,   7.],
```

```
       [  8.,   9.,  10.,  11.]])

In [145]: arr[0]
Out[145]: array([ 0.,  1.,  2.,  3.])

In [146]: arr - arr[0]
Out[146]:
array([[ 0.,  0.,  0.,  0.],
       [ 4.,  4.,  4.,  4.],
       [ 8.,  8.,  8.,  8.]])
```

This is referred to as *broadcasting* and is explained in more detail in Chapter 12. Operations between a DataFrame and a Series are similar:

```
In [147]: frame = DataFrame(np.arange(12.).reshape((4, 3)), columns=list('bde'),
   .....:                   index=['Utah', 'Ohio', 'Texas', 'Oregon'])

In [148]: series = frame.ix[0]

In [149]: frame          In [150]: series
Out[149]:                Out[150]:
        b   d   e        b    0
Utah    0   1   2        d    1
Ohio    3   4   5        e    2
Texas   6   7   8        Name: Utah
Oregon  9  10  11
```

By default, arithmetic between DataFrame and Series matches the index of the Series on the DataFrame's columns, broadcasting down the rows:

```
In [151]: frame - series
Out[151]:
        b  d  e
Utah    0  0  0
Ohio    3  3  3
Texas   6  6  6
Oregon  9  9  9
```

If an index value is not found in either the DataFrame's columns or the Series's index, the objects will be reindexed to form the union:

```
In [152]: series2 = Series(range(3), index=['b', 'e', 'f'])

In [153]: frame + series2
Out[153]:
        b   d   e   f
Utah    0 NaN   3 NaN
Ohio    3 NaN   6 NaN
Texas   6 NaN   9 NaN
Oregon  9 NaN  12 NaN
```

If you want to instead broadcast over the columns, matching on the rows, you have to use one of the arithmetic methods. For example:

```
In [154]: series3 = frame['d']

In [155]: frame      In [156]: series3
```

```
Out[155]:
        b   d   e
Utah    0   1   2
Ohio    3   4   5
Texas   6   7   8
Oregon  9  10  11

Out[156]:
Utah       1
Ohio       4
Texas      7
Oregon    10
Name: d

In [157]: frame.sub(series3, axis=0)
Out[157]:
        b  d  e
Utah   -1  0  1
Ohio   -1  0  1
Texas  -1  0  1
Oregon -1  0  1
```

The axis number that you pass is the *axis to match on*. In this case we mean to match on the DataFrame's row index and broadcast across.

Function application and mapping

NumPy ufuncs (element-wise array methods) work fine with pandas objects:

```
In [158]: frame = DataFrame(np.random.randn(4, 3), columns=list('bde'),
   .....:                   index=['Utah', 'Ohio', 'Texas', 'Oregon'])

In [159]: frame
Out[159]:
               b         d         e
Utah   -0.204708  0.478943 -0.519439
Ohio   -0.555730  1.965781  1.393406
Texas   0.092908  0.281746  0.769023
Oregon  1.246435  1.007189 -1.296221

In [160]: np.abs(frame)
Out[160]:
               b         d         e
Utah    0.204708  0.478943  0.519439
Ohio    0.555730  1.965781  1.393406
Texas   0.092908  0.281746  0.769023
Oregon  1.246435  1.007189  1.296221
```

Another frequent operation is applying a function on 1D arrays to each column or row. DataFrame's `apply` method does exactly this:

```
In [161]: f = lambda x: x.max() - x.min()

In [162]: frame.apply(f)
Out[162]:
b    1.802165
d    1.684034
e    2.689627

In [163]: frame.apply(f, axis=1)
Out[163]:
Utah      0.998382
Ohio      2.521511
Texas     0.676115
Oregon    2.542656
```

Many of the most common array statistics (like `sum` and `mean`) are DataFrame methods, so using `apply` is not necessary.

The function passed to `apply` need not return a scalar value, it can also return a Series with multiple values:

```
In [164]: def f(x):
   .....:     return Series([x.min(), x.max()], index=['min', 'max'])

In [165]: frame.apply(f)
```

```
Out[165]:
            b         d         e
min -0.555730  0.281746 -1.296221
max  1.246435  1.965781  1.393406
```

Element-wise Python functions can be used, too. Suppose you wanted to compute a formatted string from each floating point value in `frame`. You can do this with `applymap`:

```
In [166]: format = lambda x: '%.2f' % x

In [167]: frame.applymap(format)
Out[167]:
            b     d      e
Utah    -0.20  0.48  -0.52
Ohio    -0.56  1.97   1.39
Texas    0.09  0.28   0.77
Oregon   1.25  1.01  -1.30
```

The reason for the name `applymap` is that Series has a `map` method for applying an element-wise function:

```
In [168]: frame['e'].map(format)
Out[168]:
Utah      -0.52
Ohio       1.39
Texas      0.77
Oregon    -1.30
Name: e
```

Sorting and ranking

Sorting a data set by some criterion is another important built-in operation. To sort lexicographically by row or column index, use the `sort_index` method, which returns a new, sorted object:

```
In [169]: obj = Series(range(4), index=['d', 'a', 'b', 'c'])

In [170]: obj.sort_index()
Out[170]:
a    1
b    2
c    3
d    0
```

With a DataFrame, you can sort by index on either axis:

```
In [171]: frame = DataFrame(np.arange(8).reshape((2, 4)), index=['three', 'one'],
   .....:                   columns=['d', 'a', 'b', 'c'])

In [172]: frame.sort_index()
Out[172]:
       d  a  b  c
one    4  5  6  7
three  0  1  2  3
```

```
In [173]: frame.sort_index(axis=1)
Out[173]:
       a  b  c  d
three  1  2  3  0
one    5  6  7  4
```

The data is sorted in ascending order by default, but can be sorted in descending order, too:

```
In [174]: frame.sort_index(axis=1, ascending=False)
Out[174]:
       d  c  b  a
three  0  3  2  1
one    4  7  6  5
```

To sort a Series by its values, use its `order` method:

```
In [175]: obj = Series([4, 7, -3, 2])

In [176]: obj.order()
Out[176]:
2   -3
3    2
0    4
1    7
```

Any missing values are sorted to the end of the Series by default:

```
In [177]: obj = Series([4, np.nan, 7, np.nan, -3, 2])

In [178]: obj.order()
Out[178]:
4    -3
5     2
0     4
2     7
1   NaN
3   NaN
```

On DataFrame, you may want to sort by the values in one or more columns. To do so, pass one or more column names to the `by` option:

```
In [179]: frame = DataFrame({'b': [4, 7, -3, 2], 'a': [0, 1, 0, 1]})

In [180]: frame        In [181]: frame.sort_index(by='b')
Out[180]:              Out[181]:
   a  b                   a  b
0  0  4                2  0 -3
1  1  7                3  1  2
2  0 -3                0  0  4
3  1  2                1  1  7
```

To sort by multiple columns, pass a list of names:

```
In [182]: frame.sort_index(by=['a', 'b'])
Out[182]:
   a  b
2  0 -3
0  0  4
3  1  2
1  1  7
```

Ranking is closely related to sorting, assigning ranks from one through the number of valid data points in an array. It is similar to the indirect sort indices produced by `numpy.argsort`, except that ties are broken according to a rule. The `rank` methods for Series and DataFrame are the place to look; by default `rank` breaks ties by assigning each group the mean rank:

```
In [183]: obj = Series([7, -5, 7, 4, 2, 0, 4])

In [184]: obj.rank()
Out[184]:
0    6.5
1    1.0
2    6.5
3    4.5
4    3.0
5    2.0
6    4.5
```

Ranks can also be assigned according to the order they're observed in the data:

```
In [185]: obj.rank(method='first')
Out[185]:
0    6
1    1
2    7
3    4
4    3
5    2
6    5
```

Naturally, you can rank in descending order, too:

```
In [186]: obj.rank(ascending=False, method='max')
Out[186]:
0    2
1    7
2    2
3    4
4    5
5    6
6    4
```

See Table 5-8 for a list of tie-breaking methods available. DataFrame can compute ranks over the rows or the columns:

```
In [187]: frame = DataFrame({'b': [4.3, 7, -3, 2], 'a': [0, 1, 0, 1],
   .....:                    'c': [-2, 5, 8, -2.5]})

In [188]: frame        In [189]: frame.rank(axis=1)
Out[188]:              Out[189]:
   a    b    c            a  b  c
0  0  4.3 -2.0         0  2  3  1
1  1  7.0  5.0         1  1  3  2
2  0 -3.0  8.0         2  2  1  3
3  1  2.0 -2.5         3  2  3  1
```

Table 5-8. Tie-breaking methods with rank

Method	Description
`'average'`	Default: assign the average rank to each entry in the equal group.
`'min'`	Use the minimum rank for the whole group.
`'max'`	Use the maximum rank for the whole group.
`'first'`	Assign ranks in the order the values appear in the data.

Axis indexes with duplicate values

Up until now all of the examples I've showed you have had unique axis labels (index values). While many pandas functions (like `reindex`) require that the labels be unique, it's not mandatory. Let's consider a small Series with duplicate indices:

```
In [190]: obj = Series(range(5), index=['a', 'a', 'b', 'b', 'c'])

In [191]: obj
Out[191]:
a    0
a    1
b    2
b    3
c    4
```

The index's `is_unique` property can tell you whether its values are unique or not:

```
In [192]: obj.index.is_unique
Out[192]: False
```

Data selection is one of the main things that behaves differently with duplicates. Indexing a value with multiple entries returns a Series while single entries return a scalar value:

```
In [193]: obj['a']    In [194]: obj['c']
Out[193]:             Out[194]: 4
a    0
a    1
```

The same logic extends to indexing rows in a DataFrame:

```
In [195]: df = DataFrame(np.random.randn(4, 3), index=['a', 'a', 'b', 'b'])

In [196]: df
Out[196]:
          0         1         2
a  0.274992  0.228913  1.352917
a  0.886429 -2.001637 -0.371843
b  1.669025 -0.438570 -0.539741
b  0.476985  3.248944 -1.021228

In [197]: df.ix['b']
Out[197]:
          0         1         2
```

```
b  1.669025 -0.438570 -0.539741
b  0.476985  3.248944 -1.021228
```

Summarizing and Computing Descriptive Statistics

pandas objects are equipped with a set of common mathematical and statistical methods. Most of these fall into the category of *reductions* or *summary statistics*, methods that extract a single value (like the sum or mean) from a Series or a Series of values from the rows or columns of a DataFrame. Compared with the equivalent methods of vanilla NumPy arrays, they are all built from the ground up to exclude missing data. Consider a small DataFrame:

```
In [198]: df = DataFrame([[1.4, np.nan], [7.1, -4.5],
   .....:                 [np.nan, np.nan], [0.75, -1.3]],
   .....:                index=['a', 'b', 'c', 'd'],
   .....:                columns=['one', 'two'])

In [199]: df
Out[199]:
    one  two
a  1.40  NaN
b  7.10 -4.5
c   NaN  NaN
d  0.75 -1.3
```

Calling DataFrame's `sum` method returns a Series containing column sums:

```
In [200]: df.sum()
Out[200]:
one    9.25
two   -5.80
```

Passing `axis=1` sums over the rows instead:

```
In [201]: df.sum(axis=1)
Out[201]:
a    1.40
b    2.60
c     NaN
d   -0.55
```

NA values are excluded unless the entire slice (row or column in this case) is NA. This can be disabled using the `skipna` option:

```
In [202]: df.mean(axis=1, skipna=False)
Out[202]:
a      NaN
b    1.300
c      NaN
d   -0.275
```

See Table 5-9 for a list of common options for each reduction method options.

Table 5-9. Options for reduction methods

Method	Description
`axis`	Axis to reduce over. 0 for DataFrame's rows and 1 for columns.
`skipna`	Exclude missing values, `True` by default.
`level`	Reduce grouped by level if the axis is hierarchically-indexed (MultiIndex).

Some methods, like `idxmin` and `idxmax`, return indirect statistics like the index value where the minimum or maximum values are attained:

```
In [203]: df.idxmax()
Out[203]:
one    b
two    d
```

Other methods are *accumulations*:

```
In [204]: df.cumsum()
Out[204]:
    one  two
a  1.40  NaN
b  8.50 -4.5
c   NaN  NaN
d  9.25 -5.8
```

Another type of method is neither a reduction nor an accumulation. `describe` is one such example, producing multiple summary statistics in one shot:

```
In [205]: df.describe()
Out[205]:
             one       two
count  3.000000  2.000000
mean   3.083333 -2.900000
std    3.493685  2.262742
min    0.750000 -4.500000
25%    1.075000 -3.700000
50%    1.400000 -2.900000
75%    4.250000 -2.100000
max    7.100000 -1.300000
```

On non-numeric data, `describe` produces alternate summary statistics:

```
In [206]: obj = Series(['a', 'a', 'b', 'c'] * 4)

In [207]: obj.describe()
Out[207]:
count     16
unique     3
top        a
freq       8
```

See Table 5-10 for a full list of summary statistics and related methods.

Table 5-10. Descriptive and summary statistics

Method	Description
`count`	Number of non-NA values
`describe`	Compute set of summary statistics for Series or each DataFrame column
`min, max`	Compute minimum and maximum values
`argmin, argmax`	Compute index locations (integers) at which minimum or maximum value obtained, respectively
`idxmin, idxmax`	Compute index values at which minimum or maximum value obtained, respectively
`quantile`	Compute sample quantile ranging from 0 to 1
`sum`	Sum of values
`mean`	Mean of values
`median`	Arithmetic median (50% quantile) of values
`mad`	Mean absolute deviation from mean value
`var`	Sample variance of values
`std`	Sample standard deviation of values
`skew`	Sample skewness (3rd moment) of values
`kurt`	Sample kurtosis (4th moment) of values
`cumsum`	Cumulative sum of values
`cummin, cummax`	Cumulative minimum or maximum of values, respectively
`cumprod`	Cumulative product of values
`diff`	Compute 1st arithmetic difference (useful for time series)
`pct_change`	Compute percent changes

Correlation and Covariance

Some summary statistics, like correlation and covariance, are computed from pairs of arguments. Let's consider some DataFrames of stock prices and volumes obtained from Yahoo! Finance:

```
import pandas.io.data as web

all_data = {}
for ticker in ['AAPL', 'IBM', 'MSFT', 'GOOG']:
    all_data[ticker] = web.get_data_yahoo(ticker, '1/1/2000', '1/1/2010')

price = DataFrame({tic: data['Adj Close']
                   for tic, data in all_data.iteritems()})
volume = DataFrame({tic: data['Volume']
                    for tic, data in all_data.iteritems()})
```

I now compute percent changes of the prices:

```
In [209]: returns = price.pct_change()

In [210]: returns.tail()
```

```
Out[210]:
                AAPL      GOOG       IBM      MSFT
Date
2009-12-24  0.034339  0.011117  0.004420  0.002747
2009-12-28  0.012294  0.007098  0.013282  0.005479
2009-12-29 -0.011861 -0.005571 -0.003474  0.006812
2009-12-30  0.012147  0.005376  0.005468 -0.013532
2009-12-31 -0.004300 -0.004416 -0.012609 -0.015432
```

The `corr` method of Series computes the correlation of the overlapping, non-NA, aligned-by-index values in two Series. Relatedly, `cov` computes the covariance:

```
In [211]: returns.MSFT.corr(returns.IBM)
Out[211]: 0.49609291822168838

In [212]: returns.MSFT.cov(returns.IBM)
Out[212]: 0.00021600332437329015
```

DataFrame's `corr` and `cov` methods, on the other hand, return a full correlation or covariance matrix as a DataFrame, respectively:

```
In [213]: returns.corr()
Out[213]:
          AAPL      GOOG       IBM      MSFT
AAPL  1.000000  0.470660  0.410648  0.424550
GOOG  0.470660  1.000000  0.390692  0.443334
IBM   0.410648  0.390692  1.000000  0.496093
MSFT  0.424550  0.443334  0.496093  1.000000

In [214]: returns.cov()
Out[214]:
          AAPL      GOOG       IBM      MSFT
AAPL  0.001028  0.000303  0.000252  0.000309
GOOG  0.000303  0.000580  0.000142  0.000205
IBM   0.000252  0.000142  0.000367  0.000216
MSFT  0.000309  0.000205  0.000216  0.000516
```

Using DataFrame's `corrwith` method, you can compute pairwise correlations between a DataFrame's columns or rows with another Series or DataFrame. Passing a Series returns a Series with the correlation value computed for each column:

```
In [215]: returns.corrwith(returns.IBM)
Out[215]:
AAPL    0.410648
GOOG    0.390692
IBM     1.000000
MSFT    0.496093
```

Passing a DataFrame computes the correlations of matching column names. Here I compute correlations of percent changes with volume:

```
In [216]: returns.corrwith(volume)
Out[216]:
AAPL   -0.057461
GOOG    0.062644
```

```
IBM    -0.007900
MSFT   -0.014175
```

Passing `axis=1` does things row-wise instead. In all cases, the data points are aligned by label before computing the correlation.

Unique Values, Value Counts, and Membership

Another class of related methods extracts information about the values contained in a one-dimensional Series. To illustrate these, consider this example:

```
In [217]: obj = Series(['c', 'a', 'd', 'a', 'a', 'b', 'b', 'c', 'c'])
```

The first function is `unique`, which gives you an array of the unique values in a Series:

```
In [218]: uniques = obj.unique()

In [219]: uniques
Out[219]: array([c, a, d, b], dtype=object)
```

The unique values are not necessarily returned in sorted order, but could be sorted after the fact if needed (`uniques.sort()`). Relatedly, `value_counts` computes a Series containing value frequencies:

```
In [220]: obj.value_counts()
Out[220]:
c    3
a    3
b    2
d    1
```

The Series is sorted by value in descending order as a convenience. `value_counts` is also available as a top-level pandas method that can be used with any array or sequence:

```
In [221]: pd.value_counts(obj.values, sort=False)
Out[221]:
a    3
b    2
c    3
d    1
```

Lastly, `isin` is responsible for vectorized set membership and can be very useful in filtering a data set down to a subset of values in a Series or column in a DataFrame:

```
In [222]: mask = obj.isin(['b', 'c'])

In [223]: mask        In [224]: obj[mask]
Out[223]:             Out[224]:
0     True            0    c
1    False            5    b
2    False            6    b
3    False            7    c
4    False            8    c
5     True
6     True
```

```
7      True
8      True
```

See Table 5-11 for a reference on these methods.

Table 5-11. Unique, value counts, and binning methods

Method	Description
`isin`	Compute boolean array indicating whether each Series value is contained in the passed sequence of values.
`unique`	Compute array of unique values in a Series, returned in the order observed.
`value_counts`	Return a Series containing unique values as its index and frequencies as its values, ordered count in descending order.

In some cases, you may want to compute a histogram on multiple related columns in a DataFrame. Here's an example:

```
In [225]: data = DataFrame({'Qu1': [1, 3, 4, 3, 4],
   .....:                   'Qu2': [2, 3, 1, 2, 3],
   .....:                   'Qu3': [1, 5, 2, 4, 4]})

In [226]: data
Out[226]:
   Qu1  Qu2  Qu3
0    1    2    1
1    3    3    5
2    4    1    2
3    3    2    4
4    4    3    4
```

Passing `pandas.value_counts` to this DataFrame's `apply` function gives:

```
In [227]: result = data.apply(pd.value_counts).fillna(0)

In [228]: result
Out[228]:
   Qu1  Qu2  Qu3
1    1    1    1
2    0    2    1
3    2    2    0
4    2    0    2
5    0    0    1
```

Handling Missing Data

Missing data is common in most data analysis applications. One of the goals in designing pandas was to make working with missing data as painless as possible. For example, all of the descriptive statistics on pandas objects exclude missing data as you've seen earlier in the chapter.

pandas uses the floating point value `NaN` (Not a Number) to represent missing data in both floating as well as in non-floating point arrays. It is just used as a *sentinel* that can be easily detected:

```
In [229]: string_data = Series(['aardvark', 'artichoke', np.nan, 'avocado'])

In [230]: string_data        In [231]: string_data.isnull()
Out[230]:                    Out[231]:
0     aardvark               0    False
1    artichoke               1    False
2          NaN               2     True
3      avocado               3    False
```

The built-in Python `None` value is also treated as NA in object arrays:

```
In [232]: string_data[0] = None

In [233]: string_data.isnull()
Out[233]:
0     True
1    False
2     True
3    False
```

I do not claim that pandas's NA representation is optimal, but it is simple and reasonably consistent. It's the best solution, with good all-around performance characteristics and a simple API, that I could concoct in the absence of a true NA data type or bit pattern in NumPy's data types. Ongoing development work in NumPy may change this in the future.

Table 5-12. NA handling methods

Argument	Description
`dropna`	Filter axis labels based on whether values for each label have missing data, with varying thresholds for how much missing data to tolerate.
`fillna`	Fill in missing data with some value or using an interpolation method such as `'ffill'` or `'bfill'`.
`isnull`	Return like-type object containing boolean values indicating which values are missing / NA.
`notnull`	Negation of `isnull`.

Filtering Out Missing Data

You have a number of options for filtering out missing data. While doing it by hand is always an option, `dropna` can be very helpful. On a Series, it returns the Series with only the non-null data and index values:

```
In [234]: from numpy import nan as NA

In [235]: data = Series([1, NA, 3.5, NA, 7])

In [236]: data.dropna()
Out[236]:
```

```
0    1.0
2    3.5
4    7.0
```

Naturally, you could have computed this yourself by boolean indexing:

```
In [237]: data[data.notnull()]
Out[237]:
0    1.0
2    3.5
4    7.0
```

With DataFrame objects, these are a bit more complex. You may want to drop rows or columns which are all NA or just those containing any NAs. `dropna` by default drops any row containing a missing value:

```
In [238]: data = DataFrame([[1., 6.5, 3.], [1., NA, NA],
   .....:                  [NA, NA, NA], [NA, 6.5, 3.]])

In [239]: cleaned = data.dropna()

In [240]: data        In [241]: cleaned
Out[240]:             Out[241]:
    0    1   2           0    1  2
0   1  6.5   3        0  1  6.5  3
1   1  NaN NaN
2 NaN  NaN NaN
3 NaN  6.5   3
```

Passing `how='all'` will only drop rows that are all NA:

```
In [242]: data.dropna(how='all')
Out[242]:
    0    1   2
0   1  6.5   3
1   1  NaN NaN
3 NaN  6.5   3
```

Dropping columns in the same way is only a matter of passing `axis=1`:

```
In [243]: data[4] = NA

In [244]: data            In [245]: data.dropna(axis=1, how='all')
Out[244]:                 Out[245]:
    0    1   2   4            0    1   2
0   1  6.5   3 NaN        0   1  6.5   3
1   1  NaN NaN NaN        1   1  NaN NaN
2 NaN  NaN NaN NaN        2 NaN  NaN NaN
3 NaN  6.5   3 NaN        3 NaN  6.5   3
```

A related way to filter out DataFrame rows tends to concern time series data. Suppose you want to keep only rows containing a certain number of observations. You can indicate this with the `thresh` argument:

```
In [246]: df = DataFrame(np.random.randn(7, 3))

In [247]: df.ix[:4, 1] = NA; df.ix[:2, 2] = NA
```

```
In [248]: df
Out[248]:
          0         1         2
0 -0.577087       NaN       NaN
1  0.523772       NaN       NaN
2 -0.713544       NaN       NaN
3 -1.860761       NaN  0.560145
4 -1.265934       NaN -1.063512
5  0.332883 -2.359419 -0.199543
6 -1.541996 -0.970736 -1.307030
```

```
In [249]: df.dropna(thresh=3)
Out[249]:
          0         1         2
5  0.332883 -2.359419 -0.199543
6 -1.541996 -0.970736 -1.307030
```

Filling in Missing Data

Rather than filtering out missing data (and potentially discarding other data along with it), you may want to fill in the "holes" in any number of ways. For most purposes, the `fillna` method is the workhorse function to use. Calling `fillna` with a constant replaces missing values with that value:

```
In [250]: df.fillna(0)
Out[250]:
          0         1         2
0 -0.577087  0.000000  0.000000
1  0.523772  0.000000  0.000000
2 -0.713544  0.000000  0.000000
3 -1.860761  0.000000  0.560145
4 -1.265934  0.000000 -1.063512
5  0.332883 -2.359419 -0.199543
6 -1.541996 -0.970736 -1.307030
```

Calling `fillna` with a dict you can use a different fill value for each column:

```
In [251]: df.fillna({1: 0.5, 3: -1})
Out[251]:
          0         1         2
0 -0.577087  0.500000       NaN
1  0.523772  0.500000       NaN
2 -0.713544  0.500000       NaN
3 -1.860761  0.500000  0.560145
4 -1.265934  0.500000 -1.063512
5  0.332883 -2.359419 -0.199543
6 -1.541996 -0.970736 -1.307030
```

`fillna` returns a new object, but you can modify the existing object in place:

```
# always returns a reference to the filled object
In [252]: _ = df.fillna(0, inplace=True)

In [253]: df
Out[253]:
          0         1         2
0 -0.577087  0.000000  0.000000
1  0.523772  0.000000  0.000000
2 -0.713544  0.000000  0.000000
3 -1.860761  0.000000  0.560145
```

```
4 -1.265934  0.000000 -1.063512
5  0.332883 -2.359419 -0.199543
6 -1.541996 -0.970736 -1.307030
```

The same interpolation methods available for reindexing can be used with `fillna`:

```
In [254]: df = DataFrame(np.random.randn(6, 3))

In [255]: df.ix[2:, 1] = NA; df.ix[4:, 2] = NA

In [256]: df
Out[256]:
          0         1         2
0  0.286350  0.377984 -0.753887
1  0.331286  1.349742  0.069877
2  0.246674       NaN  1.004812
3  1.327195       NaN -1.549106
4  0.022185       NaN       NaN
5  0.862580       NaN       NaN

In [257]: df.fillna(method='ffill')
Out[257]:
          0         1         2
0  0.286350  0.377984 -0.753887
1  0.331286  1.349742  0.069877
2  0.246674  1.349742  1.004812
3  1.327195  1.349742 -1.549106
4  0.022185  1.349742 -1.549106
5  0.862580  1.349742 -1.549106

In [258]: df.fillna(method='ffill', limit=2)
Out[258]:
          0         1         2
0  0.286350  0.377984 -0.753887
1  0.331286  1.349742  0.069877
2  0.246674  1.349742  1.004812
3  1.327195  1.349742 -1.549106
4  0.022185       NaN -1.549106
5  0.862580       NaN -1.549106
```

With `fillna` you can do lots of other things with a little creativity. For example, you might pass the mean or median value of a Series:

```
In [259]: data = Series([1., NA, 3.5, NA, 7])

In [260]: data.fillna(data.mean())
Out[260]:
0    1.000000
1    3.833333
2    3.500000
3    3.833333
4    7.000000
```

See Table 5-13 for a reference on `fillna`.

Table 5-13. fillna function arguments

Argument	Description
`value`	Scalar value or dict-like object to use to fill missing values
`method`	Interpolation, by default `'ffill'` if function called with no other arguments
`axis`	Axis to fill on, default `axis=0`
`inplace`	Modify the calling object without producing a copy
`limit`	For forward and backward filling, maximum number of consecutive periods to fill

Hierarchical Indexing

Hierarchical indexing is an important feature of pandas enabling you to have multiple (two or more) index *levels* on an axis. Somewhat abstractly, it provides a way for you to work with higher dimensional data in a lower dimensional form. Let's start with a simple example; create a Series with a list of lists or arrays as the index:

```
In [261]: data = Series(np.random.randn(10),
   .....:               index=[['a', 'a', 'a', 'b', 'b', 'b', 'c', 'c', 'd', 'd'],
   .....:                      [1, 2, 3, 1, 2, 3, 1, 2, 2, 3]])

In [262]: data
Out[262]:
a  1    0.670216
   2    0.852965
   3   -0.955869
b  1   -0.023493
   2   -2.304234
   3   -0.652469
c  1   -1.218302
   2   -1.332610
d  2    1.074623
   3    0.723642
```

What you're seeing is a prettified view of a Series with a `MultiIndex` as its index. The "gaps" in the index display mean "use the label directly above":

```
In [263]: data.index
Out[263]:
MultiIndex
[('a', 1) ('a', 2) ('a', 3) ('b', 1) ('b', 2) ('b', 3) ('c', 1)
 ('c', 2) ('d', 2) ('d', 3)]
```

With a hierarchically-indexed object, so-called *partial* indexing is possible, enabling you to concisely select subsets of the data:

```
In [264]: data['b']
Out[264]:
1   -0.023493
2   -2.304234
3   -0.652469

In [265]: data['b':'c']
Out[265]:
b  1   -0.023493
   2   -2.304234
   3   -0.652469
c  1   -1.218302
   2   -1.332610
```

```
In [266]: data.ix[['b', 'd']]
Out[266]:
b  1   -0.023493
   2   -2.304234
   3   -0.652469
d  2    1.074623
   3    0.723642
```

Selection is even possible in some cases from an "inner" level:

```
In [267]: data[:, 2]
Out[267]:
a    0.852965
```

```
b   -2.304234
c   -1.332610
d    1.074623
```

Hierarchical indexing plays a critical role in reshaping data and group-based operations like forming a pivot table. For example, this data could be rearranged into a DataFrame using its `unstack` method:

```
In [268]: data.unstack()
Out[268]:
          1         2         3
a  0.670216  0.852965 -0.955869
b -0.023493 -2.304234 -0.652469
c -1.218302 -1.332610       NaN
d       NaN  1.074623  0.723642
```

The inverse operation of `unstack` is `stack`:

```
In [269]: data.unstack().stack()
Out[269]:
a  1    0.670216
   2    0.852965
   3   -0.955869
b  1   -0.023493
   2   -2.304234
   3   -0.652469
c  1   -1.218302
   2   -1.332610
d  2    1.074623
   3    0.723642
```

`stack` and `unstack` will be explored in more detail in Chapter 7.

With a DataFrame, either axis can have a hierarchical index:

```
In [270]: frame = DataFrame(np.arange(12).reshape((4, 3)),
   .....:                   index=[['a', 'a', 'b', 'b'], [1, 2, 1, 2]],
   .....:                   columns=[['Ohio', 'Ohio', 'Colorado'],
   .....:                            ['Green', 'Red', 'Green']])

In [271]: frame
Out[271]:
      Ohio       Colorado
     Green  Red     Green
a 1      0    1         2
  2      3    4         5
b 1      6    7         8
  2      9   10        11
```

The hierarchical levels can have names (as strings or any Python objects). If so, these will show up in the console output (don't confuse the index names with the axis labels!):

```
In [272]: frame.index.names = ['key1', 'key2']

In [273]: frame.columns.names = ['state', 'color']

In [274]: frame
```

```
Out[274]:
state       Ohio       Colorado
color      Green  Red     Green
key1 key2
a    1         0    1         2
     2         3    4         5
b    1         6    7         8
     2         9   10        11
```

With partial column indexing you can similarly select groups of columns:

```
In [275]: frame['Ohio']
Out[275]:
color      Green  Red
key1 key2
a    1         0    1
     2         3    4
b    1         6    7
     2         9   10
```

A `MultiIndex` can be created by itself and then reused; the columns in the above DataFrame with level names could be created like this:

```
MultiIndex.from_arrays([['Ohio', 'Ohio', 'Colorado'], ['Green', 'Red', 'Green']],
                       names=['state', 'color'])
```

Reordering and Sorting Levels

At times you will need to rearrange the order of the levels on an axis or sort the data by the values in one specific level. The `swaplevel` takes two level numbers or names and returns a new object with the levels interchanged (but the data is otherwise unaltered):

```
In [276]: frame.swaplevel('key1', 'key2')
Out[276]:
state       Ohio       Colorado
color      Green  Red     Green
key2 key1
1    a         0    1         2
2    a         3    4         5
1    b         6    7         8
2    b         9   10        11
```

`sortlevel`, on the other hand, sorts the data (stably) using only the values in a single level. When swapping levels, it's not uncommon to also use `sortlevel` so that the result is lexicographically sorted:

```
In [277]: frame.sortlevel(1)
Out[277]:
state       Ohio       Colorado
color      Green  Red     Green
key1 key2
a    1         0    1         2
b    1         6    7         8
a    2         3    4         5
b    2         9   10        11
```

```
In [278]: frame.swaplevel(0, 1).sortlevel(0)
Out[278]:
state       Ohio       Colorado
color      Green  Red     Green
key2 key1
1    a         0    1         2
     b         6    7         8
2    a         3    4         5
     b         9   10        11
```

Data selection performance is much better on hierarchically indexed objects if the index is lexicographically sorted starting with the outermost level, that is, the result of calling `sortlevel(0)` or `sort_index()`.

Summary Statistics by Level

Many descriptive and summary statistics on DataFrame and Series have a `level` option in which you can specify the level you want to sum by on a particular axis. Consider the above DataFrame; we can sum by level on either the rows or columns like so:

```
In [279]: frame.sum(level='key2')
Out[279]:
state   Ohio       Colorado
color  Green  Red     Green
key2
1          6    8        10
2         12   14        16

In [280]: frame.sum(level='color', axis=1)
Out[280]:
color      Green  Red
key1 key2
a    1         2    1
     2         8    4
b    1        14    7
     2        20   10
```

Under the hood, this utilizes pandas's `groupby` machinery which will be discussed in more detail later in the book.

Using a DataFrame's Columns

It's not unusual to want to use one or more columns from a DataFrame as the row index; alternatively, you may wish to move the row index into the DataFrame's columns. Here's an example DataFrame:

```
In [281]: frame = DataFrame({'a': range(7), 'b': range(7, 0, -1),
   .....:                   'c': ['one', 'one', 'one', 'two', 'two', 'two', 'two'],
   .....:                   'd': [0, 1, 2, 0, 1, 2, 3]})

In [282]: frame
Out[282]:
   a  b    c  d
0  0  7  one  0
1  1  6  one  1
2  2  5  one  2
3  3  4  two  0
4  4  3  two  1
5  5  2  two  2
6  6  1  two  3
```

DataFrame's `set_index` function will create a new DataFrame using one or more of its columns as the index:

```
In [283]: frame2 = frame.set_index(['c', 'd'])

In [284]: frame2
Out[284]:
       a  b
c   d
one 0  0  7
    1  1  6
    2  2  5
two 0  3  4
    1  4  3
    2  5  2
    3  6  1
```

By default the columns are removed from the DataFrame, though you can leave them in:

```
In [285]: frame.set_index(['c', 'd'], drop=False)
Out[285]:
       a  b    c  d
c   d
one 0  0  7  one  0
    1  1  6  one  1
    2  2  5  one  2
two 0  3  4  two  0
    1  4  3  two  1
    2  5  2  two  2
    3  6  1  two  3
```

`reset_index`, on the other hand, does the opposite of `set_index`; the hierarchical index levels are are moved into the columns:

```
In [286]: frame2.reset_index()
Out[286]:
     c  d  a  b
0  one  0  0  7
1  one  1  1  6
2  one  2  2  5
3  two  0  3  4
4  two  1  4  3
5  two  2  5  2
6  two  3  6  1
```

Other pandas Topics

Here are some additional topics that may be of use to you in your data travels.

Integer Indexing

Working with pandas objects indexed by integers is something that often trips up new users due to some differences with indexing semantics on built-in Python data

structures like lists and tuples. For example, you would not expect the following code to generate an error:

```
ser = Series(np.arange(3.))
ser[-1]
```

In this case, pandas could "fall back" on integer indexing, but there's not a safe and general way (that I know of) to do this without introducing subtle bugs. Here we have an index containing 0, 1, 2, but inferring what the user wants (label-based indexing or position-based) is difficult::

```
In [288]: ser
Out[288]:
0    0
1    1
2    2
```

On the other hand, with a non-integer index, there is no potential for ambiguity:

```
In [289]: ser2 = Series(np.arange(3.), index=['a', 'b', 'c'])

In [290]: ser2[-1]
Out[290]: 2.0
```

To keep things consistent, if you have an axis index containing indexers, data selection with integers will always be label-oriented. This includes slicing with `ix`, too:

```
In [291]: ser.ix[:1]
Out[291]:
0    0
1    1
```

In cases where you need reliable position-based indexing regardless of the index type, you can use the `iget_value` method from Series and `irow` and `icol` methods from DataFrame:

```
In [292]: ser3 = Series(range(3), index=[-5, 1, 3])

In [293]: ser3.iget_value(2)
Out[293]: 2

In [294]: frame = DataFrame(np.arange(6).reshape(3, 2)), index=[2, 0, 1])

In [295]: frame.irow(0)
Out[295]:
0    0
1    1
Name: 2
```

Panel Data

While not a major topic of this book, pandas has a Panel data structure, which you can think of as a three-dimensional analogue of DataFrame. Much of the development focus of pandas has been in tabular data manipulations as these are easier to reason about,

and hierarchical indexing makes using truly N-dimensional arrays unnecessary in a lot of cases.

To create a Panel, you can use a dict of DataFrame objects or a three-dimensional ndarray:

```
import pandas.io.data as web

pdata = pd.Panel(dict((stk, web.get_data_yahoo(stk, '1/1/2009', '6/1/2012'))
                      for stk in ['AAPL', 'GOOG', 'MSFT', 'DELL']))
```

Each item (the analogue of columns in a DataFrame) in the Panel is a DataFrame:

```
In [297]: pdata
Out[297]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 861 (major) x 6 (minor)
Items: AAPL to MSFT
Major axis: 2009-01-02 00:00:00 to 2012-06-01 00:00:00
Minor axis: Open to Adj Close

In [298]: pdata = pdata.swapaxes('items', 'minor')

In [299]: pdata['Adj Close']
Out[299]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 861 entries, 2009-01-02 00:00:00 to 2012-06-01 00:00:00
Data columns:
AAPL    861  non-null values
DELL    861  non-null values
GOOG    861  non-null values
MSFT    861  non-null values
dtypes: float64(4)
```

`ix`-based label indexing generalizes to three dimensions, so we can select all data at a particular date or a range of dates like so:

```
In [300]: pdata.ix[:, '6/1/2012', :]
Out[300]:
        Open    High     Low   Close    Volume  Adj Close
AAPL  569.16  572.65  560.52  560.99  18606700     560.99
DELL   12.15   12.30   12.05   12.07  19396700      12.07
GOOG  571.79  572.65  568.35  570.98   3057900     570.98
MSFT   28.76   28.96   28.44   28.45  56634300      28.45

In [301]: pdata.ix['Adj Close', '5/22/2012':, :]
Out[301]:
              AAPL   DELL    GOOG   MSFT
Date
2012-05-22  556.97  15.08  600.80  29.76
2012-05-23  570.56  12.49  609.46  29.11
2012-05-24  565.32  12.45  603.66  29.07
2012-05-25  562.29  12.46  591.53  29.06
2012-05-29  572.27  12.66  594.34  29.56
2012-05-30  579.17  12.56  588.23  29.34
```

```
2012-05-31  577.73  12.33  580.86  29.19
2012-06-01  560.99  12.07  570.98  28.45
```

An alternate way to represent panel data, especially for fitting statistical models, is in "stacked" DataFrame form:

```
In [302]: stacked = pdata.ix[:, '5/30/2012':, :].to_frame()

In [303]: stacked
Out[303]:
                     Open    High     Low   Close    Volume  Adj Close
major      minor
2012-05-30 AAPL   569.20  579.99  566.56  579.17  18908200     579.17
           DELL    12.59   12.70   12.46   12.56  19787800      12.56
           GOOG   588.16  591.90  583.53  588.23   1906700     588.23
           MSFT    29.35   29.48   29.12   29.34  41585500      29.34
2012-05-31 AAPL   580.74  581.50  571.46  577.73  17559800     577.73
           DELL    12.53   12.54   12.33   12.33  19955500      12.33
           GOOG   588.72  590.00  579.00  580.86   2968300     580.86
           MSFT    29.30   29.42   28.94   29.19  39134000      29.19
2012-06-01 AAPL   569.16  572.65  560.52  560.99  18606700     560.99
           DELL    12.15   12.30   12.05   12.07  19396700      12.07
           GOOG   571.79  572.65  568.35  570.98   3057900     570.98
           MSFT    28.76   28.96   28.44   28.45  56634300      28.45
```

DataFrame has a related `to_panel` method, the inverse of `to_frame`:

```
In [304]: stacked.to_panel()
Out[304]:
<class 'pandas.core.panel.Panel'>
Dimensions: 6 (items) x 3 (major) x 4 (minor)
Items: Open to Adj Close
Major axis: 2012-05-30 00:00:00 to 2012-06-01 00:00:00
Minor axis: AAPL to MSFT
```

CHAPTER 6

Data Loading, Storage, and File Formats

The tools in this book are of little use if you can't easily import and export data in Python. I'm going to be focused on input and output with pandas objects, though there are of course numerous tools in other libraries to aid in this process. NumPy, for example, features low-level but extremely fast binary data loading and storage, including support for memory-mapped array. See Chapter 12 for more on those.

Input and output typically falls into a few main categories: reading text files and other more efficient on-disk formats, loading data from databases, and interacting with network sources like web APIs.

Reading and Writing Data in Text Format

Python has become a beloved language for text and file munging due to its simple syntax for interacting with files, intuitive data structures, and convenient features like tuple packing and unpacking.

pandas features a number of functions for reading tabular data as a DataFrame object. Table 6-1 has a summary of all of them, though `read_csv` and `read_table` are likely the ones you'll use the most.

Table 6-1. Parsing functions in pandas

Function	Description
`read_csv`	Load delimited data from a file, URL, or file-like object. Use comma as default delimiter
`read_table`	Load delimited data from a file, URL, or file-like object. Use tab (`'\t'`) as default delimiter
`read_fwf`	Read data in fixed-width column format (that is, no delimiters)
`read_clipboard`	Version of `read_table` that reads data from the clipboard. Useful for converting tables from web pages

I'll give an overview of the mechanics of these functions, which are meant to convert text data into a DataFrame. The options for these functions fall into a few categories:

- Indexing: can treat one or more columns as the returned DataFrame, and whether to get column names from the file, the user, or not at all.
- Type inference and data conversion: this includes the user-defined value conversions and custom list of missing value markers.
- Datetime parsing: includes combining capability, including combining date and time information spread over multiple columns into a single column in the result.
- Iterating: support for iterating over chunks of very large files.
- Unclean data issues: skipping rows or a footer, comments, or other minor things like numeric data with thousands separated by commas.

Type inference is one of the more important features of these functions; that means you don't have to specify which columns are numeric, integer, boolean, or string. Handling dates and other custom types requires a bit more effort, though. Let's start with a small comma-separated (CSV) text file:

```
In [846]: !cat ch06/ex1.csv
a,b,c,d,message
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,foo
```

Since this is comma-delimited, we can use `read_csv` to read it into a DataFrame:

```
In [847]: df = pd.read_csv('ch06/ex1.csv')

In [848]: df
Out[848]:
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
```

We could also have used `read_table` and specifying the delimiter:

```
In [849]: pd.read_table('ch06/ex1.csv', sep=',')
Out[849]:
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
```

Here I used the Unix `cat` shell command to print the raw contents of the file to the screen. If you're on Windows, you can use `type` instead of `cat` to achieve the same effect.

A file will not always have a header row. Consider this file:

```
In [850]: !cat ch06/ex2.csv
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,foo
```

To read this in, you have a couple of options. You can allow pandas to assign default column names, or you can specify names yourself:

```
In [851]: pd.read_csv('ch06/ex2.csv', header=None)
Out[851]:
   X.1  X.2  X.3  X.4    X.5
0    1    2    3    4  hello
1    5    6    7    8  world
2    9   10   11   12    foo

In [852]: pd.read_csv('ch06/ex2.csv', names=['a', 'b', 'c', 'd', 'message'])
Out[852]:
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
```

Suppose you wanted the `message` column to be the index of the returned DataFrame. You can either indicate you want the column at index 4 or named `'message'` using the `index_col` argument:

```
In [853]: names = ['a', 'b', 'c', 'd', 'message']

In [854]: pd.read_csv('ch06/ex2.csv', names=names, index_col='message')
Out[854]:
         a   b   c   d
message
hello    1   2   3   4
world    5   6   7   8
foo      9  10  11  12
```

In the event that you want to form a hierarchical index from multiple columns, just pass a list of column numbers or names:

```
In [855]: !cat ch06/csv_mindex.csv
key1,key2,value1,value2
one,a,1,2
one,b,3,4
one,c,5,6
one,d,7,8
two,a,9,10
two,b,11,12
two,c,13,14
two,d,15,16

In [856]: parsed = pd.read_csv('ch06/csv_mindex.csv', index_col=['key1', 'key2'])

In [857]: parsed
Out[857]:
```

```
           value1  value2
key1 key2
one  a          1       2
     b          3       4
     c          5       6
     d          7       8
two  a          9      10
     b         11      12
     c         13      14
     d         15      16
```

In some cases, a table might not have a fixed delimiter, using whitespace or some other pattern to separate fields. In these cases, you can pass a regular expression as a delimiter for `read_table`. Consider a text file that looks like this:

```
In [858]: list(open('ch06/ex3.txt'))
Out[858]:
['            A         B         C\n',
 'aaa -0.264438 -1.026059 -0.619500\n',
 'bbb  0.927272  0.302904 -0.032399\n',
 'ccc -0.264273 -0.386314 -0.217601\n',
 'ddd -0.871858 -0.348382  1.100491\n']
```

While you could do some munging by hand, in this case fields are separated by a variable amount of whitespace. This can be expressed by the regular expression `\s+`, so we have then:

```
In [859]: result = pd.read_table('ch06/ex3.txt', sep='\s+')

In [860]: result
Out[860]:
            A         B         C
aaa -0.264438 -1.026059 -0.619500
bbb  0.927272  0.302904 -0.032399
ccc -0.264273 -0.386314 -0.217601
ddd -0.871858 -0.348382  1.100491
```

Because there was one fewer column name than the number of data rows, `read_table` infers that the first column should be the DataFrame's index in this special case.

The parser functions have many additional arguments to help you handle the wide variety of exception file formats that occur (see Table 6-2). For example, you can skip the first, third, and fourth rows of a file with `skiprows`:

```
In [861]: !cat ch06/ex4.csv
# hey!
a,b,c,d,message
# just wanted to make things more difficult for you
# who reads CSV files with computers, anyway?
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,foo
In [862]: pd.read_csv('ch06/ex4.csv', skiprows=[0, 2, 3])
Out[862]:
   a   b   c   d message
```

```
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
```

Handling missing values is an important and frequently nuanced part of the file parsing process. Missing data is usually either not present (empty string) or marked by some *sentinel* value. By default, pandas uses a set of commonly occurring sentinels, such as `NA`, `-1.#IND`, and `NULL`:

```
In [863]: !cat ch06/ex5.csv
something,a,b,c,d,message
one,1,2,3,4,NA
two,5,6,,8,world
three,9,10,11,12,foo
In [864]: result = pd.read_csv('ch06/ex5.csv')

In [865]: result
Out[865]:
  something  a   b   c   d message
0       one  1   2   3   4     NaN
1       two  5   6 NaN   8   world
2     three  9  10  11  12     foo

In [866]: pd.isnull(result)
Out[866]:
  something      a      b      c      d message
0     False  False  False  False  False    True
1     False  False  False   True  False   False
2     False  False  False  False  False   False
```

The `na_values` option can take either a list or set of strings to consider missing values:

```
In [867]: result = pd.read_csv('ch06/ex5.csv', na_values=['NULL'])

In [868]: result
Out[868]:
  something  a   b   c   d message
0       one  1   2   3   4     NaN
1       two  5   6 NaN   8   world
2     three  9  10  11  12     foo
```

Different NA sentinels can be specified for each column in a dict:

```
In [869]: sentinels = {'message': ['foo', 'NA'], 'something': ['two']}

In [870]: pd.read_csv('ch06/ex5.csv', na_values=sentinels)
Out[870]:
  something  a   b   c   d message
0       one  1   2   3   4     NaN
1       NaN  5   6 NaN   8   world
2     three  9  10  11  12     NaN
```

Table 6-2. read_csv /read_table function arguments

Argument	Description
`path`	String indicating filesystem location, URL, or file-like object
`sep` or `delimiter`	Character sequence or regular expression to use to split fields in each row
`header`	Row number to use as column names. Defaults to 0 (first row), but should be `None` if there is no header row
`index_col`	Column numbers or names to use as the row index in the result. Can be a single name/number or a list of them for a hierarchical index
`names`	List of column names for result, combine with `header=None`
`skiprows`	Number of rows at beginning of file to ignore or list of row numbers (starting from 0) to skip
`na_values`	Sequence of values to replace with NA
`comment`	Character or characters to split comments off the end of lines
`parse_dates`	Attempt to parse data to datetime; False by default. If True, will attempt to parse all columns. Otherwise can specify a list of column numbers or name to parse. If element of list is tuple or list, will combine multiple columns together and parse to date (for example if date/time split across two columns)
`keep_date_col`	If joining columns to parse date, drop the joined columns. Default True
`converters`	Dict containing column number of name mapping to functions. For example `{'foo': f}` would apply the function `f` to all values in the `'foo'` column
`dayfirst`	When parsing potentially ambiguous dates, treat as international format (e.g. 7/6/2012 -> June 7, 2012). Default False
`date_parser`	Function to use to parse dates
`nrows`	Number of rows to read from beginning of file
`iterator`	Return a TextParser object for reading file piecemeal
`chunksize`	For iteration, size of file chunks
`skip_footer`	Number of lines to ignore at end of file
`verbose`	Print various parser output information, like the number of missing values placed in non-numeric columns
`encoding`	Text encoding for unicode. For example `'utf-8'` for UTF-8 encoded text
`squeeze`	If the parsed data only contains one column return a Series
`thousands`	Separator for thousands, e.g. `','` or `'.'`

Reading Text Files in Pieces

When processing very large files or figuring out the right set of arguments to correctly process a large file, you may only want to read in a small piece of a file or iterate through smaller chunks of the file.

```
In [871]: result = pd.read_csv('ch06/ex6.csv')

In [872]: result
Out[872]:
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 0 to 9999
Data columns:
one      10000  non-null values
two      10000  non-null values
three    10000  non-null values
four     10000  non-null values
key      10000  non-null values
dtypes: float64(4), object(1)
```

If you want to only read out a small number of rows (avoiding reading the entire file), specify that with `nrows`:

```
In [873]: pd.read_csv('ch06/ex6.csv', nrows=5)
Out[873]:
        one       two     three      four key
0  0.467976 -0.038649 -0.295344 -1.824726   L
1 -0.358893  1.404453  0.704965 -0.200638   B
2 -0.501840  0.659254 -0.421691 -0.057688   G
3  0.204886  1.074134  1.388361 -0.982404   R
4  0.354628 -0.133116  0.283763 -0.837063   Q
```

To read out a file in pieces, specify a `chunksize` as a number of rows:

```
In [874]: chunker = pd.read_csv('ch06/ex6.csv', chunksize=1000)

In [875]: chunker
Out[875]: <pandas.io.parsers.TextParser at 0x8398150>
```

The `TextParser` object returned by `read_csv` allows you to iterate over the parts of the file according to the `chunksize`. For example, we can iterate over `ex6.csv`, aggregating the value counts in the `'key'` column like so:

```
chunker = pd.read_csv('ch06/ex6.csv', chunksize=1000)

tot = Series([])
for piece in chunker:
    tot = tot.add(piece['key'].value_counts(), fill_value=0)

tot = tot.order(ascending=False)
```

We have then:

```
In [877]: tot[:10]
Out[877]:
E    368
X    364
L    346
O    343
Q    340
M    338
J    337
F    335
K    334
H    330
```

`TextParser` is also equipped with a `get_chunk` method which enables you to read pieces of an arbitrary size.

Writing Data Out to Text Format

Data can also be exported to delimited format. Let's consider one of the CSV files read above:

```
In [878]: data = pd.read_csv('ch06/ex5.csv')

In [879]: data
Out[879]:
  something  a   b   c   d message
0       one  1   2   3   4     NaN
1       two  5   6 NaN   8   world
2     three  9  10  11  12     foo
```

Using DataFrame's `to_csv` method, we can write the data out to a comma-separated file:

```
In [880]: data.to_csv('ch06/out.csv')

In [881]: !cat ch06/out.csv
,something,a,b,c,d,message
0,one,1,2,3.0,4,
1,two,5,6,,8,world
2,three,9,10,11.0,12,foo
```

Other delimiters can be used, of course (writing to `sys.stdout` so it just prints the text result):

```
In [882]: data.to_csv(sys.stdout, sep='|')
|something|a|b|c|d|message
0|one|1|2|3.0|4|
1|two|5|6||8|world
2|three|9|10|11.0|12|foo
```

Missing values appear as empty strings in the output. You might want to denote them by some other sentinel value:

```
In [883]: data.to_csv(sys.stdout, na_rep='NULL')
,something,a,b,c,d,message
0,one,1,2,3.0,4,NULL
1,two,5,6,NULL,8,world
2,three,9,10,11.0,12,foo
```

With no other options specified, both the row and column labels are written. Both of these can be disabled:

```
In [884]: data.to_csv(sys.stdout, index=False, header=False)
one,1,2,3.0,4,
two,5,6,,8,world
three,9,10,11.0,12,foo
```

You can also write only a subset of the columns, and in an order of your choosing:

```
In [885]: data.to_csv(sys.stdout, index=False, cols=['a', 'b', 'c'])
a,b,c
1,2,3.0
5,6,
9,10,11.0
```

Series also has a `to_csv` method:

```
In [886]: dates = pd.date_range('1/1/2000', periods=7)

In [887]: ts = Series(np.arange(7), index=dates)

In [888]: ts.to_csv('ch06/tseries.csv')

In [889]: !cat ch06/tseries.csv
2000-01-01 00:00:00,0
2000-01-02 00:00:00,1
2000-01-03 00:00:00,2
2000-01-04 00:00:00,3
2000-01-05 00:00:00,4
2000-01-06 00:00:00,5
2000-01-07 00:00:00,6
```

With a bit of wrangling (no header, first column as index), you can read a CSV version of a Series with `read_csv`, but there is also a `from_csv` convenience method that makes it a bit simpler:

```
In [890]: Series.from_csv('ch06/tseries.csv', parse_dates=True)
Out[890]:
2000-01-01    0
2000-01-02    1
2000-01-03    2
2000-01-04    3
2000-01-05    4
2000-01-06    5
2000-01-07    6
```

See the docstrings for `to_csv` and `from_csv` in IPython for more information.

Manually Working with Delimited Formats

Most forms of tabular data can be loaded from disk using functions like `pandas.read_table`. In some cases, however, some manual processing may be necessary. It's not uncommon to receive a file with one or more malformed lines that trip up `read_table`. To illustrate the basic tools, consider a small CSV file:

```
In [891]: !cat ch06/ex7.csv
"a","b","c"
"1","2","3"
"1","2","3","4"
```

For any file with a single-character delimiter, you can use Python's built-in `csv` module. To use it, pass any open file or file-like object to `csv.reader`:

```
import csv
f = open('ch06/ex7.csv')

reader = csv.reader(f)
```

Iterating through the reader like a file yields tuples of values in each like with any quote characters removed:

```
In [893]: for line in reader:
   .....:     print line
['a', 'b', 'c']
['1', '2', '3']
['1', '2', '3', '4']
```

From there, it's up to you to do the wrangling necessary to put the data in the form that you need it. For example:

```
In [894]: lines = list(csv.reader(open('ch06/ex7.csv')))

In [895]: header, values = lines[0], lines[1:]

In [896]: data_dict = {h: v for h, v in zip(header, zip(*values))}

In [897]: data_dict
Out[897]: {'a': ('1', '1'), 'b': ('2', '2'), 'c': ('3', '3')}
```

CSV files come in many different flavors. Defining a new format with a different delimiter, string quoting convention, or line terminator is done by defining a simple subclass of `csv.Dialect`:

```
class my_dialect(csv.Dialect):
    lineterminator = '\n'
    delimiter = ';'
    quotechar = '"'

reader = csv.reader(f, dialect=my_dialect)
```

Individual CSV dialect parameters can also be given as keywords to `csv.reader` without having to define a subclass:

```
reader = csv.reader(f, delimiter='|')
```

The possible options (attributes of `csv.Dialect`) and what they do can be found in Table 6-3.

Table 6-3. CSV dialect options

Argument	Description
`delimiter`	One-character string to separate fields. Defaults to `','`.
`lineterminator`	Line terminator for writing, defaults to `'\r\n'`. Reader ignores this and recognizes cross-platform line terminators.
`quotechar`	Quote character for fields with special characters (like a delimiter). Default is `'"'`.
`quoting`	Quoting convention. Options include `csv.QUOTE_ALL` (quote all fields), `csv.QUOTE_MINIMAL` (only fields with special characters like the delimiter),

Argument	Description
	csv.QUOTE_NONNUMERIC, and csv.QUOTE_NON (no quoting). See Python's documentation for full details. Defaults to QUOTE_MINIMAL.
skipinitialspace	Ignore whitespace after each delimiter. Default False.
doublequote	How to handle quoting character inside a field. If True, it is doubled. See online documentation for full detail and behavior.
escapechar	String to escape the delimiter if quoting is set to csv.QUOTE_NONE. Disabled by default

For files with more complicated or fixed multicharacter delimiters, you will not be able to use the `csv` module. In those cases, you'll have to do the line splitting and other cleanup using string's `split` method or the regular expression method `re.split`.

To *write* delimited files manually, you can use `csv.writer`. It accepts an open, writable file object and the same dialect and format options as `csv.reader`:

```
with open('mydata.csv', 'w') as f:
    writer = csv.writer(f, dialect=my_dialect)
    writer.writerow(('one', 'two', 'three'))
    writer.writerow(('1', '2', '3'))
    writer.writerow(('4', '5', '6'))
    writer.writerow(('7', '8', '9'))
```

JSON Data

JSON (short for JavaScript Object Notation) has become one of the standard formats for sending data by HTTP request between web browsers and other applications. It is a much more flexible data format than a tabular text form like CSV. Here is an example:

```
obj = """
{"name": "Wes",
 "places_lived": ["United States", "Spain", "Germany"],
 "pet": null,
 "siblings": [{"name": "Scott", "age": 25, "pet": "Zuko"},
              {"name": "Katie", "age": 33, "pet": "Cisco"}]
}
"""
```

JSON is very nearly valid Python code with the exception of its null value `null` and some other nuances (such as disallowing trailing commas at the end of lists). The basic types are objects (dicts), arrays (lists), strings, numbers, booleans, and nulls. All of the keys in an object must be strings. There are several Python libraries for reading and writing JSON data. I'll use `json` here as it is built into the Python standard library. To convert a JSON string to Python form, use `json.loads`:

```
In [899]: import json
```

```
In [900]: result = json.loads(obj)

In [901]: result
Out[901]:
{u'name': u'Wes',
 u'pet': None,
 u'places_lived': [u'United States', u'Spain', u'Germany'],
 u'siblings': [{u'age': 25, u'name': u'Scott', u'pet': u'Zuko'},
  {u'age': 33, u'name': u'Katie', u'pet': u'Cisco'}]}
```

`json.dumps` on the other hand converts a Python object back to JSON:

```
In [902]: asjson = json.dumps(result)
```

How you convert a JSON object or list of objects to a DataFrame or some other data structure for analysis will be up to you. Conveniently, you can pass a list of JSON objects to the DataFrame constructor and select a subset of the data fields:

```
In [903]: siblings = DataFrame(result['siblings'], columns=['name', 'age'])

In [904]: siblings
Out[904]:
    name  age
0  Scott   25
1  Katie   33
```

For an extended example of reading and manipulating JSON data (including nested records), see the USDA Food Database example in the next chapter.

An effort is underway to add fast native JSON export (`to_json`) and decoding (`from_json`) to pandas. This was not ready at the time of writing.

XML and HTML: Web Scraping

Python has many libraries for reading and writing data in the ubiquitous HTML and XML formats. lxml (*http://lxml.de*) is one that has consistently strong performance in parsing very large files. lxml has multiple programmer interfaces; first I'll show using `lxml.html` for HTML, then parse some XML using `lxml.objectify`.

Many websites make data available in HTML tables for viewing in a browser, but not downloadable as an easily machine-readable format like JSON, HTML, or XML. I noticed that this was the case with Yahoo! Finance's stock options data. If you aren't familiar with this data; options are derivative contracts giving you the right to buy (*call* option) or sell (*put* option) a company's stock at some particular price (the *strike*) between now and some fixed point in the future (the *expiry*). People trade both `call` and `put` options across many strikes and expiries; this data can all be found together in tables on Yahoo! Finance.

To get started, find the URL you want to extract data from, open it with `urllib2` and parse the stream with lxml like so:

```
from lxml.html import parse
from urllib2 import urlopen

parsed = parse(urlopen('http://finance.yahoo.com/q/op?s=AAPL+Options'))

doc = parsed.getroot()
```

Using this object, you can extract all HTML tags of a particular type, such as `table` tags containing the data of interest. As a simple motivating example, suppose you wanted to get a list of every URL linked to in the document; links are `a` tags in HTML. Using the document root's `findall` method along with an XPath (a means of expressing "queries" on the document):

```
In [906]: links = doc.findall('.//a')

In [907]: links[15:20]
Out[907]:
[<Element a at 0x6c488f0>,
 <Element a at 0x6c48950>,
 <Element a at 0x6c489b0>,
 <Element a at 0x6c48a10>,
 <Element a at 0x6c48a70>]
```

But these are objects representing HTML elements; to get the URL and link text you have to use each element's `get` method (for the URL) and `text_content` method (for the display text):

```
In [908]: lnk = links[28]

In [909]: lnk
Out[909]: <Element a at 0x6c48dd0>

In [910]: lnk.get('href')
Out[910]: 'http://biz.yahoo.com/special.html'

In [911]: lnk.text_content()
Out[911]: 'Special Editions'
```

Thus, getting a list of all URLs in the document is a matter of writing this list comprehension:

```
In [912]: urls = [lnk.get('href') for lnk in doc.findall('.//a')]

In [913]: urls[-10:]
Out[913]:
['http://info.yahoo.com/privacy/us/yahoo/finance/details.html',
 'http://info.yahoo.com/relevantads/',
 'http://docs.yahoo.com/info/terms/',
 'http://docs.yahoo.com/info/copyright/copyright.html',
 'http://help.yahoo.com/l/us/yahoo/finance/forms_index.html',
 'http://help.yahoo.com/l/us/yahoo/finance/quotes/fitadelay.html',
 'http://help.yahoo.com/l/us/yahoo/finance/quotes/fitadelay.html',
```

```
 'http://www.capitaliq.com',
 'http://www.csidata.com',
 'http://www.morningstar.com/']
```

Now, finding the right tables in the document can be a matter of trial and error; some websites make it easier by giving a table of interest an `id` attribute. I determined that these were the two tables containing the call data and put data, respectively:

```
tables = doc.findall('.//table')
calls = tables[9]
puts = tables[13]
```

Each table has a header row followed by each of the data rows:

```
In [915]: rows = calls.findall('.//tr')
```

For the header as well as the data rows, we want to extract the text from each cell; in the case of the header these are `th` cells and `td` cells for the data:

```
def _unpack(row, kind='td'):
    elts = row.findall('.//%s' % kind)
    return [val.text_content() for val in elts]
```

Thus, we obtain:

```
In [917]: _unpack(rows[0], kind='th')
Out[917]: ['Strike', 'Symbol', 'Last', 'Chg', 'Bid', 'Ask', 'Vol', 'Open Int']

In [918]: _unpack(rows[1], kind='td')
Out[918]:
['295.00',
 'AAPL120818C00295000',
 '310.40',
 ' 0.00',
 '289.80',
 '290.80',
 '1',
 '169']
```

Now, it's a matter of combining all of these steps together to convert this data into a DataFrame. Since the numerical data is still in string format, we want to convert some, but perhaps not all of the columns to floating point format. You could do this by hand, but, luckily, pandas has a class `TextParser` that is used internally in the `read_csv` and other parsing functions to do the appropriate automatic type conversion:

```
from pandas.io.parsers import TextParser

def parse_options_data(table):
    rows = table.findall('.//tr')
    header = _unpack(rows[0], kind='th')
    data = [_unpack(r) for r in rows[1:]]
    return TextParser(data, names=header).get_chunk()
```

Finally, we invoke this parsing function on the lxml table objects and get DataFrame results:

```
In [920]: call_data = parse_options_data(calls)

In [921]: put_data = parse_options_data(puts)

In [922]: call_data[:10]
Out[922]:
   Strike              Symbol    Last  Chg     Bid     Ask  Vol Open Int
0     295  AAPL120818C00295000  310.40  0.0  289.80  290.80    1      169
1     300  AAPL120818C00300000  277.10  1.7  284.80  285.60    2      478
2     305  AAPL120818C00305000  300.97  0.0  279.80  280.80   10      316
3     310  AAPL120818C00310000  267.05  0.0  274.80  275.65    6      239
4     315  AAPL120818C00315000  296.54  0.0  269.80  270.80   22       88
5     320  AAPL120818C00320000  291.63  0.0  264.80  265.80   96      173
6     325  AAPL120818C00325000  261.34  0.0  259.80  260.80  N/A      108
7     330  AAPL120818C00330000  230.25  0.0  254.80  255.80  N/A       21
8     335  AAPL120818C00335000  266.03  0.0  249.80  250.65    4       46
9     340  AAPL120818C00340000  272.58  0.0  244.80  245.80    4       30
```

Parsing XML with lxml.objectify

XML (extensible markup language) is another common structured data format supporting hierarchical, nested data with metadata. The files that generate the book you are reading actually form a series of large XML documents.

Above, I showed the lxml library and its `lxml.html` interface. Here I show an alternate interface that's convenient for XML data, `lxml.objectify`.

The New York Metropolitan Transportation Authority (MTA) publishes a number of data series about its bus and train services (*http://www.mta.info/developers/download.html*). Here we'll look at the performance data which is contained in a set of XML files. Each train or bus service has a different file (like `Performance_MNR.xml` for the Metro-North Railroad) containing monthly data as a series of XML records that look like this:

```
<INDICATOR>
  <INDICATOR_SEQ>373889</INDICATOR_SEQ>
  <PARENT_SEQ></PARENT_SEQ>
  <AGENCY_NAME>Metro-North Railroad</AGENCY_NAME>
  <INDICATOR_NAME>Escalator Availability</INDICATOR_NAME>
  <DESCRIPTION>Percent of the time that escalators are operational
  systemwide. The availability rate is based on physical observations performed
  the morning of regular business days only. This is a new indicator the agency
  began reporting in 2009.</DESCRIPTION>
  <PERIOD_YEAR>2011</PERIOD_YEAR>
  <PERIOD_MONTH>12</PERIOD_MONTH>
  <CATEGORY>Service Indicators</CATEGORY>
  <FREQUENCY>M</FREQUENCY>
  <DESIRED_CHANGE>U</DESIRED_CHANGE>
  <INDICATOR_UNIT>%</INDICATOR_UNIT>
  <DECIMAL_PLACES>1</DECIMAL_PLACES>
  <YTD_TARGET>97.00</YTD_TARGET>
  <YTD_ACTUAL></YTD_ACTUAL>
  <MONTHLY_TARGET>97.00</MONTHLY_TARGET>
  <MONTHLY_ACTUAL></MONTHLY_ACTUAL>
</INDICATOR>
```

Using `lxml.objectify`, we parse the file and get a reference to the root node of the XML file with `getroot`:

```
from lxml import objectify

path = 'Performance_MNR.xml'
parsed = objectify.parse(open(path))
root = parsed.getroot()
```

`root.INDICATOR` return a generator yielding each `<INDICATOR>` XML element. For each record, we can populate a dict of tag names (like `YTD_ACTUAL`) to data values (excluding a few tags):

```
data = []

skip_fields = ['PARENT_SEQ', 'INDICATOR_SEQ',
               'DESIRED_CHANGE', 'DECIMAL_PLACES']

for elt in root.INDICATOR:
    el_data = {}
    for child in elt.getchildren():
        if child.tag in skip_fields:
            continue
        el_data[child.tag] = child.pyval
    data.append(el_data)
```

Lastly, convert this list of dicts into a DataFrame:

```
In [927]: perf = DataFrame(data)

In [928]: perf
Out[928]:
Empty DataFrame
Columns: array([], dtype=int64)
Index: array([], dtype=int64)
```

XML data can get much more complicated than this example. Each tag can have metadata, too. Consider an HTML link tag which is also valid XML:

```
from StringIO import StringIO
tag = '<a href="http://www.google.com">Google</a>'

root = objectify.parse(StringIO(tag)).getroot()
```

You can now access any of the fields (like `href`) in the tag or the link text:

```
In [930]: root
Out[930]: <Element a at 0x88bd4b0>

In [931]: root.get('href')
Out[931]: 'http://www.google.com'

In [932]: root.text
Out[932]: 'Google'
```

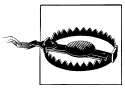
Binary Data Formats

One of the easiest ways to store data efficiently in binary format is using Python's built-in `pickle` serialization. Conveniently, pandas objects all have a `save` method which writes the data to disk as a pickle:

```
In [933]: frame = pd.read_csv('ch06/ex1.csv')

In [934]: frame
Out[934]:
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo

In [935]: frame.save('ch06/frame_pickle')
```

You read the data back into Python with `pandas.load`, another pickle convenience function:

```
In [936]: pd.load('ch06/frame_pickle')
Out[936]:
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
```



`pickle` is only recommended as a short-term storage format. The problem is that it is hard to guarantee that the format will be stable over time; an object pickled today may not unpickle with a later version of a library. I have made every effort to ensure that this does not occur with pandas, but at some point in the future it may be necessary to "break" the pickle format.

Using HDF5 Format

There are a number of tools that facilitate efficiently reading and writing large amounts of scientific data in binary format on disk. A popular industry-grade library for this is HDF5, which is a C library with interfaces in many other languages like Java, Python, and MATLAB. The "HDF" in HDF5 stands for *hierarchical data format*. Each HDF5 file contains an internal file system-like node structure enabling you to store multiple datasets and supporting metadata. Compared with simpler formats, HDF5 supports on-the-fly compression with a variety of compressors, enabling data with repeated patterns to be stored more efficiently. For very large datasets that don't fit into memory, HDF5 is a good choice as you can efficiently read and write small sections of much larger arrays.

There are not one but two interfaces to the HDF5 library in Python, PyTables and h5py, each of which takes a different approach to the problem. h5py provides a direct, but high-level interface to the HDF5 API, while PyTables abstracts many of the details of

HDF5 to provide multiple flexible data containers, table indexing, querying capability, and some support for out-of-core computations.

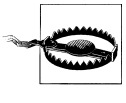
pandas has a minimal dict-like `HDFStore` class, which uses PyTables to store pandas objects:

```
In [937]: store = pd.HDFStore('mydata.h5')

In [938]: store['obj1'] = frame

In [939]: store['obj1_col'] = frame['a']

In [940]: store
Out[940]:
<class 'pandas.io.pytables.HDFStore'>
File path: mydata.h5
obj1        DataFrame
obj1_col    Series
```

Objects contained in the HDF5 file can be retrieved in a dict-like fashion:

```
In [941]: store['obj1']
Out[941]:
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
```

If you work with huge quantities of data, I would encourage you to explore PyTables and h5py to see how they can suit your needs. Since many data analysis problems are IO-bound (rather than CPU-bound), using a tool like HDF5 can massively accelerate your applications.



HDF5 is *not* a database. It is best suited for write-once, read-many datasets. While data can be added to a file at any time, if multiple writers do so simultaneously, the file can become corrupted.

Reading Microsoft Excel Files

pandas also supports reading tabular data stored in Excel 2003 (and higher) files using the `ExcelFile` class. Interally `ExcelFile` uses the xlrd and openpyxl packages, so you may have to install them first. To use `ExcelFile`, create an instance by passing a path to an `xls` or `xlsx` file:

```
xls_file = pd.ExcelFile('data.xls')
```

Data stored in a sheet can then be read into DataFrame using `parse`:

```
table = xls_file.parse('Sheet1')
```

Interacting with HTML and Web APIs

Many websites have public APIs providing data feeds via JSON or some other format. There are a number of ways to access these APIs from Python; one easy-to-use method that I recommend is the requests package (*http://docs.python-requests.org*). To search for the words "python pandas" on Twitter, we can make an HTTP `GET` request like so:

```
In [944]: import requests

In [945]: url = 'http://search.twitter.com/search.json?q=python%20pandas'

In [946]: resp = requests.get(url)

In [947]: resp
Out[947]: <Response [200]>
```

The Response object's `text` attribute contains the content of the `GET` query. Many web APIs will return a JSON string that must be loaded into a Python object:

```
In [948]: import json

In [949]: data = json.loads(resp.text)

In [950]: data.keys()
Out[950]:
[u'next_page',
 u'completed_in',
 u'max_id_str',
 u'since_id_str',
 u'refresh_url',
 u'results',
 u'since_id',
 u'results_per_page',
 u'query',
 u'max_id',
 u'page']
```

The `results` field in the response contains a list of tweets, each of which is represented as a Python dict that looks like:

```
{u'created_at': u'Mon, 25 Jun 2012 17:50:33 +0000',
 u'from_user': u'wesmckinn',
 u'from_user_id': 115494880,
 u'from_user_id_str': u'115494880',
 u'from_user_name': u'Wes McKinney',
 u'geo': None,
 u'id': 217313849177686018,
 u'id_str': u'217313849177686018',
 u'iso_language_code': u'pt',
 u'metadata': {u'result_type': u'recent'},
 u'source': u'<a href="http://twitter.com/">web</a>',
 u'text': u'Lunchtime pandas-fu http://t.co/SI70xZZQ #pydata',
 u'to_user': None,
 u'to_user_id': 0,
```

```
 u'to_user_id_str': u'0',
 u'to_user_name': None}
```

We can then make a list of the tweet fields of interest then pass the results list to DataFrame:

```
In [951]: tweet_fields = ['created_at', 'from_user', 'id', 'text']

In [952]: tweets = DataFrame(data['results'], columns=tweet_fields)

In [953]: tweets
Out[953]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15 entries, 0 to 14
Data columns:
created_at    15  non-null values
from_user     15  non-null values
id            15  non-null values
text          15  non-null values
dtypes: int64(1), object(3)
```

Each row in the DataFrame now has the extracted data from each tweet:

```
In [121]: tweets.ix[7]
Out[121]:
created_at                  Thu, 23 Jul 2012 09:54:00 +0000
from_user                                            deblike
id                                        227419585803059201
text          pandas: powerful Python data analysis toolkit
Name: 7
```

With a bit of elbow grease, you can create some higher-level interfaces to common web APIs that return DataFrame objects for easy analysis.

Interacting with Databases

In many applications data rarely comes from text files, that being a fairly inefficient way to store large amounts of data. SQL-based relational databases (such as SQL Server, PostgreSQL, and MySQL) are in wide use, and many alternative non-SQL (so-called *NoSQL*) databases have become quite popular. The choice of database is usually dependent on the performance, data integrity, and scalability needs of an application.

Loading data from SQL into a DataFrame is fairly straightforward, and pandas has some functions to simplify the process. As an example, I'll use an in-memory SQLite database using Python's built-in `sqlite3` driver:

```
import sqlite3

query = """
CREATE TABLE test
(a VARCHAR(20), b VARCHAR(20),
 c REAL,        d INTEGER
);"""
```

```
con = sqlite3.connect(':memory:')
con.execute(query)
con.commit()
```

Then, insert a few rows of data:

```
data = [('Atlanta', 'Georgia', 1.25, 6),
        ('Tallahassee', 'Florida', 2.6, 3),
        ('Sacramento', 'California', 1.7, 5)]
stmt = "INSERT INTO test VALUES(?, ?, ?, ?)"

con.executemany(stmt, data)
con.commit()
```

Most Python SQL drivers (PyODBC, psycopg2, MySQLdb, pymssql, etc.) return a list of tuples when selecting data from a table:

```
In [956]: cursor = con.execute('select * from test')

In [957]: rows = cursor.fetchall()

In [958]: rows
Out[958]:
[(u'Atlanta', u'Georgia', 1.25, 6),
 (u'Tallahassee', u'Florida', 2.6, 3),
 (u'Sacramento', u'California', 1.7, 5)]
```

You can pass the list of tuples to the DataFrame constructor, but you also need the column names, contained in the cursor's `description` attribute:

```
In [959]: cursor.description
Out[959]:
(('a', None, None, None, None, None, None),
 ('b', None, None, None, None, None, None),
 ('c', None, None, None, None, None, None),
 ('d', None, None, None, None, None, None))

In [960]: DataFrame(rows, columns=zip(*cursor.description)[0])
Out[960]:
            a           b     c  d
0     Atlanta     Georgia  1.25  6
1  Tallahassee     Florida  2.60  3
2   Sacramento  California  1.70  5
```

This is quite a bit of munging that you'd rather not repeat each time you query the database. pandas has a `read_frame` function in its `pandas.io.sql` module that simplifies the process. Just pass the select statement and the connection object:

```
In [961]: import pandas.io.sql as sql

In [962]: sql.read_frame('select * from test', con)
Out[962]:
            a           b     c  d
0     Atlanta     Georgia  1.25  6
1  Tallahassee     Florida  2.60  3
2   Sacramento  California  1.70  5
```

Storing and Loading Data in MongoDB

NoSQL databases take many different forms. Some are simple dict-like key-value stores like BerkeleyDB or Tokyo Cabinet, while others are document-based, with a dict-like object being the basic unit of storage. I've chosen MongoDB (*http://mongodb.org*) for my example. I started a MongoDB instance locally on my machine, and connect to it on the default port using `pymongo`, the official driver for MongoDB:

```
import pymongo
con = pymongo.Connection('localhost', port=27017)
```

Documents stored in MongoDB are found in collections inside databases. Each running instance of the MongoDB server can have multiple databases, and each database can have multiple collections. Suppose I wanted to store the Twitter API data from earlier in the chapter. First, I can access the (currently empty) tweets collection:

```
tweets = con.db.tweets
```

Then, I load the list of tweets and write each of them to the collection using `tweets.save` (which writes the Python dict to MongoDB):

```
import requests, json
url = 'http://search.twitter.com/search.json?q=python%20pandas'
data = json.loads(requests.get(url).text)

for tweet in data['results']:
    tweets.save(tweet)
```

Now, if I wanted to get all of my tweets (if any) from the collection, I can query the collection with the following syntax:

```
cursor = tweets.find({'from_user': 'wesmckinn'})
```

The cursor returned is an iterator that yields each document as a dict. As above I can convert this into a DataFrame, optionally extracting a subset of the data fields in each tweet:

```
tweet_fields = ['created_at', 'from_user', 'id', 'text']
result = DataFrame(list(cursor), columns=tweet_fields)
```

CHAPTER 7

Data Wrangling: Clean, Transform, Merge, Reshape

Much of the programming work in data analysis and modeling is spent on data preparation: loading, cleaning, transforming, and rearranging. Sometimes the way that data is stored in files or databases is not the way you need it for a data processing application. Many people choose to do ad hoc processing of data from one form to another using a general purpose programming, like Python, Perl, R, or Java, or UNIX text processing tools like sed or awk. Fortunately, pandas along with the Python standard library provide you with a high-level, flexible, and high-performance set of core manipulations and algorithms to enable you to wrangle data into the right form without much trouble.

If you identify a type of data manipulation that isn't anywhere in this book or elsewhere in the pandas library, feel free to suggest it on the mailing list or GitHub site. Indeed, much of the design and implementation of pandas has been driven by the needs of real world applications.

Combining and Merging Data Sets

Data contained in pandas objects can be combined together in a number of built-in ways:

- `pandas.merge` connects rows in DataFrames based on one or more keys. This will be familiar to users of SQL or other relational databases, as it implements database *join* operations.
- `pandas.concat` glues or stacks together objects along an axis.
- `combine_first` instance method enables splicing together overlapping data to fill in missing values in one object with values from another.

I will address each of these and give a number of examples. They'll be utilized in examples throughout the rest of the book.

Database-style DataFrame Merges

Merge or *join* operations combine data sets by linking rows using one or more *keys*. These operations are central to relational databases. The `merge` function in pandas is the main entry point for using these algorithms on your data.

Let's start with a simple example:

```
In [15]: df1 = DataFrame({'key': ['b', 'b', 'a', 'c', 'a', 'a', 'b'],
   ....:                  'data1': range(7)})

In [16]: df2 = DataFrame({'key': ['a', 'b', 'd'],
   ....:                  'data2': range(3)})

In [17]: df1        In [18]: df2
Out[17]:            Out[18]:
   data1 key           data2 key
0      0   b        0      0   a
1      1   b        1      1   b
2      2   a        2      2   d
3      3   c
4      4   a
5      5   a
6      6   b
```

This is an example of a *many-to-one* merge situation; the data in `df1` has multiple rows labeled `a` and `b`, whereas `df2` has only one row for each value in the `key` column. Calling `merge` with these objects we obtain:

```
In [19]: pd.merge(df1, df2)
Out[19]:
   data1 key  data2
0      2   a      0
1      4   a      0
2      5   a      0
3      0   b      1
4      1   b      1
5      6   b      1
```

Note that I didn't specify which column to join on. If not specified, `merge` uses the overlapping column names as the keys. It's a good practice to specify explicitly, though:

```
In [20]: pd.merge(df1, df2, on='key')
Out[20]:
   data1 key  data2
0      2   a      0
1      4   a      0
2      5   a      0
3      0   b      1
4      1   b      1
5      6   b      1
```

If the column names are different in each object, you can specify them separately:

```
In [21]: df3 = DataFrame({'lkey': ['b', 'b', 'a', 'c', 'a', 'a', 'b'],
   ....:                  'data1': range(7)})
```

```
In [22]: df4 = DataFrame({'rkey': ['a', 'b', 'd'],
   ....:                  'data2': range(3)})

In [23]: pd.merge(df3, df4, left_on='lkey', right_on='rkey')
Out[23]:
   data1 lkey  data2 rkey
0      2    a      0    a
1      4    a      0    a
2      5    a      0    a
3      0    b      1    b
4      1    b      1    b
5      6    b      1    b
```

You probably noticed that the `'c'` and `'d'` values and associated data are missing from the result. By default `merge` does an `'inner'` join; the keys in the result are the intersection. Other possible options are `'left'`, `'right'`, and `'outer'`. The outer join takes the union of the keys, combining the effect of applying both left and right joins:

```
In [24]: pd.merge(df1, df2, how='outer')
Out[24]:
   data1 key  data2
0      2   a      0
1      4   a      0
2      5   a      0
3      0   b      1
4      1   b      1
5      6   b      1
6      3   c    NaN
7    NaN   d      2
```

Many-to-many merges have well-defined though not necessarily intuitive behavior. Here's an example:

```
In [25]: df1 = DataFrame({'key': ['b', 'b', 'a', 'c', 'a', 'b'],
   ....:                  'data1': range(6)})

In [26]: df2 = DataFrame({'key': ['a', 'b', 'a', 'b', 'd'],
   ....:                  'data2': range(5)})

In [27]: df1        In [28]: df2
Out[27]:            Out[28]:
   data1 key           data2 key
0      0   b        0      0   a
1      1   b        1      1   b
2      2   a        2      2   a
3      3   c        3      3   b
4      4   a        4      4   d
5      5   b

In [29]: pd.merge(df1, df2, on='key', how='left')
Out[29]:
    data1 key  data2
0       2   a      0
1       2   a      2
```

```
2       4   a      0
3       4   a      2
4       0   b      1
5       0   b      3
6       1   b      1
7       1   b      3
8       5   b      1
9       5   b      3
10      3   c    NaN
```

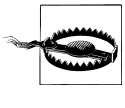
Many-to-many joins form the Cartesian product of the rows. Since there were 3 `'b'` rows in the left DataFrame and 2 in the right one, there are 6 `'b'` rows in the result. The join method only affects the distinct key values appearing in the result:

```
In [30]: pd.merge(df1, df2, how='inner')
Out[30]:
   data1 key  data2
0      2   a      0
1      2   a      2
2      4   a      0
3      4   a      2
4      0   b      1
5      0   b      3
6      1   b      1
7      1   b      3
8      5   b      1
9      5   b      3
```

To merge with multiple keys, pass a list of column names:

```
In [31]: left = DataFrame({'key1': ['foo', 'foo', 'bar'],
   ....:                   'key2': ['one', 'two', 'one'],
   ....:                   'lval': [1, 2, 3]})

In [32]: right = DataFrame({'key1': ['foo', 'foo', 'bar', 'bar'],
   ....:                    'key2': ['one', 'one', 'one', 'two'],
   ....:                    'rval': [4, 5, 6, 7]})

In [33]: pd.merge(left, right, on=['key1', 'key2'], how='outer')
Out[33]:
  key1 key2  lval  rval
0  bar  one     3     6
1  bar  two   NaN     7
2  foo  one     1     4
3  foo  one     1     5
4  foo  two     2   NaN
```

To determine which key combinations will appear in the result depending on the choice of merge method, think of the multiple keys as forming an array of tuples to be used as a single join key (even though it's not actually implemented that way).



When joining columns-on-columns, the indexes on the passed DataFrame objects are discarded.

A last issue to consider in merge operations is the treatment of overlapping column names. While you can address the overlap manually (see the later section on renaming axis labels), `merge` has a `suffixes` option for specifying strings to append to overlapping names in the left and right DataFrame objects:

```
In [34]: pd.merge(left, right, on='key1')
Out[34]:
  key1 key2_x  lval key2_y  rval
0  bar    one     3    one     6
1  bar    one     3    two     7
2  foo    one     1    one     4
3  foo    one     1    one     5
4  foo    two     2    one     4
5  foo    two     2    one     5

In [35]: pd.merge(left, right, on='key1', suffixes=('_left', '_right'))
Out[35]:
  key1 key2_left  lval key2_right  rval
0  bar       one     3        one     6
1  bar       one     3        two     7
2  foo       one     1        one     4
3  foo       one     1        one     5
4  foo       two     2        one     4
5  foo       two     2        one     5
```

See Table 7-1 for an argument reference on `merge`. Joining on index is the subject of the next section.

Table 7-1. merge function arguments

Argument	Description
`left`	DataFrame to be merged on the left side
`right`	DataFrame to be merged on the right side
`how`	One of `'inner'`, `'outer'`, `'left'` or `'right'`. `'inner'` by default
`on`	Column names to join on. Must be found in both DataFrame objects. If not specified and no other join keys given, will use the intersection of the column names in `left` and `right` as the join keys
`left_on`	Columns in `left` DataFrame to use as join keys
`right_on`	Analogous to `left_on` for `left` DataFrame
`left_index`	Use row index in `left` as its join key (or keys, if a MultiIndex)
`right_index`	Analogous to `left_index`
`sort`	Sort merged data lexicographically by join keys; `True` by default. Disable to get better performance in some cases on large datasets
`suffixes`	Tuple of string values to append to column names in case of overlap; defaults to `('_x', '_y')`. For example, if `'data'` in both DataFrame objects, would appear as `'data_x'` and `'data_y'` in result
`copy`	If `False`, avoid copying data into resulting data structure in some exceptional cases. By default always copies

Merging on Index

In some cases, the merge key or keys in a DataFrame will be found in its index. In this case, you can pass `left_index=True` or `right_index=True` (or both) to indicate that the index should be used as the merge key:

```
In [36]: left1 = DataFrame({'key': ['a', 'b', 'a', 'a', 'b', 'c'],
   ....:                    'value': range(6)})

In [37]: right1 = DataFrame({'group_val': [3.5, 7]}, index=['a', 'b'])

In [38]: left1        In [39]: right1
Out[38]:              Out[39]:
  key  value             group_val
0   a      0          a        3.5
1   b      1          b        7.0
2   a      2
3   a      3
4   b      4
5   c      5

In [40]: pd.merge(left1, right1, left_on='key', right_index=True)
Out[40]:
  key  value  group_val
0   a      0        3.5
2   a      2        3.5
3   a      3        3.5
1   b      1        7.0
4   b      4        7.0
```

Since the default merge method is to intersect the join keys, you can instead form the union of them with an outer join:

```
In [41]: pd.merge(left1, right1, left_on='key', right_index=True, how='outer')
Out[41]:
  key  value  group_val
0   a      0        3.5
2   a      2        3.5
3   a      3        3.5
1   b      1        7.0
4   b      4        7.0
5   c      5        NaN
```

With hierarchically-indexed data, things are a bit more complicated:

```
In [42]: lefth = DataFrame({'key1': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada'],
   ....:                    'key2': [2000, 2001, 2002, 2001, 2002],
   ....:                    'data': np.arange(5.)})

In [43]: righth = DataFrame(np.arange(12).reshape((6, 2)),
   ....:                    index=[['Nevada', 'Nevada', 'Ohio', 'Ohio', 'Ohio', 'Ohio'],
   ....:                           [2001, 2000, 2000, 2000, 2001, 2002]],
   ....:                    columns=['event1', 'event2'])

In [44]: lefth               In [45]: righth
Out[44]:                     Out[45]:
```

```
   data    key1  key2                     event1  event2
0     0    Ohio  2000        Nevada 2001       0       1
1     1    Ohio  2001               2000       2       3
2     2    Ohio  2002        Ohio   2000       4       5
3     3  Nevada  2001               2000       6       7
4     4  Nevada  2002               2001       8       9
                                    2002      10      11
```

In this case, you have to indicate multiple columns to merge on as a list (pay attention to the handling of duplicate index values):

```
In [46]: pd.merge(lefth, righth, left_on=['key1', 'key2'], right_index=True)
Out[46]:
   data    key1  key2  event1  event2
3     3  Nevada  2001       0       1
0     0    Ohio  2000       4       5
0     0    Ohio  2000       6       7
1     1    Ohio  2001       8       9
2     2    Ohio  2002      10      11

In [47]: pd.merge(lefth, righth, left_on=['key1', 'key2'],
   ....:          right_index=True, how='outer')
Out[47]:
   data    key1  key2  event1  event2
4   NaN  Nevada  2000       2       3
3     3  Nevada  2001       0       1
4     4  Nevada  2002     NaN     NaN
0     0    Ohio  2000       4       5
0     0    Ohio  2000       6       7
1     1    Ohio  2001       8       9
2     2    Ohio  2002      10      11
```

Using the indexes of both sides of the merge is also not an issue:

```
In [48]: left2 = DataFrame([[1., 2.], [3., 4.], [5., 6.]], index=['a', 'c', 'e'],
   ....:                   columns=['Ohio', 'Nevada'])

In [49]: right2 = DataFrame([[7., 8.], [9., 10.], [11., 12.], [13, 14]],
   ....:                    index=['b', 'c', 'd', 'e'], columns=['Missouri', 'Alabama'])

In [50]: left2          In [51]: right2
Out[50]:                Out[51]:
   Ohio  Nevada           Missouri  Alabama
a     1       2        b         7        8
c     3       4        c         9       10
e     5       6        d        11       12
                       e        13       14

In [52]: pd.merge(left2, right2, how='outer', left_index=True, right_index=True)
Out[52]:
   Ohio  Nevada  Missouri  Alabama
a     1       2       NaN      NaN
b   NaN     NaN         7        8
c     3       4         9       10
d   NaN     NaN        11       12
e     5       6        13       14
```

DataFrame has a more convenient `join` instance for merging by index. It can also be used to combine together many DataFrame objects having the same or similar indexes but non-overlapping columns. In the prior example, we could have written:

```
In [53]: left2.join(right2, how='outer')
Out[53]:
   Ohio  Nevada  Missouri  Alabama
a     1       2       NaN      NaN
b   NaN     NaN         7        8
c     3       4         9       10
d   NaN     NaN        11       12
e     5       6        13       14
```

In part for legacy reasons (much earlier versions of pandas), DataFrame's `join` method performs a left join on the join keys. It also supports joining the index of the passed DataFrame on one of the columns of the calling DataFrame:

```
In [54]: left1.join(right1, on='key')
Out[54]:
  key  value  group_val
0   a      0        3.5
1   b      1        7.0
2   a      2        3.5
3   a      3        3.5
4   b      4        7.0
5   c      5        NaN
```

Lastly, for simple index-on-index merges, you can pass a list of DataFrames to `join` as an alternative to using the more general `concat` function described below:

```
In [55]: another = DataFrame([[7., 8.], [9., 10.], [11., 12.], [16., 17.]],
   ....:                     index=['a', 'c', 'e', 'f'], columns=['New York', 'Oregon'])

In [56]: left2.join([right2, another])
Out[56]:
   Ohio  Nevada  Missouri  Alabama  New York  Oregon
a     1       2       NaN      NaN         7       8
c     3       4         9       10         9      10
e     5       6        13       14        11      12

In [57]: left2.join([right2, another], how='outer')
Out[57]:
   Ohio  Nevada  Missouri  Alabama  New York  Oregon
a     1       2       NaN      NaN         7       8
b   NaN     NaN         7        8       NaN     NaN
c     3       4         9       10         9      10
d   NaN     NaN        11       12       NaN     NaN
e     5       6        13       14        11      12
f   NaN     NaN       NaN      NaN        16      17
```

Concatenating Along an Axis

Another kind of data combination operation is alternatively referred to as concatenation, binding, or stacking. NumPy has a `concatenate` function for doing this with raw NumPy arrays:

```
In [58]: arr = np.arange(12).reshape((3, 4))

In [59]: arr
Out[59]:
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])

In [60]: np.concatenate([arr, arr], axis=1)
Out[60]:
array([[ 0,  1,  2,  3,  0,  1,  2,  3],
       [ 4,  5,  6,  7,  4,  5,  6,  7],
       [ 8,  9, 10, 11,  8,  9, 10, 11]])
```

In the context of pandas objects such as Series and DataFrame, having labeled axes enable you to further generalize array concatenation. In particular, you have a number of additional things to think about:

- If the objects are indexed differently on the other axes, should the collection of axes be unioned or intersected?
- Do the groups need to be identifiable in the resulting object?
- Does the concatenation axis matter at all?

The `concat` function in pandas provides a consistent way to address each of these concerns. I'll give a number of examples to illustrate how it works. Suppose we have three Series with no index overlap:

```
In [61]: s1 = Series([0, 1], index=['a', 'b'])

In [62]: s2 = Series([2, 3, 4], index=['c', 'd', 'e'])

In [63]: s3 = Series([5, 6], index=['f', 'g'])
```

Calling `concat` with these object in a list glues together the values and indexes:

```
In [64]: pd.concat([s1, s2, s3])
Out[64]:
a    0
b    1
c    2
d    3
e    4
f    5
g    6
```

By default `concat` works along `axis=0`, producing another Series. If you pass `axis=1`, the result will instead be a DataFrame (`axis=1` is the columns):

```
In [65]: pd.concat([s1, s2, s3], axis=1)
Out[65]:
    0   1   2
a   0 NaN NaN
b   1 NaN NaN
c NaN   2 NaN
d NaN   3 NaN
e NaN   4 NaN
f NaN NaN   5
g NaN NaN   6
```

In this case there is no overlap on the other axis, which as you can see is the sorted union (the `'outer'` join) of the indexes. You can instead intersect them by passing `join='inner'`:

```
In [66]: s4 = pd.concat([s1 * 5, s3])

In [67]: pd.concat([s1, s4], axis=1)
Out[67]:
    0  1
a   0  0
b   1  5
f NaN  5
g NaN  6

In [68]: pd.concat([s1, s4], axis=1, join='inner')
Out[68]:
   0  1
a  0  0
b  1  5
```

You can even specify the axes to be used on the other axes with `join_axes`:

```
In [69]: pd.concat([s1, s4], axis=1, join_axes=[['a', 'c', 'b', 'e']])
Out[69]:
    0   1
a   0   0
c NaN NaN
b   1   5
e NaN NaN
```

One issue is that the concatenated pieces are not identifiable in the result. Suppose instead you wanted to create a hierarchical index on the concatenation axis. To do this, use the `keys` argument:

```
In [70]: result = pd.concat([s1, s1, s3], keys=['one', 'two', 'three'])

In [71]: result
Out[71]:
one    a    0
       b    1
two    a    0
       b    1
three  f    5
       g    6

# Much more on the unstack function later
In [72]: result.unstack()
Out[72]:
```

```
        a   b   f   g
one     0   1 NaN NaN
two     0   1 NaN NaN
three NaN NaN   5   6
```

In the case of combining Series along `axis=1`, the `keys` become the DataFrame column headers:

```
In [73]: pd.concat([s1, s2, s3], axis=1, keys=['one', 'two', 'three'])
Out[73]:
   one  two  three
a    0  NaN    NaN
b    1  NaN    NaN
c  NaN    2    NaN
d  NaN    3    NaN
e  NaN    4    NaN
f  NaN  NaN      5
g  NaN  NaN      6
```

The same logic extends to DataFrame objects:

```
In [74]: df1 = DataFrame(np.arange(6).reshape(3, 2), index=['a', 'b', 'c'],
   ....:                 columns=['one', 'two'])

In [75]: df2 = DataFrame(5 + np.arange(4).reshape(2, 2), index=['a', 'c'],
   ....:                 columns=['three', 'four'])

In [76]: pd.concat([df1, df2], axis=1, keys=['level1', 'level2'])
Out[76]:
   level1       level2
      one  two   three  four
a       0    1       5     6
b       2    3     NaN   NaN
c       4    5       7     8
```

If you pass a dict of objects instead of a list, the dict's keys will be used for the `keys` option:

```
In [77]: pd.concat({'level1': df1, 'level2': df2}, axis=1)
Out[77]:
   level1       level2
      one  two   three  four
a       0    1       5     6
b       2    3     NaN   NaN
c       4    5       7     8
```

There are a couple of additional arguments governing how the hierarchical index is created (see Table 7-2):

```
In [78]: pd.concat([df1, df2], axis=1, keys=['level1', 'level2'],
   ....:           names=['upper', 'lower'])
Out[78]:
upper  level1       level2
lower     one  two   three  four
a           0    1       5     6
b           2    3     NaN   NaN
c           4    5       7     8
```

A last consideration concerns DataFrames in which the row index is not meaningful in the context of the analysis:

```
In [79]: df1 = DataFrame(np.random.randn(3, 4), columns=['a', 'b', 'c', 'd'])

In [80]: df2 = DataFrame(np.random.randn(2, 3), columns=['b', 'd', 'a'])

In [81]: df1
Out[81]:
          a         b         c         d
0 -0.204708  0.478943 -0.519439 -0.555730
1  1.965781  1.393406  0.092908  0.281746
2  0.769023  1.246435  1.007189 -1.296221
```

```
In [82]: df2
Out[82]:
          b         d         a
0  0.274992  0.228913  1.352917
1  0.886429 -2.001637 -0.371843
```

In this case, you can pass `ignore_index=True`:

```
In [83]: pd.concat([df1, df2], ignore_index=True)
Out[83]:
          a         b         c         d
0 -0.204708  0.478943 -0.519439 -0.555730
1  1.965781  1.393406  0.092908  0.281746
2  0.769023  1.246435  1.007189 -1.296221
3  1.352917  0.274992       NaN  0.228913
4 -0.371843  0.886429       NaN -2.001637
```

Table 7-2. concat function arguments

Argument	Description
`objs`	List or dict of pandas objects to be concatenated. The only required argument
`axis`	Axis to concatenate along; defaults to 0
`join`	One of `'inner'`, `'outer'`, defaulting to `'outer'`; whether to intersection (inner) or union (outer) together indexes along the other axes
`join_axes`	Specific indexes to use for the other n-1 axes instead of performing union/intersection logic
`keys`	Values to associate with objects being concatenated, forming a hierarchical index along the concatenation axis. Can either be a list or array of arbitrary values, an array of tuples, or a list of arrays (if multiple level arrays passed in `levels`)
`levels`	Specific indexes to use as hierarchical index level or levels if keys passed
`names`	Names for created hierarchical levels if `keys` and / or `levels` passed
`verify_integrity`	Check new axis in concatenated object for duplicates and raise exception if so. By default (`False`) allows duplicates
`ignore_index`	Do not preserve indexes along concatenation `axis`, instead producing a new `range(total_length)` index

Combining Data with Overlap

Another data combination situation can't be expressed as either a merge or concatenation operation. You may have two datasets whose indexes overlap in full or part. As a motivating example, consider NumPy's `where` function, which expressed a vectorized if-else:

```
In [84]: a = Series([np.nan, 2.5, np.nan, 3.5, 4.5, np.nan],
   ....:            index=['f', 'e', 'd', 'c', 'b', 'a'])

In [85]: b = Series(np.arange(len(a), dtype=np.float64),
   ....:            index=['f', 'e', 'd', 'c', 'b', 'a'])

In [86]: b[-1] = np.nan

In [87]: a        In [88]: b        In [89]: np.where(pd.isnull(a), b, a)
Out[87]:          Out[88]:          Out[89]:
f    NaN          f     0           f    0.0
e    2.5          e     1           e    2.5
d    NaN          d     2           d    2.0
c    3.5          c     3           c    3.5
b    4.5          b     4           b    4.5
a    NaN          a   NaN           a    NaN
```

Series has a `combine_first` method, which performs the equivalent of this operation plus data alignment:

```
In [90]: b[:-2].combine_first(a[2:])
Out[90]:
a    NaN
b    4.5
c    3.0
d    2.0
e    1.0
f    0.0
```

With DataFrames, `combine_first` naturally does the same thing column by column, so you can think of it as "patching" missing data in the calling object with data from the object you pass:

```
In [91]: df1 = DataFrame({'a': [1., np.nan, 5., np.nan],
   ....:                  'b': [np.nan, 2., np.nan, 6.],
   ....:                  'c': range(2, 18, 4)})

In [92]: df2 = DataFrame({'a': [5., 4., np.nan, 3., 7.],
   ....:                  'b': [np.nan, 3., 4., 6., 8.]})

In [93]: df1.combine_first(df2)
Out[93]:
   a   b   c
0  1 NaN   2
1  4   2   6
2  5   4  10
3  3   6  14
4  7   8 NaN
```

Reshaping and Pivoting

There are a number of fundamental operations for rearranging tabular data. These are alternatingly referred to as *reshape* or *pivot* operations.

Reshaping with Hierarchical Indexing

Hierarchical indexing provides a consistent way to rearrange data in a DataFrame. There are two primary actions:

- `stack`: this "rotates" or pivots from the columns in the data to the rows
- `unstack`: this pivots from the rows into the columns

I'll illustrate these operations through a series of examples. Consider a small DataFrame with string arrays as row and column indexes:

```
In [94]: data = DataFrame(np.arange(6).reshape((2, 3)),
   ....:                  index=pd.Index(['Ohio', 'Colorado'], name='state'),
   ....:                  columns=pd.Index(['one', 'two', 'three'], name='number'))

In [95]: data
Out[95]:
number    one  two  three
state
Ohio        0    1      2
Colorado    3    4      5
```

Using the `stack` method on this data pivots the columns into the rows, producing a Series:

```
In [96]: result = data.stack()

In [97]: result
Out[97]:
state     number
Ohio      one       0
          two       1
          three     2
Colorado  one       3
          two       4
          three     5
```

From a hierarchically-indexed Series, you can rearrange the data back into a DataFrame with `unstack`:

```
In [98]: result.unstack()
Out[98]:
number    one  two  three
state
Ohio        0    1      2
Colorado    3    4      5
```

By default the innermost level is unstacked (same with `stack`). You can unstack a different level by passing a level number or name:

```
In [99]: result.unstack(0)
Out[99]:
state   Ohio  Colorado
number
one        0         3
```

```
In [100]: result.unstack('state')
Out[100]:
state   Ohio  Colorado
number
one        0         3
```

```
two        1         4            two        1         4
three      2         5            three      2         5
```

Unstacking might introduce missing data if all of the values in the level aren't found in each of the subgroups:

```
In [101]: s1 = Series([0, 1, 2, 3], index=['a', 'b', 'c', 'd'])

In [102]: s2 = Series([4, 5, 6], index=['c', 'd', 'e'])

In [103]: data2 = pd.concat([s1, s2], keys=['one', 'two'])

In [104]: data2.unstack()
Out[104]:
      a   b  c  d   e
one   0   1  2  3 NaN
two NaN NaN  4  5   6
```

Stacking filters out missing data by default, so the operation is easily invertible:

```
In [105]: data2.unstack().stack()
Out[105]:
one  a    0
     b    1
     c    2
     d    3
two  c    4
     d    5
     e    6
```

```
In [106]: data2.unstack().stack(dropna=False)
Out[106]:
one  a     0
     b     1
     c     2
     d     3
     e   NaN
two  a   NaN
     b   NaN
     c     4
     d     5
     e     6
```

When unstacking in a DataFrame, the level unstacked becomes the lowest level in the result:

```
In [107]: df = DataFrame({'left': result, 'right': result + 5},
   .....:                columns=pd.Index(['left', 'right'], name='side'))

In [108]: df
Out[108]:
side             left  right
state    number
Ohio     one        0      5
         two        1      6
         three      2      7
Colorado one        3      8
         two        4      9
         three      5     10
```

```
In [109]: df.unstack('state')
Out[109]:
side    left            right
state   Ohio  Colorado   Ohio  Colorado
number
one        0         3      5         8
two        1         4      6         9
```

```
In [110]: df.unstack('state').stack('side')
Out[110]:
state         Ohio  Colorado
number side
one    left      0         3
       right     5         8
two    left      1         4
```

```
three      2         5      7        10            right     6         9
                                             three  left      2         5
                                                    right     7        10
```

Pivoting "long" to "wide" Format

A common way to store multiple time series in databases and CSV is in so-called *long* or *stacked* format:

```
In [116]: ldata[:10]
Out[116]:
                 date     item     value
0 1959-03-31 00:00:00  realgdp  2710.349
1 1959-03-31 00:00:00     infl     0.000
2 1959-03-31 00:00:00    unemp     5.800
3 1959-06-30 00:00:00  realgdp  2778.801
4 1959-06-30 00:00:00     infl     2.340
5 1959-06-30 00:00:00    unemp     5.100
6 1959-09-30 00:00:00  realgdp  2775.488
7 1959-09-30 00:00:00     infl     2.740
8 1959-09-30 00:00:00    unemp     5.300
9 1959-12-31 00:00:00  realgdp  2785.204
```

Data is frequently stored this way in relational databases like MySQL as a fixed schema (column names and data types) allows the number of distinct values in the `item` column to increase or decrease as data is added or deleted in the table. In the above example `date` and `item` would usually be the primary keys (in relational database parlance), offering both relational integrity and easier joins and programmatic queries in many cases. The downside, of course, is that the data may not be easy to work with in long format; you might prefer to have a DataFrame containing one column per distinct `item` value indexed by timestamps in the `date` column. DataFrame's `pivot` method performs exactly this transformation:

```
In [117]: pivoted = ldata.pivot('date', 'item', 'value')

In [118]: pivoted.head()
Out[118]:
item        infl   realgdp  unemp
date
1959-03-31  0.00  2710.349    5.8
1959-06-30  2.34  2778.801    5.1
1959-09-30  2.74  2775.488    5.3
1959-12-31  0.27  2785.204    5.6
1960-03-31  2.31  2847.699    5.2
```

The first two values passed are the columns to be used as the row and column index, and finally an optional value column to fill the DataFrame. Suppose you had two value columns that you wanted to reshape simultaneously:

```
In [119]: ldata['value2'] = np.random.randn(len(ldata))

In [120]: ldata[:10]
Out[120]:
```

```
                 date     item     value    value2
0 1959-03-31 00:00:00  realgdp  2710.349  1.669025
1 1959-03-31 00:00:00     infl     0.000 -0.438570
2 1959-03-31 00:00:00    unemp     5.800 -0.539741
3 1959-06-30 00:00:00  realgdp  2778.801  0.476985
4 1959-06-30 00:00:00     infl     2.340  3.248944
5 1959-06-30 00:00:00    unemp     5.100 -1.021228
6 1959-09-30 00:00:00  realgdp  2775.488 -0.577087
7 1959-09-30 00:00:00     infl     2.740  0.124121
8 1959-09-30 00:00:00    unemp     5.300  0.302614
9 1959-12-31 00:00:00  realgdp  2785.204  0.523772
```

By omitting the last argument, you obtain a DataFrame with hierarchical columns:

```
In [121]: pivoted = ldata.pivot('date', 'item')

In [122]: pivoted[:5]
Out[122]:
            value                     value2
item         infl   realgdp  unemp      infl   realgdp     unemp
date
1959-03-31   0.00  2710.349    5.8 -0.438570  1.669025 -0.539741
1959-06-30   2.34  2778.801    5.1  3.248944  0.476985 -1.021228
1959-09-30   2.74  2775.488    5.3  0.124121 -0.577087  0.302614
1959-12-31   0.27  2785.204    5.6  0.000940  0.523772  1.343810
1960-03-31   2.31  2847.699    5.2 -0.831154 -0.713544 -2.370232

In [123]: pivoted['value'][:5]
Out[123]:
item        infl   realgdp  unemp
date
1959-03-31  0.00  2710.349    5.8
1959-06-30  2.34  2778.801    5.1
1959-09-30  2.74  2775.488    5.3
1959-12-31  0.27  2785.204    5.6
1960-03-31  2.31  2847.699    5.2
```

Note that `pivot` is just a shortcut for creating a hierarchical index using `set_index` and reshaping with `unstack`:

```
In [124]: unstacked = ldata.set_index(['date', 'item']).unstack('item')

In [125]: unstacked[:7]
Out[125]:
            value                     value2
item         infl   realgdp  unemp      infl   realgdp     unemp
date
1959-03-31   0.00  2710.349    5.8 -0.438570  1.669025 -0.539741
1959-06-30   2.34  2778.801    5.1  3.248944  0.476985 -1.021228
1959-09-30   2.74  2775.488    5.3  0.124121 -0.577087  0.302614
1959-12-31   0.27  2785.204    5.6  0.000940  0.523772  1.343810
1960-03-31   2.31  2847.699    5.2 -0.831154 -0.713544 -2.370232
1960-06-30   0.14  2834.390    5.2 -0.860757 -1.860761  0.560145
1960-09-30   2.70  2839.022    5.6  0.119827 -1.265934 -1.063512
```

Data Transformation

So far in this chapter we've been concerned with rearranging data. Filtering, cleaning, and other tranformations are another class of important operations.

Removing Duplicates

Duplicate rows may be found in a DataFrame for any number of reasons. Here is an example:

```
In [126]: data = DataFrame({'k1': ['one'] * 3 + ['two'] * 4,
   .....:                   'k2': [1, 1, 2, 3, 3, 4, 4]})

In [127]: data
Out[127]:
    k1  k2
0  one   1
1  one   1
2  one   2
3  two   3
4  two   3
5  two   4
6  two   4
```

The DataFrame method `duplicated` returns a boolean Series indicating whether each row is a duplicate or not:

```
In [128]: data.duplicated()
Out[128]:
0    False
1     True
2    False
3    False
4     True
5    False
6     True
```

Relatedly, `drop_duplicates` returns a DataFrame where the `duplicated` array is `True`:

```
In [129]: data.drop_duplicates()
Out[129]:
    k1  k2
0  one   1
2  one   2
3  two   3
5  two   4
```

Both of these methods by default consider all of the columns; alternatively you can specify any subset of them to detect duplicates. Suppose we had an additional column of values and wanted to filter duplicates only based on the `'k1'` column:

```
In [130]: data['v1'] = range(7)

In [131]: data.drop_duplicates(['k1'])
```

```
Out[131]:
    k1  k2  v1
0  one   1   0
3  two   3   3
```

`duplicated` and `drop_duplicates` by default keep the first observed value combination. Passing `take_last=True` will return the last one:

```
In [132]: data.drop_duplicates(['k1', 'k2'], take_last=True)
Out[132]:
    k1  k2  v1
1  one   1   1
2  one   2   2
4  two   3   4
6  two   4   6
```

Transforming Data Using a Function or Mapping

For many data sets, you may wish to perform some transformation based on the values in an array, Series, or column in a DataFrame. Consider the following hypothetical data collected about some kinds of meat:

```
In [133]: data = DataFrame({'food': ['bacon', 'pulled pork', 'bacon', 'Pastrami',
   .....:                           'corned beef', 'Bacon', 'pastrami', 'honey ham',
   .....:                           'nova lox'],
   .....:                   'ounces': [4, 3, 12, 6, 7.5, 8, 3, 5, 6]})

In [134]: data
Out[134]:
          food  ounces
0        bacon     4.0
1  pulled pork     3.0
2        bacon    12.0
3     Pastrami     6.0
4  corned beef     7.5
5        Bacon     8.0
6     pastrami     3.0
7    honey ham     5.0
8     nova lox     6.0
```

Suppose you wanted to add a column indicating the type of animal that each food came from. Let's write down a mapping of each distinct meat type to the kind of animal:

```
meat_to_animal = {
  'bacon': 'pig',
  'pulled pork': 'pig',
  'pastrami': 'cow',
  'corned beef': 'cow',
  'honey ham': 'pig',
  'nova lox': 'salmon'
}
```

The `map` method on a Series accepts a function or dict-like object containing a mapping, but here we have a small problem in that some of the meats above are capitalized and others are not. Thus, we also need to convert each value to lower case:

```
In [136]: data['animal'] = data['food'].map(str.lower).map(meat_to_animal)

In [137]: data
Out[137]:
          food  ounces  animal
0        bacon     4.0     pig
1  pulled pork     3.0     pig
2        bacon    12.0     pig
3     Pastrami     6.0     cow
4  corned beef     7.5     cow
5        Bacon     8.0     pig
6     pastrami     3.0     cow
7    honey ham     5.0     pig
8     nova lox     6.0  salmon
```

We could also have passed a function that does all the work:

```
In [138]: data['food'].map(lambda x: meat_to_animal[x.lower()])
Out[138]:
0       pig
1       pig
2       pig
3       cow
4       cow
5       pig
6       cow
7       pig
8    salmon
Name: food
```

Using `map` is a convenient way to perform element-wise transformations and other data cleaning-related operations.

Replacing Values

Filling in missing data with the `fillna` method can be thought of as a special case of more general value replacement. While `map`, as you've seen above, can be used to modify a subset of values in an object, `replace` provides a simpler and more flexible way to do so. Let's consider this Series:

```
In [139]: data = Series([1., -999., 2., -999., -1000., 3.])

In [140]: data
Out[140]:
0       1
1    -999
2       2
3    -999
4   -1000
5       3
```

The `-999` values might be sentinel values for missing data. To replace these with NA values that pandas understands, we can use `replace`, producing a new Series:

```
In [141]: data.replace(-999, np.nan)
Out[141]:
0       1
1     NaN
2       2
3     NaN
4   -1000
5       3
```

If you want to replace multiple values at once, you instead pass a list then the substitute value:

```
In [142]: data.replace([-999, -1000], np.nan)
Out[142]:
0     1
1   NaN
2     2
3   NaN
4   NaN
5     3
```

To use a different replacement for each value, pass a list of substitutes:

```
In [143]: data.replace([-999, -1000], [np.nan, 0])
Out[143]:
0     1
1   NaN
2     2
3   NaN
4     0
5     3
```

The argument passed can also be a dict:

```
In [144]: data.replace({-999: np.nan, -1000: 0})
Out[144]:
0     1
1   NaN
2     2
3   NaN
4     0
5     3
```

Renaming Axis Indexes

Like values in a Series, axis labels can be similarly transformed by a function or mapping of some form to produce new, differently labeled objects. The axes can also be modified in place without creating a new data structure. Here's a simple example:

```
In [145]: data = DataFrame(np.arange(12).reshape((3, 4)),
   .....:                  index=['Ohio', 'Colorado', 'New York'],
   .....:                  columns=['one', 'two', 'three', 'four'])
```

Like a Series, the axis indexes have a `map` method:

```
In [146]: data.index.map(str.upper)
Out[146]: array([OHIO, COLORADO, NEW YORK], dtype=object)
```

You can assign to `index`, modifying the DataFrame in place:

```
In [147]: data.index = data.index.map(str.upper)

In [148]: data
Out[148]:
          one  two  three  four
OHIO        0    1      2     3
COLORADO    4    5      6     7
NEW YORK    8    9     10    11
```

If you want to create a transformed version of a data set without modifying the original, a useful method is `rename`:

```
In [149]: data.rename(index=str.title, columns=str.upper)
Out[149]:
          ONE  TWO  THREE  FOUR
Ohio        0    1      2     3
Colorado    4    5      6     7
New York    8    9     10    11
```

Notably, `rename` can be used in conjunction with a dict-like object providing new values for a subset of the axis labels:

```
In [150]: data.rename(index={'OHIO': 'INDIANA'},
   .....:             columns={'three': 'peekaboo'})
Out[150]:
          one  two  peekaboo  four
INDIANA     0    1         2     3
COLORADO    4    5         6     7
NEW YORK    8    9        10    11
```

`rename` saves having to copy the DataFrame manually and assign to its `index` and `columns` attributes. Should you wish to modify a data set in place, pass `inplace=True`:

```
# Always returns a reference to a DataFrame
In [151]: _ = data.rename(index={'OHIO': 'INDIANA'}, inplace=True)

In [152]: data
Out[152]:
          one  two  three  four
INDIANA     0    1      2     3
COLORADO    4    5      6     7
NEW YORK    8    9     10    11
```

Discretization and Binning

Continuous data is often discretized or otherwised separated into "bins" for analysis. Suppose you have data about a group of people in a study, and you want to group them into discrete age buckets:

```
In [153]: ages = [20, 22, 25, 27, 21, 23, 37, 31, 61, 45, 41, 32]
```

Let's divide these into bins of 18 to 25, 26 to 35, 35 to 60, and finally 60 and older. To do so, you have to use `cut`, a function in pandas:

```
In [154]: bins = [18, 25, 35, 60, 100]

In [155]: cats = pd.cut(ages, bins)

In [156]: cats
Out[156]:
Categorical:
array([(18, 25], (18, 25], (18, 25], (25, 35], (18, 25], (18, 25],
       (35, 60], (25, 35], (60, 100], (35, 60], (35, 60], (25, 35]], dtype=object)
Levels (4): Index([(18, 25], (25, 35], (35, 60], (60, 100]], dtype=object)
```

The object pandas returns is a special `Categorical` object. You can treat it like an array of strings indicating the bin name; internally it contains a `levels` array indicating the distinct category names along with a labeling for the `ages` data in the `labels` attribute:

```
In [157]: cats.labels
Out[157]: array([0, 0, 0, 1, 0, 0, 2, 1, 3, 2, 2, 1])

In [158]: cats.levels
Out[158]: Index([(18, 25], (25, 35], (35, 60], (60, 100]], dtype=object)

In [159]: pd.value_counts(cats)
Out[159]:
(18, 25]     5
(35, 60]     3
(25, 35]     3
(60, 100]    1
```

Consistent with mathematical notation for intervals, a parenthesis means that the side is *open* while the square bracket means it is *closed* (inclusive). Which side is closed can be changed by passing `right=False`:

```
In [160]: pd.cut(ages, [18, 26, 36, 61, 100], right=False)
Out[160]:
Categorical:
array([[18, 26), [18, 26), [18, 26), [26, 36), [18, 26), [18, 26),
       [36, 61), [26, 36), [61, 100), [36, 61), [36, 61), [26, 36)], dtype=object)
Levels (4): Index([[18, 26), [26, 36), [36, 61), [61, 100)], dtype=object)
```

You can also pass your own bin names by passing a list or array to the `labels` option:

```
In [161]: group_names = ['Youth', 'YoungAdult', 'MiddleAged', 'Senior']

In [162]: pd.cut(ages, bins, labels=group_names)
Out[162]:
```

```
Categorical:
array([Youth, Youth, Youth, YoungAdult, Youth, Youth, MiddleAged,
       YoungAdult, Senior, MiddleAged, MiddleAged, YoungAdult], dtype=object)
Levels (4): Index([Youth, YoungAdult, MiddleAged, Senior], dtype=object)
```

If you pass `cut` a integer number of bins instead of explicit bin edges, it will compute equal-length bins based on the minimum and maximum values in the data. Consider the case of some uniformly distributed data chopped into fourths:

```
In [163]: data = np.random.rand(20)

In [164]: pd.cut(data, 4, precision=2)
Out[164]:
Categorical:
array([(0.45, 0.67], (0.23, 0.45], (0.0037, 0.23], (0.45, 0.67],
       (0.67, 0.9], (0.45, 0.67], (0.67, 0.9], (0.23, 0.45], (0.23, 0.45],
       (0.67, 0.9], (0.67, 0.9], (0.67, 0.9], (0.23, 0.45], (0.23, 0.45],
       (0.23, 0.45], (0.67, 0.9], (0.0037, 0.23], (0.0037, 0.23],
       (0.23, 0.45], (0.23, 0.45]], dtype=object)
Levels (4): Index([(0.0037, 0.23], (0.23, 0.45], (0.45, 0.67],
                   (0.67, 0.9]], dtype=object)
```

A closely related function, `qcut`, bins the data based on sample quantiles. Depending on the distribution of the data, using `cut` will not usually result in each bin having the same number of data points. Since `qcut` uses sample quantiles instead, by definition you will obtain roughly equal-size bins:

```
In [165]: data = np.random.randn(1000) # Normally distributed

In [166]: cats = pd.qcut(data, 4) # Cut into quartiles

In [167]: cats
Out[167]:
Categorical:
array([(-0.022, 0.641], [-3.745, -0.635], (0.641, 3.26], ...,
       (-0.635, -0.022], (0.641, 3.26], (-0.635, -0.022]], dtype=object)
Levels (4): Index([[-3.745, -0.635], (-0.635, -0.022], (-0.022, 0.641],
                   (0.641, 3.26]], dtype=object)

In [168]: pd.value_counts(cats)
Out[168]:
[-3.745, -0.635]    250
(0.641, 3.26]       250
(-0.635, -0.022]    250
(-0.022, 0.641]     250
```

Similar to `cut` you can pass your own quantiles (numbers between 0 and 1, inclusive):

```
In [169]: pd.qcut(data, [0, 0.1, 0.5, 0.9, 1.])
Out[169]:
Categorical:
array([(-0.022, 1.302], (-1.266, -0.022], (-0.022, 1.302], ...,
       (-1.266, -0.022], (-0.022, 1.302], (-1.266, -0.022]], dtype=object)
Levels (4): Index([[-3.745, -1.266], (-1.266, -0.022], (-0.022, 1.302],
                   (1.302, 3.26]], dtype=object)
```

We'll return to `cut` and `qcut` later in the chapter on aggregation and group operations, as these discretization functions are especially useful for quantile and group analysis.

Detecting and Filtering Outliers

Filtering or transforming outliers is largely a matter of applying array operations. Consider a DataFrame with some normally distributed data:

```
In [170]: np.random.seed(12345)

In [171]: data = DataFrame(np.random.randn(1000, 4))

In [172]: data.describe()
Out[172]:
                 0            1            2            3
count  1000.000000  1000.000000  1000.000000  1000.000000
mean     -0.067684     0.067924     0.025598    -0.002298
std       0.998035     0.992106     1.006835     0.996794
min      -3.428254    -3.548824    -3.184377    -3.745356
25%      -0.774890    -0.591841    -0.641675    -0.644144
50%      -0.116401     0.101143     0.002073    -0.013611
75%       0.616366     0.780282     0.680391     0.654328
max       3.366626     2.653656     3.260383     3.927528
```

Suppose you wanted to find values in one of the columns exceeding three in magnitude:

```
In [173]: col = data[3]

In [174]: col[np.abs(col) > 3]
Out[174]:
97     3.927528
305   -3.399312
400   -3.745356
Name: 3
```

To select all rows having a value exceeding 3 or -3, you can use the `any` method on a boolean DataFrame:

```
In [175]: data[(np.abs(data) > 3).any(1)]
Out[175]:
            0         1         2         3
5   -0.539741  0.476985  3.248944 -1.021228
97  -0.774363  0.552936  0.106061  3.927528
102 -0.655054 -0.565230  3.176873  0.959533
305 -2.315555  0.457246 -0.025907 -3.399312
324  0.050188  1.951312  3.260383  0.963301
400  0.146326  0.508391 -0.196713 -3.745356
499 -0.293333 -0.242459 -3.056990  1.918403
523 -3.428254 -0.296336 -0.439938 -0.867165
586  0.275144  1.179227 -3.184377  1.369891
808 -0.362528 -3.548824  1.553205 -2.186301
900  3.366626 -2.372214  0.851010  1.332846
```

Values can just as easily be set based on these criteria. Here is code to cap values outside the interval -3 to 3:

```
In [176]: data[np.abs(data) > 3] = np.sign(data) * 3

In [177]: data.describe()
Out[177]:
                 0            1            2            3
count  1000.000000  1000.000000  1000.000000  1000.000000
mean     -0.067623     0.068473     0.025153    -0.002081
std       0.995485     0.990253     1.003977     0.989736
min      -3.000000    -3.000000    -3.000000    -3.000000
25%      -0.774890    -0.591841    -0.641675    -0.644144
50%      -0.116401     0.101143     0.002073    -0.013611
75%       0.616366     0.780282     0.680391     0.654328
max       3.000000     2.653656     3.000000     3.000000
```

The ufunc `np.sign` returns an array of 1 and -1 depending on the sign of the values.

Permutation and Random Sampling

Permuting (randomly reordering) a Series or the rows in a DataFrame is easy to do using the `numpy.random.permutation` function. Calling `permutation` with the length of the axis you want to permute produces an array of integers indicating the new ordering:

```
In [178]: df = DataFrame(np.arange(5 * 4).reshape(5, 4))

In [179]: sampler = np.random.permutation(5)

In [180]: sampler
Out[180]: array([1, 0, 2, 3, 4])
```

That array can then be used in `ix`-based indexing or the `take` function:

```
In [181]: df
Out[181]:
    0   1   2   3
0   0   1   2   3
1   4   5   6   7
2   8   9  10  11
3  12  13  14  15
4  16  17  18  19
```

```
In [182]: df.take(sampler)
Out[182]:
    0   1   2   3
1   4   5   6   7
0   0   1   2   3
2   8   9  10  11
3  12  13  14  15
4  16  17  18  19
```

To select a random subset without replacement, one way is to slice off the first `k` elements of the array returned by `permutation`, where `k` is the desired subset size. There are much more efficient sampling-without-replacement algorithms, but this is an easy strategy that uses readily available tools:

```
In [183]: df.take(np.random.permutation(len(df))[:3])
Out[183]:
    0   1   2   3
1   4   5   6   7
3  12  13  14  15
4  16  17  18  19
```

To generate a sample *with* replacement, the fastest way is to use `np.random.randint` to draw random integers:

```
In [184]: bag = np.array([5, 7, -1, 6, 4])

In [185]: sampler = np.random.randint(0, len(bag), size=10)

In [186]: sampler
Out[186]: array([4, 4, 2, 2, 2, 0, 3, 0, 4, 1])

In [187]: draws = bag.take(sampler)

In [188]: draws
Out[188]: array([ 4,  4, -1, -1, -1,  5,  6,  5,  4,  7])
```

Computing Indicator/Dummy Variables

Another type of transformation for statistical modeling or machine learning applications is converting a categorical variable into a "dummy" or "indicator" matrix. If a column in a DataFrame has `k` distinct values, you would derive a matrix or DataFrame containing `k` columns containing all 1's and 0's. pandas has a `get_dummies` function for doing this, though devising one yourself is not difficult. Let's return to an earlier example DataFrame:

```
In [189]: df = DataFrame({'key': ['b', 'b', 'a', 'c', 'a', 'b'],
   .....:                 'data1': range(6)})

In [190]: pd.get_dummies(df['key'])
Out[190]:
   a  b  c
0  0  1  0
1  0  1  0
2  1  0  0
3  0  0  1
4  1  0  0
5  0  1  0
```

In some cases, you may want to add a prefix to the columns in the indicator DataFrame, which can then be merged with the other data. `get_dummies` has a prefix argument for doing just this:

```
In [191]: dummies = pd.get_dummies(df['key'], prefix='key')

In [192]: df_with_dummy = df[['data1']].join(dummies)

In [193]: df_with_dummy
Out[193]:
   data1  key_a  key_b  key_c
0      0      0      1      0
1      1      0      1      0
2      2      1      0      0
3      3      0      0      1
4      4      1      0      0
5      5      0      1      0
```

If a row in a DataFrame belongs to multiple categories, things are a bit more complicated. Let's return to the MovieLens 1M dataset from earlier in the book:

```
In [194]: mnames = ['movie_id', 'title', 'genres']

In [195]: movies = pd.read_table('ch07/movies.dat', sep='::', header=None,
   .....:                        names=mnames)

In [196]: movies[:10]
Out[196]:
   movie_id                               title                        genres
0         1                    Toy Story (1995)   Animation|Children's|Comedy
1         2                      Jumanji (1995)  Adventure|Children's|Fantasy
2         3             Grumpier Old Men (1995)                Comedy|Romance
3         4            Waiting to Exhale (1995)                  Comedy|Drama
4         5  Father of the Bride Part II (1995)                        Comedy
5         6                         Heat (1995)         Action|Crime|Thriller
6         7                       Sabrina (1995)                Comedy|Romance
7         8                  Tom and Huck (1995)          Adventure|Children's
8         9                  Sudden Death (1995)                        Action
9        10                     GoldenEye (1995)     Action|Adventure|Thriller
```

Adding indicator variables for each genre requires a little bit of wrangling. First, we extract the list of unique genres in the dataset (using a nice `set.union` trick):

```
In [197]: genre_iter = (set(x.split('|')) for x in movies.genres)

In [198]: genres = sorted(set.union(*genre_iter))
```

Now, one way to construct the indicator DataFrame is to start with a DataFrame of all zeros:

```
In [199]: dummies = DataFrame(np.zeros((len(movies), len(genres))), columns=genres)
```

Now, iterate through each movie and set entries in each row of `dummies` to 1:

```
In [200]: for i, gen in enumerate(movies.genres):
   .....:     dummies.ix[i, gen.split('|')] = 1
```

Then, as above, you can combine this with `movies`:

```
In [201]: movies_windic = movies.join(dummies.add_prefix('Genre_'))

In [202]: movies_windic.ix[0]
Out[202]:
movie_id                                        1
title                             Toy Story (1995)
genres                Animation|Children's|Comedy
Genre_Action                                    0
Genre_Adventure                                 0
Genre_Animation                                 1
Genre_Children's                                1
Genre_Comedy                                    1
Genre_Crime                                     0
Genre_Documentary                               0
Genre_Drama                                     0
Genre_Fantasy                                   0
```

```
Genre_Film-Noir                              0
Genre_Horror                                 0
Genre_Musical                                0
Genre_Mystery                                0
Genre_Romance                                0
Genre_Sci-Fi                                 0
Genre_Thriller                               0
Genre_War                                    0
Genre_Western                                0
Name: 0
```

For much larger data, this method of constructing indicator variables with multiple membership is not especially speedy. A lower-level function leveraging the internals of the DataFrame could certainly be written.

A useful recipe for statistical applications is to combine `get_dummies` with a discretization function like `cut`:

```
In [204]: values = np.random.rand(10)

In [205]: values
Out[205]:
array([ 0.9296,  0.3164,  0.1839,  0.2046,  0.5677,  0.5955,  0.9645,
        0.6532,  0.7489,  0.6536])

In [206]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]

In [207]: pd.get_dummies(pd.cut(values, bins))
Out[207]:
   (0, 0.2]  (0.2, 0.4]  (0.4, 0.6]  (0.6, 0.8]  (0.8, 1]
0         0           0           0           0         1
1         0           1           0           0         0
2         1           0           0           0         0
3         0           1           0           0         0
4         0           0           1           0         0
5         0           0           1           0         0
6         0           0           0           0         1
7         0           0           0           1         0
8         0           0           0           1         0
9         0           0           0           1         0
```

String Manipulation

Python has long been a popular data munging language in part due to its ease-of-use for string and text processing. Most text operations are made simple with the string object's built-in methods. For more complex pattern matching and text manipulations, regular expressions may be needed. pandas adds to the mix by enabling you to apply string and regular expressions concisely on whole arrays of data, additionally handling the annoyance of missing data.

String Object Methods

In many string munging and scripting applications, built-in string methods are sufficient. As an example, a comma-separated string can be broken into pieces with `split`:

```
In [208]: val = 'a,b,  guido'

In [209]: val.split(',')
Out[209]: ['a', 'b', '  guido']
```

`split` is often combined with `strip` to trim whitespace (including newlines):

```
In [210]: pieces = [x.strip() for x in val.split(',')]

In [211]: pieces
Out[211]: ['a', 'b', 'guido']
```

These substrings could be concatenated together with a two-colon delimiter using addition:

```
In [212]: first, second, third = pieces

In [213]: first + '::' + second + '::' + third
Out[213]: 'a::b::guido'
```

But, this isn't a practical generic method. A faster and more Pythonic way is to pass a list or tuple to the `join` method on the string `'::'`:

```
In [214]: '::'.join(pieces)
Out[214]: 'a::b::guido'
```

Other methods are concerned with locating substrings. Using Python's `in` keyword is the best way to detect a substring, though `index` and `find` can also be used:

```
In [215]: 'guido' in val
Out[215]: True

In [216]: val.index(',')        In [217]: val.find(':')
Out[216]: 1                     Out[217]: -1
```

Note the difference between `find` and `index` is that `index` raises an exception if the string isn't found (versus returning -1):

```
In [218]: val.index(':')
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-218-280f8b2856ce> in <module>()
----> 1 val.index(':')
ValueError: substring not found
```

Relatedly, `count` returns the number of occurrences of a particular substring:

```
In [219]: val.count(',')
Out[219]: 2
```

`replace` will substitute occurrences of one pattern for another. This is commonly used to delete patterns, too, by passing an empty string:

```
In [220]: val.replace(',', '::')
Out[220]: 'a::b::  guido'
```

```
In [221]: val.replace(',', '')
Out[221]: 'ab  guido'
```

Regular expressions can also be used with many of these operations as you'll see below.

Table 7-3. Python built-in string methods

Argument	Description
`count`	Return the number of non-overlapping occurrences of substring in the string.
`endswith, startswith`	Returns True if string ends with suffix (starts with prefix).
`join`	Use string as delimiter for concatenating a sequence of other strings.
`index`	Return position of first character in substring if found in the string. Raises `ValueEr ror` if not found.
`find`	Return position of first character of *first* occurrence of substring in the string. Like `index`, but returns -1 if not found.
`rfind`	Return position of first character of *last* occurrence of substring in the string. Returns -1 if not found.
`replace`	Replace occurrences of string with another string.
`strip, rstrip, lstrip`	Trim whitespace, including newlines; equivalent to `x.strip()` (and `rstrip, lstrip`, respectively) for each element.
`split`	Break string into list of substrings using passed delimiter.
`lower, upper`	Convert alphabet characters to lowercase or uppercase, respectively.
`ljust, rjust`	Left justify or right justify, respectively. Pad opposite side of string with spaces (or some other fill character) to return a string with a minimum width.

Regular expressions

Regular expressions provide a flexible way to search or match string patterns in text. A single expression, commonly called a *regex*, is a string formed according to the regular expression language. Python's built-in `re` module is responsible for applying regular expressions to strings; I'll give a number of examples of its use here.

The art of writing regular expressions could be a chapter of its own and thus is outside the book's scope. There are many excellent tutorials and references on the internet, such as Zed Shaw's *Learn Regex The Hard Way* (*http://regex.learncodethehardway.org/book/*).

The `re` module functions fall into three categories: pattern matching, substitution, and splitting. Naturally these are all related; a regex describes a pattern to locate in the text, which can then be used for many purposes. Let's look at a simple example: suppose I wanted to split a string with a variable number of whitespace characters (tabs, spaces, and newlines). The regex describing one or more whitespace characters is `\s+`:

```
In [222]: import re

In [223]: text = "foo    bar\t baz  \tqux"

In [224]: re.split('\s+', text)
Out[224]: ['foo', 'bar', 'baz', 'qux']
```

When you call `re.split('\s+', text)`, the regular expression is first *compiled*, then its `split` method is called on the passed text. You can compile the regex yourself with `re.compile`, forming a reusable regex object:

```
In [225]: regex = re.compile('\s+')

In [226]: regex.split(text)
Out[226]: ['foo', 'bar', 'baz', 'qux']
```

If, instead, you wanted to get a list of all patterns matching the regex, you can use the `findall` method:

```
In [227]: regex.findall(text)
Out[227]: ['    ', '\t ', '  \t']
```

To avoid unwanted escaping with `\` in a regular expression, use *raw* string literals like `r'C:\x'` instead of the equivalent `'C:\\x'`.

Creating a regex object with `re.compile` is highly recommended if you intend to apply the same expression to many strings; doing so will save CPU cycles.

`match` and `search` are closely related to `findall`. While `findall` returns all matches in a string, `search` returns only the first match. More rigidly, `match` *only* matches at the beginning of the string. As a less trivial example, let's consider a block of text and a regular expression capable of identifying most email addresses:

```
text = """Dave dave@google.com
Steve steve@gmail.com
Rob rob@gmail.com
Ryan ryan@yahoo.com
"""
pattern = r'[A-Z0-9._%+-]+@[A-Z0-9.-]+\.[A-Z]{2,4}'

# re.IGNORECASE makes the regex case-insensitive
regex = re.compile(pattern, flags=re.IGNORECASE)
```

Using `findall` on the text produces a list of the e-mail addresses:

```
In [229]: regex.findall(text)
Out[229]: ['dave@google.com', 'steve@gmail.com', 'rob@gmail.com', 'ryan@yahoo.com']
```

`search` returns a special match object for the first email address in the text. For the above regex, the match object can only tell us the start and end position of the pattern in the string:

```
In [230]: m = regex.search(text)

In [231]: m
Out[231]: <_sre.SRE_Match at 0x10a05de00>

In [232]: text[m.start():m.end()]
Out[232]: 'dave@google.com'
```

`regex.match` returns `None`, as it only will match if the pattern occurs at the start of the string:

```
In [233]: print regex.match(text)
None
```

Relatedly, `sub` will return a new string with occurrences of the pattern replaced by the a new string:

```
In [234]: print regex.sub('REDACTED', text)
Dave REDACTED
Steve REDACTED
Rob REDACTED
Ryan REDACTED
```

Suppose you wanted to find email addresses and simultaneously segment each address into its 3 components: username, domain name, and domain suffix. To do this, put parentheses around the parts of the pattern to segment:

```
In [235]: pattern = r'([A-Z0-9._%+-]+)@([A-Z0-9.-]+)\.([A-Z]{2,4})'

In [236]: regex = re.compile(pattern, flags=re.IGNORECASE)
```

A match object produced by this modified regex returns a tuple of the pattern components with its `groups` method:

```
In [237]: m = regex.match('wesm@bright.net')

In [238]: m.groups()
Out[238]: ('wesm', 'bright', 'net')
```

`findall` returns a list of tuples when the pattern has groups:

```
In [239]: regex.findall(text)
Out[239]:
[('dave', 'google', 'com'),
 ('steve', 'gmail', 'com'),
 ('rob', 'gmail', 'com'),
 ('ryan', 'yahoo', 'com')]
```

`sub` also has access to groups in each match using special symbols like `\1, \2`, etc.:

```
In [240]: print regex.sub(r'Username: \1, Domain: \2, Suffix: \3', text)
Dave Username: dave, Domain: google, Suffix: com
Steve Username: steve, Domain: gmail, Suffix: com
Rob Username: rob, Domain: gmail, Suffix: com
Ryan Username: ryan, Domain: yahoo, Suffix: com
```

There is much more to regular expressions in Python, most of which is outside the book's scope. To give you a flavor, one variation on the above email regex gives names to the match groups:

```
regex = re.compile(r"""
    (?P<username>[A-Z0-9._%+-]+)
    @
    (?P<domain>[A-Z0-9.-]+)
    \.
    (?P<suffix>[A-Z]{2,4})""", flags=re.IGNORECASE|re.VERBOSE)
```

The match object produced by such a regex can produce a handy dict with the specified group names:

```
In [242]: m = regex.match('wesm@bright.net')

In [243]: m.groupdict()
Out[243]: {'domain': 'bright', 'suffix': 'net', 'username': 'wesm'}
```

Table 7-4. Regular expression methods

Argument	Description
`findall, finditer`	Return all non-overlapping matching patterns in a string. `findall` returns a list of all patterns while `finditer` returns them one by one from an iterator.
`match`	Match pattern at start of string and optionally segment pattern components into groups. If the pattern matches, returns a match object, otherwise `None`.
`search`	Scan string for match to pattern; returning a match object if so. Unlike `match`, the match can be anywhere in the string as opposed to only at the beginning.
`split`	Break string into pieces at each occurrence of pattern.
`sub, subn`	Replace all (`sub`) or first n occurrences (`subn`) of pattern in string with replacement expression. Use symbols `\1, \2, ...` to refer to match group elements in the replacement string.

Vectorized string functions in pandas

Cleaning up a messy data set for analysis often requires a lot of string munging and regularization. To complicate matters, a column containing strings will sometimes have missing data:

```
In [244]: data = {'Dave': 'dave@google.com', 'Steve': 'steve@gmail.com',
   .....:         'Rob': 'rob@gmail.com', 'Wes': np.nan}

In [245]: data = Series(data)

In [246]: data                  In [247]: data.isnull()
Out[246]:                       Out[247]:
Dave     dave@google.com        Dave     False
Rob        rob@gmail.com        Rob      False
Steve    steve@gmail.com        Steve    False
Wes                  NaN        Wes       True
```

String and regular expression methods can be applied (passing a `lambda` or other function) to each value using `data.map`, but it will fail on the NA. To cope with this, Series has concise methods for string operations that skip NA values. These are accessed through Series's `str` attribute; for example, we could check whether each email address has `'gmail'` in it with `str.contains`:

```
In [248]: data.str.contains('gmail')
Out[248]:
Dave     False
Rob       True
Steve     True
Wes        NaN
```

Regular expressions can be used, too, along with any `re` options like `IGNORECASE`:

```
In [249]: pattern
Out[249]: '([A-Z0-9._%+-]+)@([A-Z0-9.-]+)\\.([A-Z]{2,4})'

In [250]: data.str.findall(pattern, flags=re.IGNORECASE)
Out[250]:
Dave     [('dave', 'google', 'com')]
Rob        [('rob', 'gmail', 'com')]
Steve    [('steve', 'gmail', 'com')]
Wes                             NaN
```

There are a couple of ways to do vectorized element retrieval. Either use `str.get` or index into the `str` attribute:

```
In [251]: matches = data.str.match(pattern, flags=re.IGNORECASE)

In [252]: matches
Out[252]:
Dave     ('dave', 'google', 'com')
Rob        ('rob', 'gmail', 'com')
Steve    ('steve', 'gmail', 'com')
Wes                            NaN

In [253]: matches.str.get(1)
Out[253]:
Dave     google
Rob       gmail
Steve     gmail
Wes         NaN

In [254]: matches.str[0]
Out[254]:
Dave      dave
Rob        rob
Steve    steve
Wes        NaN
```

You can similarly slice strings using this syntax:

```
In [255]: data.str[:5]
Out[255]:
Dave     dave@
Rob      rob@g
Steve    steve
Wes        NaN
```

Table 7-5. Vectorized string methods

Method	Description
`cat`	Concatenate strings element-wise with optional delimiter
`contains`	Return boolean array if each string contains pattern/regex
`count`	Count occurrences of pattern
`endswith, startswith`	Equivalent to `x.endswith(pattern)` or `x.startswith(pattern)` for each element.
`findall`	Compute list of all occurrences of pattern/regex for each string
`get`	Index into each element (retrieve i-th element)
`join`	Join strings in each element of the Series with passed separator
`len`	Compute length of each string
`lower, upper`	Convert cases; equivalent to `x.lower()` or `x.upper()` for each element.
`match`	Use `re.match` with the passed regular expression on each element, returning matched groups as list.
`pad`	Add whitespace to left, right, or both sides of strings
`center`	Equivalent to `pad(side='both')`
`repeat`	Duplicate values; for example `s.str.repeat(3)` equivalent to `x * 3` for each string.
`replace`	Replace occurrences of pattern/regex with some other string
`slice`	Slice each string in the Series.
`split`	Split strings on delimiter or regular expression
`strip, rstrip, lstrip`	Trim whitespace, including newlines; equivalent to `x.strip()` (and `rstrip, lstrip`, respectively) for each element.

Example: USDA Food Database

The US Department of Agriculture makes available a database of food nutrient information. Ashley Williams, an English hacker, has made available a version of this database in JSON format (*http://ashleyw.co.uk/project/food-nutrient-database*). The records look like this:

```
{
  "id": 21441,
  "description": "KENTUCKY FRIED CHICKEN, Fried Chicken, EXTRA CRISPY,
Wing, meat and skin with breading",
  "tags": ["KFC"],
  "manufacturer": "Kentucky Fried Chicken",
  "group": "Fast Foods",
  "portions": [
    {
      "amount": 1,
      "unit": "wing, with skin",
      "grams": 68.0
    },
```

```
    ...
  ],
  "nutrients": [
    {
      "value": 20.8,
      "units": "g",
      "description": "Protein",
      "group": "Composition"
    },

    ...
  ]
}
```

Each food has a number of identifying attributes along with two lists of nutrients and portion sizes. Having the data in this form is not particularly amenable for analysis, so we need to do some work to wrangle the data into a better form.

After downloading and extracting the data from the link above, you can load it into Python with any JSON library of your choosing. I'll use the built-in Python `json` module:

```
In [256]: import json

In [257]: db = json.load(open('ch07/foods-2011-10-03.json'))

In [258]: len(db)
Out[258]: 6636
```

Each entry in `db` is a dict containing all the data for a single food. The `'nutrients'` field is a list of dicts, one for each nutrient:

```
In [259]: db[0].keys()
Out[259]:
[u'portions',
 u'description',
 u'tags',
 u'nutrients',
 u'group',
 u'id',
 u'manufacturer']

In [260]: db[0]['nutrients'][0]
Out[260]:
{u'description': u'Protein',
 u'group': u'Composition',
 u'units': u'g',
 u'value': 25.18}

In [261]: nutrients = DataFrame(db[0]['nutrients'])

In [262]: nutrients[:7]
Out[262]:
                   description        group units    value
0                      Protein  Composition     g    25.18
1            Total lipid (fat)  Composition     g    29.20
2  Carbohydrate, by difference  Composition     g     3.06
3                          Ash        Other     g     3.28
4                       Energy       Energy  kcal   376.00
5                        Water  Composition     g    39.28
6                       Energy       Energy    kJ  1573.00
```

When converting a list of dicts to a DataFrame, we can specify a list of fields to extract. We'll take the food names, group, id, and manufacturer:

```
In [263]: info_keys = ['description', 'group', 'id', 'manufacturer']

In [264]: info = DataFrame(db, columns=info_keys)

In [265]: info[:5]
Out[265]:
                          description                    group    id manufacturer
0                      Cheese, caraway  Dairy and Egg Products  1008
1                      Cheese, cheddar  Dairy and Egg Products  1009
2                         Cheese, edam  Dairy and Egg Products  1018
3                         Cheese, feta  Dairy and Egg Products  1019
4  Cheese, mozzarella, part skim milk  Dairy and Egg Products  1028

In [266]: info
Out[266]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6636 entries, 0 to 6635
Data columns:
description     6636  non-null values
group           6636  non-null values
id              6636  non-null values
manufacturer    5195  non-null values
dtypes: int64(1), object(3)
```

You can see the distribution of food groups with `value_counts`:

```
In [267]: pd.value_counts(info.group)[:10]
Out[267]:
Vegetables and Vegetable Products    812
Beef Products                        618
Baked Products                       496
Breakfast Cereals                    403
Legumes and Legume Products          365
Fast Foods                           365
Lamb, Veal, and Game Products        345
Sweets                               341
Pork Products                        328
Fruits and Fruit Juices              328
```

Now, to do some analysis on all of the nutrient data, it's easiest to assemble the nutrients for each food into a single large table. To do so, we need to take several steps. First, I'll convert each list of food nutrients to a DataFrame, add a column for the food `id`, and append the DataFrame to a list. Then, these can be concatenated together with `concat`:

```
nutrients = []

for rec in db:
    fnuts = DataFrame(rec['nutrients'])
    fnuts['id'] = rec['id']
    nutrients.append(fnuts)

nutrients = pd.concat(nutrients, ignore_index=True)
```

If all goes well, `nutrients` should look like this:

```
In [269]: nutrients
Out[269]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 389355 entries, 0 to 389354
Data columns:
description    389355  non-null values
group          389355  non-null values
units          389355  non-null values
value          389355  non-null values
id             389355  non-null values
dtypes: float64(1), int64(1), object(3)
```

I noticed that, for whatever reason, there are duplicates in this DataFrame, so it makes things easier to drop them:

```
In [270]: nutrients.duplicated().sum()
Out[270]: 14179

In [271]: nutrients = nutrients.drop_duplicates()
```

Since `'group'` and `'description'` is in both DataFrame objects, we can rename them to make it clear what is what:

```
In [272]: col_mapping = {'description' : 'food',
   .....:                'group'       : 'fgroup'}

In [273]: info = info.rename(columns=col_mapping, copy=False)

In [274]: info
Out[274]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6636 entries, 0 to 6635
Data columns:
food           6636  non-null values
fgroup         6636  non-null values
id             6636  non-null values
manufacturer   5195  non-null values
dtypes: int64(1), object(3)

In [275]: col_mapping = {'description' : 'nutrient',
   .....:                'group' : 'nutgroup'}

In [276]: nutrients = nutrients.rename(columns=col_mapping, copy=False)

In [277]: nutrients
Out[277]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 375176 entries, 0 to 389354
Data columns:
nutrient    375176  non-null values
nutgroup    375176  non-null values
units       375176  non-null values
value       375176  non-null values
```

```
id          375176  non-null values
dtypes: float64(1), int64(1), object(3)
```

With all of this done, we're ready to merge `info` with `nutrients`:

```
In [278]: ndata = pd.merge(nutrients, info, on='id', how='outer')

In [279]: ndata
Out[279]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 375176 entries, 0 to 375175
Data columns:
nutrient        375176  non-null values
nutgroup        375176  non-null values
units           375176  non-null values
value           375176  non-null values
id              375176  non-null values
food            375176  non-null values
fgroup          375176  non-null values
manufacturer    293054  non-null values
dtypes: float64(1), int64(1), object(6)

In [280]: ndata.ix[30000]
Out[280]:
nutrient                       Folic acid
nutgroup                         Vitamins
units                                 mcg
value                                   0
id                                   5658
food            Ostrich, top loin, cooked
fgroup                   Poultry Products
manufacturer
Name: 30000
```

The tools that you need to slice and dice, aggregate, and visualize this dataset will be explored in detail in the next two chapters, so after you get a handle on those methods you might return to this dataset. For example, we could a plot of median values by food group and nutrient type (see Figure 7-1):

```
In [281]: result = ndata.groupby(['nutrient', 'fgroup'])['value'].quantile(0.5)

In [282]: result['Zinc, Zn'].order().plot(kind='barh')
```

With a little cleverness, you can find which food is most dense in each nutrient:

```
by_nutrient = ndata.groupby(['nutgroup', 'nutrient'])

get_maximum = lambda x: x.xs(x.value.idxmax())
get_minimum = lambda x: x.xs(x.value.idxmin())

max_foods = by_nutrient.apply(get_maximum)[['value', 'food']]

# make the food a little smaller
max_foods.food = max_foods.food.str[:50]
```

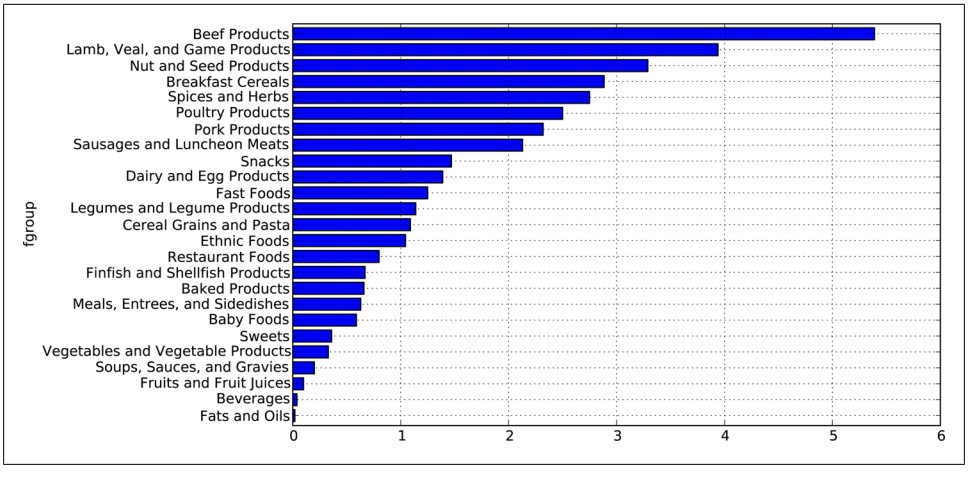


Figure 7-1. Median Zinc values by nutrient group

The resulting DataFrame is a bit too large to display in the book; here is just the `'Amino Acids'` nutrient group:

```
In [284]: max_foods.ix['Amino Acids']['food']
Out[284]:
nutrient
Alanine                          Gelatins, dry powder, unsweetened
Arginine                              Seeds, sesame flour, low-fat
Aspartic acid                                  Soy protein isolate
Cystine                Seeds, cottonseed flour, low fat (glandless)
Glutamic acid                                  Soy protein isolate
Glycine                          Gelatins, dry powder, unsweetened
Histidine                Whale, beluga, meat, dried (Alaska Native)
Hydroxyproline     KENTUCKY FRIED CHICKEN, Fried Chicken, ORIGINAL R
Isoleucine         Soy protein isolate, PROTEIN TECHNOLOGIES INTERNA
Leucine            Soy protein isolate, PROTEIN TECHNOLOGIES INTERNA
Lysine             Seal, bearded (Oogruk), meat, dried (Alaska Nativ
Methionine                    Fish, cod, Atlantic, dried and salted
Phenylalanine      Soy protein isolate, PROTEIN TECHNOLOGIES INTERNA
Proline                          Gelatins, dry powder, unsweetened
Serine             Soy protein isolate, PROTEIN TECHNOLOGIES INTERNA
Threonine          Soy protein isolate, PROTEIN TECHNOLOGIES INTERNA
Tryptophan          Sea lion, Steller, meat with fat (Alaska Native)
Tyrosine           Soy protein isolate, PROTEIN TECHNOLOGIES INTERNA
Valine             Soy protein isolate, PROTEIN TECHNOLOGIES INTERNA
Name: food
```

CHAPTER 8

Plotting and Visualization

Making plots and static or interactive visualizations is one of the most important tasks in data analysis. It may be a part of the exploratory process; for example, helping identify outliers, needed data transformations, or coming up with ideas for models. For others, building an interactive visualization for the web using a toolkit like d3.js (*http://d3js.org/*) may be the end goal. Python has many visualization tools (see the end of this chapter), but I'll be mainly focused on matplotlib (*http://matplotlib.sourceforge.net*).

matplotlib is a (primarily 2D) desktop plotting package designed for creating publication-quality plots. The project was started by John Hunter in 2002 to enable a MATLAB-like plotting interface in Python. He, Fernando Pérez (of IPython), and others have collaborated for many years since then to make IPython combined with matplotlib a very functional and productive environment for scientific computing. When used in tandem with a GUI toolkit (for example, within IPython), matplotlib has interactive features like zooming and panning. It supports many different GUI backends on all operating systems and additionally can export graphics to all of the common vector and raster graphics formats: PDF, SVG, JPG, PNG, BMP, GIF, etc. I have used it to produce almost all of the graphics outside of diagrams in this book.

matplotlib has a number of add-on toolkits, such as `mplot3d` for 3D plots and `basemap` for mapping and projections. I will give an example using `basemap` to plot data on a map and to read *shapefiles* at the end of the chapter.

To follow along with the code examples in the chapter, make sure you have started IPython in Pylab mode (`ipython --pylab`) or enabled GUI event loop integration with the `%gui` magic.

A Brief matplotlib API Primer

There are several ways to interact with matplotlib. The most common is through *pylab mode* in IPython by running `ipython --pylab`. This launches IPython configured to be able to support the matplotlib GUI backend of your choice (Tk, wxPython, PyQt, Mac

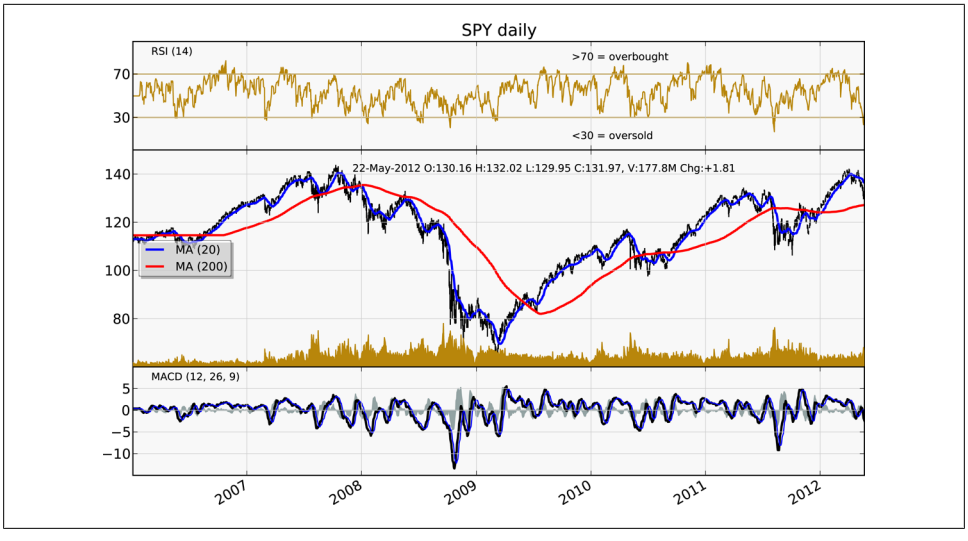


Figure 8-1. A more complex matplotlib financial plot

OS X native, GTK). For most users, the default backend will be sufficient. Pylab mode also imports a large set of modules and functions into IPython to provide a more MATLAB-like interface. You can test that everything is working by making a simple plot:

```
plot(np.arange(10))
```

If everything is set up right, a new window should pop up with a line plot. You can close it by using the mouse or entering `close()`. Matplotlib API functions like `plot` and `close` are all in the `matplotlib.pyplot` module, which is typically imported by convention as:

```
import matplotlib.pyplot as plt
```

While the pandas plotting functions described later deal with many of the mundane details of making plots, should you wish to customize them beyond the function options provided you will need to learn a bit about the matplotlib API.

There is not enough room in the book to give a comprehensive treatment to the breadth and depth of functionality in matplotlib. It should be enough to teach you the ropes to get up and running. The matplotlib gallery and documentation are the best resource for becoming a plotting guru and using advanced features.

Figures and Subplots

Plots in matplotlib reside within a `Figure` object. You can create a new figure with `plt.figure`:

```
In [13]: fig = plt.figure()
```

If you are in pylab mode in IPython, a new empty window should pop up. `plt.figure` has a number of options, notably `figsize` will guarantee the figure has a certain size and aspect ratio if saved to disk. Figures in matplotlib also support a numbering scheme (for example, `plt.figure(2)`) that mimics MATLAB. You can get a reference to the active figure using `plt.gcf()`.

You can't make a plot with a blank figure. You have to create one or more `subplots` using `add_subplot`:

```
In [14]: ax1 = fig.add_subplot(2, 2, 1)
```

This means that the figure should be 2 × 2, and we're selecting the first of 4 subplots (numbered from 1). If you create the next two subplots, you'll end up with a figure that looks like Figure 8-2.

```
In [15]: ax2 = fig.add_subplot(2, 2, 2)

In [16]: ax3 = fig.add_subplot(2, 2, 3)
```

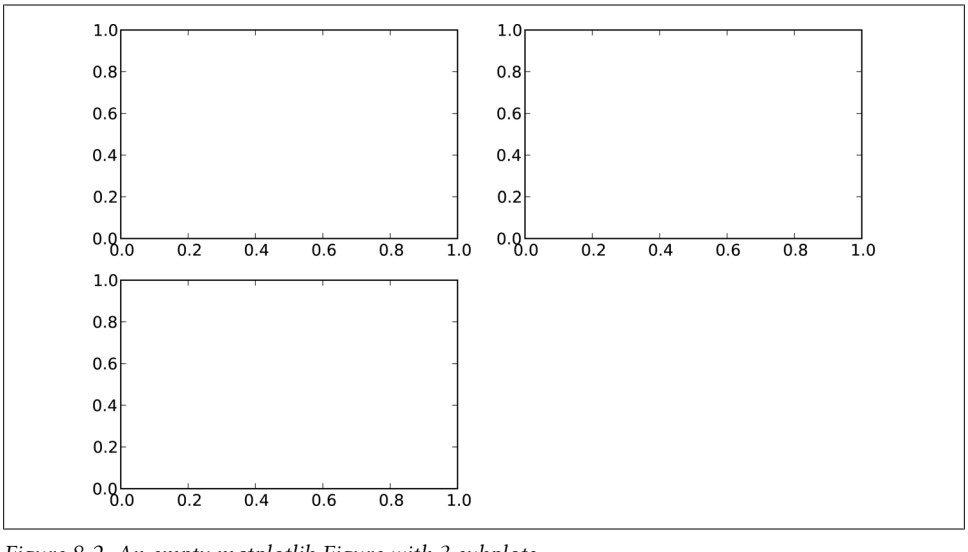


Figure 8-2. An empty matplotlib Figure with 3 subplots

When you issue a plotting command like `plt.plot([1.5, 3.5, -2, 1.6])`, matplotlib draws on the last figure and subplot used (creating one if necessary), thus hiding the figure and subplot creation. Thus, if we run the following command, you'll get something like Figure 8-3:

```
In [17]: from numpy.random import randn

In [18]: plt.plot(randn(50).cumsum(), 'k--')
```

The `'k--'` is a *style* option instructing matplotlib to plot a black dashed line. The objects returned by `fig.add_subplot` above are `AxesSubplot` objects, on which you can directly plot on the other empty subplots by calling each one's instance methods, see Figure 8-4:

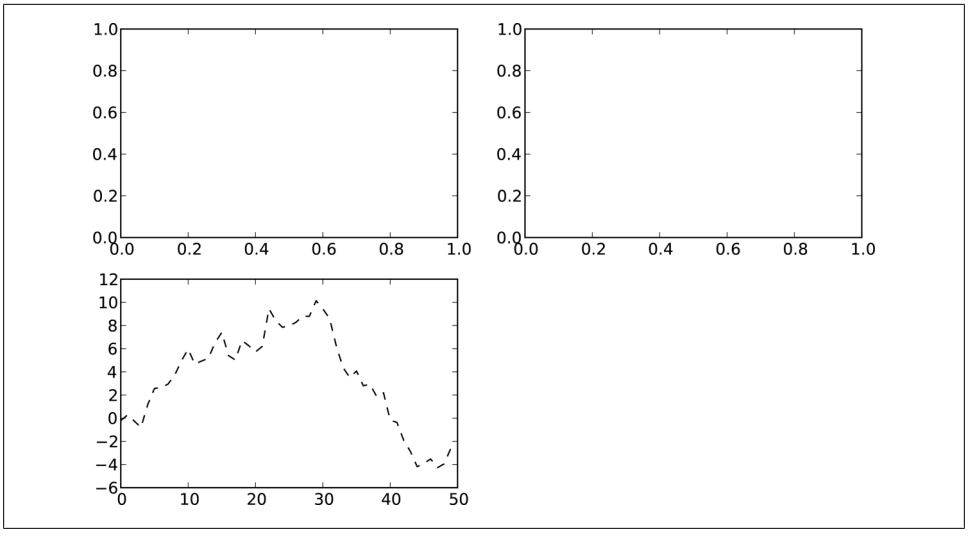


Figure 8-3. Figure after single plot

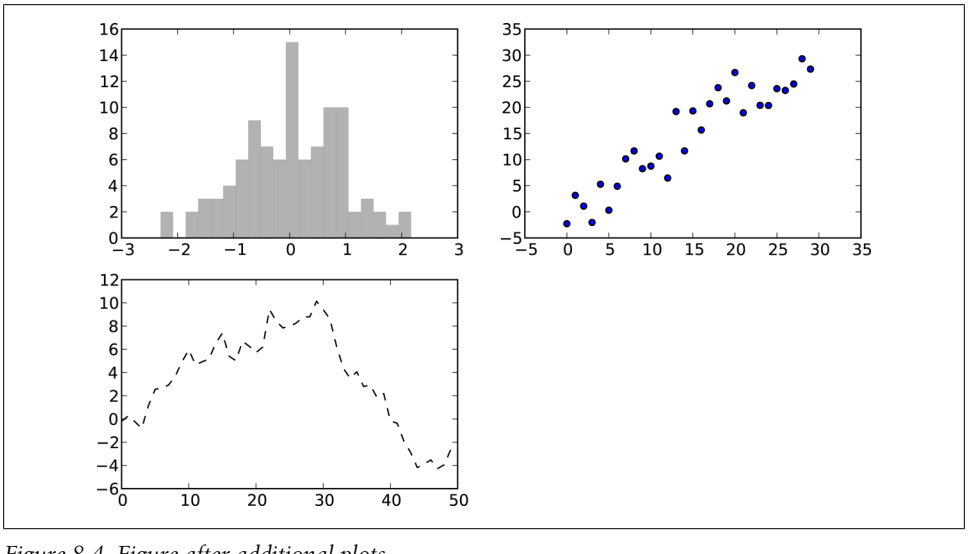


Figure 8-4. Figure after additional plots

```
In [19]: _ = ax1.hist(randn(100), bins=20, color='k', alpha=0.3)

In [20]: ax2.scatter(np.arange(30), np.arange(30) + 3 * randn(30))
```

You can find a comprehensive catalogue of plot types in the matplotlib documentation.

Since creating a figure with multiple subplots according to a particular layout is such a common task, there is a convenience method, `plt.subplots`, that creates a new figure and returns a NumPy array containing the created subplot objects:

```
In [22]: fig, axes = plt.subplots(2, 3)

In [23]: axes
Out[23]:
array([[Axes(0.125,0.536364;0.227941x0.363636),
        Axes(0.398529,0.536364;0.227941x0.363636),
        Axes(0.672059,0.536364;0.227941x0.363636)],
       [Axes(0.125,0.1;0.227941x0.363636),
        Axes(0.398529,0.1;0.227941x0.363636),
        Axes(0.672059,0.1;0.227941x0.363636)]], dtype=object)
```

This is very useful as the `axes` array can be easily indexed like a two-dimensional array; for example, `axes[0, 1]`. You can also indicate that subplots should have the same X or Y axis using `sharex` and `sharey`, respectively. This is especially useful when comparing data on the same scale; otherwise, matplotlib auto-scales plot limits independently. See Table 8-1 for more on this method.

Table 8-1. pyplot.subplots options

Argument	Description
`nrows`	Number of rows of subplots
`ncols`	Number of columns of subplots
`sharex`	All subplots should use the same X-axis ticks (adjusting the `xlim` will affect all subplots)
`sharey`	All subplots should use the same Y-axis ticks (adjusting the `ylim` will affect all subplots)
`subplot_kw`	Dict of keywords for creating the
`**fig_kw`	Additional keywords to `subplots` are used when creating the figure, such as `plt.subplots(2, 2, figsize=(8, 6))`

Adjusting the spacing around subplots

By default matplotlib leaves a certain amount of padding around the outside of the subplots and spacing between subplots. This spacing is all specified relative to the height and width of the plot, so that if you resize the plot either programmatically or manually using the GUI window, the plot will dynamically adjust itself. The spacing can be most easily changed using the `subplots_adjust` `Figure` method, also available as a top-level function:

```
subplots_adjust(left=None, bottom=None, right=None, top=None,
                wspace=None, hspace=None)
```

`wspace` and `hspace` controls the percent of the figure width and figure height, respectively, to use as spacing between subplots. Here is a small example where I shrink the spacing all the way to zero (see Figure 8-5):

```
fig, axes = plt.subplots(2, 2, sharex=True, sharey=True)
for i in range(2):
    for j in range(2):
        axes[i, j].hist(randn(500), bins=50, color='k', alpha=0.5)
plt.subplots_adjust(wspace=0, hspace=0)
```

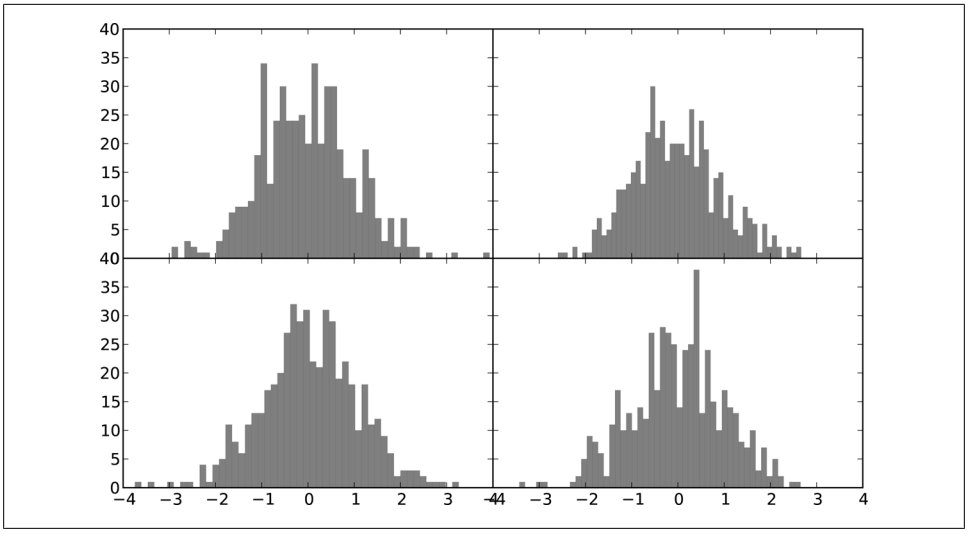


Figure 8-5. Figure with no inter-subplot spacing

You may notice that the axis labels overlap. matplotlib doesn't check whether the labels overlap, so in a case like this you would need to fix the labels yourself by specifying explicit tick locations and tick labels. More on this in the coming sections.

Colors, Markers, and Line Styles

Matplotlib's main `plot` function accepts arrays of X and Y coordinates and optionally a string abbreviation indicating color and line style. For example, to plot `x` versus `y` with green dashes, you would execute:

```
ax.plot(x, y, 'g--')
```

This way of specifying both color and linestyle in a string is provided as a convenience; in practice if you were creating plots programmatically you might prefer not to have to munge strings together to create plots with the desired style. The same plot could also have been expressed more explicitly as:

```
ax.plot(x, y, linestyle='--', color='g')
```

There are a number of color abbreviations provided for commonly-used colors, but any color on the spectrum can be used by specifying its RGB value (for example, `'#CECECE'`). You can see the full set of linestyles by looking at the docstring for `plot`.

Line plots can additionally have *markers* to highlight the actual data points. Since matplotlib creates a continuous line plot, interpolating between points, it can occasionally be unclear where the points lie. The marker can be part of the style string, which must have color followed by marker type and line style (see Figure 8-6):

```
In [28]: plt.plot(randn(30).cumsum(), 'ko--')
```

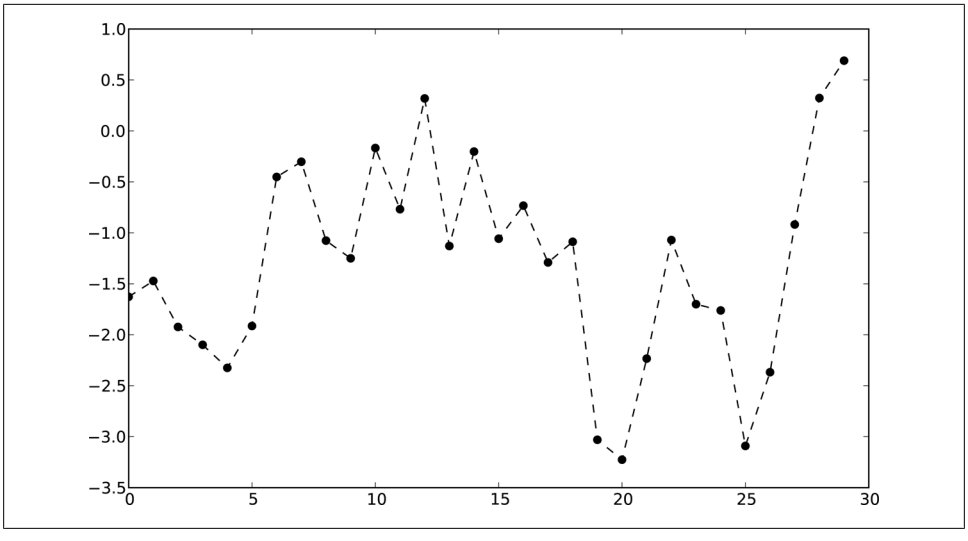


Figure 8-6. Line plot with markers example

This could also have been written more explicitly as:

```
plot(randn(30).cumsum(), color='k', linestyle='dashed', marker='o')
```

For line plots, you will notice that subsequent points are linearly interpolated by default. This can be altered with the `drawstyle` option:

```
In [30]: data = randn(30).cumsum()

In [31]: plt.plot(data, 'k--', label='Default')
Out[31]: [<matplotlib.lines.Line2D at 0x461cdd0>]

In [32]: plt.plot(data, 'k-', drawstyle='steps-post', label='steps-post')
Out[32]: [<matplotlib.lines.Line2D at 0x461f350>]

In [33]: plt.legend(loc='best')
```

Ticks, Labels, and Legends

For most kinds of plot decorations, there are two main ways to do things: using the procedural `pyplot` interface (which will be very familiar to MATLAB users) and the more object-oriented native matplotlib API.

The `pyplot` interface, designed for interactive use, consists of methods like `xlim`, `xticks`, and `xticklabels`. These control the plot range, tick locations, and tick labels, respectively. They can be used in two ways:

- Called with no arguments returns the current parameter value. For example `plt.xlim()` returns the current X axis plotting range

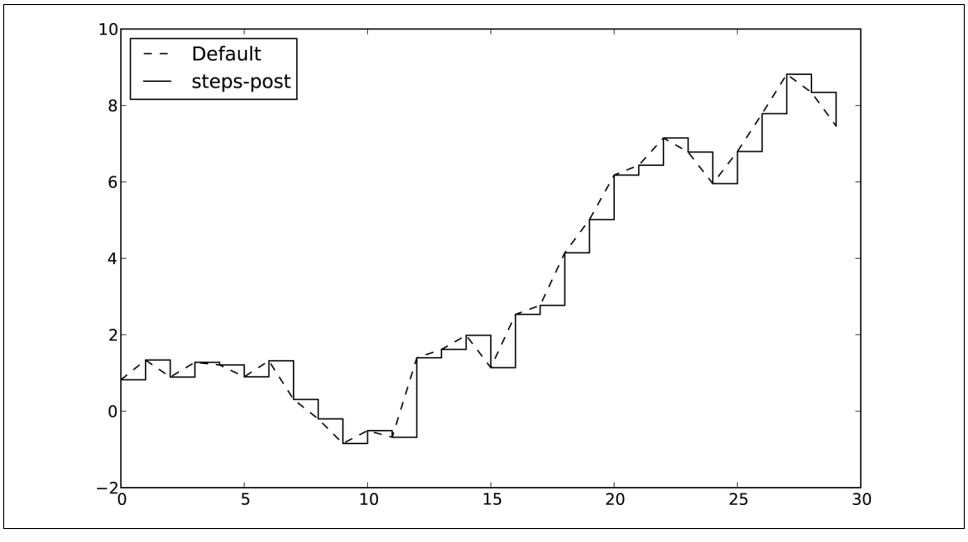


Figure 8-7. Line plot with different drawstyle options

- Called with parameters sets the parameter value. So `plt.xlim([0, 10])`, sets the X axis range to 0 to 10

All such methods act on the active or most recently-created `AxesSubplot`. Each of them corresponds to two methods on the subplot object itself; in the case of `xlim` these are `ax.get_xlim` and `ax.set_xlim`. I prefer to use the subplot instance methods myself in the interest of being explicit (and especially when working with multiple subplots), but you can certainly use whichever you find more convenient.

Setting the title, axis labels, ticks, and ticklabels

To illustrate customizing the axes, I'll create a simple figure and plot of a random walk (see Figure 8-8):

```
In [34]: fig = plt.figure(); ax = fig.add_subplot(1, 1, 1)

In [35]: ax.plot(randn(1000).cumsum())
```

To change the X axis ticks, it's easiest to use `set_xticks` and `set_xticklabels`. The former instructs matplotlib where to place the ticks along the data range; by default these locations will also be the labels. But we can set any other values as the labels using `set_xticklabels`:

```
In [36]: ticks = ax.set_xticks([0, 250, 500, 750, 1000])

In [37]: labels = ax.set_xticklabels(['one', 'two', 'three', 'four', 'five'],
   ....:                             rotation=30, fontsize='small')
```

Lastly, `set_xlabel` gives a name to the X axis and `set_title` the subplot title:

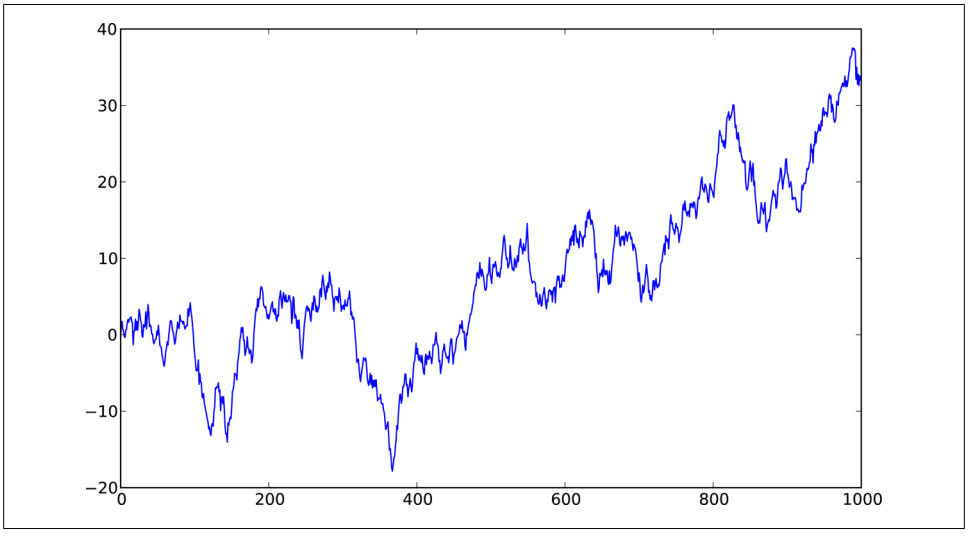


Figure 8-8. Simple plot for illustrating xticks

```
In [38]: ax.set_title('My first matplotlib plot')
Out[38]: <matplotlib.text.Text at 0x7f9190912850>

In [39]: ax.set_xlabel('Stages')
```

See Figure 8-9 for the resulting figure. Modifying the Y axis consists of the same process, substituting `y` for `x` in the above.

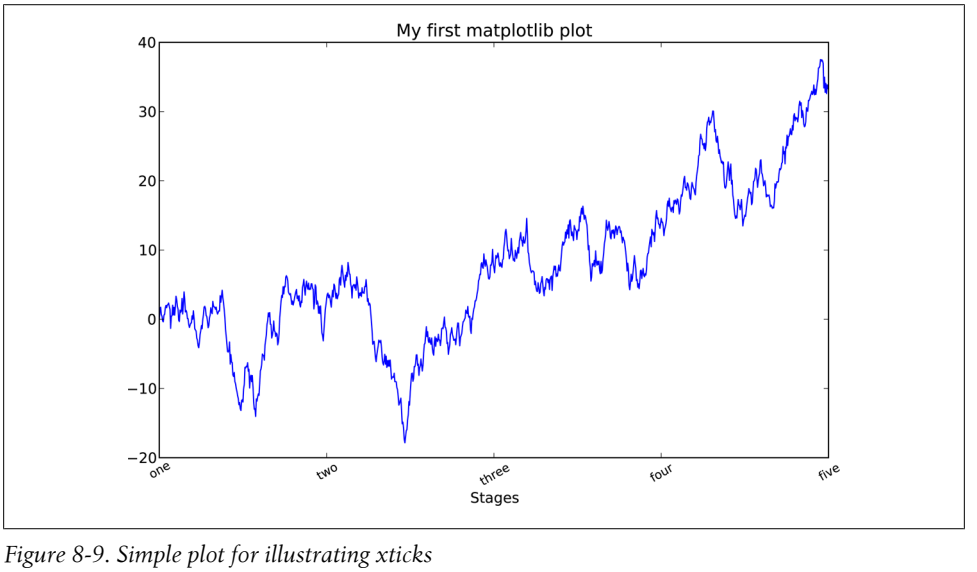


Figure 8-9. Simple plot for illustrating xticks

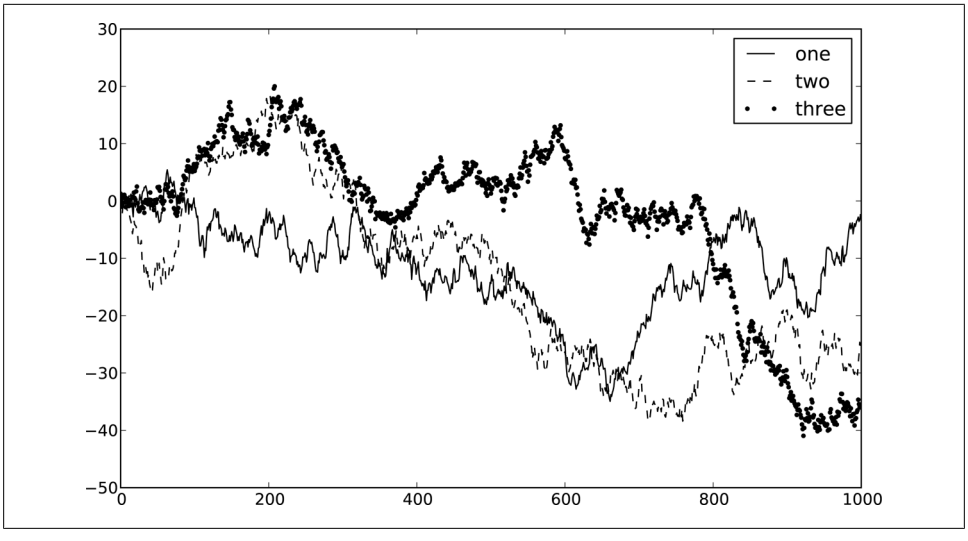


Figure 8-10. Simple plot with 3 lines and legend

Adding legends

Legends are another critical element for identifying plot elements. There are a couple of ways to add one. The easiest is to pass the `label` argument when adding each piece of the plot:

```
In [40]: fig = plt.figure(); ax = fig.add_subplot(1, 1, 1)

In [41]: ax.plot(randn(1000).cumsum(), 'k', label='one')
Out[41]: [<matplotlib.lines.Line2D at 0x4720a90>]

In [42]: ax.plot(randn(1000).cumsum(), 'k--', label='two')
Out[42]: [<matplotlib.lines.Line2D at 0x4720f90>]

In [43]: ax.plot(randn(1000).cumsum(), 'k.', label='three')
Out[43]: [<matplotlib.lines.Line2D at 0x4723550>]
```

Once you've done this, you can either call `ax.legend()` or `plt.legend()` to automatically create a legend:

```
In [44]: ax.legend(loc='best')
```

See Figure 8-10. The `loc` tells matplotlib where to place the plot. If you aren't picky `'best'` is a good option, as it will choose a location that is most out of the way. To exclude one or more elements from the legend, pass no label or `label='_nolegend_'`.

Annotations and Drawing on a Subplot

In addition to the standard plot types, you may wish to draw your own plot annotations, which could consist of text, arrows, or other shapes.

Annotations and text can be added using the `text`, `arrow`, and `annotate` functions. `text` draws text at given coordinates `(x, y)` on the plot with optional custom styling:

```
ax.text(x, y, 'Hello world!',
        family='monospace', fontsize=10)
```

Annotations can draw both text and arrows arranged appropriately. As an example, let's plot the closing S&P 500 index price since 2007 (obtained from Yahoo! Finance) and annotate it with some of the important dates from the 2008-2009 financial crisis. See Figure 8-11 for the result:

```
from datetime import datetime

fig = plt.figure()
ax = fig.add_subplot(1, 1, 1)

data = pd.read_csv('ch08/spx.csv', index_col=0, parse_dates=True)
spx = data['SPX']

spx.plot(ax=ax, style='k-')

crisis_data = [
    (datetime(2007, 10, 11), 'Peak of bull market'),
    (datetime(2008, 3, 12), 'Bear Stearns Fails'),
    (datetime(2008, 9, 15), 'Lehman Bankruptcy')
]

for date, label in crisis_data:
    ax.annotate(label, xy=(date, spx.asof(date) + 50),
                xytext=(date, spx.asof(date) + 200),
                arrowprops=dict(facecolor='black'),
                horizontalalignment='left', verticalalignment='top')

# Zoom in on 2007-2010
ax.set_xlim(['1/1/2007', '1/1/2011'])
ax.set_ylim([600, 1800])

ax.set_title('Important dates in 2008-2009 financial crisis')
```

See the online matplotlib gallery for many more annotation examples to learn from.

Drawing shapes requires some more care. matplotlib has objects that represent many common shapes, referred to as *patches*. Some of these, like `Rectangle` and `Circle` are found in `matplotlib.pyplot`, but the full set is located in `matplotlib.patches`.

To add a shape to a plot, you create the patch object `shp` and add it to a subplot by calling `ax.add_patch(shp)` (see Figure 8-12):

```
fig = plt.figure()
ax = fig.add_subplot(1, 1, 1)

rect = plt.Rectangle((0.2, 0.75), 0.4, 0.15, color='k', alpha=0.3)
circ = plt.Circle((0.7, 0.2), 0.15, color='b', alpha=0.3)
pgon = plt.Polygon([[0.15, 0.15], [0.35, 0.4], [0.2, 0.6]],
                   color='g', alpha=0.5)
```

```
ax.add_patch(rect)
ax.add_patch(circ)
ax.add_patch(pgon)
```

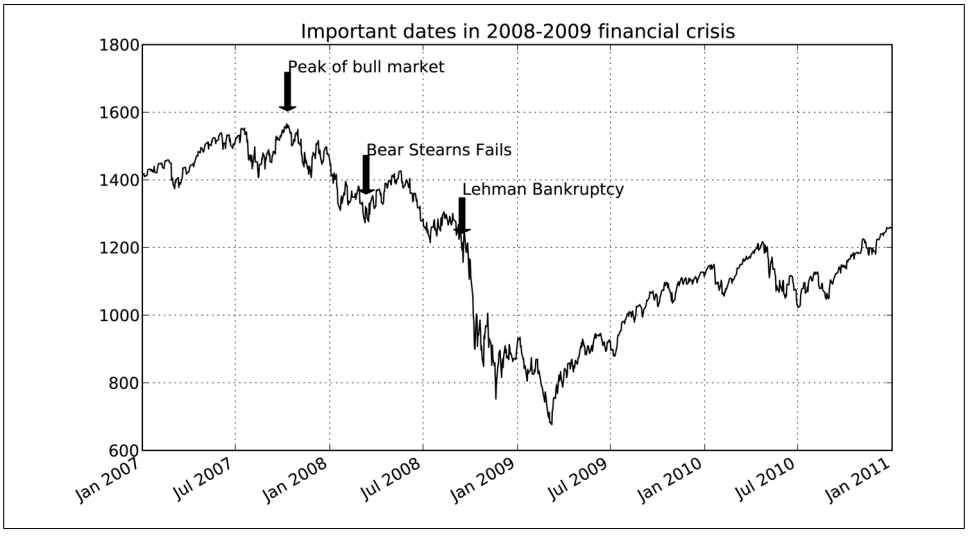


Figure 8-11. Important dates in 2008-2009 financial crisis

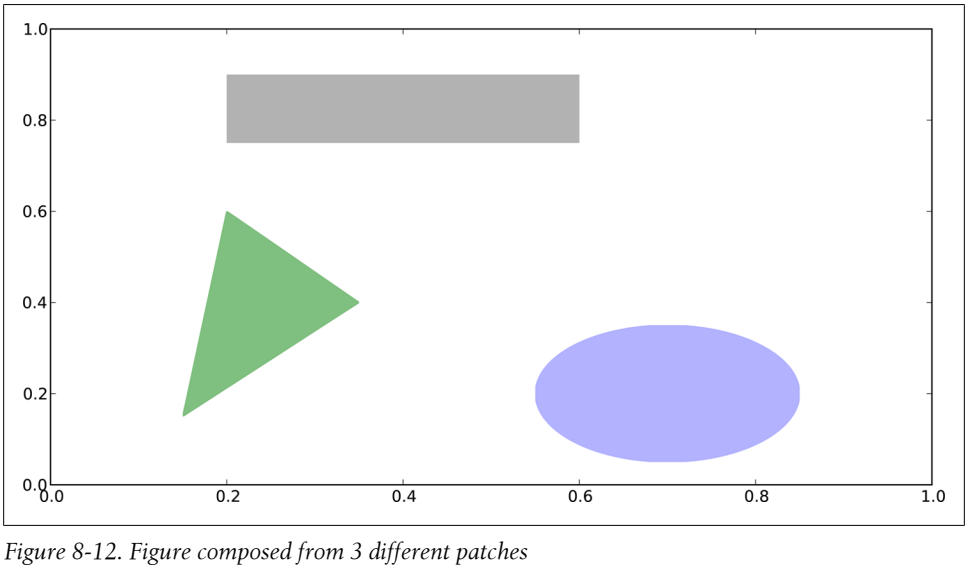


Figure 8-12. Figure composed from 3 different patches

If you look at the implementation of many familiar plot types, you will see that they are assembled from patches.

Saving Plots to File

The active figure can be saved to file using `plt.savefig`. This method is equivalent to the figure object's `savefig` instance method. For example, to save an SVG version of a figure, you need only type:

```
plt.savefig('figpath.svg')
```

The file type is inferred from the file extension. So if you used `.pdf` instead you would get a PDF. There are a couple of important options that I use frequently for publishing graphics: `dpi`, which controls the dots-per-inch resolution, and `bbox_inches`, which can trim the whitespace around the actual figure. To get the same plot as a PNG above with minimal whitespace around the plot and at 400 DPI, you would do:

```
plt.savefig('figpath.png', dpi=400, bbox_inches='tight')
```

`savefig` doesn't have to write to disk; it can also write to any file-like object, such as a `StringIO`:

```
from io import StringIO
buffer = StringIO()
plt.savefig(buffer)
plot_data = buffer.getvalue()
```

For example, this is useful for serving dynamically-generated images over the web.

Table 8-2. Figure.savefig options

Argument	Description
`fname`	String containing a filepath or a Python file-like object. The figure format is inferred from the file extension, e.g. `.pdf` for PDF or `.png` for PNG.
`dpi`	The figure resolution in dots per inch; defaults to 100 out of the box but can be configured
`facecolor, edge color`	The color of the figure background outside of the subplots. `'w'` (white), by default
`format`	The explicit file format to use (`'png', 'pdf', 'svg', 'ps', 'eps', ...`)
`bbox_inches`	The portion of the figure to save. If `'tight'` is passed, will attempt to trim the empty space around the figure

matplotlib Configuration

matplotlib comes configured with color schemes and defaults that are geared primarily toward preparing figures for publication. Fortunately, nearly all of the default behavior can be customized via an extensive set of global parameters governing figure size, subplot spacing, colors, font sizes, grid styles, and so on. There are two main ways to interact with the matplotlib configuration system. The first is programmatically from Python using the `rc` method. For example, to set the global default figure size to be 10 x 10, you could enter:

```
plt.rc('figure', figsize=(10, 10))
```

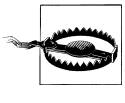
The first argument to `rc` is the component you wish to customize, such as `'figure'`, `'axes'`, `'xtick'`, `'ytick'`, `'grid'`, `'legend'` or many others. After that can follow a sequence of keyword arguments indicating the new parameters. An easy way to write down the options in your program is as a dict:

```
font_options = {'family' : 'monospace',
                'weight' : 'bold',
                'size'   : 'small'}
plt.rc('font', **font_options)
```

For more extensive customization and to see a list of all the options, matplotlib comes with a configuration file `matplotlibrc` in the `matplotlib/mpl-data` directory. If you customize this file and place it in your home directory titled `.matplotlibrc`, it will be loaded each time you use matplotlib.

Plotting Functions in pandas

As you've seen, matplotlib is actually a fairly low-level tool. You assemble a plot from its base components: the data display (the type of plot: line, bar, box, scatter, contour, etc.), legend, title, tick labels, and other annotations. Part of the reason for this is that in many cases the data needed to make a complete plot is spread across many objects. In pandas we have row labels, column labels, and possibly grouping information. This means that many kinds of fully-formed plots that would ordinarily require a lot of matplotlib code can be expressed in one or two concise statements. Therefore, pandas has an increasing number of high-level plotting methods for creating standard visualizations that take advantage of how data is organized in DataFrame objects.



As of this writing, the plotting functionality in pandas is undergoing quite a bit of work. As part of the 2012 Google Summer of Code program, a student is working full time to add features and to make the interface more consistent and usable. Thus, it's possible that this code may fall out-of-date faster than the other things in this book. The online pandas documentation will be the best resource in that event.

Line Plots

Series and DataFrame each have a `plot` method for making many different plot types. By default, they make line plots (see Figure 8-13):

```
In [55]: s = Series(np.random.randn(10).cumsum(), index=np.arange(0, 100, 10))

In [56]: s.plot()
```

The Series object's index is passed to matplotlib for plotting on the X axis, though this can be disabled by passing `use_index=False`. The X axis ticks and limits can be adjusted using the `xticks` and `xlim` options, and Y axis respectively using `yticks` and `ylim`. See

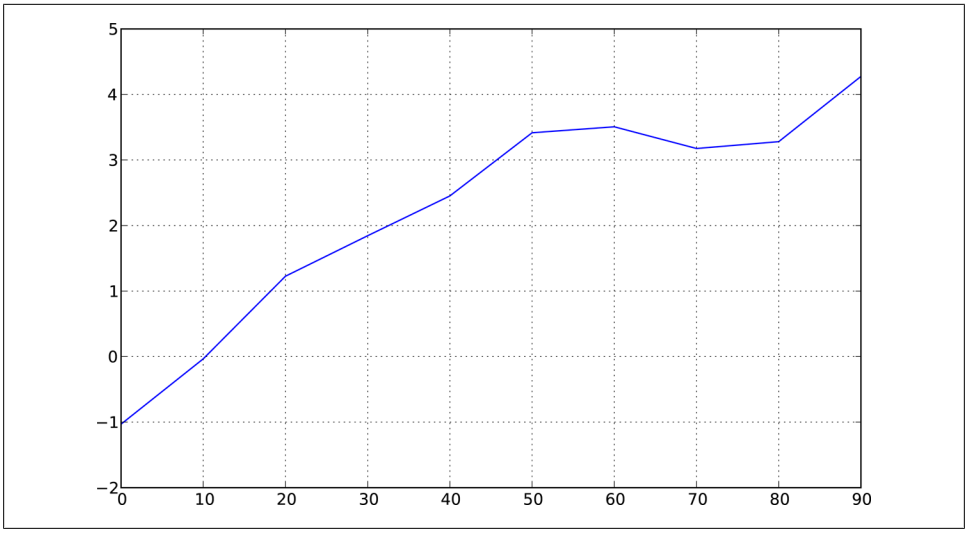


Figure 8-13. Simple Series plot example

Table 8-3 for a full listing of `plot` options. I'll comment on a few more of them throughout this section and leave the rest to you to explore.

Most of pandas's plotting methods accept an optional `ax` parameter, which can be a matplotlib subplot object. This gives you more flexible placement of subplots in a grid layout. There will be more on this in the later section on the matplotlib API.

DataFrame's `plot` method plots each of its columns as a different line on the same subplot, creating a legend automatically (see Figure 8-14):

```
In [57]: df = DataFrame(np.random.randn(10, 4).cumsum(0),
   ....:                columns=['A', 'B', 'C', 'D'],
   ....:                index=np.arange(0, 100, 10))

In [58]: df.plot()
```

Additional keyword arguments to `plot` are passed through to the respective matplotlib plotting function, so you can further customize these plots by learning more about the matplotlib API.

Table 8-3. Series.plot method arguments

Argument	Description
`label`	Label for plot legend
`ax`	matplotlib subplot object to plot on. If nothing passed, uses active matplotlib subplot
`style`	Style string, like `'ko--'`, to be passed to matplotlib.
`alpha`	The plot fill opacity (from 0 to 1)

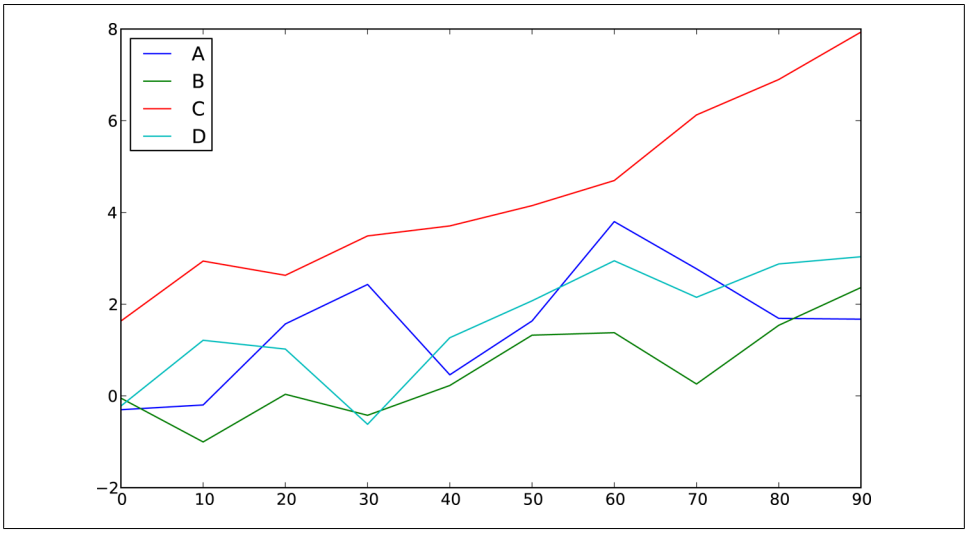


Figure 8-14. Simple DataFrame plot example

Argument	Description
`kind`	Can be `'line'`, `'bar'`, `'barh'`, `'kde'`
`logy`	Use logarithmic scaling on the Y axis
`use_index`	Use the object index for tick labels
`rot`	Rotation of tick labels (0 through 360)
`xticks`	Values to use for X axis ticks
`yticks`	Values to use for Y axis ticks
`xlim`	X axis limits (e.g. `[0, 10]`)
`ylim`	Y axis limits
`grid`	Display axis grid (on by default)

DataFrame has a number of options allowing some flexibility with how the columns are handled; for example, whether to plot them all on the same subplot or to create separate subplots. See Table 8-4 for more on these.

Table 8-4. DataFrame-specific plot arguments

Argument	Description
`subplots`	Plot each DataFrame column in a separate subplot
`sharex`	If `subplots=True`, share the same X axis, linking ticks and limits
`sharey`	If `subplots=True`, share the same Y axis
`figsize`	Size of figure to create as tuple

Argument	Description
`title`	Plot title as string
`legend`	Add a subplot legend (`True` by default)
`sort_columns`	Plot columns in alphabetical order; by default uses existing column order

For time series plotting, see Chapter 10.

Bar Plots

Making bar plots instead of line plots is a simple as passing `kind='bar'` (for vertical bars) or `kind='barh'` (for horizontal bars). In this case, the Series or DataFrame index will be used as the X (`bar`) or Y (`barh`) ticks (see Figure 8-15):

```
In [59]: fig, axes = plt.subplots(2, 1)

In [60]: data = Series(np.random.rand(16), index=list('abcdefghijklmnop'))

In [61]: data.plot(kind='bar', ax=axes[0], color='k', alpha=0.7)
Out[61]: <matplotlib.axes.AxesSubplot at 0x4ee7750>

In [62]: data.plot(kind='barh', ax=axes[1], color='k', alpha=0.7)
```

For more on the `plt.subplots` function and matplotlib axes and figures, see the later section in this chapter.

With a DataFrame, bar plots group the values in each row together in a group in bars, side by side, for each value. See Figure 8-16:

```
In [63]: df = DataFrame(np.random.rand(6, 4),
   ....:                index=['one', 'two', 'three', 'four', 'five', 'six'],
   ....:                columns=pd.Index(['A', 'B', 'C', 'D'], name='Genus'))

In [64]: df
Out[64]:
Genus         A         B         C         D
one    0.301686  0.156333  0.371943  0.270731
two    0.750589  0.525587  0.689429  0.358974
three  0.381504  0.667707  0.473772  0.632528
four   0.942408  0.180186  0.708284  0.641783
five   0.840278  0.909589  0.010041  0.653207
six    0.062854  0.589813  0.811318  0.060217

In [65]: df.plot(kind='bar')
```

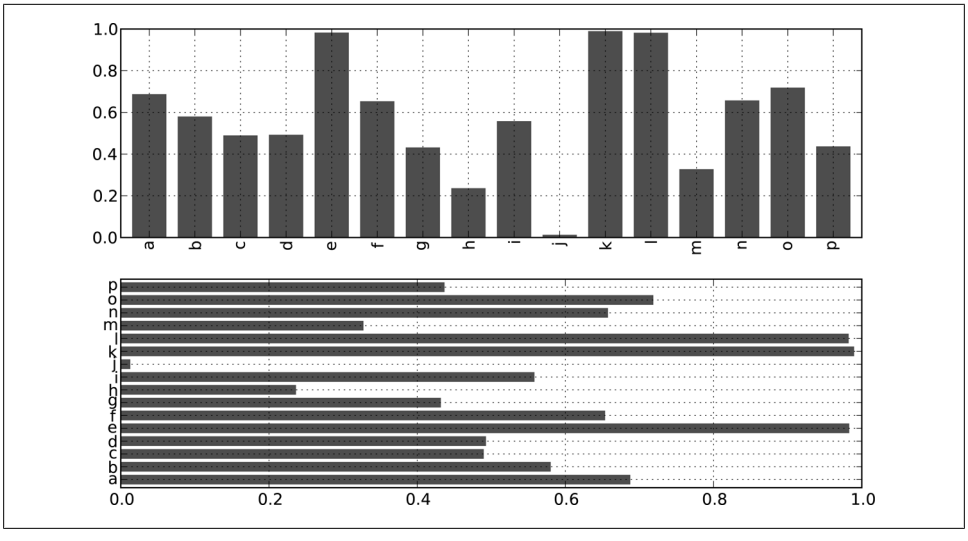


Figure 8-15. Horizonal and vertical bar plot example

Note that the name "Genus" on the DataFrame's columns is used to title the legend.

Stacked bar plots are created from a DataFrame by passing `stacked=True`, resulting in the value in each row being stacked together (see Figure 8-17):

```
In [67]: df.plot(kind='barh', stacked=True, alpha=0.5)
```

A useful recipe for bar plots (as seen in an earlier chapter) is to visualize a Series's value frequency using `value_counts`: `s.value_counts().plot(kind='bar')`.

Returning to the tipping data set used earlier in the book, suppose we wanted to make a stacked bar plot showing the percentage of data points for each party size on each day. I load the data using `read_csv` and make a cross-tabulation by day and party size:

```
In [68]: tips = pd.read_csv('ch08/tips.csv')

In [69]: party_counts = pd.crosstab(tips.day, tips.size)

In [70]: party_counts
Out[70]:
size  1   2   3   4  5  6
day
Fri   1  16   1   1  0  0
Sat   2  53  18  13  1  0
Sun   0  39  15  18  3  1
Thur  1  48   4   5  1  3
```

```
# Not many 1- and 6-person parties
In [71]: party_counts = party_counts.ix[:, 2:5]
```

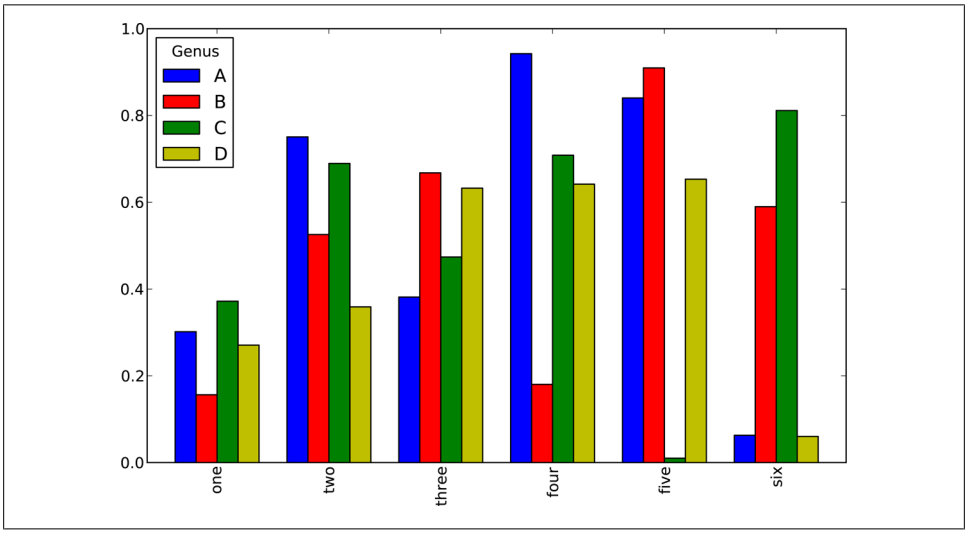


Figure 8-16. DataFrame bar plot example

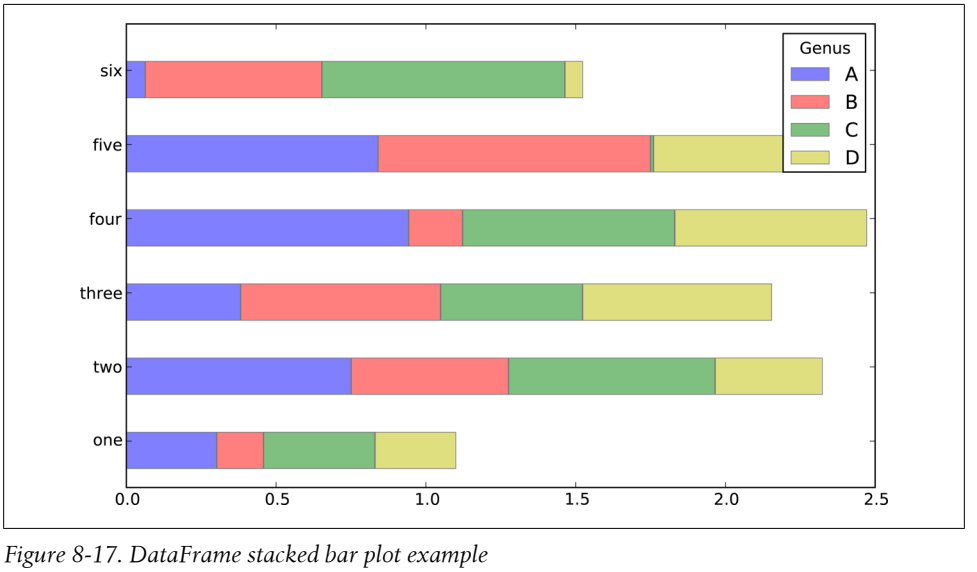


Figure 8-17. DataFrame stacked bar plot example

Then, normalize so that each row sums to 1 (I have to cast to float to avoid integer division issues on Python 2.7) and make the plot (see Figure 8-18):

```
# Normalize to sum to 1
In [72]: party_pcts = party_counts.div(party_counts.sum(1).astype(float), axis=0)
```

```
In [73]: party_pcts
Out[73]:
size         2         3         4         5
day
Fri   0.888889  0.055556  0.055556  0.000000
Sat   0.623529  0.211765  0.152941  0.011765
Sun   0.520000  0.200000  0.240000  0.040000
Thur  0.827586  0.068966  0.086207  0.017241

In [74]: party_pcts.plot(kind='bar', stacked=True)
```

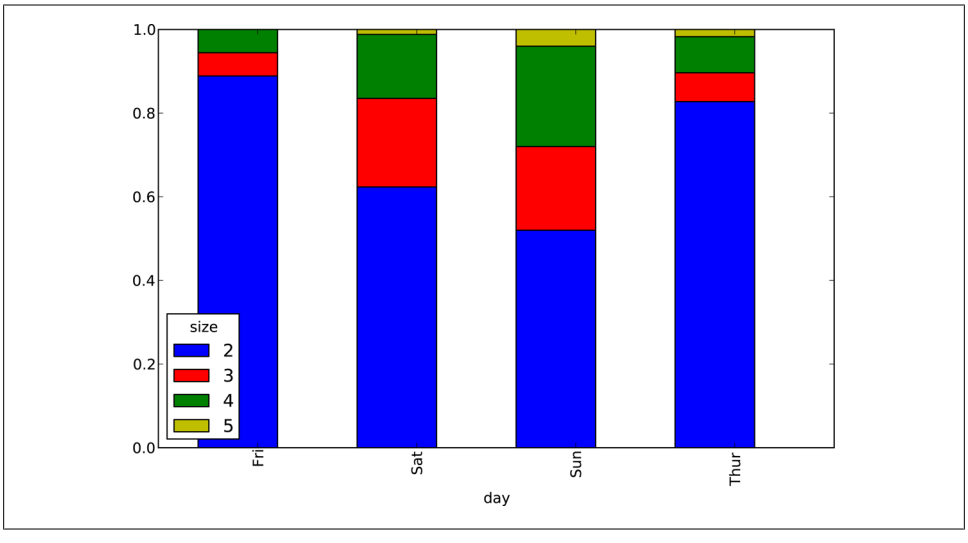


Figure 8-18. Fraction of parties by size on each day

So you can see that party sizes appear to increase on the weekend in this data set.

Histograms and Density Plots

A histogram, with which you may be well-acquainted, is a kind of bar plot that gives a discretized display of value frequency. The data points are split into discrete, evenly spaced bins, and the number of data points in each bin is plotted. Using the tipping data from before, we can make a histogram of tip percentages of the total bill using the `hist` method on the Series (see Figure 8-19):

```
In [76]: tips['tip_pct'] = tips['tip'] / tips['total_bill']

In [77]: tips['tip_pct'].hist(bins=50)
```

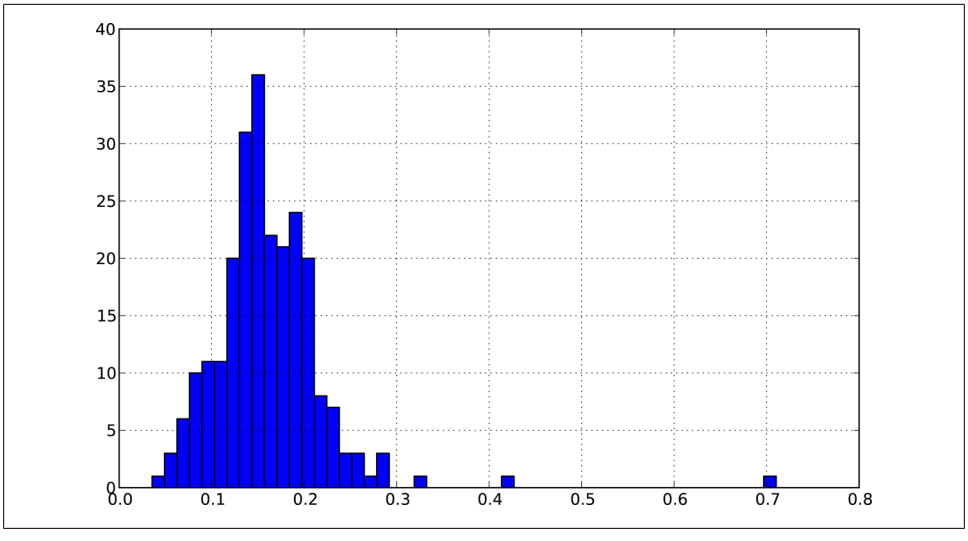


Figure 8-19. Histogram of tip percentages

A related plot type is a *density plot*, which is formed by computing an estimate of a continuous probability distribution that might have generated the observed data. A usual procedure is to approximate this distribution as a mixture of `kernels`, that is, simpler distributions like the normal (Gaussian) distribution. Thus, density plots are also known as KDE (kernel density estimate) plots. Using `plot` with `kind='kde'` makes a density plot using the standard mixture-of-normals KDE (see Figure 8-20):

```
In [79]: tips['tip_pct'].plot(kind='kde')
```

These two plot types are often plotted together; the histogram in normalized form (to give a binned density) with a kernel density estimate plotted on top. As an example, consider a bimodal distribution consisting of draws from two different standard normal distributions (see Figure 8-21):

```
In [81]: comp1 = np.random.normal(0, 1, size=200)  # N(0, 1)

In [82]: comp2 = np.random.normal(10, 2, size=200)  # N(10, 4)

In [83]: values = Series(np.concatenate([comp1, comp2]))

In [84]: values.hist(bins=100, alpha=0.3, color='k', normed=True)
Out[84]: <matplotlib.axes.AxesSubplot at 0x5cd2350>

In [85]: values.plot(kind='kde', style='k--')
```

Scatter Plots

Scatter plots are a useful way of examining the relationship between two one-dimensional data series. matplotlib has a `scatter` plotting method that is the workhorse of

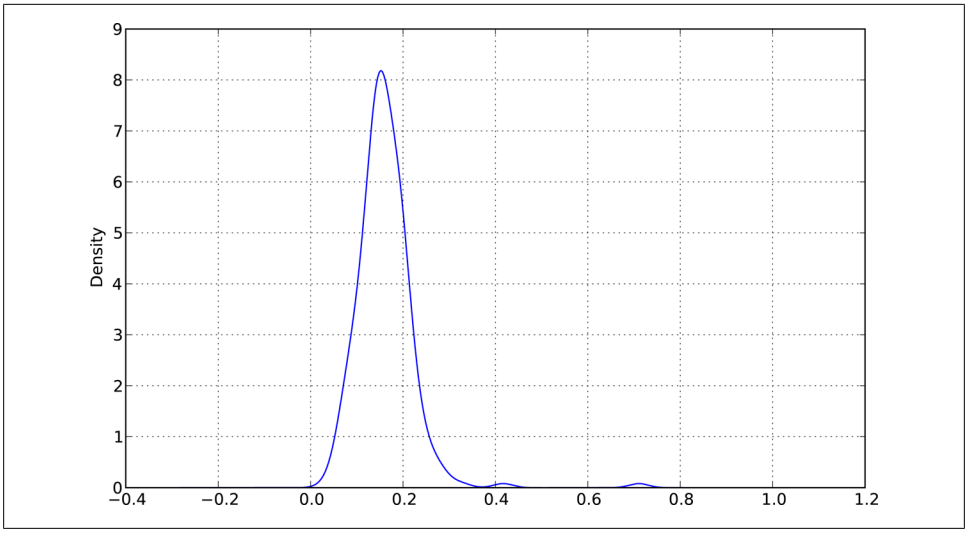


Figure 8-20. Density plot of tip percentages

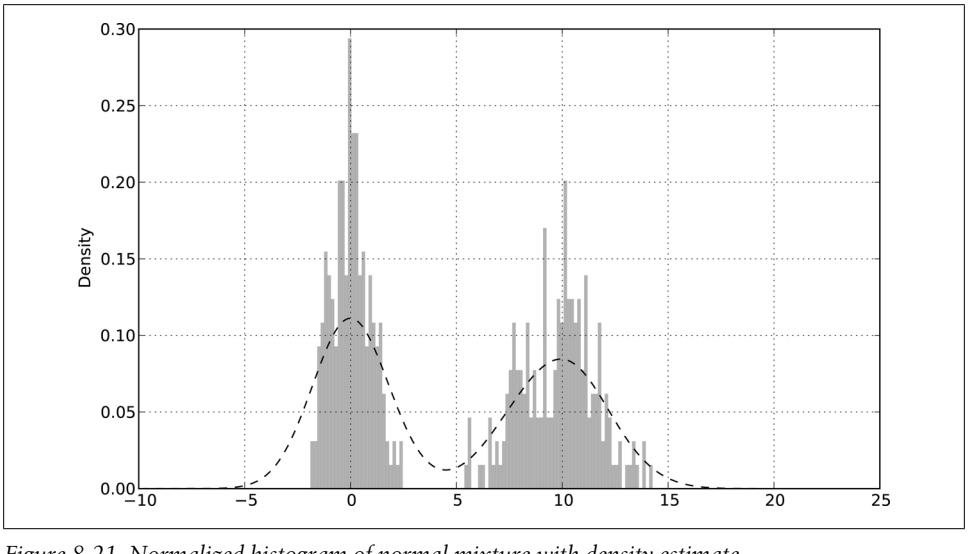


Figure 8-21. Normalized histogram of normal mixture with density estimate

making these kinds of plots. To give an example, I load the `macrodata` dataset from the statsmodels project, select a few variables, then compute log differences:

```
In [86]: macro = pd.read_csv('ch08/macrodata.csv')

In [87]: data = macro[['cpi', 'm1', 'tbilrate', 'unemp']]

In [88]: trans_data = np.log(data).diff().dropna()
```

```
In [89]: trans_data[-5:]
Out[89]:
          cpi        m1  tbilrate     unemp
198 -0.007904  0.045361 -0.396881  0.105361
199 -0.021979  0.066753 -2.277267  0.139762
200  0.002340  0.010286  0.606136  0.160343
201  0.008419  0.037461 -0.200671  0.127339
202  0.008894  0.012202 -0.405465  0.042560
```

It's easy to plot a simple scatter plot using `plt.scatter` (see Figure 8-22):

```
In [91]: plt.scatter(trans_data['m1'], trans_data['unemp'])
Out[91]: <matplotlib.collections.PathCollection at 0x43c31d0>

In [92]: plt.title('Changes in log %s vs. log %s' % ('m1', 'unemp'))
```

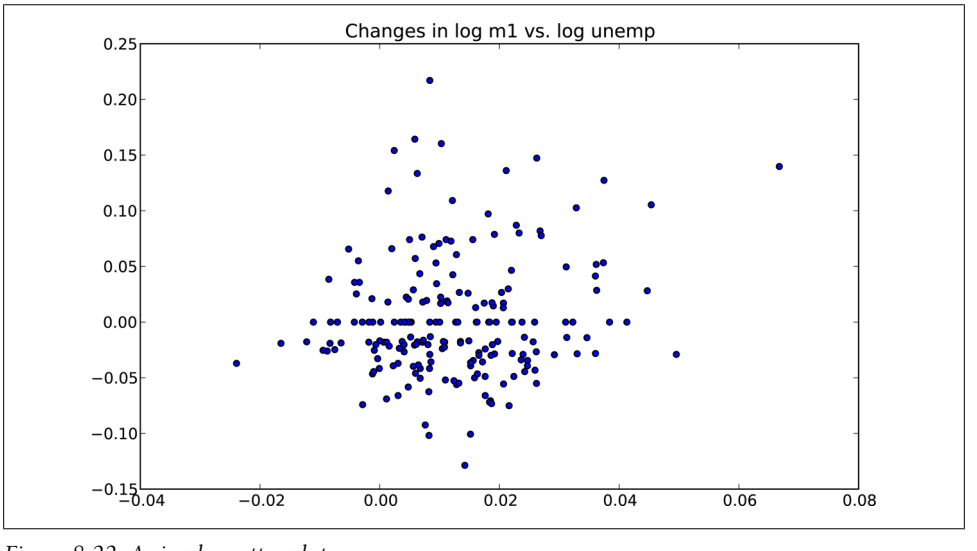


Figure 8-22. A simple scatter plot

In exploratory data analysis it's helpful to be able to look at all the scatter plots among a group of variables; this is known as a *pairs* plot or *scatter plot matrix*. Making such a plot from scratch is a bit of work, so pandas has a `scatter_matrix` function for creating one from a DataFrame. It also supports placing histograms or density plots of each variable along the diagonal. See Figure 8-23 for the resulting plot:

```
In [93]: scatter_matrix(trans_data, diagonal='kde', color='k', alpha=0.3)
```

Plotting Maps: Visualizing Haiti Earthquake Crisis Data

Ushahidi is a non-profit software company that enables crowdsourcing of information related to natural disasters and geopolitical events via text message. Many of these data sets are then published on their website for analysis and visualization. I downloaded

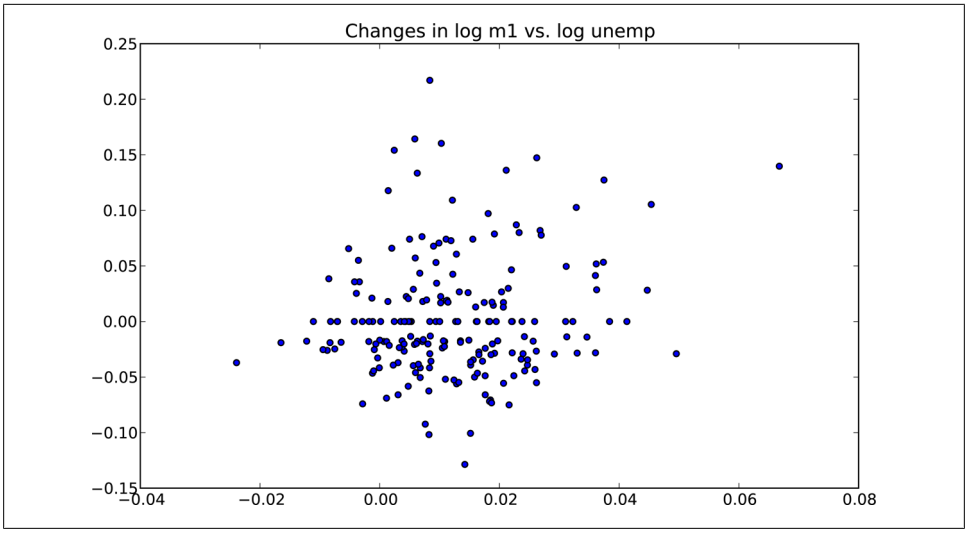


Figure 8-23. Scatter plot matrix of statsmodels macro data

the data collected during the 2010 Haiti earthquake crisis and aftermath, and I'll show you how I prepared the data for analysis and visualization using pandas and other tools we have looked at thus far. After downloading the CSV file from the above link, we can load it into a DataFrame using `read_csv`:

```
In [94]: data = pd.read_csv('ch08/Haiti.csv')

In [95]: data
Out[95]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3593 entries, 0 to 3592
Data columns:
Serial            3593  non-null values
INCIDENT TITLE    3593  non-null values
INCIDENT DATE     3593  non-null values
LOCATION          3593  non-null values
DESCRIPTION       3593  non-null values
CATEGORY          3587  non-null values
LATITUDE          3593  non-null values
LONGITUDE         3593  non-null values
APPROVED          3593  non-null values
VERIFIED          3593  non-null values
dtypes: float64(2), int64(1), object(7)
```

It's easy now to tinker with this data set to see what kinds of things we might want to do with it. Each row represents a report sent from someone's mobile phone indicating an emergency or some other problem. Each has an associated timestamp and a location as latitude and longitude:

```
In [96]: data[['INCIDENT DATE', 'LATITUDE', 'LONGITUDE']][:10]
Out[96]:
      INCIDENT DATE   LATITUDE   LONGITUDE
```

```
0  05/07/2010 17:26  18.233333  -72.533333
1  28/06/2010 23:06  50.226029    5.729886
2  24/06/2010 16:21  22.278381  114.174287
3  20/06/2010 21:59  44.407062    8.933989
4  18/05/2010 16:26  18.571084  -72.334671
5  26/04/2010 13:14  18.593707  -72.310079
6  26/04/2010 14:19  18.482800  -73.638800
7  26/04/2010 14:27  18.415000  -73.195000
8  15/03/2010 10:58  18.517443  -72.236841
9  15/03/2010 11:00  18.547790  -72.410010
```

The `CATEGORY` field contains a comma-separated list of codes indicating the type of message:

```
In [97]: data['CATEGORY'][:6]
Out[97]:
0          1. Urgences | Emergency, 3. Public Health,
1    1. Urgences | Emergency, 2. Urgences logistiques
2    2. Urgences logistiques | Vital Lines, 8. Autre |
3                            1. Urgences | Emergency,
4                            1. Urgences | Emergency,
5                       5e. Communication lines down,
Name: CATEGORY
```

If you notice above in the data summary, some of the categories are missing, so we might want to drop these data points. Additionally, calling `describe` shows that there are some aberrant locations:

```
In [98]: data.describe()
Out[98]:
            Serial     LATITUDE    LONGITUDE
count  3593.000000  3593.000000  3593.000000
mean   2080.277484    18.611495   -72.322680
std    1171.100360     0.738572     3.650776
min       4.000000    18.041313   -74.452757
25%    1074.000000    18.524070   -72.417500
50%    2163.000000    18.539269   -72.335000
75%    3088.000000    18.561820   -72.293570
max    4052.000000    50.226029   114.174287
```

Cleaning the bad locations and removing the missing categories is now fairly simple:

```
In [99]: data = data[(data.LATITUDE > 18) & (data.LATITUDE < 20) &
   ....:             (data.LONGITUDE > -75) & (data.LONGITUDE < -70)
   ....:             & data.CATEGORY.notnull()]
```

Now we might want to do some analysis or visualization of this data by category, but each category field may have multiple categories. Additionally, each category is given as a code plus an English and possibly also a French code name. Thus, a little bit of wrangling is required to get the data into a more agreeable form. First, I wrote these two functions to get a list of all the categories and to split each category into a code and an English name:

```
def to_cat_list(catstr):
    stripped = (x.strip() for x in catstr.split(','))
```

```
    return [x for x in stripped if x]

def get_all_categories(cat_series):
    cat_sets = (set(to_cat_list(x)) for x in cat_series)
    return sorted(set.union(*cat_sets))

def get_english(cat):
    code, names = cat.split('.')
    if '|' in names:
        names = names.split(' | ')[1]
    return code, names.strip()
```

You can test out that the `get_english` function does what you expect:

```
In [101]: get_english('2. Urgences logistiques | Vital Lines')
Out[101]: ('2', 'Vital Lines')
```

Now, I make a `dict` mapping code to name because we'll use the codes for analysis. We'll use this later when adorning plots (note the use of a generator expression in lieu of a list comprehension):

```
In [102]: all_cats = get_all_categories(data.CATEGORY)

# Generator expression
In [103]: english_mapping = dict(get_english(x) for x in all_cats)

In [104]: english_mapping['2a']
Out[104]: 'Food Shortage'

In [105]: english_mapping['6c']
Out[105]: 'Earthquake and aftershocks'
```

There are many ways to go about augmenting the data set to be able to easily select records by category. One way is to add indicator (or dummy) columns, one for each category. To do that, first extract the unique category codes and construct a DataFrame of zeros having those as its columns and the same index as `data`:

```
def get_code(seq):
    return [x.split('.')[0] for x in seq if x]

all_codes = get_code(all_cats)
code_index = pd.Index(np.unique(all_codes))
dummy_frame = DataFrame(np.zeros((len(data), len(code_index))),
                        index=data.index, columns=code_index)
```

If all goes well, `dummy_frame` should look something like this:

```
In [107]: dummy_frame.ix[:, :6]
Out[107]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3569 entries, 0 to 3592
Data columns:
1     3569  non-null values
1a    3569  non-null values
1b    3569  non-null values
1c    3569  non-null values
```

```
1d    3569  non-null values
2     3569  non-null values
dtypes: float64(6)
```

As you recall, the trick is then to set the appropriate entries of each row to 1, lastly joining this with `data`:

```
for row, cat in zip(data.index, data.CATEGORY):
    codes = get_code(to_cat_list(cat))
    dummy_frame.ix[row, codes] = 1

data = data.join(dummy_frame.add_prefix('category_'))
```

`data` finally now has new columns like:

```
In [109]: data.ix[:, 10:15]
Out[109]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3569 entries, 0 to 3592
Data columns:
category_1     3569  non-null values
category_1a    3569  non-null values
category_1b    3569  non-null values
category_1c    3569  non-null values
category_1d    3569  non-null values
dtypes: float64(5)
```

Let's make some plots! As this is spatial data, we'd like to plot the data by category on a map of Haiti. The `basemap` toolkit (*http://matplotlib.github.com/basemap*), an add-on to matplotlib, enables plotting 2D data on maps in Python. `basemap` provides many different globe projections and a means for transforming projecting latitude and longitude coordinates on the globe onto a two-dimensional matplotlib plot. After some trial and error and using the above data as a guideline, I wrote this function which draws a simple black and white map of Haiti:

```
from mpl_toolkits.basemap import Basemap
import matplotlib.pyplot as plt

def basic_haiti_map(ax=None, lllat=17.25, urlat=20.25,
                    lllon=-75, urlon=-71):
    # create polar stereographic Basemap instance.
    m = Basemap(ax=ax, projection='stere',
                lon_0=(urlon + lllon) / 2,
                lat_0=(urlat + lllat) / 2,
                llcrnrlat=lllat, urcrnrlat=urlat,
                llcrnrlon=lllon, urcrnrlon=urlon,
                resolution='f')
    # draw coastlines, state and country boundaries, edge of map.
    m.drawcoastlines()
    m.drawstates()
    m.drawcountries()
    return m
```

The idea, now, is that the returned `Basemap` object, knows how to transform coordinates onto the canvas. I wrote the following code to plot the data observations for a number

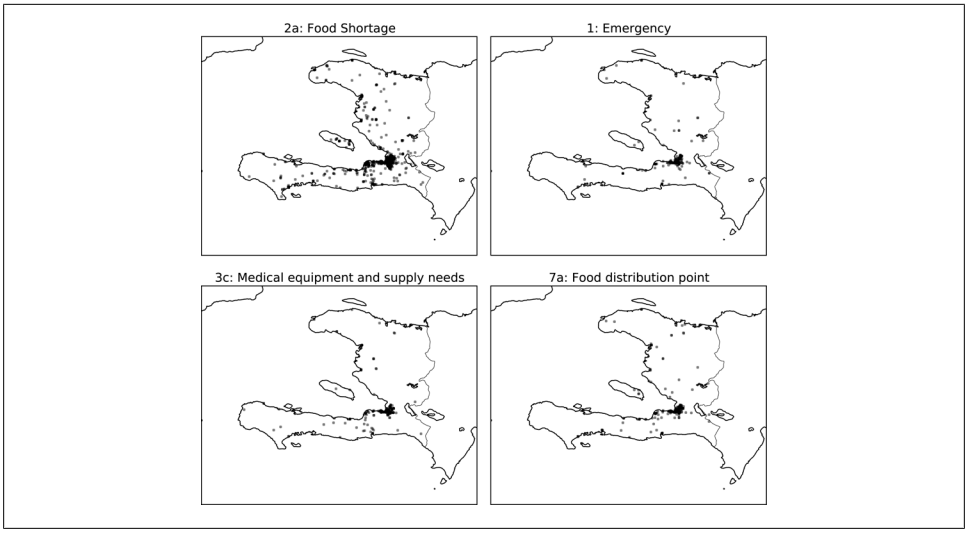


Figure 8-24. Haiti crisis data for 4 categories

of report categories. For each category, I filter down the data set to the coordinates labeled by that category, plot a `Basemap` on the appropriate subplot, transform the coordinates, then plot the points using the `Basemap's plot` method:

```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))
fig.subplots_adjust(hspace=0.05, wspace=0.05)

to_plot = ['2a', '1', '3c', '7a']

lllat=17.25; urlat=20.25; lllon=-75; urlon=-71

for code, ax in zip(to_plot, axes.flat):
    m = basic_haiti_map(ax, lllat=lllat, urlat=urlat,
                        lllon=lllon, urlon=urlon)

    cat_data = data[data['category_%s' % code] == 1]

    # compute map proj coordinates.
    x, y = m(cat_data.LONGITUDE, cat_data.LATITUDE)

    m.plot(x, y, 'k.', alpha=0.5)
    ax.set_title('%s: %s' % (code, english_mapping[code]))
```

The resulting figure can be seen in Figure 8-24.

It seems from the plot that most of the data is concentrated around the most populous city, Port-au-Prince. `basemap` allows you to overlap additional map data which comes from what are called *shapefiles*. I first downloaded a shapefile with roads in Port-au-Prince (see *http://cegrp.cga.harvard.edu/haiti/?q=resources_data*). The `Basemap` object conveniently has a `readshapefile` method so that, after extracting the road data archive, I added just the following lines to my code:

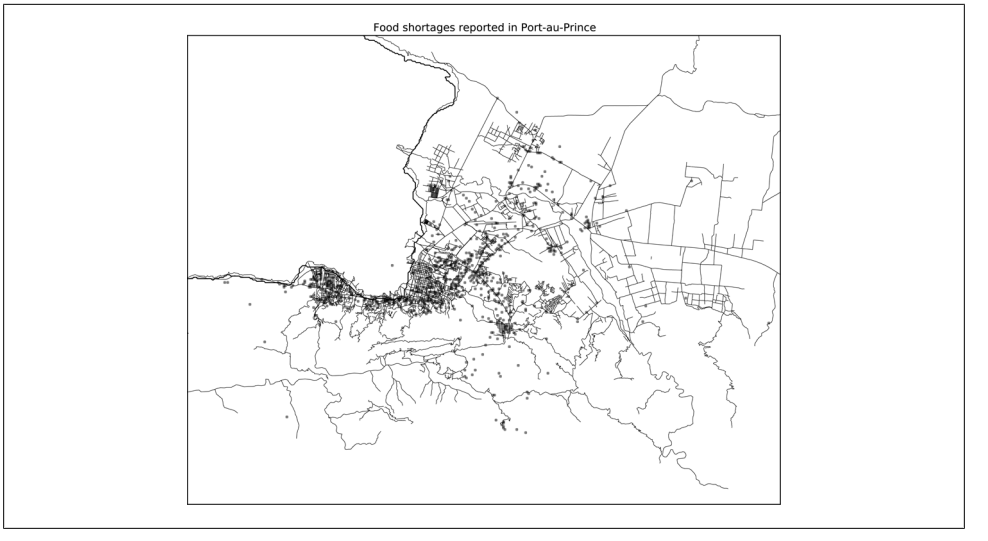


Figure 8-25. Food shortage reports in Port-au-Prince during the Haiti earthquake crisis

```
shapefile_path = 'ch08/PortAuPrince_Roads/PortAuPrince_Roads'
m.readshapefile(shapefile_path, 'roads')
```

After a little more trial and error with the latitude and longitude boundaries, I was able to make Figure 8-25 for the "Food shortage" category.

Python Visualization Tool Ecosystem

As is common with open source, there are a plethora of options for creating graphics in Python (too many to list). In addition to open source, there are numerous commercial libraries with Python bindings.

In this chapter and throughout the book, I have been primarily concerned with matplotlib as it is the most widely used plotting tool in Python. While it's an important part of the scientific Python ecosystem, matplotlib has plenty of shortcomings when it comes to the creation and display of statistical graphics. MATLAB users will likely find matplotlib familiar, while R users (especially users of the excellent `ggplot2` and `trellis` packages) may be somewhat disappointed (at least as of this writing). It is possible to make beautiful plots for display on the web in matplotlib, but doing so often requires significant effort as the library is designed for the printed page. Aesthetics aside, it is sufficient for most needs. In pandas, I, along with the other developers, have sought to build a convenient user interface that makes it easier to make most kinds of plots commonplace in data analysis.

There are a number of other visualization tools in wide use. I list a few of them here and encourage you to explore the ecosystem.

Chaco

Chaco (*http://code.enthought.com/chaco/*), developed by Enthought, is a plotting toolkit suitable both for static plotting and interactive visualizations. It is especially well-suited for expressing complex visualizations with data interrelationships. Compared with matplotlib, Chaco has much better support for interacting with plot elements and rendering is very fast, making it a good choice for building interactive GUI applications.

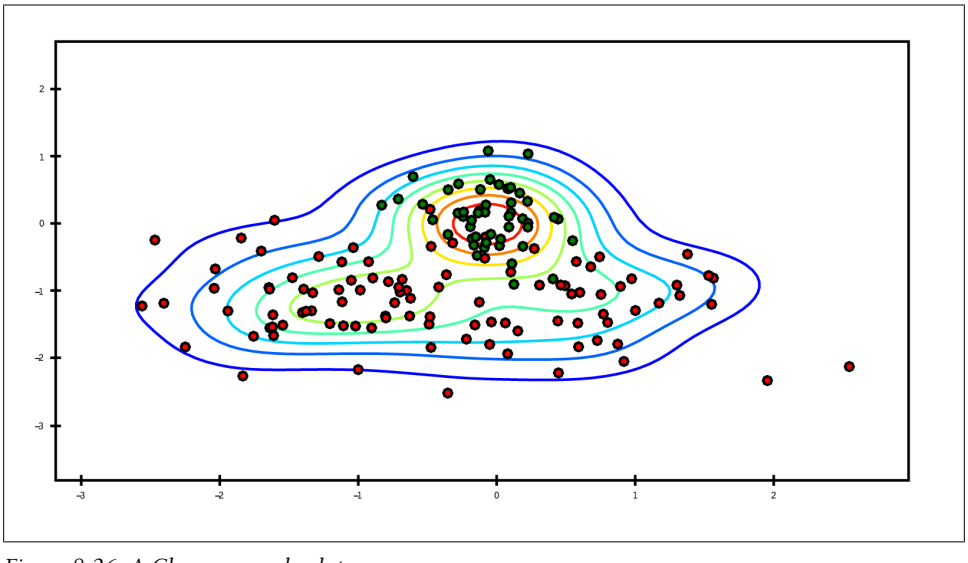


Figure 8-26. A Chaco example plot

mayavi

The mayavi project, developed by Prabhu Ramachandran, Gaël Varoquaux, and others, is a 3D graphics toolkit built on the open source C++ graphics library VTK. mayavi, like matplotlib, integrates with IPython so that it is easy to use interactively. The plots can be panned, rotated, and zoomed using the mouse and keyboard. I used mayavi to make one of the illustrations of broadcasting in Chapter 12. While I don't show any mayavi-using code here, there is plenty of documentation and examples available online. In many cases, I believe it is a good alternative to a technology like WebGL, though the graphics are harder to share in interactive form.

Other Packages

Of course, there are numerous other visualization libraries and applications available in Python: PyQwt, Veusz, gnuplot-py, biggles, and others. I have seen PyQwt put to good use in GUI applications built using the Qt application framework using PyQt. While many of these libraries continue to be under active development (some of them

are part of much larger applications), I have noted in the last few years a general trend toward web-based technologies and away from desktop graphics. I'll say a few more words about this in the next section.

The Future of Visualization Tools?

Visualizations built on web technologies (that is, JavaScript-based) appear to be the inevitable future. Doubtlessly you have used many different kinds of static or interactive visualizations built in Flash or JavaScript over the years. New toolkits (such as d3.js and its numerous off-shoot projects) for building such displays are appearing all the time. In contrast, development in non web-based visualization has slowed significantly in recent years. This holds true of Python as well as other data analysis and statistical computing environments like R.

The development challenge, then, will be in building tighter integration between data analysis and preparation tools, such as pandas, and the web browser. I am hopeful that this will become a fruitful point of collaboration between Python and non-Python users as well.

CHAPTER 9

Data Aggregation and Group Operations

Categorizing a data set and applying a function to each group, whether an aggregation or transformation, is often a critical component of a data analysis workflow. After loading, merging, and preparing a data set, a familiar task is to compute group statistics or possibly *pivot tables* for reporting or visualization purposes. pandas provides a flexible and high-performance `groupby` facility, enabling you to slice and dice, and summarize data sets in a natural way.

One reason for the popularity of relational databases and SQL (which stands for "structured query language") is the ease with which data can be joined, filtered, transformed, and aggregated. However, query languages like SQL are rather limited in the kinds of group operations that can be performed. As you will see, with the expressiveness and power of Python and pandas, we can perform much more complex grouped operations by utilizing any function that accepts a pandas object or NumPy array. In this chapter, you will learn how to:

- Split a pandas object into pieces using one or more keys (in the form of functions, arrays, or DataFrame column names)
- Computing group summary statistics, like count, mean, or standard deviation, or a user-defined function
- Apply a varying set of functions to each column of a DataFrame
- Apply within-group transformations or other manipulations, like normalization, linear regression, rank, or subset selection
- Compute pivot tables and cross-tabulations
- Perform quantile analysis and other data-derived group analyses

Aggregation of time series data, a special use case of `groupby`, is referred to as *resampling* in this book and will receive separate treatment in Chapter 10.

GroupBy Mechanics

Hadley Wickham, an author of many popular packages for the R programming language, coined the term *split-apply-combine* for talking about group operations, and I think that's a good description of the process. In the first stage of the process, data contained in a pandas object, whether a Series, DataFrame, or otherwise, is *split* into groups based on one or more *keys* that you provide. The splitting is performed on a particular axis of an object. For example, a DataFrame can be grouped on its rows (`axis=0`) or its columns (`axis=1`). Once this is done, a function is *applied* to each group, producing a new value. Finally, the results of all those function applications are *combined* into a result object. The form of the resulting object will usually depend on what's being done to the data. See Figure 9-1 for a mockup of a simple group aggregation.

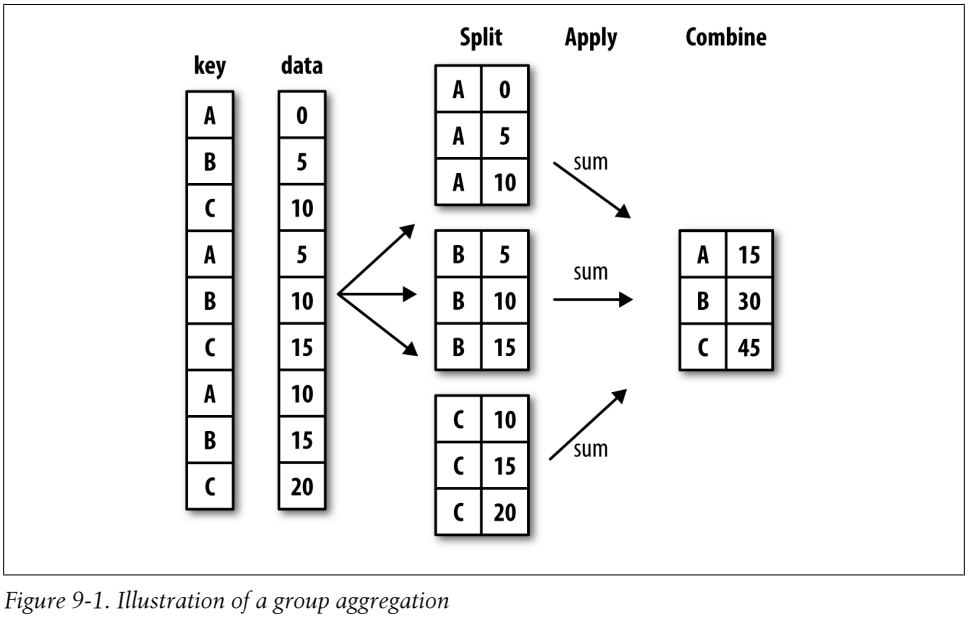


Figure 9-1. Illustration of a group aggregation

Each grouping key can take many forms, and the keys do not have to be all of the same type:

- A list or array of values that is the same length as the axis being grouped
- A value indicating a column name in a DataFrame

- A dict or Series giving a correspondence between the values on the axis being grouped and the group names
- A function to be invoked on the axis index or the individual labels in the index

Note that the latter three methods are all just shortcuts for producing an array of values to be used to split up the object. Don't worry if this all seems very abstract. Throughout this chapter, I will give many examples of all of these methods. To get started, here is a very simple small tabular dataset as a DataFrame:

```
In [13]: df = DataFrame({'key1' : ['a', 'a', 'b', 'b', 'a'],
   ....:                 'key2' : ['one', 'two', 'one', 'two', 'one'],
   ....:                 'data1' : np.random.randn(5),
   ....:                 'data2' : np.random.randn(5)})

In [14]: df
Out[14]:
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
1  0.478943  0.092908    a  two
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
4  1.965781  1.246435    a  one
```

Suppose you wanted to compute the mean of the `data1` column using the groups labels from `key1`. There are a number of ways to do this. One is to access `data1` and call `groupby` with the column (a Series) at `key1`:

```
In [15]: grouped = df['data1'].groupby(df['key1'])

In [16]: grouped
Out[16]: <pandas.core.groupby.SeriesGroupBy at 0x2d78b10>
```

This `grouped` variable is now a *GroupBy* object. It has not actually computed anything yet except for some intermediate data about the group key `df['key1']`. The idea is that this object has all of the information needed to then apply some operation to each of the groups. For example, to compute group means we can call the GroupBy's `mean` method:

```
In [17]: grouped.mean()
Out[17]:
key1
a       0.746672
b      -0.537585
```

Later, I'll explain more about what's going on when you call `.mean()`. The important thing here is that the data (a Series) has been aggregated according to the group key, producing a new Series that is now indexed by the unique values in the `key1` column. The result index has the name `'key1'` because the DataFrame column `df['key1']` did.

If instead we had passed multiple arrays as a list, we get something different:

```
In [18]: means = df['data1'].groupby([df['key1'], df['key2']]).mean()
```

```
In [19]: means
Out[19]:
key1  key2
a     one     0.880536
      two     0.478943
b     one    -0.519439
      two    -0.555730
```

In this case, we grouped the data using two keys, and the resulting Series now has a hierarchical index consisting of the unique pairs of keys observed:

```
In [20]: means.unstack()
Out[20]:
key2       one       two
key1
a     0.880536  0.478943
b    -0.519439 -0.555730
```

In these examples, the group keys are all Series, though they could be any arrays of the right length:

```
In [21]: states = np.array(['Ohio', 'California', 'California', 'Ohio', 'Ohio'])

In [22]: years = np.array([2005, 2005, 2006, 2005, 2006])

In [23]: df['data1'].groupby([states, years]).mean()
Out[23]:
California  2005    0.478943
            2006   -0.519439
Ohio        2005   -0.380219
            2006    1.965781
```

Frequently the grouping information to be found in the same DataFrame as the data you want to work on. In that case, you can pass column names (whether those are strings, numbers, or other Python objects) as the group keys:

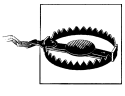
```
In [24]: df.groupby('key1').mean()
Out[24]:
         data1     data2
key1
a     0.746672  0.910916
b    -0.537585  0.525384

In [25]: df.groupby(['key1', 'key2']).mean()
Out[25]:
               data1     data2
key1 key2
a    one   0.880536  1.319920
     two   0.478943  0.092908
b    one  -0.519439  0.281746
     two  -0.555730  0.769023
```

You may have noticed in the first case `df.groupby('key1').mean()` that there is no `key2` column in the result. Because `df['key2']` is not numeric data, it is said to be a *nuisance column*, which is therefore excluded from the result. By default, all of the

numeric columns are aggregated, though it is possible to filter down to a subset as you'll see soon.

Regardless of the objective in using `groupby`, a generally useful GroupBy method is `size` which return a Series containing group sizes:

```
In [26]: df.groupby(['key1', 'key2']).size()
Out[26]:
key1  key2
a     one     2
      two     1
b     one     1
      two     1
```



As of this writing, any missing values in a group key will be excluded from the result. It's possible (and, in fact, quite likely), that by the time you are reading this there will be an option to include the `NA` group in the result.

Iterating Over Groups

The GroupBy object supports iteration, generating a sequence of 2-tuples containing the group name along with the chunk of data. Consider the following small example data set:

```
In [27]: for name, group in df.groupby('key1'):
   ....:     print name
   ....:     print group
   ....:
a
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
1  0.478943  0.092908    a  two
4  1.965781  1.246435    a  one
b
      data1     data2 key1 key2
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
```

In the case of multiple keys, the first element in the tuple will be a tuple of key values:

```
In [28]: for (k1, k2), group in df.groupby(['key1', 'key2']):
   ....:     print k1, k2
   ....:     print group
   ....:
a one
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
4  1.965781  1.246435    a  one
a two
      data1     data2 key1 key2
1  0.478943  0.092908    a  two
b one
      data1     data2 key1 key2
```

```
2 -0.519439  0.281746    b  one
b two
     data1     data2 key1 key2
3 -0.55573  0.769023    b  two
```

Of course, you can choose to do whatever you want with the pieces of data. A recipe you may find useful is computing a dict of the data pieces as a one-liner:

```
In [29]: pieces = dict(list(df.groupby('key1')))

In [30]: pieces['b']
Out[30]:
      data1     data2 key1 key2
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
```

By default `groupby` groups on `axis=0`, but you can group on any of the other axes. For example, we could group the columns of our example `df` here by `dtype` like so:

```
In [31]: df.dtypes
Out[31]:
data1    float64
data2    float64
key1      object
key2      object

In [32]: grouped = df.groupby(df.dtypes, axis=1)

In [33]: dict(list(grouped))
Out[33]:
{dtype('float64'):       data1     data2
0 -0.204708  1.393406
1  0.478943  0.092908
2 -0.519439  0.281746
3 -0.555730  0.769023
4  1.965781  1.246435,
 dtype('object'):   key1 key2
0    a  one
1    a  two
2    b  one
3    b  two
4    a  one}
```

Selecting a Column or Subset of Columns

Indexing a GroupBy object created from a DataFrame with a column name or array of column names has the effect of *selecting those columns* for aggregation. This means that:

```
df.groupby('key1')['data1']
df.groupby('key1')[['data2']]
```

are syntactic sugar for:

```
df['data1'].groupby(df['key1'])
df[['data2']].groupby(df['key1'])
```

Especially for large data sets, it may be desirable to aggregate only a few columns. For example, in the above data set, to compute means for just the `data2` column and get the result as a DataFrame, we could write:

```
In [34]: df.groupby(['key1', 'key2'])[['data2']].mean()
Out[34]:
               data2
key1 key2
a    one   1.319920
     two   0.092908
b    one   0.281746
     two   0.769023
```

The object returned by this indexing operation is a grouped DataFrame if a list or array is passed and a grouped Series is just a single column name that is passed as a scalar:

```
In [35]: s_grouped = df.groupby(['key1', 'key2'])['data2']

In [36]: s_grouped
Out[36]: <pandas.core.groupby.SeriesGroupBy at 0x2e215d0>

In [37]: s_grouped.mean()
Out[37]:
key1  key2
a     one     1.319920
      two     0.092908
b     one     0.281746
      two     0.769023
Name: data2
```

Grouping with Dicts and Series

Grouping information may exist in a form other than an array. Let's consider another example DataFrame:

```
In [38]: people = DataFrame(np.random.randn(5, 5),
   ....:                    columns=['a', 'b', 'c', 'd', 'e'],
   ....:                    index=['Joe', 'Steve', 'Wes', 'Jim', 'Travis'])

In [39]: people.ix[2:3, ['b', 'c']] = np.nan # Add a few NA values

In [40]: people
Out[40]:
               a         b         c         d         e
Joe     1.007189 -1.296221  0.274992  0.228913  1.352917
Steve   0.886429 -2.001637 -0.371843  1.669025 -0.438570
Wes    -0.539741       NaN       NaN -1.021228 -0.577087
Jim     0.124121  0.302614  0.523772  0.000940  1.343810
Travis -0.713544 -0.831154 -2.370232 -1.860761 -0.860757
```

Now, suppose I have a group correspondence for the columns and want to sum together the columns by group:

```
In [41]: mapping = {'a': 'red', 'b': 'red', 'c': 'blue',
   ....:            'd': 'blue', 'e': 'red', 'f' : 'orange'}
```

Now, you could easily construct an array from this dict to pass to `groupby`, but instead we can just pass the dict:

```
In [42]: by_column = people.groupby(mapping, axis=1)

In [43]: by_column.sum()
Out[43]:
           blue       red
Joe     0.503905  1.063885
Steve   1.297183 -1.553778
Wes    -1.021228 -1.116829
Jim     0.524712  1.770545
Travis -4.230992 -2.405455
```

The same functionality holds for Series, which can be viewed as a fixed size mapping. When I used Series as group keys in the above examples, pandas does, in fact, inspect each Series to ensure that its index is aligned with the axis it's grouping:

```
In [44]: map_series = Series(mapping)

In [45]: map_series
Out[45]:
a       red
b       red
c      blue
d      blue
e       red
f    orange

In [46]: people.groupby(map_series, axis=1).count()
Out[46]:
        blue  red
Joe        2    3
Steve      2    3
Wes        1    2
Jim        2    3
Travis     2    3
```

Grouping with Functions

Using Python functions in what can be fairly creative ways is a more abstract way of defining a group mapping compared with a dict or Series. Any function passed as a group key will be called once per index value, with the return values being used as the group names. More concretely, consider the example DataFrame from the previous section, which has people's first names as index values. Suppose you wanted to group by the length of the names; you could compute an array of string lengths, but instead you can just pass the `len` function:

```
In [47]: people.groupby(len).sum()
Out[47]:
          a         b         c         d         e
3  0.591569 -0.993608  0.798764 -0.791374  2.119639
```

```
5  0.886429 -2.001637 -0.371843  1.669025 -0.438570
6 -0.713544 -0.831154 -2.370232 -1.860761 -0.860757
```

Mixing functions with arrays, dicts, or Series is not a problem as everything gets converted to arrays internally:

```
In [48]: key_list = ['one', 'one', 'one', 'two', 'two']

In [49]: people.groupby([len, key_list]).min()
Out[49]:
              a         b         c         d         e
3 one -0.539741 -1.296221  0.274992 -1.021228 -0.577087
  two  0.124121  0.302614  0.523772  0.000940  1.343810
5 one  0.886429 -2.001637 -0.371843  1.669025 -0.438570
6 two -0.713544 -0.831154 -2.370232 -1.860761 -0.860757
```

Grouping by Index Levels

A final convenience for hierarchically-indexed data sets is the ability to aggregate using one of the levels of an axis index. To do this, pass the level number or name using the `level` keyword:

```
In [50]: columns = pd.MultiIndex.from_arrays([['US', 'US', 'US', 'JP', 'JP'],
   ....:                                      [1, 3, 5, 1, 3]], names=['cty', 'tenor'])

In [51]: hier_df = DataFrame(np.random.randn(4, 5), columns=columns)

In [52]: hier_df
Out[52]:
cty          US                            JP
tenor         1         3         5         1         3
0      0.560145 -1.265934  0.119827 -1.063512  0.332883
1     -2.359419 -0.199543 -1.541996 -0.970736 -1.307030
2      0.286350  0.377984 -0.753887  0.331286  1.349742
3      0.069877  0.246674 -0.011862  1.004812  1.327195

In [53]: hier_df.groupby(level='cty', axis=1).count()
Out[53]:
cty  JP  US
0     2   3
1     2   3
2     2   3
3     2   3
```

Data Aggregation

By aggregation, I am generally referring to any data transformation that produces scalar values from arrays. In the examples above I have used several of them, such as `mean`, `count`, `min` and `sum`. You may wonder what is going on when you invoke `mean()` on a GroupBy object. Many common aggregations, such as those found in Table 9-1, have optimized implementations that compute the statistics on the dataset *in place*. However, you are not limited to only this set of methods. You can use aggregations of your

own devising and additionally call any method that is also defined on the grouped object. For example, as you recall `quantile` computes sample quantiles of a Series or a DataFrame's columns [1]:

```
In [54]: df
Out[54]:
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
1  0.478943  0.092908    a  two
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
4  1.965781  1.246435    a  one

In [55]: grouped = df.groupby('key1')

In [56]: grouped['data1'].quantile(0.9)
Out[56]:
key1
a       1.668413
b      -0.523068
```

While `quantile` is not explicitly implemented for GroupBy, it is a Series method and thus available for use. Internally, GroupBy efficiently slices up the Series, calls `piece.quantile(0.9)` for each piece, then assembles those results together into the result object.

To use your own aggregation functions, pass any function that aggregates an array to the `aggregate` or `agg` method:

```
In [57]: def peak_to_peak(arr):
   ....:     return arr.max() - arr.min()

In [58]: grouped.agg(peak_to_peak)
Out[58]:
         data1     data2
key1
a     2.170488  1.300498
b     0.036292  0.487276
```

You'll notice that some methods like `describe` also work, even though they are not aggregations, strictly speaking:

```
In [59]: grouped.describe()
Out[59]:
                data1     data2
key1
a    count  3.000000  3.000000
     mean   0.746672  0.910916
     std    1.109736  0.712217
     min   -0.204708  0.092908
     25%    0.137118  0.669671
     50%    0.478943  1.246435
```

1. Note that `quantile` performs linear interpolation if there is no value at exactly the passed percentile.

```
        75%    1.222362  1.319920
        max    1.965781  1.393406
b       count  2.000000  2.000000
        mean  -0.537585  0.525384
        std    0.025662  0.344556
        min   -0.555730  0.281746
        25%   -0.546657  0.403565
        50%   -0.537585  0.525384
        75%   -0.528512  0.647203
        max   -0.519439  0.769023
```

I will explain in more detail what has happened here in the next major section on group-wise operations and transformations.

You may notice that custom aggregation functions are much slower than the optimized functions found in Table 9-1. This is because there is significant overhead (function calls, data rearrangement) in constructing the intermediate group data chunks.

Table 9-1. Optimized groupby methods

Function name	Description
`count`	Number of non-NA values in the group
`sum`	Sum of non-NA values
`mean`	Mean of non-NA values
`median`	Arithmetic median of non-NA values
`std, var`	Unbiased (n - 1 denominator) standard deviation and variance
`min, max`	Minimum and maximum of non-NA values
`prod`	Product of non-NA values
`first, last`	First and last non-NA values

To illustrate some more advanced aggregation features, I'll use a less trivial dataset, a dataset on restaurant tipping. I obtained it from the R `reshape2` package; it was originally found in Bryant & Smith's 1995 text on business statistics (and found in the book's GitHub repository). After loading it with `read_csv`, I add a tipping percentage column `tip_pct`.

```
In [60]: tips = pd.read_csv('ch08/tips.csv')

# Add tip percentage of total bill
In [61]: tips['tip_pct'] = tips['tip'] / tips['total_bill']

In [62]: tips[:6]
Out[62]:
   total_bill   tip     sex smoker  day    time  size   tip_pct
0       16.99  1.01  Female     No  Sun  Dinner     2  0.059447
1       10.34  1.66    Male     No  Sun  Dinner     3  0.160542
```

```
2       21.01  3.50    Male     No  Sun  Dinner     3  0.166587
3       23.68  3.31    Male     No  Sun  Dinner     2  0.139780
4       24.59  3.61  Female     No  Sun  Dinner     4  0.146808
5       25.29  4.71    Male     No  Sun  Dinner     4  0.186240
```

Column-wise and Multiple Function Application

As you've seen above, aggregating a Series or all of the columns of a DataFrame is a matter of using `aggregate` with the desired function or calling a method like `mean` or `std`. However, you may want to aggregate using a different function depending on the column or multiple functions at once. Fortunately, this is straightforward to do, which I'll illustrate through a number of examples. First, I'll group the `tips` by `sex` and `smoker`:

```
In [63]: grouped = tips.groupby(['sex', 'smoker'])
```

Note that for descriptive statistics like those in Table 9-1, you can pass the name of the function as a string:

```
In [64]: grouped_pct = grouped['tip_pct']

In [65]: grouped_pct.agg('mean')
Out[65]:
sex     smoker
Female  No        0.156921
        Yes       0.182150
Male    No        0.160669
        Yes       0.152771
Name: tip_pct
```

If you pass a list of functions or function names instead, you get back a DataFrame with column names taken from the functions:

```
In [66]: grouped_pct.agg(['mean', 'std', peak_to_peak])
Out[66]:
                   mean       std  peak_to_peak
sex    smoker
Female No      0.156921  0.036421      0.195876
       Yes     0.182150  0.071595      0.360233
Male   No      0.160669  0.041849      0.220186
       Yes     0.152771  0.090588      0.674707
```

You don't need to accept the names that GroupBy gives to the columns; notably `lambda` functions have the name `'<lambda>'` which make them hard to identify (you can see for yourself by looking at a function's `__name__` attribute). As such, if you pass a list of `(name, function)` tuples, the first element of each tuple will be used as the DataFrame column names (you can think of a list of 2-tuples as an ordered mapping):

```
In [67]: grouped_pct.agg([('foo', 'mean'), ('bar', np.std)])
Out[67]:
                     foo       bar
sex    smoker
Female No      0.156921  0.036421
       Yes     0.182150  0.071595
```

```
Male   No      0.160669  0.041849
       Yes     0.152771  0.090588
```

With a DataFrame, you have more options as you can specify a list of functions to apply to all of the columns or different functions per column. To start, suppose we wanted to compute the same three statistics for the `tip_pct` and `total_bill` columns:

```
In [68]: functions = ['count', 'mean', 'max']

In [69]: result = grouped['tip_pct', 'total_bill'].agg(functions)

In [70]: result
Out[70]:
               tip_pct                     total_bill
                 count      mean       max       count       mean    max
sex    smoker
Female No           54  0.156921  0.252672          54  18.105185  35.83
       Yes          33  0.182150  0.416667          33  17.977879  44.30
Male   No           97  0.160669  0.291990          97  19.791237  48.33
       Yes          60  0.152771  0.710345          60  22.284500  50.81
```

As you can see, the resulting DataFrame has hierarchical columns, the same as you would get aggregating each column separately and using `concat` to glue the results together using the column names as the `keys` argument:

```
In [71]: result['tip_pct']
Out[71]:
               count      mean       max
sex    smoker
Female No         54  0.156921  0.252672
       Yes        33  0.182150  0.416667
Male   No         97  0.160669  0.291990
       Yes        60  0.152771  0.710345
```

As above, a list of tuples with custom names can be passed:

```
In [72]: ftuples = [('Durchschnitt', 'mean'), ('Abweichung', np.var)]

In [73]: grouped['tip_pct', 'total_bill'].agg(ftuples)
Out[73]:
                    tip_pct                total_bill
               Durchschnitt  Abweichung  Durchschnitt  Abweichung
sex    smoker
Female No          0.156921    0.001327     18.105185   53.092422
       Yes         0.182150    0.005126     17.977879   84.451517
Male   No          0.160669    0.001751     19.791237   76.152961
       Yes         0.152771    0.008206     22.284500   98.244673
```

Now, suppose you wanted to apply potentially different functions to one or more of the columns. The trick is to pass a dict to `agg` that contains a mapping of column names to any of the function specifications listed so far:

```
In [74]: grouped.agg({'tip' : np.max, 'size' : 'sum'})
Out[74]:
               size   tip
sex    smoker
```

```
Female No       140   5.2
       Yes       74   6.5
Male   No       263   9.0
       Yes      150  10.0

In [75]: grouped.agg({'tip_pct' : ['min', 'max', 'mean', 'std'],
   ....:              'size' : 'sum'})
Out[75]:
                tip_pct                               size
                    min       max      mean       std   sum
sex    smoker
Female No      0.056797  0.252672  0.156921  0.036421   140
       Yes     0.056433  0.416667  0.182150  0.071595    74
Male   No      0.071804  0.291990  0.160669  0.041849   263
       Yes     0.035638  0.710345  0.152771  0.090588   150
```

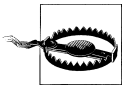
A DataFrame will have hierarchical columns only if multiple functions are applied to at least one column.

Returning Aggregated Data in "unindexed" Form

In all of the examples up until now, the aggregated data comes back with an index, potentially hierarchical, composed from the unique group key combinations observed. Since this isn't always desirable, you can disable this behavior in most cases by passing `as_index=False` to `groupby`:

```
In [76]: tips.groupby(['sex', 'smoker'], as_index=False).mean()
Out[76]:
      sex smoker  total_bill       tip      size   tip_pct
0  Female     No   18.105185  2.773519  2.592593  0.156921
1  Female    Yes   17.977879  2.931515  2.242424  0.182150
2    Male     No   19.791237  3.113402  2.711340  0.160669
3    Male    Yes   22.284500  3.051167  2.500000  0.152771
```

Of course, it's always possible to obtain the result in this format by calling `reset_index` on the result.



Using `groupby` in this way is generally less flexible; results with hierarchical columns, for example, are not currently implemented as the form of the result would have to be somewhat arbitrary.

Group-wise Operations and Transformations

Aggregation is only one kind of group operation. It is a special case in the more general class of data transformations; that is, it accepts functions that reduce a one-dimensional array to a scalar value. In this section, I will introduce you to the `transform` and `apply` methods, which will enable you to do many other kinds of group operations.

Suppose, instead, we wanted to add a column to a DataFrame containing group means for each index. One way to do this is to aggregate, then merge:

```
In [77]: df
Out[77]:
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
1  0.478943  0.092908    a  two
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
4  1.965781  1.246435    a  one

In [78]: k1_means = df.groupby('key1').mean().add_prefix('mean_')

In [79]: k1_means
Out[79]:
      mean_data1  mean_data2
key1
a       0.746672    0.910916
b      -0.537585    0.525384

In [80]: pd.merge(df, k1_means, left_on='key1', right_index=True)
Out[80]:
      data1     data2 key1 key2  mean_data1  mean_data2
0 -0.204708  1.393406    a  one    0.746672    0.910916
1  0.478943  0.092908    a  two    0.746672    0.910916
4  1.965781  1.246435    a  one    0.746672    0.910916
2 -0.519439  0.281746    b  one   -0.537585    0.525384
3 -0.555730  0.769023    b  two   -0.537585    0.525384
```

This works, but is somewhat inflexible. You can think of the operation as transforming the two data columns using the `np.mean` function. Let's look back at the `people` DataFrame from earlier in the chapter and use the `transform` method on GroupBy:

```
In [81]: key = ['one', 'two', 'one', 'two', 'one']

In [82]: people.groupby(key).mean()
Out[82]:
            a         b         c         d         e
one -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
two  0.505275 -0.849512  0.075965  0.834983  0.452620

In [83]: people.groupby(key).transform(np.mean)
Out[83]:
               a         b         c         d         e
Joe    -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
Steve   0.505275 -0.849512  0.075965  0.834983  0.452620
Wes    -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
Jim     0.505275 -0.849512  0.075965  0.834983  0.452620
Travis -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
```

As you may guess, `transform` applies a function to each group, then places the results in the appropriate locations. If each group produces a scalar value, it will be propagated (broadcasted). Suppose instead you wanted to subtract the mean value from each group. To do this, create a demeaning function and pass it to `transform`:

```
In [84]: def demean(arr):
   ....:     return arr - arr.mean()
```

```
In [85]: demeaned = people.groupby(key).transform(demean)

In [86]: demeaned
Out[86]:
               a         b         c         d         e
Joe     1.089221 -0.232534  1.322612  1.113271  1.381226
Steve   0.381154 -1.152125 -0.447807  0.834043 -0.891190
Wes    -0.457709       NaN       NaN -0.136869 -0.548778
Jim    -0.381154  1.152125  0.447807 -0.834043  0.891190
Travis -0.631512  0.232534 -1.322612 -0.976402 -0.832448
```

You can check that `demeaned` now has zero group means:

```
In [87]: demeaned.groupby(key).mean()
Out[87]:
     a  b  c  d  e
one  0 -0  0  0  0
two -0  0  0  0  0
```

As you'll see in the next section, group demeaning can be achieved using `apply` also.

Apply: General split-apply-combine

Like `aggregate`, `transform` is a more specialized function having rigid requirements: the passed function must either produce a scalar value to be broadcasted (like `np.mean`) or a transformed array of the same size. The most general purpose GroupBy method is `apply`, which is the subject of the rest of this section. As in Figure 9-1, `apply` splits the object being manipulated into pieces, invokes the passed function on each piece, then attempts to concatenate the pieces together.

Returning to the tipping data set above, suppose you wanted to select the top five `tip_pct` values by group. First, it's straightforward to write a function that selects the rows with the largest values in a particular column:

```
In [88]: def top(df, n=5, column='tip_pct'):
   ....:     return df.sort_index(by=column)[-n:]

In [89]: top(tips, n=6)
Out[89]:
     total_bill   tip     sex smoker  day    time  size   tip_pct
109       14.31  4.00  Female    Yes  Sat  Dinner     2  0.279525
183       23.17  6.50    Male    Yes  Sun  Dinner     4  0.280535
232       11.61  3.39    Male     No  Sat  Dinner     2  0.291990
67         3.07  1.00  Female    Yes  Sat  Dinner     1  0.325733
178        9.60  4.00  Female    Yes  Sun  Dinner     2  0.416667
172        7.25  5.15    Male    Yes  Sun  Dinner     2  0.710345
```

Now, if we group by `smoker`, say, and call `apply` with this function, we get the following:

```
In [90]: tips.groupby('smoker').apply(top)
Out[90]:
            total_bill   tip     sex smoker   day    time  size   tip_pct
smoker
```

```
No     88        24.71  5.85    Male     No  Thur   Lunch     2  0.236746
       185       20.69  5.00    Male     No   Sun  Dinner     5  0.241663
       51        10.29  2.60  Female     No   Sun  Dinner     2  0.252672
       149        7.51  2.00    Male     No  Thur   Lunch     2  0.266312
       232       11.61  3.39    Male     No   Sat  Dinner     2  0.291990
Yes    109       14.31  4.00  Female    Yes   Sat  Dinner     2  0.279525
       183       23.17  6.50    Male    Yes   Sun  Dinner     4  0.280535
       67         3.07  1.00  Female    Yes   Sat  Dinner     1  0.325733
       178        9.60  4.00  Female    Yes   Sun  Dinner     2  0.416667
       172        7.25  5.15    Male    Yes   Sun  Dinner     2  0.710345
```

What has happened here? The `top` function is called on each piece of the DataFrame, then the results are glued together using `pandas.concat`, labeling the pieces with the group names. The result therefore has a hierarchical index whose inner level contains index values from the original DataFrame.

If you pass a function to `apply` that takes other arguments or keywords, you can pass these after the function:

```
In [91]: tips.groupby(['smoker', 'day']).apply(top, n=1, column='total_bill')
Out[91]:
                  total_bill    tip     sex smoker   day    time  size   tip_pct
smoker day
No     Fri  94        22.75   3.25  Female     No   Fri  Dinner     2  0.142857
       Sat  212       48.33   9.00    Male     No   Sat  Dinner     4  0.186220
       Sun  156       48.17   5.00    Male     No   Sun  Dinner     6  0.103799
       Thur 142       41.19   5.00    Male     No  Thur   Lunch     5  0.121389
Yes    Fri  95        40.17   4.73    Male    Yes   Fri  Dinner     4  0.117750
       Sat  170       50.81  10.00    Male    Yes   Sat  Dinner     3  0.196812
       Sun  182       45.35   3.50    Male    Yes   Sun  Dinner     3  0.077178
       Thur 197       43.11   5.00  Female    Yes  Thur   Lunch     4  0.115982
```

Beyond these basic usage mechanics, getting the most out of `apply` is largely a matter of creativity. What occurs inside the function passed is up to you; it only needs to return a pandas object or a scalar value. The rest of this chapter will mainly consist of examples showing you how to solve various problems using `groupby`.

You may recall above I called `describe` on a GroupBy object:

```
In [92]: result = tips.groupby('smoker')['tip_pct'].describe()

In [93]: result
Out[93]:
smoker
No      count    151.000000
        mean       0.159328
        std        0.039910
        min        0.056797
        25%        0.136906
        50%        0.155625
        75%        0.185014
        max        0.291990
```

```
Yes     count     93.000000
        mean       0.163196
        std        0.085119
        min        0.035638
        25%        0.106771
        50%        0.153846
        75%        0.195059
        max        0.710345

In [94]: result.unstack('smoker')
Out[94]:
smoker          No        Yes
count   151.000000  93.000000
mean      0.159328   0.163196
std       0.039910   0.085119
min       0.056797   0.035638
25%       0.136906   0.106771
50%       0.155625   0.153846
75%       0.185014   0.195059
max       0.291990   0.710345
```

Inside GroupBy, when you invoke a method like `describe`, it is actually just a shortcut for:

```
f = lambda x: x.describe()
grouped.apply(f)
```

Suppressing the group keys

In the examples above, you see that the resulting object has a hierarchical index formed from the group keys along with the indexes of each piece of the original object. This can be disabled by passing `group_keys=False` to `groupby`:

```
In [95]: tips.groupby('smoker', group_keys=False).apply(top)
Out[95]:
     total_bill   tip     sex smoker   day    time  size   tip_pct
88        24.71  5.85    Male     No  Thur   Lunch     2  0.236746
185       20.69  5.00    Male     No   Sun  Dinner     5  0.241663
51        10.29  2.60  Female     No   Sun  Dinner     2  0.252672
149        7.51  2.00    Male     No  Thur   Lunch     2  0.266312
232       11.61  3.39    Male     No   Sat  Dinner     2  0.291990
109       14.31  4.00  Female    Yes   Sat  Dinner     2  0.279525
183       23.17  6.50    Male    Yes   Sun  Dinner     4  0.280535
67         3.07  1.00  Female    Yes   Sat  Dinner     1  0.325733
178        9.60  4.00  Female    Yes   Sun  Dinner     2  0.416667
172        7.25  5.15    Male    Yes   Sun  Dinner     2  0.710345
```

Quantile and Bucket Analysis

As you may recall from Chapter 7, pandas has some tools, in particular `cut` and `qcut`, for slicing data up into buckets with bins of your choosing or by sample quantiles. Combining these functions with `groupby`, it becomes very simple to perform bucket or

quantile analysis on a data set. Consider a simple random data set and an equal-length bucket categorization using `cut`:

```
In [96]: frame = DataFrame({'data1': np.random.randn(1000),
   ....:                    'data2': np.random.randn(1000)})

In [97]: factor = pd.cut(frame.data1, 4)

In [98]: factor[:10]
Out[98]:
Categorical:
array([(-1.23, 0.489], (-2.956, -1.23], (-1.23, 0.489], (0.489, 2.208],
       (-1.23, 0.489], (0.489, 2.208], (-1.23, 0.489], (-1.23, 0.489],
       (0.489, 2.208], (0.489, 2.208]], dtype=object)
Levels (4): Index([(-2.956, -1.23], (-1.23, 0.489], (0.489, 2.208],
                   (2.208, 3.928]], dtype=object)
```

The `Factor` object returned by `cut` can be passed directly to `groupby`. So we could compute a set of statistics for the `data2` column like so:

```
In [99]: def get_stats(group):
   ....:     return {'min': group.min(), 'max': group.max(),
   ....:             'count': group.count(), 'mean': group.mean()}

In [100]: grouped = frame.data2.groupby(factor)

In [101]: grouped.apply(get_stats).unstack()
Out[101]:
                 count       max      mean       min
data1
(-1.23, 0.489]     598  3.260383 -0.002051 -2.989741
(-2.956, -1.23]     95  1.670835 -0.039521 -3.399312
(0.489, 2.208]     297  2.954439  0.081822 -3.745356
(2.208, 3.928]      10  1.765640  0.024750 -1.929776
```

These were equal-length buckets; to compute equal-size buckets based on sample quantiles, use `qcut`. I'll pass `labels=False` to just get quantile numbers.

```
# Return quantile numbers
In [102]: grouping = pd.qcut(frame.data1, 10, labels=False)

In [103]: grouped = frame.data2.groupby(grouping)

In [104]: grouped.apply(get_stats).unstack()
Out[104]:
   count       max      mean       min
0    100  1.670835 -0.049902 -3.399312
1    100  2.628441  0.030989 -1.950098
2    100  2.527939 -0.067179 -2.925113
3    100  3.260383  0.065713 -2.315555
4    100  2.074345 -0.111653 -2.047939
5    100  2.184810  0.052130 -2.989741
6    100  2.458842 -0.021489 -2.223506
7    100  2.954439 -0.026459 -3.056990
8    100  2.735527  0.103406 -3.745356
9    100  2.377020  0.220122 -2.064111
```

Example: Filling Missing Values with Group-specific Values

When cleaning up missing data, in some cases you will filter out data observations using `dropna`, but in others you may want to impute (fill in) the NA values using a fixed value or some value derived from the data. `fillna` is the right tool to use; for example here I fill in NA values with the mean:

```
In [105]: s = Series(np.random.randn(6))

In [106]: s[::2] = np.nan

In [107]: s
Out[107]:
0         NaN
1   -0.125921
2         NaN
3   -0.884475
4         NaN
5    0.227290

In [108]: s.fillna(s.mean())
Out[108]:
0   -0.261035
1   -0.125921
2   -0.261035
3   -0.884475
4   -0.261035
5    0.227290
```

Suppose you need the fill value to vary by group. As you may guess, you need only group the data and use `apply` with a function that calls `fillna` on each data chunk. Here is some sample data on some US states divided into eastern and western states:

```
In [109]: states = ['Ohio', 'New York', 'Vermont', 'Florida',
   .....:           'Oregon', 'Nevada', 'California', 'Idaho']

In [110]: group_key = ['East'] * 4 + ['West'] * 4

In [111]: data = Series(np.random.randn(8), index=states)

In [112]: data[['Vermont', 'Nevada', 'Idaho']] = np.nan

In [113]: data
Out[113]:
Ohio          0.922264
New York     -2.153545
Vermont            NaN
Florida      -0.375842
Oregon        0.329939
Nevada             NaN
California    1.105913
Idaho              NaN

In [114]: data.groupby(group_key).mean()
Out[114]:
```

```
East   -0.535707
West    0.717926
```

We can fill the NA values using the group means like so:

```
In [115]: fill_mean = lambda g: g.fillna(g.mean())

In [116]: data.groupby(group_key).apply(fill_mean)
Out[116]:
Ohio          0.922264
New York     -2.153545
Vermont      -0.535707
Florida      -0.375842
Oregon        0.329939
Nevada        0.717926
California    1.105913
Idaho         0.717926
```

In another case, you might have pre-defined fill values in your code that vary by group. Since the groups have a `name` attribute set internally, we can use that:

```
In [117]: fill_values = {'East': 0.5, 'West': -1}

In [118]: fill_func = lambda g: g.fillna(fill_values[g.name])

In [119]: data.groupby(group_key).apply(fill_func)
Out[119]:
Ohio          0.922264
New York     -2.153545
Vermont       0.500000
Florida      -0.375842
Oregon        0.329939
Nevada       -1.000000
California    1.105913
Idaho        -1.000000
```

Example: Random Sampling and Permutation

Suppose you wanted to draw a random sample (with or without replacement) from a large dataset for Monte Carlo simulation purposes or some other application. There are a number of ways to perform the "draws"; some are much more efficient than others. One way is to select the first `K` elements of `np.random.permutation(N)`, where `N` is the size of your complete dataset and `K` the desired sample size. As a more fun example, here's a way to construct a deck of English-style playing cards:

```
# Hearts, Spades, Clubs, Diamonds
suits = ['H', 'S', 'C', 'D']
card_val = (range(1, 11) + [10] * 3) * 4
base_names = ['A'] + range(2, 11) + ['J', 'K', 'Q']
cards = []
for suit in ['H', 'S', 'C', 'D']:
    cards.extend(str(num) + suit for num in base_names)

deck = Series(card_val, index=cards)
```

So now we have a Series of length 52 whose index contains card names and values are the ones used in blackjack and other games (to keep things simple, I just let the ace be 1):

```
In [121]: deck[:13]
Out[121]:
AH      1
2H      2
3H      3
4H      4
5H      5
6H      6
7H      7
8H      8
9H      9
10H    10
JH     10
KH     10
QH     10
```

Now, based on what I said above, drawing a hand of 5 cards from the desk could be written as:

```
In [122]: def draw(deck, n=5):
   .....:     return deck.take(np.random.permutation(len(deck))[:n])

In [123]: draw(deck)
Out[123]:
AD     1
8C     8
5H     5
KC    10
2C     2
```

Suppose you wanted two random cards from each suit. Because the suit is the last character of each card name, we can group based on this and use `apply`:

```
In [124]: get_suit = lambda card: card[-1] # last letter is suit

In [125]: deck.groupby(get_suit).apply(draw, n=2)
Out[125]:
C  2C     2
   3C     3
D  KD    10
   8D     8
H  KH    10
   3H     3
S  2S     2
   4S     4

# alternatively
In [126]: deck.groupby(get_suit, group_keys=False).apply(draw, n=2)
Out[126]:
KC    10
JC    10
AD     1
```

```
5D     5
5H     5
6H     6
7S     7
KS    10
```

Example: Group Weighted Average and Correlation

Under the split-apply-combine paradigm of `groupby`, operations between columns in a DataFrame or two Series, such a group weighted average, become a routine affair. As an example, take this dataset containing group keys, values, and some weights:

```
In [127]: df = DataFrame({'category': ['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'],
   .....:                 'data': np.random.randn(8),
   .....:                 'weights': np.random.rand(8)})

In [128]: df
Out[128]:
  category      data   weights
0        a  1.561587  0.957515
1        a  1.219984  0.347267
2        a -0.482239  0.581362
3        a  0.315667  0.217091
4        b -0.047852  0.894406
5        b -0.454145  0.918564
6        b -0.556774  0.277825
7        b  0.253321  0.955905
```

The group weighted average by `category` would then be:

```
In [129]: grouped = df.groupby('category')

In [130]: get_wavg = lambda g: np.average(g['data'], weights=g['weights'])

In [131]: grouped.apply(get_wavg)
Out[131]:
category
a           0.811643
b          -0.122262
```

As a less trivial example, consider a data set from Yahoo! Finance containing end of day prices for a few stocks and the S&P 500 index (the `SPX` ticker):

```
In [132]: close_px = pd.read_csv('ch09/stock_px.csv', parse_dates=True, index_col=0)

In [133]: close_px
Out[133]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2214 entries, 2003-01-02 00:00:00 to 2011-10-14 00:00:00
Data columns:
AAPL    2214  non-null values
MSFT    2214  non-null values
XOM     2214  non-null values
SPX     2214  non-null values
dtypes: float64(4)
```

```
In [134]: close_px[-4:]
Out[134]:
              AAPL   MSFT    XOM      SPX
2011-10-11  400.29  27.00  76.27  1195.54
2011-10-12  402.19  26.96  77.16  1207.25
2011-10-13  408.43  27.18  76.37  1203.66
2011-10-14  422.00  27.27  78.11  1224.58
```

One task of interest might be to compute a DataFrame consisting of the yearly correlations of daily returns (computed from percent changes) with `SPX`. Here is one way to do it:

```
In [135]: rets = close_px.pct_change().dropna()

In [136]: spx_corr = lambda x: x.corrwith(x['SPX'])

In [137]: by_year = rets.groupby(lambda x: x.year)

In [138]: by_year.apply(spx_corr)
Out[138]:
          AAPL      MSFT       XOM  SPX
2003  0.541124  0.745174  0.661265    1
2004  0.374283  0.588531  0.557742    1
2005  0.467540  0.562374  0.631010    1
2006  0.428267  0.406126  0.518514    1
2007  0.508118  0.658770  0.786264    1
2008  0.681434  0.804626  0.828303    1
2009  0.707103  0.654902  0.797921    1
2010  0.710105  0.730118  0.839057    1
2011  0.691931  0.800996  0.859975    1
```

There is, of course, nothing to stop you from computing inter-column correlations:

```
# Annual correlation of Apple with Microsoft
In [139]: by_year.apply(lambda g: g['AAPL'].corr(g['MSFT']))
Out[139]:
2003    0.480868
2004    0.259024
2005    0.300093
2006    0.161735
2007    0.417738
2008    0.611901
2009    0.432738
2010    0.571946
2011    0.581987
```

Example: Group-wise Linear Regression

In the same vein as the previous example, you can use `groupby` to perform more complex group-wise statistical analysis, as long as the function returns a pandas object or scalar value. For example, I can define the following `regress` function (using the `statsmodels` econometrics library) which executes an ordinary least squares (OLS) regression on each chunk of data:

```
import statsmodels.api as sm
def regress(data, yvar, xvars):
    Y = data[yvar]
    X = data[xvars]
    X['intercept'] = 1.
    result = sm.OLS(Y, X).fit()
    return result.params
```

Now, to run a yearly linear regression of `AAPL` on `SPX` returns, I execute:

```
In [141]: by_year.apply(regress, 'AAPL', ['SPX'])
Out[141]:
          SPX  intercept
2003  1.195406   0.000710
2004  1.363463   0.004201
2005  1.766415   0.003246
2006  1.645496   0.000080
2007  1.198761   0.003438
2008  0.968016  -0.001110
2009  0.879103   0.002954
2010  1.052608   0.001261
2011  0.806605   0.001514
```

Pivot Tables and Cross-Tabulation

A *pivot table* is a data summarization tool frequently found in spreadsheet programs and other data analysis software. It aggregates a table of data by one or more keys, arranging the data in a rectangle with some of the group keys along the rows and some along the columns. Pivot tables in Python with pandas are made possible using the `groupby` facility described in this chapter combined with reshape operations utilizing hierarchical indexing. DataFrame has a `pivot_table` method, and additionally there is a top-level `pandas.pivot_table` function. In addition to providing a convenience interface to `groupby`, `pivot_table` also can add partial totals, also known as *margins*.

Returning to the tipping data set, suppose I wanted to compute a table of group means (the default `pivot_table` aggregation type) arranged by `sex` and `smoker` on the rows:

```
In [142]: tips.pivot_table(rows=['sex', 'smoker'])
Out[142]:
                  size       tip   tip_pct  total_bill
sex    smoker
Female No      2.592593  2.773519  0.156921   18.105185
       Yes     2.242424  2.931515  0.182150   17.977879
Male   No      2.711340  3.113402  0.160669   19.791237
       Yes     2.500000  3.051167  0.152771   22.284500
```

This could have been easily produced using `groupby`. Now, suppose we want to aggregate only `tip_pct` and `size`, and additionally group by `day`. I'll put `smoker` in the table columns and `day` in the rows:

```
In [143]: tips.pivot_table(['tip_pct', 'size'], rows=['sex', 'day'],
   .....:                  cols='smoker')
Out[143]:
```

```
              tip_pct                size
smoker             No       Yes        No       Yes
sex    day
Female Fri   0.165296  0.209129  2.500000  2.000000
       Sat   0.147993  0.163817  2.307692  2.200000
       Sun   0.165710  0.237075  3.071429  2.500000
       Thur  0.155971  0.163073  2.480000  2.428571
Male   Fri   0.138005  0.144730  2.000000  2.125000
       Sat   0.162132  0.139067  2.656250  2.629630
       Sun   0.158291  0.173964  2.883721  2.600000
       Thur  0.165706  0.164417  2.500000  2.300000
```

This table could be augmented to include partial totals by passing `margins=True`. This has the effect of adding `All` row and column labels, with corresponding values being the group statistics for all the data within a single tier. In this below example, the `All` values are means without taking into account smoker vs. non-smoker (the `All` columns) or any of the two levels of grouping on the rows (the `All` row):

```
In [144]: tips.pivot_table(['tip_pct', 'size'], rows=['sex', 'day'],
   .....:                  cols='smoker', margins=True)
Out[144]:
                 size                       tip_pct
smoker             No       Yes       All        No       Yes       All
sex    day
Female Fri   2.500000  2.000000  2.111111  0.165296  0.209129  0.199388
       Sat   2.307692  2.200000  2.250000  0.147993  0.163817  0.156470
       Sun   3.071429  2.500000  2.944444  0.165710  0.237075  0.181569
       Thur  2.480000  2.428571  2.468750  0.155971  0.163073  0.157525
Male   Fri   2.000000  2.125000  2.100000  0.138005  0.144730  0.143385
       Sat   2.656250  2.629630  2.644068  0.162132  0.139067  0.151577
       Sun   2.883721  2.600000  2.810345  0.158291  0.173964  0.162344
       Thur  2.500000  2.300000  2.433333  0.165706  0.164417  0.165276
All          2.668874  2.408602  2.569672  0.159328  0.163196  0.160803
```

To use a different aggregation function, pass it to `aggfunc`. For example, `'count'` or `len` will give you a cross-tabulation (count or frequency) of group sizes:

```
In [145]: tips.pivot_table('tip_pct', rows=['sex', 'smoker'], cols='day',
   .....:                  aggfunc=len, margins=True)
Out[145]:
day            Fri  Sat  Sun  Thur  All
sex    smoker
Female No        2   13   14    25   54
       Yes       7   15    4     7   33
Male   No        2   32   43    20   97
       Yes       8   27   15    10   60
All             19   87   76    62  244
```

If some combinations are empty (or otherwise NA), you may wish to pass a `fill_value`:

```
In [146]: tips.pivot_table('size', rows=['time', 'sex', 'smoker'],
   .....:                  cols='day', aggfunc='sum', fill_value=0)
Out[146]:
day                  Fri  Sat  Sun  Thur
time   sex    smoker
Dinner Female No       2   30   43     2
```

```
                Yes       8   33   10     0
        Male    No        4   85  124     0
                Yes      12   71   39     0
Lunch   Female  No        3    0    0    60
                Yes       6    0    0    17
        Male    No        0    0    0    50
                Yes       5    0    0    23
```

See Table 9-2 for a summary of `pivot_table` methods.

Table 9-2. pivot_table options

Function name	Description
`values`	Column name or names to aggregate. By default aggregates all numeric columns
`rows`	Column names or other group keys to group on the rows of the resulting pivot table
`cols`	Column names or other group keys to group on the columns of the resulting pivot table
`aggfunc`	Aggregation function or list of functions; `'mean'` by default. Can be any function valid in a groupby context
`fill_value`	Replace missing values in result table
`margins`	Add row/column subtotals and grand total, False by default

Cross-Tabulations: Crosstab

A cross-tabulation (or *crosstab* for short) is a special case of a pivot table that computes group frequencies. Here is a canonical example taken from the Wikipedia page on cross-tabulation:

```
In [150]: data
Out[150]:
   Sample  Gender    Handedness
0       1  Female  Right-handed
1       2    Male   Left-handed
2       3  Female  Right-handed
3       4    Male  Right-handed
4       5    Male   Left-handed
5       6    Male  Right-handed
6       7  Female  Right-handed
7       8  Female   Left-handed
8       9    Male  Right-handed
9      10  Female  Right-handed
```

As part of some survey analysis, we might want to summarize this data by gender and handedness. You could use `pivot_table` to do this, but the `pandas.crosstab` function is very convenient:

```
In [151]: pd.crosstab(data.Gender, data.Handedness, margins=True)
Out[151]:
Handedness  Left-handed  Right-handed  All
Gender
Female                1             4    5
Male                  2             3    5
All                   3             7   10
```

The first two arguments to `crosstab` can each either be an array or Series or a list of arrays. As in the tips data:

```
In [152]: pd.crosstab([tips.time, tips.day], tips.smoker, margins=True)
Out[152]:
smoker        No  Yes  All
time   day
Dinner Fri     3    9   12
       Sat    45   42   87
       Sun    57   19   76
       Thur    1    0    1
Lunch  Fri     1    6    7
       Thur   44   17   61
All          151   93  244
```

Example: 2012 Federal Election Commission Database

The US Federal Election Commission publishes data on contributions to political campaigns. This includes contributor names, occupation and employer, address, and contribution amount. An interesting dataset is from the 2012 US presidential election (*http://www.fec.gov/disclosurep/PDownload.do*). As of this writing (June 2012), the full dataset for all states is a 150 megabyte CSV file `P00000001-ALL.csv`, which can be loaded with `pandas.read_csv`:

```
In [13]: fec = pd.read_csv('ch09/P00000001-ALL.csv')
```

```
In [14]: fec
Out[14]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1001731 entries, 0 to 1001730
Data columns:
cmte_id              1001731  non-null values
cand_id              1001731  non-null values
cand_nm              1001731  non-null values
contbr_nm            1001731  non-null values
contbr_city          1001716  non-null values
contbr_st            1001727  non-null values
contbr_zip           1001620  non-null values
contbr_employer      994314   non-null values
contbr_occupation    994433   non-null values
contb_receipt_amt    1001731  non-null values
contb_receipt_dt     1001731  non-null values
receipt_desc         14166    non-null values
memo_cd              92482    non-null values
memo_text            97770    non-null values
form_tp              1001731  non-null values
file_num             1001731  non-null values
dtypes: float64(1), int64(1), object(14)
```

A sample record in the DataFrame looks like this:

```
In [15]: fec.ix[123456]
Out[15]:
cmte_id                            C00431445
```

```
cand_id                            P80003338
cand_nm                        Obama, Barack
contbr_nm                        ELLMAN, IRA
contbr_city                            TEMPE
contbr_st                                 AZ
contbr_zip                         852816719
contbr_employer      ARIZONA STATE UNIVERSITY
contbr_occupation                  PROFESSOR
contb_receipt_amt                         50
contb_receipt_dt                   01-DEC-11
receipt_desc                             NaN
memo_cd                                  NaN
memo_text                                NaN
form_tp                                 SA17A
file_num                               772372
Name: 123456
```

You can probably think of many ways to start slicing and dicing this data to extract informative statistics about donors and patterns in the campaign contributions. I'll spend the next several pages showing you a number of different analyses that apply techniques you have learned about so far.

You can see that there are no political party affiliations in the data, so this would be useful to add. You can get a list of all the unique political candidates using `unique` (note that NumPy suppresses the quotes around the strings in the output):

```
In [16]: unique_cands = fec.cand_nm.unique()

In [17]: unique_cands
Out[17]:
array([Bachmann, Michelle, Romney, Mitt, Obama, Barack,
       Roemer, Charles E. 'Buddy' III, Pawlenty, Timothy,
       Johnson, Gary Earl, Paul, Ron, Santorum, Rick, Cain, Herman,
       Gingrich, Newt, McCotter, Thaddeus G, Huntsman, Jon, Perry, Rick], dtype=object)

In [18]: unique_cands[2]
Out[18]: 'Obama, Barack'
```

An easy way to indicate party affiliation is using a dict:[2]

```
parties = {'Bachmann, Michelle': 'Republican',
           'Cain, Herman': 'Republican',
           'Gingrich, Newt': 'Republican',
           'Huntsman, Jon': 'Republican',
           'Johnson, Gary Earl': 'Republican',
           'McCotter, Thaddeus G': 'Republican',
           'Obama, Barack': 'Democrat',
           'Paul, Ron': 'Republican',
           'Pawlenty, Timothy': 'Republican',
           'Perry, Rick': 'Republican',
           "Roemer, Charles E. 'Buddy' III": 'Republican',
```

2. This makes the simplifying assumption that Gary Johnson is a Republican even though he later became the Libertarian party candidate.

```
                 'Romney, Mitt': 'Republican',
                 'Santorum, Rick': 'Republican'}
```

Now, using this mapping and the `map` method on Series objects, you can compute an array of political parties from the candidate names:

```
In [20]: fec.cand_nm[123456:123461]
Out[20]:
123456    Obama, Barack
123457    Obama, Barack
123458    Obama, Barack
123459    Obama, Barack
123460    Obama, Barack
Name: cand_nm

In [21]: fec.cand_nm[123456:123461].map(parties)
Out[21]:
123456    Democrat
123457    Democrat
123458    Democrat
123459    Democrat
123460    Democrat
Name: cand_nm

# Add it as a column
In [22]: fec['party'] = fec.cand_nm.map(parties)

In [23]: fec['party'].value_counts()
Out[23]:
Democrat      593746
Republican    407985
```

A couple of data preparation points. First, this data includes both contributions and refunds (negative contribution amount):

```
In [24]: (fec.contb_receipt_amt > 0).value_counts()
Out[24]:
True     991475
False     10256
```

To simplify the analysis, I'll restrict the data set to positive contributions:

```
In [25]: fec = fec[fec.contb_receipt_amt > 0]
```

Since Barack Obama and Mitt Romney are the main two candidates, I'll also prepare a subset that just has contributions to their campaigns:

```
In [26]: fec_mrbo = fec[fec.cand_nm.isin(['Obama, Barack', 'Romney, Mitt'])]
```

Donation Statistics by Occupation and Employer

Donations by occupation is another oft-studied statistic. For example, lawyers (attorneys) tend to donate more money to Democrats, while business executives tend to donate more to Republicans. You have no reason to believe me; you can see for yourself in the data. First, the total number of donations by occupation is easy:

```
In [27]: fec.contbr_occupation.value_counts()[:10]
Out[27]:
RETIRED                                   233990
INFORMATION REQUESTED                      35107
ATTORNEY                                   34286
HOMEMAKER                                  29931
PHYSICIAN                                  23432
INFORMATION REQUESTED PER BEST EFFORTS     21138
ENGINEER                                   14334
TEACHER                                    13990
CONSULTANT                                 13273
PROFESSOR                                  12555
```

You will notice by looking at the occupations that many refer to the same basic job type, or there are several variants of the same thing. Here is a code snippet illustrates a technique for cleaning up a few of them by mapping from one occupation to another; note the "trick" of using `dict.get` to allow occupations with no mapping to "pass through":

```
occ_mapping = {
   'INFORMATION REQUESTED PER BEST EFFORTS' : 'NOT PROVIDED',
   'INFORMATION REQUESTED' : 'NOT PROVIDED',
   'INFORMATION REQUESTED (BEST EFFORTS)' : 'NOT PROVIDED',
   'C.E.O.': 'CEO'
}

# If no mapping provided, return x
f = lambda x: occ_mapping.get(x, x)
fec.contbr_occupation = fec.contbr_occupation.map(f)
```

I'll also do the same thing for employers:

```
emp_mapping = {
   'INFORMATION REQUESTED PER BEST EFFORTS' : 'NOT PROVIDED',
   'INFORMATION REQUESTED' : 'NOT PROVIDED',
   'SELF' : 'SELF-EMPLOYED',
   'SELF EMPLOYED' : 'SELF-EMPLOYED',
}

# If no mapping provided, return x
f = lambda x: emp_mapping.get(x, x)
fec.contbr_employer = fec.contbr_employer.map(f)
```

Now, you can use `pivot_table` to aggregate the data by party and occupation, then filter down to the subset that donated at least $2 million overall:

```
In [34]: by_occupation = fec.pivot_table('contb_receipt_amt',
   ....:                                 rows='contbr_occupation',
   ....:                                 cols='party', aggfunc='sum')

In [35]: over_2mm = by_occupation[by_occupation.sum(1) > 2000000]

In [36]: over_2mm
Out[36]:
party                 Democrat       Republican
contbr_occupation
```

```
ATTORNEY          11141982.97   7477194.430000
CEO                2074974.79   4211040.520000
CONSULTANT         2459912.71   2544725.450000
ENGINEER            951525.55   1818373.700000
EXECUTIVE          1355161.05   4138850.090000
HOMEMAKER          4248875.80  13634275.780000
INVESTOR            884133.00   2431768.920000
LAWYER             3160478.87    391224.320000
MANAGER             762883.22   1444532.370000
NOT PROVIDED       4866973.96  20565473.010000
OWNER              1001567.36   2408286.920000
PHYSICIAN          3735124.94   3594320.240000
PRESIDENT          1878509.95   4720923.760000
PROFESSOR          2165071.08    296702.730000
REAL ESTATE         528902.09   1625902.250000
RETIRED           25305116.38  23561244.489999
SELF-EMPLOYED       672393.40   1640252.540000
```

It can be easier to look at this data graphically as a bar plot (`'barh'` means horizontal bar plot, see Figure 9-2):

```
In [38]: over_2mm.plot(kind='barh')
```

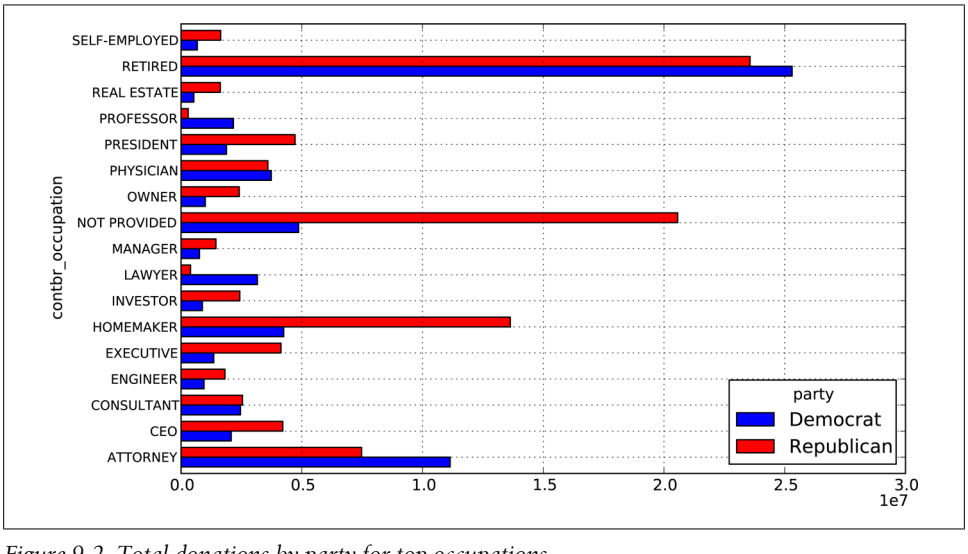


Figure 9-2. Total donations by party for top occupations

You might be interested in the top donor occupations or top companies donating to Obama and Romney. To do this, you can group by candidate name and use a variant of the `top` method from earlier in the chapter:

```
def get_top_amounts(group, key, n=5):
    totals = group.groupby(key)['contb_receipt_amt'].sum()

    # Order totals by key in descending order
    return totals.order(ascending=False)[-n:]
```

Then aggregated by occupation and employer:

```
In [40]: grouped = fec_mrbo.groupby('cand_nm')

In [41]: grouped.apply(get_top_amounts, 'contbr_occupation', n=7)
Out[41]:
cand_nm        contbr_occupation
Obama, Barack  RETIRED              25305116.38
               ATTORNEY             11141982.97
               NOT PROVIDED          4866973.96
               HOMEMAKER             4248875.80
               PHYSICIAN             3735124.94
               LAWYER                3160478.87
               CONSULTANT            2459912.71
Romney, Mitt   RETIRED              11508473.59
               NOT PROVIDED         11396894.84
               HOMEMAKER             8147446.22
               ATTORNEY              5364718.82
               PRESIDENT             2491244.89
               EXECUTIVE             2300947.03
               C.E.O.                1968386.11
Name: contb_receipt_amt

In [42]: grouped.apply(get_top_amounts, 'contbr_employer', n=10)
Out[42]:
cand_nm        contbr_employer
Obama, Barack  RETIRED               22694358.85
               SELF-EMPLOYED         18626807.16
               NOT EMPLOYED           8586308.70
               NOT PROVIDED           5053480.37
               HOMEMAKER              2605408.54
               STUDENT                 318831.45
               VOLUNTEER               257104.00
               MICROSOFT               215585.36
               SIDLEY AUSTIN LLP       168254.00
               REFUSED                 149516.07
Romney, Mitt   NOT PROVIDED          12059527.24
               RETIRED               11506225.71
               HOMEMAKER              8147196.22
               SELF-EMPLOYED          7414115.22
               STUDENT                 496490.94
               CREDIT SUISSE           281150.00
               MORGAN STANLEY          267266.00
               GOLDMAN SACH & CO.      238250.00
               BARCLAYS CAPITAL        162750.00
               H.I.G. CAPITAL          139500.00
Name: contb_receipt_amt
```

Bucketing Donation Amounts

A useful way to analyze this data is to use the `cut` function to discretize the contributor amounts into buckets by contribution size:

```
In [43]: bins = np.array([0, 1, 10, 100, 1000, 10000, 100000, 1000000, 10000000])
```

```
In [44]: labels = pd.cut(fec_mrbo.contb_receipt_amt, bins)

In [45]: labels
Out[45]:
Categorical:contb_receipt_amt
array([(10, 100], (100, 1000], (100, 1000], ..., (1, 10], (10, 100],
       (100, 1000]], dtype=object)
Levels (8): array([(0, 1], (1, 10], (10, 100], (100, 1000], (1000, 10000],
       (10000, 100000], (100000, 1000000], (1000000, 10000000]], dtype=object)
```

We can then group the data for Obama and Romney by name and bin label to get a histogram by donation size:

```
In [46]: grouped = fec_mrbo.groupby(['cand_nm', labels])

In [47]: grouped.size().unstack(0)
Out[47]:
cand_nm              Obama, Barack  Romney, Mitt
contb_receipt_amt
(0, 1]                         493            77
(1, 10]                      40070          3681
(10, 100]                   372280         31853
(100, 1000]                 153991         43357
(1000, 10000]                22284         26186
(10000, 100000]                  2             1
(100000, 1000000]                3           NaN
(1000000, 10000000]              4           NaN
```

This data shows that Obama has received a significantly larger number of small donations than Romney. You can also sum the contribution amounts and normalize within buckets to visualize percentage of total donations of each size by candidate:

```
In [48]: bucket_sums = grouped.contb_receipt_amt.sum().unstack(0)

In [49]: bucket_sums
Out[49]:
cand_nm              Obama, Barack  Romney, Mitt
contb_receipt_amt
(0, 1]                      318.24         77.00
(1, 10]                   337267.62      29819.66
(10, 100]               20288981.41    1987783.76
(100, 1000]             54798531.46   22363381.69
(1000, 10000]           51753705.67   63942145.42
(10000, 100000]            59100.00      12700.00
(100000, 1000000]        1490683.08           NaN
(1000000, 10000000]      7148839.76           NaN

In [50]: normed_sums = bucket_sums.div(bucket_sums.sum(axis=1), axis=0)

In [51]: normed_sums
Out[51]:
cand_nm              Obama, Barack  Romney, Mitt
contb_receipt_amt
(0, 1]                    0.805182      0.194818
(1, 10]                   0.918767      0.081233
(10, 100]                 0.910769      0.089231
```

```
(100, 1000]              0.710176      0.289824
(1000, 10000]            0.447326      0.552674
(10000, 100000]          0.823120      0.176880
(100000, 1000000]        1.000000           NaN
(1000000, 10000000]      1.000000           NaN

In [52]: normed_sums[:-2].plot(kind='barh', stacked=True)
```

I excluded the two largest bins as these are not donations by individuals. See Figure 9-3 for the resulting figure.

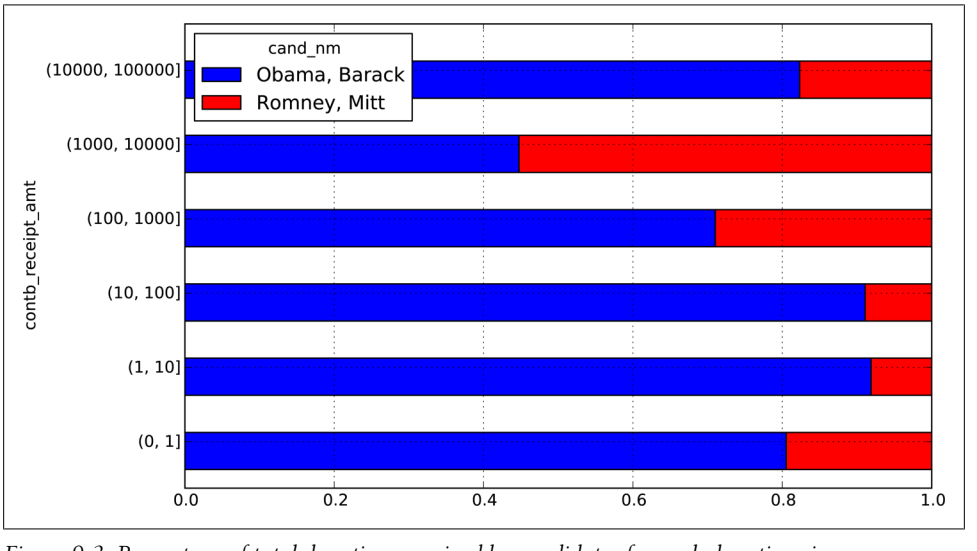


Figure 9-3. Percentage of total donations received by candidates for each donation size

There are of course many refinements and improvements of this analysis. For example, you could aggregate donations by donor name and zip code to adjust for donors who gave many small amounts versus one or more large donations. I encourage you to download it and explore it yourself.

Donation Statistics by State

Aggregating the data by candidate and state is a routine affair:

```
In [53]: grouped = fec_mrbo.groupby(['cand_nm', 'contbr_st'])

In [54]: totals = grouped.contb_receipt_amt.sum().unstack(0).fillna(0)

In [55]: totals = totals[totals.sum(1) > 100000]

In [56]: totals[:10]
Out[56]:
cand_nm    Obama, Barack  Romney, Mitt
contbr_st
```

```
AK            281840.15      86204.24
AL            543123.48     527303.51
AR            359247.28     105556.00
AZ           1506476.98    1888436.23
CA          23824984.24   11237636.60
CO           2132429.49    1506714.12
CT           2068291.26    3499475.45
DC           4373538.80    1025137.50
DE            336669.14      82712.00
FL           7318178.58    8338458.81
```

If you divide each row by the total contribution amount, you get the relative percentage of total donations by state for each candidate:

```
In [57]: percent = totals.div(totals.sum(1), axis=0)

In [58]: percent[:10]
Out[58]:
cand_nm    Obama, Barack  Romney, Mitt
contbr_st
AK              0.765778      0.234222
AL              0.507390      0.492610
AR              0.772902      0.227098
AZ              0.443745      0.556255
CA              0.679498      0.320502
CO              0.585970      0.414030
CT              0.371476      0.628524
DC              0.810113      0.189887
DE              0.802776      0.197224
FL              0.467417      0.532583
```

I thought it would be interesting to look at this data plotted on a map, using ideas from Chapter 8. After locating a shape file for the state boundaries (*http://nationalatlas.gov/atlasftp.html?openChapters=chpbound*) and learning a bit more about matplotlib and its `basemap` toolkit (I was aided by a blog posting from Thomas Lecocq)[3], I ended up with the following code for plotting these relative percentages:

```
from mpl_toolkits.basemap import Basemap, cm
import numpy as np
from matplotlib import rcParams
from matplotlib.collections import LineCollection
import matplotlib.pyplot as plt

from shapelib import ShapeFile
import dbflib

obama = percent['Obama, Barack']

fig = plt.figure(figsize=(12, 12))
ax = fig.add_axes([0.1,0.1,0.8,0.8])

lllat = 21; urlat = 53; lllon = -118; urlon = -62
```

3. *http://www.geophysique.be/2011/01/27/matplotlib-basemap-tutorial-07-shapefiles-unleached/*

```
m = Basemap(ax=ax, projection='stere',
            lon_0=(urlon + lllon) / 2, lat_0=(urlat + lllat) / 2,
            llcrnrlat=lllat, urcrnrlat=urlat, llcrnrlon=lllon,
            urcrnrlon=urlon, resolution='l')
m.drawcoastlines()
m.drawcountries()

shp = ShapeFile('../states/statesp020')
dbf = dbflib.open('../states/statesp020')

for npoly in range(shp.info()[0]):
    # Draw colored polygons on the map
    shpsegs = []
    shp_object = shp.read_object(npoly)
    verts = shp_object.vertices()
    rings = len(verts)
    for ring in range(rings):
        lons, lats = zip(*verts[ring])
        x, y = m(lons, lats)
        shpsegs.append(zip(x,y))
        if ring == 0:
            shapedict = dbf.read_record(npoly)
        name = shapedict['STATE']
    lines = LineCollection(shpsegs,antialiaseds=(1,))

    # state_to_code dict, e.g. 'ALASKA' -> 'AK', omitted
    try:
        per = obama[state_to_code[name.upper()]]
    except KeyError:
        continue

    lines.set_facecolors('k')
    lines.set_alpha(0.75 * per) # Shrink the percentage a bit
    lines.set_edgecolors('k')
    lines.set_linewidth(0.3)
    ax.add_collection(lines)

plt.show()
```

See Figure 9-4 for the result.

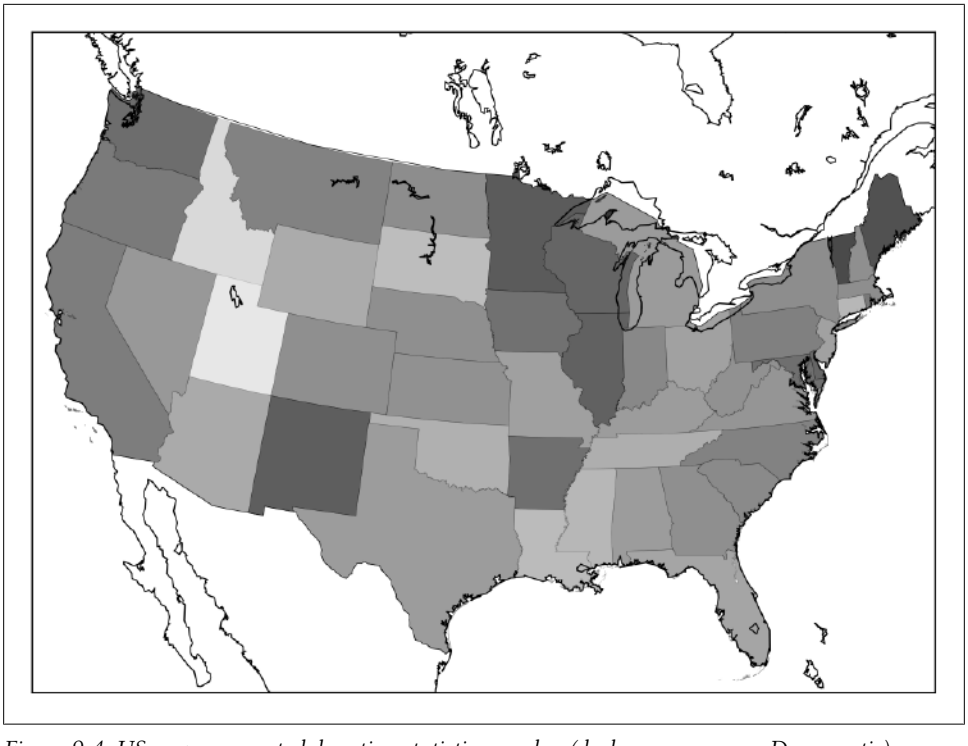


Figure 9-4. US map aggregated donation statistics overlay (darker means more Democratic)

CHAPTER 10
Time Series

Time series data is an important form of structured data in many different fields, such as finance, economics, ecology, neuroscience, or physics. Anything that is observed or measured at many points in time forms a time series. Many time series are *fixed frequency*, which is to say that data points occur at regular intervals according to some rule, such as every 15 seconds, every 5 minutes, or once per month. Time series can also be *irregular* without a fixed unit or time or offset between units. How you mark and refer to time series data depends on the application and you may have one of the following:

- *Timestamps*, specific instants in time
- Fixed *periods*, such as the month January 2007 or the full year 2010
- *Intervals* of time, indicated by a start and end timestamp. Periods can be thought of as special cases of intervals
- Experiment or elapsed time; each timestamp is a measure of time relative to a particular start time. For example, the diameter of a cookie baking each second since being placed in the oven

In this chapter, I am mainly concerned with time series in the first 3 categories, though many of the techniques can be applied to experimental time series where the index may be an integer or floating point number indicating elapsed time from the start of the experiment. The simplest and most widely used kind of time series are those indexed by timestamp.

pandas provides a standard set of time series tools and data algorithms. With this, you can efficiently work with very large time series and easily slice and dice, aggregate, and resample irregular and fixed frequency time series. As you might guess, many of these tools are especially useful for financial and economics applications, but you could certainly use them to analyze server log data, too.

Some of the features and code, in particular period logic, presented in this chapter were derived from the now defunct `scikits.timeseries` library.

Date and Time Data Types and Tools

The Python standard library includes data types for date and time data, as well as calendar-related functionality. The `datetime`, `time`, and `calendar` modules are the main places to start. The `datetime.datetime` type, or simply `datetime`, is widely used:

```
In [317]: from datetime import datetime

In [318]: now = datetime.now()

In [319]: now
Out[319]: datetime.datetime(2012, 8, 4, 17, 9, 21, 832092)

In [320]: now.year, now.month, now.day
Out[320]: (2012, 8, 4)
```

`datetime` stores both the date and time down to the microsecond. `datetime.time delta` represents the temporal difference between two `datetime` objects:

```
In [321]: delta = datetime(2011, 1, 7) - datetime(2008, 6, 24, 8, 15)

In [322]: delta
Out[322]: datetime.timedelta(926, 56700)

In [323]: delta.days        In [324]: delta.seconds
Out[323]: 926               Out[324]: 56700
```

You can add (or subtract) a `timedelta` or multiple thereof to a `datetime` object to yield a new shifted object:

```
In [325]: from datetime import timedelta

In [326]: start = datetime(2011, 1, 7)

In [327]: start + timedelta(12)
Out[327]: datetime.datetime(2011, 1, 19, 0, 0)

In [328]: start - 2 * timedelta(12)
Out[328]: datetime.datetime(2010, 12, 14, 0, 0)
```

The data types in the `datetime` module are summarized in Table 10-1. While this chapter is mainly concerned with the data types in pandas and higher level time series manipulation, you will undoubtedly encounter the `datetime`-based types in many other places in Python the wild.

Table 10-1. Types in datetime module

Type	Description
`date`	Store calendar date (year, month, day) using the Gregorian calendar.
`time`	Store time of day as hours, minutes, seconds, and microseconds
`datetime`	Stores both date and time
`timedelta`	Represents the difference between two datetime values (as days, seconds, and microseconds)

Converting between string and datetime

`datetime` objects and pandas `Timestamp` objects, which I'll introduce later, can be formatted as strings using `str` or the `strftime` method, passing a format specification:

```
In [329]: stamp = datetime(2011, 1, 3)

In [330]: str(stamp)                  In [331]: stamp.strftime('%Y-%m-%d')
Out[330]: '2011-01-03 00:00:00'       Out[331]: '2011-01-03'
```

See Table 10-2 for a complete list of the format codes. These same format codes can be used to convert strings to dates using `datetime.strptime`:

```
In [332]: value = '2011-01-03'

In [333]: datetime.strptime(value, '%Y-%m-%d')
Out[333]: datetime.datetime(2011, 1, 3, 0, 0)

In [334]: datestrs = ['7/6/2011', '8/6/2011']

In [335]: [datetime.strptime(x, '%m/%d/%Y') for x in datestrs]
Out[335]: [datetime.datetime(2011, 7, 6, 0, 0), datetime.datetime(2011, 8, 6, 0, 0)]
```

`datetime.strptime` is the best way to parse a date with a known format. However, it can be a bit annoying to have to write a format spec each time, especially for common date formats. In this case, you can use the `parser.parse` method in the third party `dateutil` package:

```
In [336]: from dateutil.parser import parse

In [337]: parse('2011-01-03')
Out[337]: datetime.datetime(2011, 1, 3, 0, 0)
```

`dateutil` is capable of parsing almost any human-intelligible date representation:

```
In [338]: parse('Jan 31, 1997 10:45 PM')
Out[338]: datetime.datetime(1997, 1, 31, 22, 45)
```

In international locales, day appearing before month is very common, so you can pass `dayfirst=True` to indicate this:

```
In [339]: parse('6/12/2011', dayfirst=True)
Out[339]: datetime.datetime(2011, 12, 6, 0, 0)
```

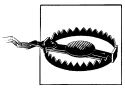
pandas is generally oriented toward working with arrays of dates, whether used as an axis index or a column in a DataFrame. The `to_datetime` method parses many different kinds of date representations. Standard date formats like ISO8601 can be parsed very quickly.

```
In [340]: datestrs
Out[340]: ['7/6/2011', '8/6/2011']

In [341]: pd.to_datetime(datestrs)
Out[341]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-07-06 00:00:00, 2011-08-06 00:00:00]
Length: 2, Freq: None, Timezone: None
```

It also handles values that should be considered missing (`None`, empty string, etc.):

```
In [342]: idx = pd.to_datetime(datestrs + [None])

In [343]: idx
Out[343]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-07-06 00:00:00, ..., NaT]
Length: 3, Freq: None, Timezone: None

In [344]: idx[2]
Out[344]: NaT

In [345]: pd.isnull(idx)
Out[345]: array([False, False, True], dtype=bool)
```

`NaT` (Not a Time) is pandas's NA value for timestamp data.



`dateutil.parser` is a useful, but not perfect tool. Notably, it will recognize some strings as dates that you might prefer that it didn't, like `'42'` will be parsed as the year `2042` with today's calendar date.

Table 10-2. Datetime format specification (ISO C89 compatible)

Type	Description
%Y	4-digit year
%y	2-digit year
%m	2-digit month [01, 12]
%d	2-digit day [01, 31]
%H	Hour (24-hour clock) [00, 23]
%I	Hour (12-hour clock) [01, 12]
%M	2-digit minute [00, 59]
%S	Second [00, 61] (seconds 60, 61 account for leap seconds)
%w	Weekday as integer [0 (Sunday), 6]

Type	Description
%U	Week number of the year [00, 53]. Sunday is considered the first day of the week, and days before the first Sunday of the year are "week 0".
%W	Week number of the year [00, 53]. Monday is considered the first day of the week, and days before the first Monday of the year are "week 0".
%z	UTC time zone offset as +HHMM or -HHMM, empty if time zone naive
%F	Shortcut for %Y-%m-%d, for example 2012-4-18
%D	Shortcut for %m/%d/%y, for example 04/18/12

`datetime` objects also have a number of locale-specific formatting options for systems in other countries or languages. For example, the abbreviated month names will be different on German or French systems compared with English systems.

Table 10-3. Locale-specific date formatting

Type	Description
%a	Abbreviated weekday name
%A	Full weekday name
%b	Abbreviated month name
%B	Full month name
%c	Full date and time, for example 'Tue 01 May 2012 04:20:57 PM'
%p	Locale equivalent of AM or PM
%x	Locale-appropriate formatted date; e.g. in US May 1, 2012 yields '05/01/2012'
%X	Locale-appropriate time, e.g. '04:24:12 PM'

Time Series Basics

The most basic kind of time series object in pandas is a Series indexed by timestamps, which is often represented external to pandas as Python strings or `datetime` objects:

```
In [346]: from datetime import datetime

In [347]: dates = [datetime(2011, 1, 2), datetime(2011, 1, 5), datetime(2011, 1, 7),
   .....:          datetime(2011, 1, 8), datetime(2011, 1, 10), datetime(2011, 1, 12)]

In [348]: ts = Series(np.random.randn(6), index=dates)

In [349]: ts
Out[349]:
2011-01-02    0.690002
2011-01-05    1.001543
2011-01-07   -0.503087
2011-01-08   -0.622274
```

```
2011-01-10   -0.921169
2011-01-12   -0.726213
```

Under the hood, these `datetime` objects have been put in a `DatetimeIndex`, and the variable `ts` is now of type `TimeSeries`:

```
In [350]: type(ts)
Out[350]: pandas.core.series.TimeSeries

In [351]: ts.index
Out[351]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-02 00:00:00, ..., 2011-01-12 00:00:00]
Length: 6, Freq: None, Timezone: None
```

It's not necessary to use the `TimeSeries` constructor explicitly; when creating a Series with a `DatetimeIndex`, pandas knows that the object is a time series.

Like other Series, arithmetic operations between differently-indexed time series automatically align on the dates:

```
In [352]: ts + ts[::2]
Out[352]:
2011-01-02    1.380004
2011-01-05         NaN
2011-01-07   -1.006175
2011-01-08         NaN
2011-01-10   -1.842337
2011-01-12         NaN
```

pandas stores timestamps using NumPy's `datetime64` data type at the nanosecond resolution:

```
In [353]: ts.index.dtype
Out[353]: dtype('datetime64[ns]')
```

Scalar values from a `DatetimeIndex` are pandas `Timestamp` objects

```
In [354]: stamp = ts.index[0]

In [355]: stamp
Out[355]: <Timestamp: 2011-01-02 00:00:00>
```

A `Timestamp` can be substituted anywhere you would use a `datetime` object. Additionally, it can store frequency information (if any) and understands how to do time zone conversions and other kinds of manipulations. More on both of these things later.

Indexing, Selection, Subsetting

TimeSeries is a subclass of Series and thus behaves in the same way with regard to indexing and selecting data based on label:

```
In [356]: stamp = ts.index[2]

In [357]: ts[stamp]
Out[357]: -0.50308739136034464
```

As a convenience, you can also pass a string that is interpretable as a date:

```
In [358]: ts['1/10/2011']
Out[358]: -0.92116860801301081
```

```
In [359]: ts['20110110']
Out[359]: -0.92116860801301081
```

For longer time series, a year or only a year and month can be passed to easily select slices of data:

```
In [360]: longer_ts = Series(np.random.randn(1000),
   .....:                    index=pd.date_range('1/1/2000', periods=1000))

In [361]: longer_ts
Out[361]:
2000-01-01    0.222896
2000-01-02    0.051316
2000-01-03   -1.157719
2000-01-04    0.816707
...
2002-09-23   -0.395813
2002-09-24   -0.180737
2002-09-25    1.337508
2002-09-26   -0.416584
Freq: D, Length: 1000
```

```
In [362]: longer_ts['2001']
Out[362]:
2001-01-01   -1.499503
2001-01-02    0.545154
2001-01-03    0.400823
2001-01-04   -1.946230
...
2001-12-28   -1.568139
2001-12-29   -0.900887
2001-12-30    0.652346
2001-12-31    0.871600
Freq: D, Length: 365
```

```
In [363]: longer_ts['2001-05']
Out[363]:
2001-05-01    1.662014
2001-05-02   -1.189203
2001-05-03    0.093597
2001-05-04   -0.539164
...
2001-05-28   -0.683066
2001-05-29   -0.950313
2001-05-30    0.400710
2001-05-31   -0.126072
Freq: D, Length: 31
```

Slicing with dates works just like with a regular Series:

```
In [364]: ts[datetime(2011, 1, 7):]
Out[364]:
2011-01-07   -0.503087
2011-01-08   -0.622274
2011-01-10   -0.921169
2011-01-12   -0.726213
```

Because most time series data is ordered chronologically, you can slice with timestamps not contained in a time series to perform a range query:

```
In [365]: ts
Out[365]:
2011-01-02    0.690002
```

```
In [366]: ts['1/6/2011':'1/11/2011']
Out[366]:
2011-01-07   -0.503087
```

```
2011-01-05    1.001543        2011-01-08   -0.622274
2011-01-07   -0.503087        2011-01-10   -0.921169
2011-01-08   -0.622274
2011-01-10   -0.921169
2011-01-12   -0.726213
```

As before you can pass either a string date, datetime, or Timestamp. Remember that slicing in this manner produces views on the source time series just like slicing NumPy arrays. There is an equivalent instance method `truncate` which slices a TimeSeries between two dates:

```
In [367]: ts.truncate(after='1/9/2011')
Out[367]:
2011-01-02    0.690002
2011-01-05    1.001543
2011-01-07   -0.503087
2011-01-08   -0.622274
```

All of the above holds true for DataFrame as well, indexing on its rows:

```
In [368]: dates = pd.date_range('1/1/2000', periods=100, freq='W-WED')

In [369]: long_df = DataFrame(np.random.randn(100, 4),
   .....:                     index=dates,
   .....:                     columns=['Colorado', 'Texas', 'New York', 'Ohio'])

In [370]: long_df.ix['5-2001']
Out[370]:
            Colorado     Texas  New York      Ohio
2001-05-02  0.943479 -0.349366  0.530412 -0.508724
2001-05-09  0.230643 -0.065569 -0.248717 -0.587136
2001-05-16 -1.022324  1.060661  0.954768 -0.511824
2001-05-23 -1.387680  0.767902 -1.164490  1.527070
2001-05-30  0.287542  0.715359 -0.345805  0.470886
```

Time Series with Duplicate Indices

In some applications, there may be multiple data observations falling on a particular timestamp. Here is an example:

```
In [371]: dates = pd.DatetimeIndex(['1/1/2000', '1/2/2000', '1/2/2000', '1/2/2000',
   .....:                           '1/3/2000'])

In [372]: dup_ts = Series(np.arange(5), index=dates)

In [373]: dup_ts
Out[373]:
2000-01-01    0
2000-01-02    1
2000-01-02    2
2000-01-02    3
2000-01-03    4
```

We can tell that the index is not unique by checking its `is_unique` property:

```
In [374]: dup_ts.index.is_unique
Out[374]: False
```

Indexing into this time series will now either produce scalar values or slices depending on whether a timestamp is duplicated:

```
In [375]: dup_ts['1/3/2000']  # not duplicated
Out[375]: 4

In [376]: dup_ts['1/2/2000']  # duplicated
Out[376]:
2000-01-02    1
2000-01-02    2
2000-01-02    3
```

Suppose you wanted to aggregate the data having non-unique timestamps. One way to do this is to use `groupby` and pass `level=0` (the only level of indexing!):

```
In [377]: grouped = dup_ts.groupby(level=0)

In [378]: grouped.mean()
Out[378]:
2000-01-01    0
2000-01-02    2
2000-01-03    4

In [379]: grouped.count()
Out[379]:
2000-01-01    1
2000-01-02    3
2000-01-03    1
```

Date Ranges, Frequencies, and Shifting

Generic time series in pandas are assumed to be irregular; that is, they have no fixed frequency. For many applications this is sufficient. However, it's often desirable to work relative to a fixed frequency, such as daily, monthly, or every 15 minutes, even if that means introducing missing values into a time series. Fortunately pandas has a full suite of standard time series frequencies and tools for resampling, inferring frequencies, and generating fixed frequency date ranges. For example, in the example time series, converting it to be fixed daily frequency can be accomplished by calling `resample`:

```
In [380]: ts
Out[380]:
2011-01-02    0.690002
2011-01-05    1.001543
2011-01-07   -0.503087
2011-01-08   -0.622274
2011-01-10   -0.921169
2011-01-12   -0.726213

In [381]: ts.resample('D')
Out[381]:
2011-01-02    0.690002
2011-01-03         NaN
2011-01-04         NaN
2011-01-05    1.001543
2011-01-06         NaN
2011-01-07   -0.503087
2011-01-08   -0.622274
2011-01-09         NaN
2011-01-10   -0.921169
2011-01-11         NaN
2011-01-12   -0.726213
Freq: D
```

Conversion between frequencies or *resampling* is a big enough topic to have its own section later. Here I'll show you how to use the base frequencies and multiples thereof.

Generating Date Ranges

While I used it previously without explanation, you may have guessed that `pandas.date_range` is responsible for generating a `DatetimeIndex` with an indicated length according to a particular frequency:

```
In [382]: index = pd.date_range('4/1/2012', '6/1/2012')

In [383]: index
Out[383]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-04-01 00:00:00, ..., 2012-06-01 00:00:00]
Length: 62, Freq: D, Timezone: None
```

By default, `date_range` generates daily timestamps. If you pass only a start or end date, you must pass a number of periods to generate:

```
In [384]: pd.date_range(start='4/1/2012', periods=20)
Out[384]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-04-01 00:00:00, ..., 2012-04-20 00:00:00]
Length: 20, Freq: D, Timezone: None

In [385]: pd.date_range(end='6/1/2012', periods=20)
Out[385]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-05-13 00:00:00, ..., 2012-06-01 00:00:00]
Length: 20, Freq: D, Timezone: None
```

The start and end dates define strict boundaries for the generated date index. For example, if you wanted a date index containing the last business day of each month, you would pass the `'BM'` frequency (business end of month) and only dates falling on or inside the date interval will be included:

```
In [386]: pd.date_range('1/1/2000', '12/1/2000', freq='BM')
Out[386]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-31 00:00:00, ..., 2000-11-30 00:00:00]
Length: 11, Freq: BM, Timezone: None
```

`date_range` by default preserves the time (if any) of the start or end timestamp:

```
In [387]: pd.date_range('5/2/2012 12:56:31', periods=5)
Out[387]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-05-02 12:56:31, ..., 2012-05-06 12:56:31]
Length: 5, Freq: D, Timezone: None
```

Sometimes you will have start or end dates with time information but want to generate a set of timestamps *normalized* to midnight as a convention. To do this, there is a `normalize` option:

```
In [388]: pd.date_range('5/2/2012 12:56:31', periods=5, normalize=True)
Out[388]:
<class 'pandas.tseries.index.DatetimeIndex'>
```

```
[2012-05-02 00:00:00, ..., 2012-05-06 00:00:00]
Length: 5, Freq: D, Timezone: None
```

Frequencies and Date Offsets

Frequencies in pandas are composed of a *base frequency* and a multiplier. Base frequencies are typically referred to by a string alias, like `'M'` for monthly or `'H'` for hourly. For each base frequency, there is an object defined generally referred to as a *date offset*. For example, hourly frequency can be represented with the `Hour` class:

```
In [389]: from pandas.tseries.offsets import Hour, Minute

In [390]: hour = Hour()

In [391]: hour
Out[391]: <1 Hour>
```

You can define a multiple of an offset by passing an integer:

```
In [392]: four_hours = Hour(4)

In [393]: four_hours
Out[393]: <4 Hours>
```

In most applications, you would never need to explicitly create one of these objects, instead using a string alias like `'H'` or `'4H'`. Putting an integer before the base frequency creates a multiple:

```
In [394]: pd.date_range('1/1/2000', '1/3/2000 23:59', freq='4h')
Out[394]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-01 00:00:00, ..., 2000-01-03 20:00:00]
Length: 18, Freq: 4H, Timezone: None
```

Many offsets can be combined together by addition:

```
In [395]: Hour(2) + Minute(30)
Out[395]: <150 Minutes>
```

Similarly, you can pass frequency strings like `'2h30min'` which will effectively be parsed to the same expression:

```
In [396]: pd.date_range('1/1/2000', periods=10, freq='1h30min')
Out[396]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-01 00:00:00, ..., 2000-01-01 13:30:00]
Length: 10, Freq: 90T, Timezone: None
```

Some frequencies describe points in time that are not evenly spaced. For example, `'M'` (calendar month end) and `'BM'` (last business/weekday of month) depend on the number of days in a month and, in the latter case, whether the month ends on a weekend or not. For lack of a better term, I call these *anchored* offsets.

See Table 10-4 for a listing of frequency codes and date offset classes available in pandas.

Users can define their own custom frequency classes to provide date logic not available in pandas, though the full details of that are outside the scope of this book.

Table 10-4. Base Time Series Frequencies

Alias	Offset Type	Description
D	Day	Calendar daily
B	BusinessDay	Business daily
H	Hour	Hourly
T or min	Minute	Minutely
S	Second	Secondly
L or ms	Milli	Millisecond (1/1000th of 1 second)
U	Micro	Microsecond (1/1000000th of 1 second)
M	MonthEnd	Last calendar day of month
BM	BusinessMonthEnd	Last business day (weekday) of month
MS	MonthBegin	First calendar day of month
BMS	BusinessMonthBegin	First weekday of month
`W-MON, W-TUE, ...`	Week	Weekly on given day of week: MON, TUE, WED, THU, FRI, SAT, or SUN.
`WOM-1MON, WOM-2MON, ...`	WeekOfMonth	Generate weekly dates in the first, second, third, or fourth week of the month. For example, `WOM-3FRI` for the 3rd Friday of each month.
`Q-JAN, Q-FEB, ...`	QuarterEnd	Quarterly dates anchored on last calendar day of each month, for year ending in indicated month: JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV, or DEC.
`BQ-JAN, BQ-FEB, ...`	BusinessQuarterEnd	Quarterly dates anchored on last weekday day of each month, for year ending in indicated month
`QS-JAN, QS-FEB, ...`	QuarterBegin	Quarterly dates anchored on first calendar day of each month, for year ending in indicated month
`BQS-JAN, BQS-FEB, ...`	BusinessQuarterBegin	Quarterly dates anchored on first weekday day of each month, for year ending in indicated month
`A-JAN, A-FEB, ...`	YearEnd	Annual dates anchored on last calendar day of given month: JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV, or DEC.
`BA-JAN, BA-FEB, ...`	BusinessYearEnd	Annual dates anchored on last weekday of given month
`AS-JAN, AS-FEB, ...`	YearBegin	Annual dates anchored on first day of given month
`BAS-JAN, BAS-FEB, ...`	BusinessYearBegin	Annual dates anchored on first weekday of given month

Week of month dates

One useful frequency class is "week of month", starting with `WOM`. This enables you to get dates like the third Friday of each month:

```
In [397]: rng = pd.date_range('1/1/2012', '9/1/2012', freq='WOM-3FRI')

In [398]: list(rng)
Out[398]:
[<Timestamp: 2012-01-20 00:00:00>,
 <Timestamp: 2012-02-17 00:00:00>,
 <Timestamp: 2012-03-16 00:00:00>,
 <Timestamp: 2012-04-20 00:00:00>,
 <Timestamp: 2012-05-18 00:00:00>,
 <Timestamp: 2012-06-15 00:00:00>,
 <Timestamp: 2012-07-20 00:00:00>,
 <Timestamp: 2012-08-17 00:00:00>]
```

Traders of US equity options will recognize these dates as the standard dates of monthly expiry.

Shifting (Leading and Lagging) Data

"Shifting" refers to moving data backward and forward through time. Both Series and DataFrame have a `shift` method for doing naive shifts forward or backward, leaving the index unmodified:

```
In [399]: ts = Series(np.random.randn(4),
   .....:             index=pd.date_range('1/1/2000', periods=4, freq='M'))

In [400]: ts                In [401]: ts.shift(2)       In [402]: ts.shift(-2)
Out[400]:                   Out[401]:                   Out[402]:
2000-01-31    0.575283      2000-01-31         NaN      2000-01-31    1.814582
2000-02-29    0.304205      2000-02-29         NaN      2000-02-29    1.634858
2000-03-31    1.814582      2000-03-31    0.575283      2000-03-31         NaN
2000-04-30    1.634858      2000-04-30    0.304205      2000-04-30         NaN
Freq: M                     Freq: M                     Freq: M
```

A common use of `shift` is computing percent changes in a time series or multiple time series as DataFrame columns. This is expressed as

```
ts / ts.shift(1) - 1
```

Because naive shifts leave the index unmodified, some data is discarded. Thus if the frequency is known, it can be passed to `shift` to advance the timestamps instead of simply the data:

```
In [403]: ts.shift(2, freq='M')
Out[403]:
2000-03-31    0.575283
2000-04-30    0.304205
2000-05-31    1.814582
2000-06-30    1.634858
Freq: M
```

Other frequencies can be passed, too, giving you a lot of flexibility in how to lead and lag the data:

```
In [404]: ts.shift(3, freq='D')
Out[404]:
2000-02-03    0.575283
2000-03-03    0.304205
2000-04-03    1.814582
2000-05-03    1.634858
```

```
In [405]: ts.shift(1, freq='3D')
Out[405]:
2000-02-03    0.575283
2000-03-03    0.304205
2000-04-03    1.814582
2000-05-03    1.634858
```

```
In [406]: ts.shift(1, freq='90T')
Out[406]:
2000-01-31 01:30:00    0.575283
2000-02-29 01:30:00    0.304205
2000-03-31 01:30:00    1.814582
2000-04-30 01:30:00    1.634858
```

Shifting dates with offsets

The pandas date offsets can also be used with `datetime` or `Timestamp` objects:

```
In [407]: from pandas.tseries.offsets import Day, MonthEnd

In [408]: now = datetime(2011, 11, 17)

In [409]: now + 3 * Day()
Out[409]: datetime.datetime(2011, 11, 20, 0, 0)
```

If you add an anchored offset like `MonthEnd`, the first increment will `roll forward` a date to the next date according to the frequency rule:

```
In [410]: now + MonthEnd()
Out[410]: datetime.datetime(2011, 11, 30, 0, 0)

In [411]: now + MonthEnd(2)
Out[411]: datetime.datetime(2011, 12, 31, 0, 0)
```

Anchored offsets can explicitly "roll" dates forward or backward using their `rollforward` and `rollback` methods, respectively:

```
In [412]: offset = MonthEnd()

In [413]: offset.rollforward(now)
Out[413]: datetime.datetime(2011, 11, 30, 0, 0)

In [414]: offset.rollback(now)
Out[414]: datetime.datetime(2011, 10, 31, 0, 0)
```

A clever use of date offsets is to use these methods with `groupby`:

```
In [415]: ts = Series(np.random.randn(20),
   .....:             index=pd.date_range('1/15/2000', periods=20, freq='4d'))

In [416]: ts.groupby(offset.rollforward).mean()
Out[416]:
2000-01-31   -0.448874
```

```
2000-02-29   -0.683663
2000-03-31    0.251920
```

Of course, an easier and faster way to do this is using `resample` (much more on this later):

```
In [417]: ts.resample('M', how='mean')
Out[417]:
2000-01-31   -0.448874
2000-02-29   -0.683663
2000-03-31    0.251920
Freq: M
```

Time Zone Handling

Working with time zones is generally considered one of the most unpleasant parts of time series manipulation. In particular, daylight savings time (DST) transitions are a common source of complication. As such, many time series users choose to work with time series in *coordinated universal time* or *UTC*, which is the successor to Greenwich Mean Time and is the current international standard. Time zones are expressed as offsets from UTC; for example, New York is four hours behind UTC during daylight savings time and 5 hours the rest of the year.

In Python, time zone information comes from the 3rd party `pytz` library, which exposes the *Olson database*, a compilation of world time zone information. This is especially important for historical data because the DST transition dates (and even UTC offsets) have been changed numerous times depending on the whims of local governments. In the United States,the DST transition times have been changed many times since 1900!

For detailed information about `pytz` library, you'll need to look at that library's documentation. As far as this book is concerned, pandas wraps `pytz`'s functionality so you can ignore its API outside of the time zone names. Time zone names can be found interactively and in the docs:

```
In [418]: import pytz

In [419]: pytz.common_timezones[-5:]
Out[419]: ['US/Eastern', 'US/Hawaii', 'US/Mountain', 'US/Pacific', 'UTC']
```

To get a time zone object from `pytz`, use `pytz.timezone`:

```
In [420]: tz = pytz.timezone('US/Eastern')

In [421]: tz
Out[421]: <DstTzInfo 'US/Eastern' EST-1 day, 19:00:00 STD>
```

Methods in pandas will accept either time zone names or these objects. I recommend just using the names.

Localization and Conversion

By default, time series in pandas are *time zone naive*. Consider the following time series:

```
rng = pd.date_range('3/9/2012 9:30', periods=6, freq='D')
ts = Series(np.random.randn(len(rng)), index=rng)
```

The index's `tz` field is `None`:

```
In [423]: print(ts.index.tz)
None
```

Date ranges can be generated with a time zone set:

```
In [424]: pd.date_range('3/9/2012 9:30', periods=10, freq='D', tz='UTC')
Out[424]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-03-09 09:30:00, ..., 2012-03-18 09:30:00]
Length: 10, Freq: D, Timezone: UTC
```

Conversion from naive to *localized* is handled by the `tz_localize` method:

```
In [425]: ts_utc = ts.tz_localize('UTC')

In [426]: ts_utc
Out[426]:
2012-03-09 09:30:00+00:00    0.414615
2012-03-10 09:30:00+00:00    0.427185
2012-03-11 09:30:00+00:00    1.172557
2012-03-12 09:30:00+00:00   -0.351572
2012-03-13 09:30:00+00:00    1.454593
2012-03-14 09:30:00+00:00    2.043319
Freq: D

In [427]: ts_utc.index
Out[427]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-03-09 09:30:00, ..., 2012-03-14 09:30:00]
Length: 6, Freq: D, Timezone: UTC
```

Once a time series has been localized to a particular time zone, it can be converted to another time zone using `tz_convert`:

```
In [428]: ts_utc.tz_convert('US/Eastern')
Out[428]:
2012-03-09 04:30:00-05:00    0.414615
2012-03-10 04:30:00-05:00    0.427185
2012-03-11 05:30:00-04:00    1.172557
2012-03-12 05:30:00-04:00   -0.351572
2012-03-13 05:30:00-04:00    1.454593
2012-03-14 05:30:00-04:00    2.043319
Freq: D
```

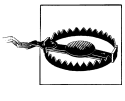
In the case of the above time series, which straddles a DST transition in the US/Eastern time zone, we could localize to EST and convert to, say, UTC or Berlin time:

```
In [429]: ts_eastern = ts.tz_localize('US/Eastern')
```

```
In [430]: ts_eastern.tz_convert('UTC')
Out[430]:
2012-03-09 14:30:00+00:00    0.414615
2012-03-10 14:30:00+00:00    0.427185
2012-03-11 13:30:00+00:00    1.172557
2012-03-12 13:30:00+00:00   -0.351572
2012-03-13 13:30:00+00:00    1.454593
2012-03-14 13:30:00+00:00    2.043319
Freq: D

In [431]: ts_eastern.tz_convert('Europe/Berlin')
Out[431]:
2012-03-09 15:30:00+01:00    0.414615
2012-03-10 15:30:00+01:00    0.427185
2012-03-11 14:30:00+01:00    1.172557
2012-03-12 14:30:00+01:00   -0.351572
2012-03-13 14:30:00+01:00    1.454593
2012-03-14 14:30:00+01:00    2.043319
Freq: D
```

`tz_localize` and `tz_convert` are also instance methods on `DatetimeIndex`:

```
In [432]: ts.index.tz_localize('Asia/Shanghai')
Out[432]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-03-09 09:30:00, ..., 2012-03-14 09:30:00]
Length: 6, Freq: D, Timezone: Asia/Shanghai
```



Localizing naive timestamps also checks for ambiguous or non-existent times around daylight savings time transitions.

Operations with Time Zone—aware Timestamp Objects

Similar to time series and date ranges, individual Timestamp objects similarly can be localized from naive to time zone-aware and converted from one time zone to another:

```
In [433]: stamp = pd.Timestamp('2011-03-12 04:00')

In [434]: stamp_utc = stamp.tz_localize('utc')

In [435]: stamp_utc.tz_convert('US/Eastern')
Out[435]: <Timestamp: 2011-03-11 23:00:00-0500 EST, tz=US/Eastern>
```

You can also pass a time zone when creating the Timestamp:

```
In [436]: stamp_moscow = pd.Timestamp('2011-03-12 04:00', tz='Europe/Moscow')

In [437]: stamp_moscow
Out[437]: <Timestamp: 2011-03-12 04:00:00+0300 MSK, tz=Europe/Moscow>
```

Time zone-aware Timestamp objects internally store a UTC timestamp value as nanoseconds since the UNIX epoch (January 1, 1970); this UTC value is invariant between time zone conversions:

```
In [438]: stamp_utc.value
Out[438]: 1299902400000000000

In [439]: stamp_utc.tz_convert('US/Eastern').value
Out[439]: 1299902400000000000
```

When performing time arithmetic using pandas's `DateOffset` objects, daylight savings time transitions are respected where possible:

```
# 30 minutes before DST transition
In [440]: from pandas.tseries.offsets import Hour

In [441]: stamp = pd.Timestamp('2012-03-12 01:30', tz='US/Eastern')

In [442]: stamp
Out[442]: <Timestamp: 2012-03-12 01:30:00-0400 EDT, tz=US/Eastern>

In [443]: stamp + Hour()
Out[443]: <Timestamp: 2012-03-12 02:30:00-0400 EDT, tz=US/Eastern>

# 90 minutes before DST transition
In [444]: stamp = pd.Timestamp('2012-11-04 00:30', tz='US/Eastern')

In [445]: stamp
Out[445]: <Timestamp: 2012-11-04 00:30:00-0400 EDT, tz=US/Eastern>

In [446]: stamp + 2 * Hour()
Out[446]: <Timestamp: 2012-11-04 01:30:00-0500 EST, tz=US/Eastern>
```

Operations between Different Time Zones

If two time series with different time zones are combined, the result will be UTC. Since the timestamps are stored under the hood in UTC, this is a straightforward operation and requires no conversion to happen:

```
In [447]: rng = pd.date_range('3/7/2012 9:30', periods=10, freq='B')

In [448]: ts = Series(np.random.randn(len(rng)), index=rng)

In [449]: ts
Out[449]:
2012-03-07 09:30:00   -1.749309
2012-03-08 09:30:00   -0.387235
2012-03-09 09:30:00   -0.208074
2012-03-12 09:30:00   -1.221957
2012-03-13 09:30:00   -0.067460
2012-03-14 09:30:00    0.229005
2012-03-15 09:30:00   -0.576234
2012-03-16 09:30:00    0.816895
2012-03-19 09:30:00   -0.772192
2012-03-20 09:30:00   -1.333576
Freq: B

In [450]: ts1 = ts[:7].tz_localize('Europe/London')
```

```
In [451]: ts2 = ts1[2:].tz_convert('Europe/Moscow')

In [452]: result = ts1 + ts2

In [453]: result.index
Out[453]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-03-07 09:30:00, ..., 2012-03-15 09:30:00]
Length: 7, Freq: B, Timezone: UTC
```

Periods and Period Arithmetic

Periods represent time spans, like days, months, quarters, or years. The `Period` class represents this data type, requiring a string or integer and a frequency from the above table:

```
In [454]: p = pd.Period(2007, freq='A-DEC')

In [455]: p
Out[455]: Period('2007', 'A-DEC')
```

In this case, the `Period` object represents the full timespan from January 1, 2007 to December 31, 2007, inclusive. Conveniently, adding and subtracting integers from periods has the effect of shifting by their frequency:

```
In [456]: p + 5                        In [457]: p - 2
Out[456]: Period('2012', 'A-DEC')      Out[457]: Period('2005', 'A-DEC')
```

If two periods have the same frequency, their difference is the number of units between them:

```
In [458]: pd.Period('2014', freq='A-DEC') - p
Out[458]: 7
```

Regular ranges of periods can be constructed using the `period_range` function:

```
In [459]: rng = pd.period_range('1/1/2000', '6/30/2000', freq='M')

In [460]: rng
Out[460]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: M
[2000-01, ..., 2000-06]
length: 6
```

The `PeriodIndex` class stores a sequence of periods and can serve as an axis index in any pandas data structure:

```
In [461]: Series(np.random.randn(6), index=rng)
Out[461]:
2000-01   -0.309119
2000-02    0.028558
2000-03    1.129605
2000-04   -0.374173
2000-05   -0.011401
```

```
2000-06    0.272924
Freq: M
```

If you have an array of strings, you can also appeal to the `PeriodIndex` class itself:

```
In [462]: values = ['2001Q3', '2002Q2', '2003Q1']

In [463]: index = pd.PeriodIndex(values, freq='Q-DEC')

In [464]: index
Out[464]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: Q-DEC
[2001Q3, ..., 2003Q1]
length: 3
```

Period Frequency Conversion

Periods and `PeriodIndex` objects can be converted to another frequency using their `asfreq` method. As an example, suppose we had an annual period and wanted to convert it into a monthly period either at the start or end of the year. This is fairly straightforward:

```
In [465]: p = pd.Period('2007', freq='A-DEC')

In [466]: p.asfreq('M', how='start')      In [467]: p.asfreq('M', how='end')
Out[466]: Period('2007-01', 'M')         Out[467]: Period('2007-12', 'M')
```

You can think of `Period('2007', 'A-DEC')` as being a cursor pointing to a span of time, subdivided by monthly periods. See Figure 10-1 for an illustration of this. For a *fiscal year* ending on a month other than December, the monthly subperiods belonging are different:

```
In [468]: p = pd.Period('2007', freq='A-JUN')

In [469]: p.asfreq('M', 'start')       In [470]: p.asfreq('M', 'end')
Out[469]: Period('2006-07', 'M')      Out[470]: Period('2007-07', 'M')
```

When converting from high to low frequency, the superperiod will be determined depending on where the subperiod "belongs". For example, in `A-JUN` frequency, the month `Aug-2007` is actually part of the `2008` period:

```
In [471]: p = pd.Period('2007-08', 'M')

In [472]: p.asfreq('A-JUN')
Out[472]: Period('2008', 'A-JUN')
```

Whole `PeriodIndex` objects or TimeSeries can be similarly converted with the same semantics:

```
In [473]: rng = pd.period_range('2006', '2009', freq='A-DEC')

In [474]: ts = Series(np.random.randn(len(rng)), index=rng)

In [475]: ts
```

```
Out[475]:
2006   -0.601544
2007    0.574265
2008   -0.194115
2009    0.202225
Freq: A-DEC

In [476]: ts.asfreq('M', how='start')
Out[476]:
2006-01   -0.601544
2007-01    0.574265
2008-01   -0.194115
2009-01    0.202225
Freq: M

In [477]: ts.asfreq('B', how='end')
Out[477]:
2006-12-29   -0.601544
2007-12-31    0.574265
2008-12-31   -0.194115
2009-12-31    0.202225
Freq: B
```

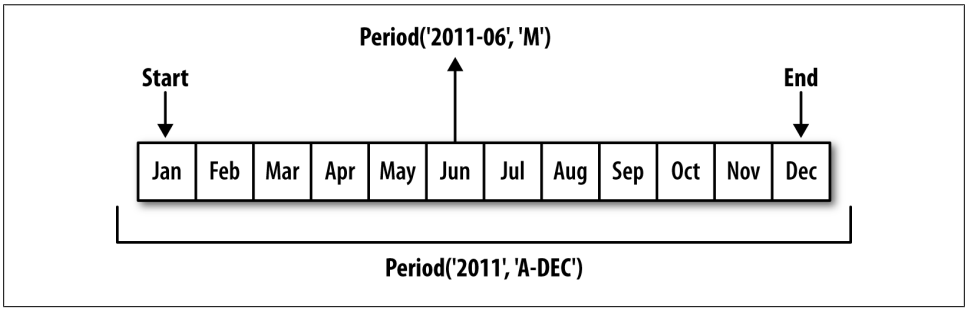


Figure 10-1. Period frequency conversion illustration

Quarterly Period Frequencies

Quarterly data is standard in accounting, finance, and other fields. Much quarterly data is reported relative to a *fiscal year end*, typically the last calendar or business day of one of the 12 months of the year. As such, the period `2012Q4` has a different meaning depending on fiscal year end. pandas supports all 12 possible quarterly frequencies as `Q-JAN` through `Q-DEC`:

```
In [478]: p = pd.Period('2012Q4', freq='Q-JAN')

In [479]: p
Out[479]: Period('2012Q4', 'Q-JAN')
```

In the case of fiscal year ending in January, `2012Q4` runs from November through January, which you can check by converting to daily frequency. See Figure 10-2 for an illustration:

```
In [480]: p.asfreq('D', 'start')
Out[480]: Period('2011-11-01', 'D')

In [481]: p.asfreq('D', 'end')
Out[481]: Period('2012-01-31', 'D')
```

Thus, it's possible to do period arithmetic very easily; for example, to get the timestamp at 4PM on the 2nd to last business day of the quarter, you could do:

```
In [482]: p4pm = (p.asfreq('B', 'e') - 1).asfreq('T', 's') + 16 * 60

In [483]: p4pm
Out[483]: Period('2012-01-30 16:00', 'T')

In [484]: p4pm.to_timestamp()
Out[484]: <Timestamp: 2012-01-30 16:00:00>
```

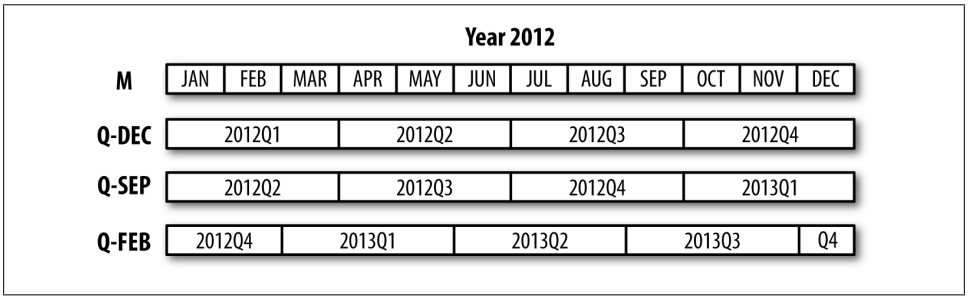


Figure 10-2. Different quarterly frequency conventions

Generating quarterly ranges works as you would expect using `period_range`. Arithmetic is identical, too:

```
In [485]: rng = pd.period_range('2011Q3', '2012Q4', freq='Q-JAN')

In [486]: ts = Series(np.arange(len(rng)), index=rng)

In [487]: ts
Out[487]:
2011Q3    0
2011Q4    1
2012Q1    2
2012Q2    3
2012Q3    4
2012Q4    5
Freq: Q-JAN

In [488]: new_rng = (rng.asfreq('B', 'e') - 1).asfreq('T', 's') + 16 * 60

In [489]: ts.index = new_rng.to_timestamp()

In [490]: ts
Out[490]:
2010-10-28 16:00:00    0
2011-01-28 16:00:00    1
2011-04-28 16:00:00    2
2011-07-28 16:00:00    3
2011-10-28 16:00:00    4
2012-01-30 16:00:00    5
```

Converting Timestamps to Periods (and Back)

Series and DataFrame objects indexed by timestamps can be converted to periods using the `to_period` method:

```
In [491]: rng = pd.date_range('1/1/2000', periods=3, freq='M')

In [492]: ts = Series(randn(3), index=rng)

In [493]: pts = ts.to_period()

In [494]: ts                    In [495]: pts
Out[494]:                       Out[495]:
2000-01-31   -0.505124          2000-01   -0.505124
2000-02-29    2.954439          2000-02    2.954439
2000-03-31   -2.630247          2000-03   -2.630247
Freq: M                         Freq: M
```

Since periods always refer to non-overlapping timespans, a timestamp can only belong to a single period for a given frequency. While the frequency of the new `PeriodIndex` is inferred from the timestamps by default, you can specify any frequency you want. There is also no problem with having duplicate periods in the result:

```
In [496]: rng = pd.date_range('1/29/2000', periods=6, freq='D')

In [497]: ts2 = Series(randn(6), index=rng)

In [498]: ts2.to_period('M')
Out[498]:
2000-01   -0.352453
2000-01   -0.477808
2000-01    0.161594
2000-02    1.686833
2000-02    0.821965
2000-02   -0.667406
Freq: M
```

To convert back to timestamps, use `to_timestamp`:

```
In [499]: pts = ts.to_period()

In [500]: pts
Out[500]:
2000-01   -0.505124
2000-02    2.954439
2000-03   -2.630247
Freq: M

In [501]: pts.to_timestamp(how='end')
Out[501]:
2000-01-31   -0.505124
2000-02-29    2.954439
2000-03-31   -2.630247
Freq: M
```

Creating a PeriodIndex from Arrays

Fixed frequency data sets are sometimes stored with timespan information spread across multiple columns. For example, in this macroeconomic data set, the year and quarter are in different columns:

```
In [502]: data = pd.read_csv('ch08/macrodata.csv')

In [503]: data.year
Out[503]:
0    1959
1    1959
2    1959
3    1959
...
199    2008
200    2009
201    2009
202    2009
Name: year, Length: 203

In [504]: data.quarter
Out[504]:
0    1
1    2
2    3
3    4
...
199    4
200    1
201    2
202    3
Name: quarter, Length: 203
```

By passing these arrays to `PeriodIndex` with a frequency, they can be combined to form an index for the DataFrame:

```
In [505]: index = pd.PeriodIndex(year=data.year, quarter=data.quarter, freq='Q-DEC')

In [506]: index
Out[506]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: Q-DEC
[1959Q1, ..., 2009Q3]
length: 203

In [507]: data.index = index

In [508]: data.infl
Out[508]:
1959Q1    0.00
1959Q2    2.34
1959Q3    2.74
1959Q4    0.27
...
2008Q4   -8.79
2009Q1    0.94
2009Q2    3.37
2009Q3    3.56
Freq: Q-DEC, Name: infl, Length: 203
```

Resampling and Frequency Conversion

Resampling refers to the process of converting a time series from one frequency to another. Aggregating higher frequency data to lower frequency is called *downsampling*, while converting lower frequency to higher frequency is called *upsampling*. Not

all resampling falls into either of these categories; for example, converting `W-WED` (weekly on Wednesday) to `W-FRI` is neither upsampling nor downstampling.

pandas objects are equipped with a `resample` method, which is the workhorse function for all frequency conversion:

```
In [509]: rng = pd.date_range('1/1/2000', periods=100, freq='D')

In [510]: ts = Series(randn(len(rng)), index=rng)

In [511]: ts.resample('M', how='mean')
Out[511]:
2000-01-31    0.170876
2000-02-29    0.165020
2000-03-31    0.095451
2000-04-30    0.363566
Freq: M

In [512]: ts.resample('M', how='mean', kind='period')
Out[512]:
2000-01    0.170876
2000-02    0.165020
2000-03    0.095451
2000-04    0.363566
Freq: M
```

`resample` is a flexible and high-performance method that can be used to process very large time series. I'll illustrate its semantics and use through a series of examples.

Table 10-5. Resample method arguments

Argument	Description
`freq`	String or DateOffset indicating desired resampled frequency, e.g. 'M', '5min', or `Second(15)`
`how='mean'`	Function name or array function producing aggregated value, for example `'mean'`, `'ohlc'`, `np.max`. Defaults to `'mean'`. Other common values: `'first'`, `'last'`, `'median'`, `'ohlc'`, `'max'`, `'min'`.
`axis=0`	Axis to resample on, default axis=0
`fill_method=None`	How to interpolate when upsampling, as in `'ffill'` or `'bfill'`. By default does no interpolation.
`closed='right'`	In downsampling, which end of each interval is closed (inclusive), `'right'` or `'left'`. Defaults to `'right'`
`label='right'`	In downsampling, how to label the aggregated result, with the `'right'` or `'left'` bin edge. For example, the 9:30 to 9:35 5-minute interval could be labeled `9:30` or `9:35`. Defaults to `'right'` (or 9:35, in this example).
`loffset=None`	Time adjustment to the bin labels, such as `'-1s'` / `Second(-1)` to shift the aggregate labels one second earlier
`limit=None`	When forward or backward filling, the maximum number of periods to fill

Argument	Description
`kind=None`	Aggregate to periods (`'period'`) or timestamps (`'timestamp'`); defaults to kind of index the time series has
`convention=None`	When resampling periods, the convention (`'start'` or `'end'`) for converting the low frequency period to high frequency. Defaults to `'end'`

Downsampling

Aggregating data to a regular, lower frequency is a pretty normal time series task. The data you're aggregating doesn't need to be fixed frequently; the desired frequency defines *bin edges* that are used to slice the time series into pieces to aggregate. For example, to convert to monthly, `'M'` or `'BM'`, the data need to be chopped up into one month intervals. Each interval is said to be *half-open*; a data point can only belong to one interval, and the union of the intervals must make up the whole time frame. There are a couple things to think about when using `resample` to downsample data:

- Which side of each interval is *closed*
- How to label each aggregated bin, either with the start of the interval or the end

To illustrate, let's look at some one-minute data:

```
In [513]: rng = pd.date_range('1/1/2000', periods=12, freq='T')

In [514]: ts = Series(np.arange(12), index=rng)

In [515]: ts
Out[515]:
2000-01-01 00:00:00     0
2000-01-01 00:01:00     1
2000-01-01 00:02:00     2
2000-01-01 00:03:00     3
2000-01-01 00:04:00     4
2000-01-01 00:05:00     5
2000-01-01 00:06:00     6
2000-01-01 00:07:00     7
2000-01-01 00:08:00     8
2000-01-01 00:09:00     9
2000-01-01 00:10:00    10
2000-01-01 00:11:00    11
Freq: T
```

Suppose you wanted to aggregate this data into five-minute chunks or *bars* by taking the sum of each group:

```
In [516]: ts.resample('5min', how='sum')
Out[516]:
2000-01-01 00:00:00     0
2000-01-01 00:05:00    15
2000-01-01 00:10:00    40
2000-01-01 00:15:00    11
Freq: 5T
```

The frequency you pass defines bin edges in five-minute increments. By default, the *right* bin edge is inclusive, so the `00:05` value is included in the `00:00` to `00:05` interval.[1] Passing `closed='left'` changes the interval to be closed on the left:

```
In [517]: ts.resample('5min', how='sum', closed='left')
Out[517]:
2000-01-01 00:05:00    10
2000-01-01 00:10:00    35
2000-01-01 00:15:00    21
Freq: 5T
```

As you can see, the resulting time series is labeled by the timestamps from the right side of each bin. By passing `label='left'` you can label them with the left bin edge:

```
In [518]: ts.resample('5min', how='sum', closed='left', label='left')
Out[518]:
2000-01-01 00:00:00    10
2000-01-01 00:05:00    35
2000-01-01 00:10:00    21
Freq: 5T
```

See Figure 10-3 for an illustration of minutely data being resampled to five-minute.

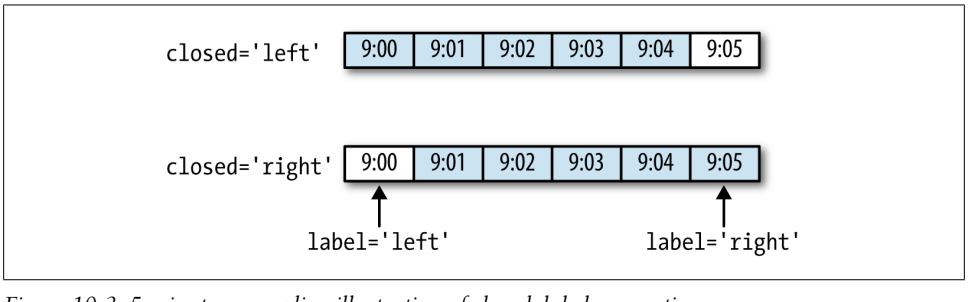


Figure 10-3. 5-minute resampling illustration of closed, label conventions

Lastly, you might want to shift the result index by some amount, say subtracting one second from the right edge to make it more clear which interval the timestamp refers to. To do this, pass a string or date offset to `loffset`:

```
In [519]: ts.resample('5min', how='sum', loffset='-1s')
Out[519]:
1999-12-31 23:59:59     0
2000-01-01 00:04:59    15
2000-01-01 00:09:59    40
2000-01-01 00:14:59    11
Freq: 5T
```

1. The choice of `closed='right', label='right'` as the default might seem a bit odd to some users. In practice the choice is somewhat arbitrary; for some target frequencies, `closed='left'` is preferable, while for others `closed='right'` makes more sense. The important thing is that you keep in mind exactly how you are segmenting the data.

This also could have been accomplished by calling the `shift` method on the result without the `loffset`.

Open-High-Low-Close (OHLC) resampling

In finance, an ubiquitous way to aggregate a time series is to compute four values for each bucket: the first (open), last (close), maximum (high), and minimal (low) values. By passing `how='ohlc'` you will obtain a DataFrame having columns containing these four aggregates, which are efficiently computed in a single sweep of the data:

```
In [520]: ts.resample('5min', how='ohlc')
Out[520]:
                     open  high  low  close
2000-01-01 00:00:00     0     0    0      0
2000-01-01 00:05:00     1     5    1      5
2000-01-01 00:10:00     6    10    6     10
2000-01-01 00:15:00    11    11   11     11
```

Resampling with GroupBy

An alternate way to downsample is to use pandas's `groupby` functionality. For example, you can group by month or weekday by passing a function that accesses those fields on the time series's index:

```
In [521]: rng = pd.date_range('1/1/2000', periods=100, freq='D')

In [522]: ts = Series(np.arange(100), index=rng)

In [523]: ts.groupby(lambda x: x.month).mean()
Out[523]:
1    15
2    45
3    75
4    95

In [524]: ts.groupby(lambda x: x.weekday).mean()
Out[524]:
0    47.5
1    48.5
2    49.5
3    50.5
4    51.5
5    49.0
6    50.0
```

Upsampling and Interpolation

When converting from a low frequency to a higher frequency, no aggregation is needed. Let's consider a DataFrame with some weekly data:

```
In [525]: frame = DataFrame(np.random.randn(2, 4),
   .....:                   index=pd.date_range('1/1/2000', periods=2, freq='W-WED'),
   .....:                   columns=['Colorado', 'Texas', 'New York', 'Ohio'])
```

```
In [526]: frame[:5]
Out[526]:
            Colorado     Texas  New York     Ohio
2000-01-05 -0.609657 -0.268837  0.195592  0.85979
2000-01-12 -0.263206  1.141350 -0.101937 -0.07666
```

When resampling this to daily frequency, by default missing values are introduced:

```
In [527]: df_daily = frame.resample('D')

In [528]: df_daily
Out[528]:
            Colorado     Texas  New York     Ohio
2000-01-05 -0.609657 -0.268837  0.195592  0.85979
2000-01-06       NaN       NaN       NaN      NaN
2000-01-07       NaN       NaN       NaN      NaN
2000-01-08       NaN       NaN       NaN      NaN
2000-01-09       NaN       NaN       NaN      NaN
2000-01-10       NaN       NaN       NaN      NaN
2000-01-11       NaN       NaN       NaN      NaN
2000-01-12 -0.263206  1.141350 -0.101937 -0.07666
```

Suppose you wanted to fill forward each weekly value on the non-Wednesdays. The same filling or interpolation methods available in the `fillna` and `reindex` methods are available for resampling:

```
In [529]: frame.resample('D', fill_method='ffill')
Out[529]:
            Colorado     Texas  New York     Ohio
2000-01-05 -0.609657 -0.268837  0.195592  0.85979
2000-01-06 -0.609657 -0.268837  0.195592  0.85979
2000-01-07 -0.609657 -0.268837  0.195592  0.85979
2000-01-08 -0.609657 -0.268837  0.195592  0.85979
2000-01-09 -0.609657 -0.268837  0.195592  0.85979
2000-01-10 -0.609657 -0.268837  0.195592  0.85979
2000-01-11 -0.609657 -0.268837  0.195592  0.85979
2000-01-12 -0.263206  1.141350 -0.101937 -0.07666
```

You can similarly choose to only fill a certain number of periods forward to limit how far to continue using an observed value:

```
In [530]: frame.resample('D', fill_method='ffill', limit=2)
Out[530]:
            Colorado     Texas  New York     Ohio
2000-01-05 -0.609657 -0.268837  0.195592  0.85979
2000-01-06 -0.609657 -0.268837  0.195592  0.85979
2000-01-07 -0.609657 -0.268837  0.195592  0.85979
2000-01-08       NaN       NaN       NaN      NaN
2000-01-09       NaN       NaN       NaN      NaN
2000-01-10       NaN       NaN       NaN      NaN
2000-01-11       NaN       NaN       NaN      NaN
2000-01-12 -0.263206  1.141350 -0.101937 -0.07666
```

Notably, the new date index need not overlap with the old one at all:

```
In [531]: frame.resample('W-THU', fill_method='ffill')
Out[531]:
            Colorado     Texas  New York     Ohio
2000-01-06 -0.609657 -0.268837  0.195592  0.85979
2000-01-13 -0.263206  1.141350 -0.101937 -0.07666
```

Resampling with Periods

Resampling data indexed by periods is reasonably straightforward and works as you would hope:

```
In [532]: frame = DataFrame(np.random.randn(24, 4),
   .....:                   index=pd.period_range('1-2000', '12-2001', freq='M'),
   .....:                   columns=['Colorado', 'Texas', 'New York', 'Ohio'])

In [533]: frame[:5]
Out[533]:
         Colorado     Texas  New York      Ohio
2000-01  0.120837  1.076607  0.434200  0.056432
2000-02 -0.378890  0.047831  0.341626  1.567920
2000-03 -0.047619 -0.821825 -0.179330 -0.166675
2000-04  0.333219 -0.544615 -0.653635 -2.311026
2000-05  1.612270 -0.806614  0.557884  0.580201

In [534]: annual_frame = frame.resample('A-DEC', how='mean')

In [535]: annual_frame
Out[535]:
      Colorado     Texas  New York      Ohio
2000  0.352070 -0.553642  0.196642 -0.094099
2001  0.158207  0.042967 -0.360755  0.184687
```

Upsampling is more nuanced as you must make a decision about which end of the timespan in the new frequency to place the values before resampling, just like the `asfreq` method. The `convention` argument defaults to `'end'` but can also be `'start'`:

```
# Q-DEC: Quarterly, year ending in December
In [536]: annual_frame.resample('Q-DEC', fill_method='ffill')
Out[536]:
        Colorado     Texas  New York      Ohio
2000Q4  0.352070 -0.553642  0.196642 -0.094099
2001Q1  0.352070 -0.553642  0.196642 -0.094099
2001Q2  0.352070 -0.553642  0.196642 -0.094099
2001Q3  0.352070 -0.553642  0.196642 -0.094099
2001Q4  0.158207  0.042967 -0.360755  0.184687

In [537]: annual_frame.resample('Q-DEC', fill_method='ffill', convention='start')
Out[537]:
        Colorado     Texas  New York      Ohio
2000Q1  0.352070 -0.553642  0.196642 -0.094099
2000Q2  0.352070 -0.553642  0.196642 -0.094099
2000Q3  0.352070 -0.553642  0.196642 -0.094099
2000Q4  0.352070 -0.553642  0.196642 -0.094099
2001Q1  0.158207  0.042967 -0.360755  0.184687
```

Since periods refer to timespans, the rules about upsampling and downsampling are more rigid:

- In downsampling, the target frequency must be a *subperiod* of the source frequency.
- In upsampling, the target frequency must be a *superperiod* of the source frequency.

If these rules are not satisfied, an exception will be raised. This mainly affects the quarterly, annual, and weekly frequencies; for example, the timespans defined by `Q-MAR` only line up with `A-MAR, A-JUN, A-SEP,` and `A-DEC`:

```
In [538]: annual_frame.resample('Q-MAR', fill_method='ffill')
Out[538]:
        Colorado     Texas  New York      Ohio
2001Q3  0.352070 -0.553642  0.196642 -0.094099
2001Q4  0.352070 -0.553642  0.196642 -0.094099
2002Q1  0.352070 -0.553642  0.196642 -0.094099
2002Q2  0.352070 -0.553642  0.196642 -0.094099
2002Q3  0.158207  0.042967 -0.360755  0.184687
```

Time Series Plotting

Plots with pandas time series have improved date formatting compared with matplotlib out of the box. As an example, I downloaded some stock price data on a few common US stock from Yahoo! Finance:

```
In [539]: close_px_all = pd.read_csv('ch09/stock_px.csv', parse_dates=True, index_col=0)

In [540]: close_px = close_px_all[['AAPL', 'MSFT', 'XOM']]

In [541]: close_px = close_px.resample('B', fill_method='ffill')

In [542]: close_px
Out[542]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2292 entries, 2003-01-02 00:00:00 to 2011-10-14 00:00:00
Freq: B
Data columns:
AAPL    2292  non-null values
MSFT    2292  non-null values
XOM     2292  non-null values
dtypes: float64(3)
```

Calling `plot` on one of the columns grenerates a simple plot, seen in Figure 10-4.

```
In [544]: close_px['AAPL'].plot()
```

When called on a DataFrame, as you would expect, all of the time series are drawn on a single subplot with a legend indicating which is which. I'll plot only the year 2009 data so you can see how both months and years are formatted on the X axis; see Figure 10-5.

```
In [546]: close_px.ix['2009'].plot()
```

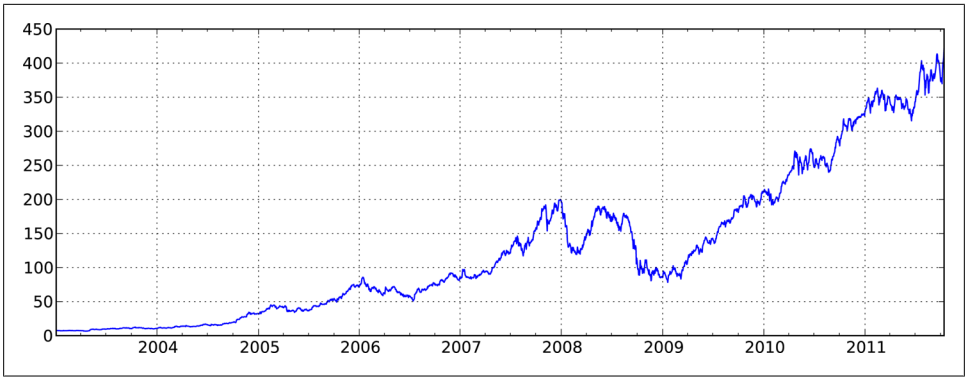


Figure 10-4. AAPL Daily Price

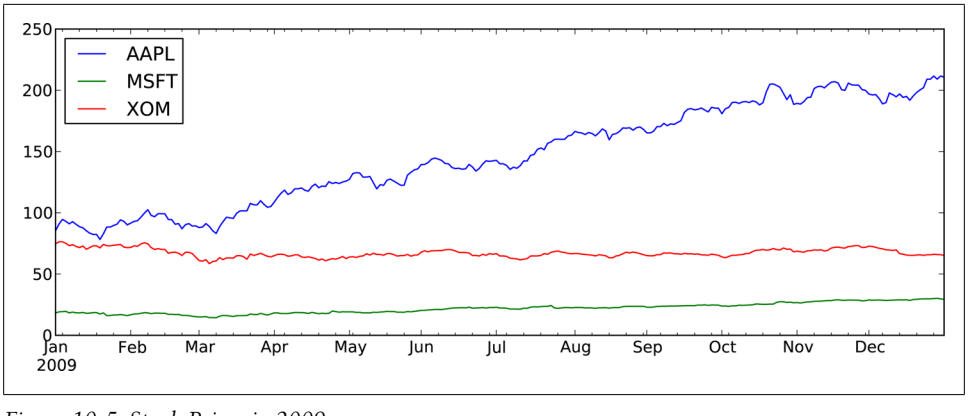


Figure 10-5. Stock Prices in 2009

```
In [548]: close_px['AAPL'].ix['01-2011':'03-2011'].plot()
```

Quarterly frequency data is also more nicely formatted with quarterly markers, something that would be quite a bit more work to do by hand. See Figure 10-7.

```
In [550]: appl_q = close_px['AAPL'].resample('Q-DEC', fill_method='ffill')

In [551]: appl_q.ix['2009':].plot()
```

A last feature of time series plotting in pandas is that by right-clicking and dragging to zoom in and out, the dates will be dynamically expanded or contracted and reformatting depending on the timespan contained in the plot view. This is of course only true when using matplotlib in interactive mode.

Moving Window Functions

A common class of array transformations intended for time series operations are statistics and other functions evaluated over a sliding window or with exponentially de-

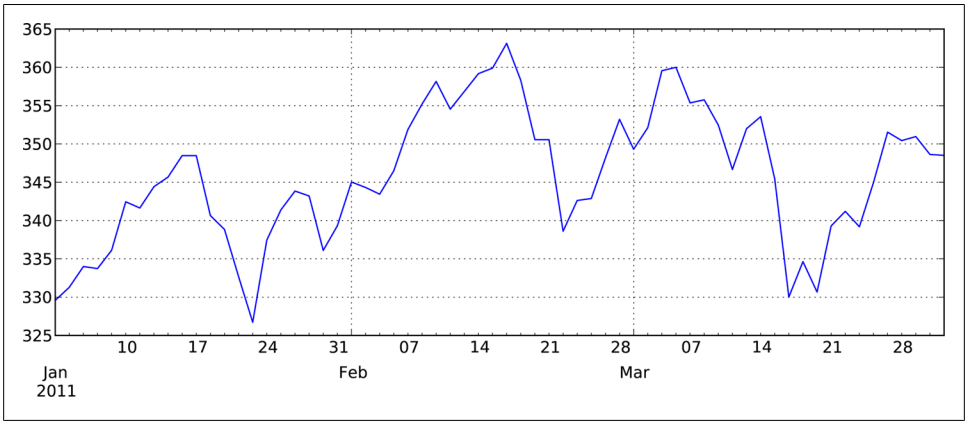


Figure 10-6. Apple Daily Price in 1/2011-3/2011

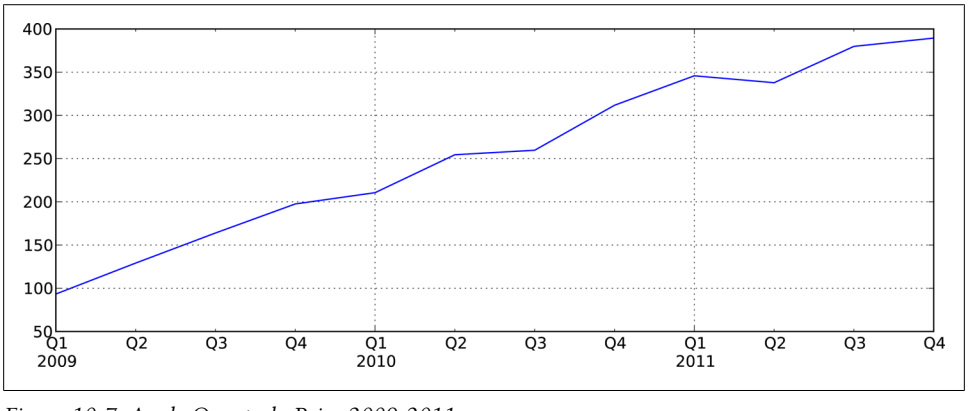


Figure 10-7. Apple Quarterly Price 2009-2011

caying weights. I call these *moving window functions*, even though it includes functions without a fixed-length window like exponentially-weighted moving average. Like other statistical functions, these also automatically exclude missing data.

`rolling_mean` is one of the simplest such functions. It takes a TimeSeries or DataFrame along with a `window` (expressed as a number of periods):

```
In [555]: close_px.AAPL.plot()
Out[555]: <matplotlib.axes.AxesSubplot at 0x1099b3990>

In [556]: pd.rolling_mean(close_px.AAPL, 250).plot()
```

See Figure 10-8 for the plot. By default functions like `rolling_mean` require the indicated number of non-NA observations. This behavior can be changed to account for missing data and, in particular, the fact that you will have fewer than `window` periods of data at the beginning of the time series (see Figure 10-9):

```
In [558]: appl_std250 = pd.rolling_std(close_px.AAPL, 250, min_periods=10)

In [559]: appl_std250[5:12]
Out[559]:
2003-01-09         NaN
2003-01-10         NaN
2003-01-13         NaN
2003-01-14         NaN
2003-01-15    0.077496
2003-01-16    0.074760
2003-01-17    0.112368
Freq: B

In [560]: appl_std250.plot()
```

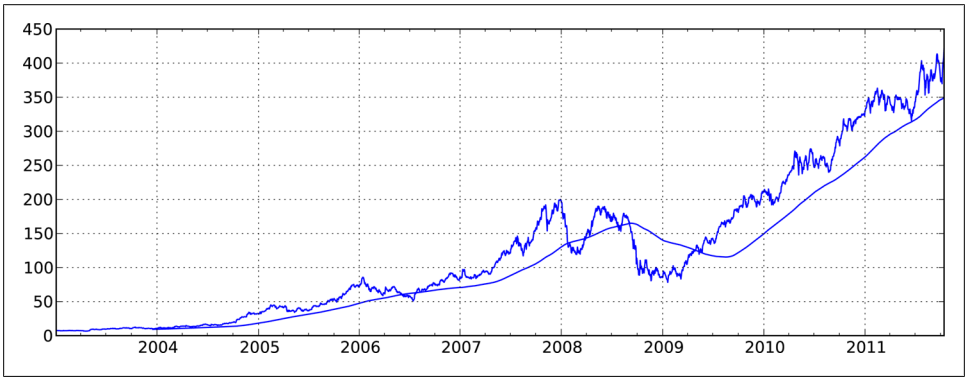


Figure 10-8. Apple Price with 250-day MA

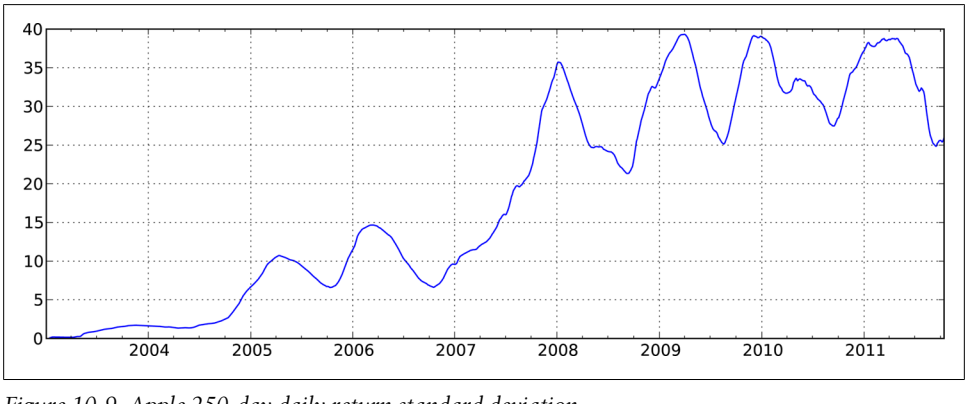


Figure 10-9. Apple 250-day daily return standard deviation

To compute an *expanding window mean*, you can see that an expanding window is just a special case where the window is the length of the time series, but only one or more periods is required to compute a value:

```
# Define expanding mean in terms of rolling_mean
In [561]: expanding_mean = lambda x: rolling_mean(x, len(x), min_periods=1)
```

Calling `rolling_mean` and friends on a DataFrame applies the transformation to each column (see Figure 10-10):

```
In [563]: pd.rolling_mean(close_px, 60).plot(logy=True)
```

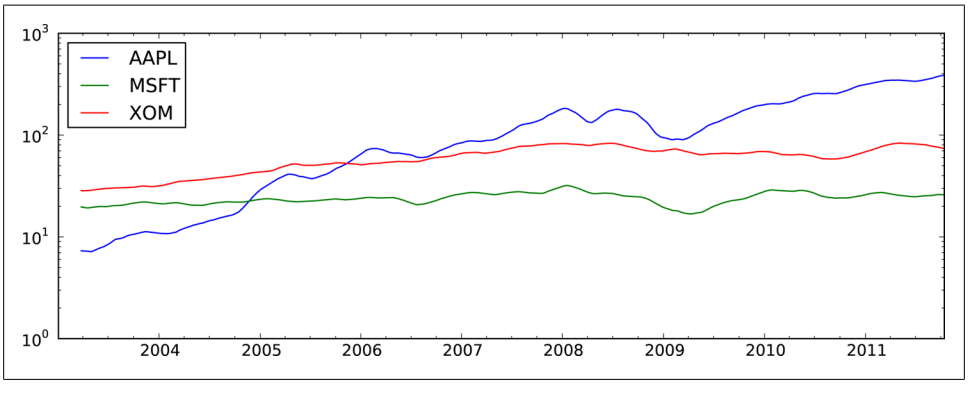


Figure 10-10. Stocks Prices 60-day MA (log Y-axis)

See Table 10-6 for a listing of related functions in pandas.

Table 10-6. Moving window and exponentially-weighted functions

Function	Description
`rolling_count`	Returns number of non-NA observations in each trailing window.
`rolling_sum`	Moving window sum.
`rolling_mean`	Moving window mean.
`rolling_median`	Moving window median.
`rolling_var, rolling_std`	Moving window variance and standard deviation, respectively. Uses n - 1 denominator.
`rolling_skew, rolling_kurt`	Moving window skewness (3rd moment) and kurtosis (4th moment), respectively.
`rolling_min, rolling_max`	Moving window minimum and maximum.
`rolling_quantile`	Moving window score at percentile/sample quantile.
`rolling_corr, rolling_cov`	Moving window correlation and covariance.
`rolling_apply`	Apply generic array function over a moving window.
`ewma`	Exponentially-weighted moving average.
`ewmvar, ewmstd`	Exponentially-weighted moving variance and standard deviation.
`ewmcorr, ewmcov`	Exponentially-weighted moving correlation and covariance.

`bottleneck`, a Python library by Keith Goodman, provides an alternate implementation of `NaN`-friendly moving window functions and may be worth looking at depending on your application.

Exponentially-weighted functions

An alternative to using a static window size with equally-weighted observations is to specify a constant *decay factor* to give more weight to more recent observations. In mathematical terms, if ma_t is the moving average result at time `t` and x is the time series in question, each value in the result is computed as $ma_t = a * ma_{t-1} + (a - 1) * x\_t$, where a is the decay factor. There are a couple of ways to specify the decay factor, a popular one is using a *span*, which makes the result comparable to a simple moving window function with window size equal to the span.

Since an exponentially-weighted statistic places more weight on more recent observations, it "adapts" faster to changes compared with the equal-weighted version. Here's an example comparing a 60-day moving average of Apple's stock price with an EW moving average with `span=60` (see Figure 10-11):

```
fig, axes = plt.subplots(nrows=2, ncols=1, sharex=True, sharey=True,
                         figsize=(12, 7))

aapl_px = close_px.AAPL['2005':'2009']

ma60 = pd.rolling_mean(aapl_px, 60, min_periods=50)
ewma60 = pd.ewma(aapl_px, span=60)

aapl_px.plot(style='k-', ax=axes[0])
ma60.plot(style='k--', ax=axes[0])
aapl_px.plot(style='k-', ax=axes[1])
ewma60.plot(style='k--', ax=axes[1])
axes[0].set_title('Simple MA')
axes[1].set_title('Exponentially-weighted MA')
```

Binary Moving Window Functions

Some statistical operators, like correlation and covariance, need to operate on two time series. As an example, financial analysts are often interested in a stock's correlation to a benchmark index like the S&P 500. We can compute that by computing the percent changes and using `rolling_corr` (see Figure 10-12):

```
In [570]: spx_rets = spx_px / spx_px.shift(1) - 1

In [571]: returns = close_px.pct_change()

In [572]: corr = pd.rolling_corr(returns.AAPL, spx_rets, 125, min_periods=100)

In [573]: corr.plot()
```

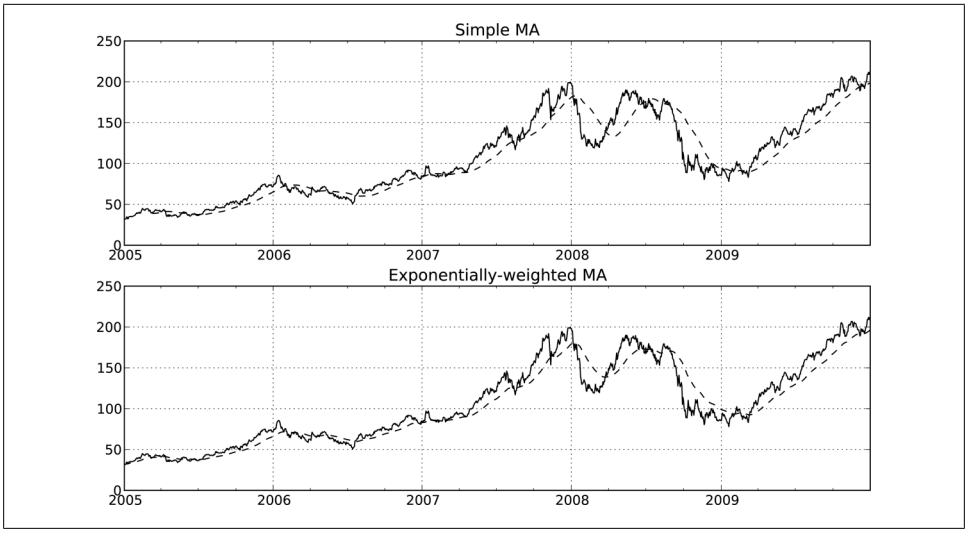


Figure 10-11. Simple moving average versus exponentially-weighted

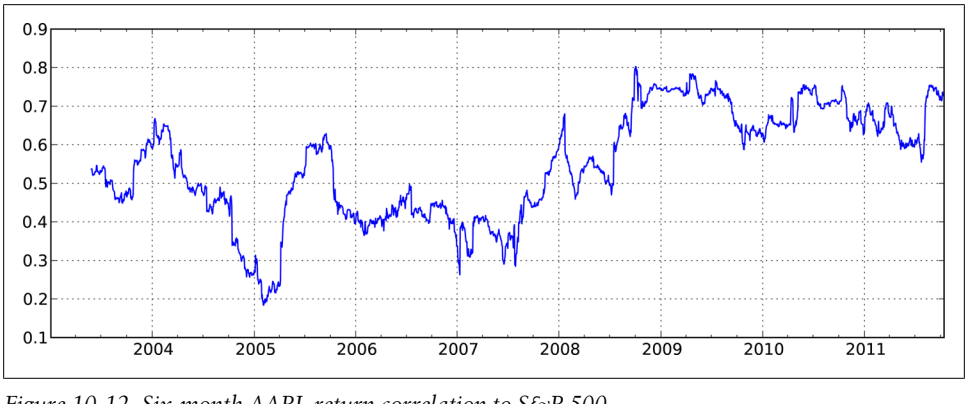


Figure 10-12. Six-month AAPL return correlation to S&P 500

Suppose you wanted to compute the correlation of the S&P 500 index with many stocks at once. Writing a loop and creating a new DataFrame would be easy but maybe get repetitive, so if you pass a TimeSeries and a DataFrame, a function like `rolling_corr` will compute the correlation of the TimeSeries (`spx_rets` in this case) with each column in the DataFrame. See Figure 10-13 for the plot of the result:

```
In [575]: corr = pd.rolling_corr(returns, spx_rets, 125, min_periods=100)

In [576]: corr.plot()
```

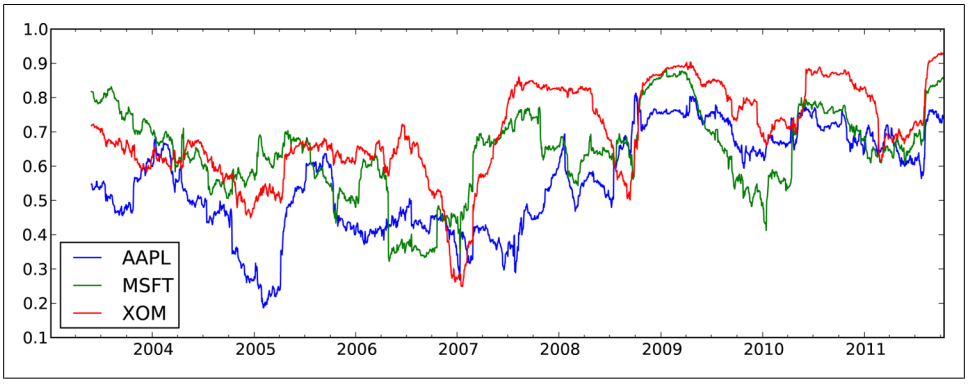


Figure 10-13. Six-month return correlations to S&P 500

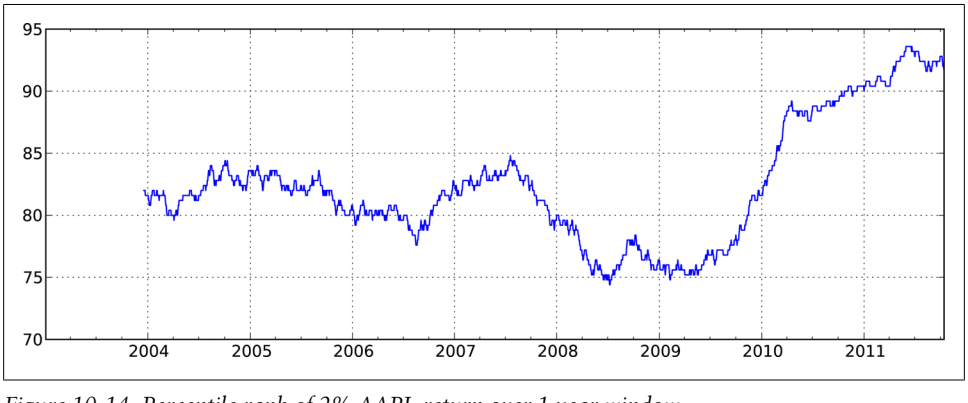


Figure 10-14. Percentile rank of 2% AAPL return over 1 year window

User-Defined Moving Window Functions

The `rolling_apply` function provides a means to apply an array function of your own devising over a moving window. The only requirement is that the function produce a single value (a reduction) from each piece of the array. For example, while we can compute sample quantiles using `rolling_quantile`, we might be interested in the percentile rank of a particular value over the sample. The `scipy.stats.percentileofscore` function does just this:

```
In [578]: from scipy.stats import percentileofscore

In [579]: score_at_2percent = lambda x: percentileofscore(x, 0.02)

In [580]: result = pd.rolling_apply(returns.AAPL, 250, score_at_2percent)

In [581]: result.plot()
```

Performance and Memory Usage Notes

Timestamps and periods are represented as 64-bit integers using NumPy's `datetime64` dtype. This means that for each data point, there is an associated 8 bytes of memory per timestamp. Thus, a time series with 1 million `float64` data points has a memory footprint of approximately 16 megabytes. Since pandas makes every effort to share indexes among time series, creating views on existing time series do not cause any more memory to be used. Additionally, indexes for lower frequencies (daily and up) are stored in a central cache, so that any fixed-frequency index is a view on the date cache. Thus, if you have a large collection of low-frequency time series, the memory footprint of the indexes will not be as significant.

Performance-wise, pandas has been highly optimized for data alignment operations (the behind-the-scenes work of differently indexed `ts1 + ts2`) and resampling. Here is an example of aggregating 10MM data points to OHLC:

```
In [582]: rng = pd.date_range('1/1/2000', periods=10000000, freq='10ms')

In [583]: ts = Series(np.random.randn(len(rng)), index=rng)

In [584]: ts
Out[584]:
2000-01-01 00:00:00          -1.402235
2000-01-01 00:00:00.010000    2.424667
2000-01-01 00:00:00.020000   -1.956042
2000-01-01 00:00:00.030000   -0.897339
...
2000-01-02 03:46:39.960000    0.495530
2000-01-02 03:46:39.970000    0.574766
2000-01-02 03:46:39.980000    1.348374
2000-01-02 03:46:39.990000    0.665034
Freq: 10L, Length: 10000000

In [585]: ts.resample('15min', how='ohlc')
Out[585]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 113 entries, 2000-01-01 00:00:00 to 2000-01-02 04:00:00
Freq: 15T
Data columns:
open     113  non-null values
high     113  non-null values
low      113  non-null values
close    113  non-null values
dtypes: float64(4)

In [586]: %timeit ts.resample('15min', how='ohlc')
10 loops, best of 3: 61.1 ms per loop
```

The runtime may depend slightly on the relative size of the aggregated result; higher frequency aggregates unsurprisingly take longer to compute:

```
In [587]: rng = pd.date_range('1/1/2000', periods=10000000, freq='1s')
```

```
In [588]: ts = Series(np.random.randn(len(rng)), index=rng)

In [589]: %timeit ts.resample('15s', how='ohlc')
1 loops, best of 3: 88.2 ms per loop
```

It's possible that by the time you read this, the performance of these algorithms may be even further improved. As an example, there are currently no optimizations for conversions between regular frequencies, but that would be fairly straightforward to do.

CHAPTER 11

Financial and Economic Data Applications

The use of Python in the financial industry has been increasing rapidly since 2005, led largely by the maturation of libraries (like NumPy and pandas) and the availability of skilled Python programmers. Institutions have found that Python is well-suited both as an interactive analysis environment as well as enabling robust systems to be developed often in a fraction of the time it would have taken in Java or C++. Python is also an ideal glue layer; it is easy to build Python interfaces to legacy libraries built in C or C++.

While the field of financial analysis is broad enough to fill an entire book, I hope to show you how the tools in this book can be applied to a number of specific problems in finance. As with other research and analysis domains, too much programming effort is often spent wrangling data rather than solving the core modeling and research problems. I personally got started building pandas in 2008 while grappling with inadequate data tools.

In these examples, I'll use the term *cross-section* to refer to data at a fixed point in time. For example, the closing prices of all the stocks in the S&P 500 index on a particular date form a cross-section. Cross-sectional data at multiple points in time over multiple data items (for example, prices together with volume) form a *panel*. Panel data can either be represented as a hierarchically-indexed DataFrame or using the three-dimensional Panel pandas object.

Data Munging Topics

Many helpful data munging tools for financial applications are spread across the earlier chapters. Here I'll highlight a number of topics as they relate to this problem domain.

Time Series and Cross-Section Alignment

One of the most time-consuming issues in working with financial data is the so-called *data alignment* problem. Two related time series may have indexes that don't line up perfectly, or two DataFrame objects might have columns or row labels that don't match. Users of MATLAB, R, and other matrix-programming languages often invest significant effort in wrangling data into perfectly aligned forms. In my experience, having to align data by hand (and worse, having to verify that data is aligned) is a far too rigid and tedious way to work. It is also rife with potential for bugs due to combining misaligned data.

pandas take an alternate approach by automatically aligning data in arithmetic operations. In practice, this grants immense freedom and enhances your productivity. As an example, let's consider a couple of DataFrames containing time series of stock prices and volume:

```
In [16]: prices
Out[16]:
              AAPL    JNJ      SPX    XOM
2011-09-06  379.74  64.64  1165.24  71.15
2011-09-07  383.93  65.43  1198.62  73.65
2011-09-08  384.14  64.95  1185.90  72.82
2011-09-09  377.48  63.64  1154.23  71.01
2011-09-12  379.94  63.59  1162.27  71.84
2011-09-13  384.62  63.61  1172.87  71.65
2011-09-14  389.30  63.73  1188.68  72.64

In [17]: volume
Out[17]:
               AAPL       JNJ       XOM
2011-09-06  18173500  15848300  25416300
2011-09-07  12492000  10759700  23108400
2011-09-08  14839800  15551500  22434800
2011-09-09  20171900  17008200  27969100
2011-09-12  16697300  13448200  26205800
```

Suppose you wanted to compute a volume-weighted average price using all available data (and making the simplifying assumption that the volume data is a subset of the price data). Since pandas aligns the data automatically in arithmetic and excludes missing data in functions like `sum`, we can express this concisely as:

```
In [18]: prices * volume
Out[18]:
                 AAPL         JNJ  SPX         XOM
2011-09-06  6901204890  1024434112  NaN  1808369745
2011-09-07  4796053560   704007171  NaN  1701933660
2011-09-08  5700560772  1010069925  NaN  1633702136
2011-09-09  7614488812  1082401848  NaN  1986085791
2011-09-12  6343972162   855171038  NaN  1882624672
2011-09-13         NaN         NaN  NaN         NaN
2011-09-14         NaN         NaN  NaN         NaN

In [19]: vwap = (prices * volume).sum() / volume.sum()
```

```
In [20]: vwap
Out[20]:
AAPL    380.655181
JNJ      64.394769
SPX            NaN
XOM      72.024288
```

```
In [21]: vwap.dropna()
Out[21]:
AAPL    380.655181
JNJ      64.394769
XOM      72.024288
```

Since `SPX` wasn't found in `volume`, you can choose to explicitly discard that at any point. Should you wish to align by hand, you can use DataFrame's `align` method, which returns a tuple of reindexed versions of the two objects:

```
In [22]: prices.align(volume, join='inner')
Out[22]:
(              AAPL    JNJ    XOM
2011-09-06  379.74  64.64  71.15
2011-09-07  383.93  65.43  73.65
2011-09-08  384.14  64.95  72.82
2011-09-09  377.48  63.64  71.01
2011-09-12  379.94  63.59  71.84,
                 AAPL       JNJ       XOM
2011-09-06  18173500  15848300  25416300
2011-09-07  12492000  10759700  23108400
2011-09-08  14839800  15551500  22434800
2011-09-09  20171900  17008200  27969100
2011-09-12  16697300  13448200  26205800)
```

Another indispensable feature is constructing a DataFrame from a collection of potentially differently indexed Series:

```
In [23]: s1 = Series(range(3), index=['a', 'b', 'c'])

In [24]: s2 = Series(range(4), index=['d', 'b', 'c', 'e'])

In [25]: s3 = Series(range(3), index=['f', 'a', 'c'])

In [26]: DataFrame({'one': s1, 'two': s2, 'three': s3})
Out[26]:
   one  three  two
a    0      1  NaN
b    1    NaN    1
c    2      2    2
d  NaN    NaN    0
e  NaN    NaN    3
f  NaN      0  NaN
```

As you have seen earlier, you can of course specify explicitly the index of the result, discarding the rest of the data:

```
In [27]: DataFrame({'one': s1, 'two': s2, 'three': s3}, index=list('face'))
Out[27]:
   one  three  two
f  NaN      0  NaN
a    0      1  NaN
c    2      2    2
e  NaN    NaN    3
```

Operations with Time Series of Different Frequencies

Economic time series are often of annual, quarterly, monthly, daily, or some other more specialized frequency. Some are completely irregular; for example, earnings revisions for a stock may arrive at any time. The two main tools for frequency conversion and realignment are the `resample` and `reindex` methods. `resample` converts data to a fixed frequency while `reindex` conforms data to a new index. Both support optional interpolation (such as forward filling) logic.

Let's consider a small weekly time series:

```
In [28]: ts1 = Series(np.random.randn(3),
   ....:              index=pd.date_range('2012-6-13', periods=3, freq='W-WED'))

In [29]: ts1
Out[29]:
2012-06-13   -1.124801
2012-06-20    0.469004
2012-06-27   -0.117439
Freq: W-WED
```

If you resample this to business daily (Monday-Friday) frequency, you get holes on the days where there is no data:

```
In [30]: ts1.resample('B')
Out[30]:
2012-06-13   -1.124801
2012-06-14         NaN
2012-06-15         NaN
2012-06-18         NaN
2012-06-19         NaN
2012-06-20    0.469004
2012-06-21         NaN
2012-06-22         NaN
2012-06-25         NaN
2012-06-26         NaN
2012-06-27   -0.117439
Freq: B
```

Of course, using `'ffill'` as the `fill_method` forward fills values in those gaps. This is a common practice with lower frequency data as you compute a time series of values on each timestamp having the latest valid or "*as of*" value:

```
In [31]: ts1.resample('B', fill_method='ffill')
Out[31]:
2012-06-13   -1.124801
2012-06-14   -1.124801
2012-06-15   -1.124801
2012-06-18   -1.124801
2012-06-19   -1.124801
2012-06-20    0.469004
2012-06-21    0.469004
2012-06-22    0.469004
2012-06-25    0.469004
2012-06-26    0.469004
```

```
2012-06-27   -0.117439
Freq: B
```

In practice, upsampling lower frequency data to a higher, regular frequency is a fine solution, but in the more general irregular time series case it may be a poor fit. Consider an irregularly sampled time series from the same general time period:

```
In [32]: dates = pd.DatetimeIndex(['2012-6-12', '2012-6-17', '2012-6-18',
   ....:                           '2012-6-21', '2012-6-22', '2012-6-29'])

In [33]: ts2 = Series(np.random.randn(6), index=dates)

In [34]: ts2
Out[34]:
2012-06-12   -0.449429
2012-06-17    0.459648
2012-06-18   -0.172531
2012-06-21    0.835938
2012-06-22   -0.594779
2012-06-29    0.027197
```

If you wanted to add the "as of" values in `ts1` (forward filling) to `ts2`. One option would be to resample both to a regular frequency then add, but if you want to maintain the date index in `ts2`, using `reindex` is a more precise solution:

```
In [35]: ts1.reindex(ts2.index, method='ffill')
Out[35]:
2012-06-12         NaN
2012-06-17   -1.124801
2012-06-18   -1.124801
2012-06-21    0.469004
2012-06-22    0.469004
2012-06-29   -0.117439

In [36]: ts2 + ts1.reindex(ts2.index, method='ffill')
Out[36]:
2012-06-12         NaN
2012-06-17   -0.665153
2012-06-18   -1.297332
2012-06-21    1.304942
2012-06-22   -0.125775
2012-06-29   -0.090242
```

Using periods instead of timestamps

Periods (representing time spans) provide an alternate means of working with different frequency time series, especially financial or economic series with annual or quarterly frequency having a particular reporting convention. For example, a company might announce its quarterly earnings with fiscal year ending in June, thus having `Q-JUN` frequency. Consider a pair of macroeconomic time series related to GDP and inflation:

```
In [37]: gdp = Series([1.78, 1.94, 2.08, 2.01, 2.15, 2.31, 2.46],
   ....:              index=pd.period_range('1984Q2', periods=7, freq='Q-SEP'))
```

```
In [38]: infl = Series([0.025, 0.045, 0.037, 0.04],
   ....:               index=pd.period_range('1982', periods=4, freq='A-DEC'))

In [39]: gdp          In [40]: infl
Out[39]:              Out[40]:
1984Q2    1.78        1982    0.025
1984Q3    1.94        1983    0.045
1984Q4    2.08        1984    0.037
1985Q1    2.01        1985    0.040
1985Q2    2.15        Freq: A-DEC
1985Q3    2.31
1985Q4    2.46
Freq: Q-SEP
```

Unlike time series with timestamps, operations between different-frequency time series indexed by periods are not possible without explicit conversions. In this case, if we know that `infl` values were observed at the end of each year, we can then convert to `Q-SEP` to get the right periods in that frequency:

```
In [41]: infl_q = infl.asfreq('Q-SEP', how='end')

In [42]: infl_q
Out[42]:
1983Q1    0.025
1984Q1    0.045
1985Q1    0.037
1986Q1    0.040
Freq: Q-SEP
```

That time series can then be reindexed with forward-filling to match `gdp`:

```
In [43]: infl_q.reindex(gdp.index, method='ffill')
Out[43]:
1984Q2    0.045
1984Q3    0.045
1984Q4    0.045
1985Q1    0.037
1985Q2    0.037
1985Q3    0.037
1985Q4    0.037
Freq: Q-SEP
```

Time of Day and "as of" Data Selection

Suppose you have a long time series containing intraday market data and you want to extract the prices at a particular time of day on each day of the data. What if the data are irregular such that observations do not fall exactly on the desired time? In practice this task can make for error-prone data munging if you are not careful. Here is an example for illustration purposes:

```
# Make an intraday date range and time series
In [44]: rng = pd.date_range('2012-06-01 09:30', '2012-06-01 15:59', freq='T')

# Make a 5-day series of 9:30-15:59 values
```

```
In [45]: rng = rng.append([rng + pd.offsets.BDay(i) for i in range(1, 4)])

In [46]: ts = Series(np.arange(len(rng), dtype=float), index=rng)

In [47]: ts
Out[47]:
2012-06-01 09:30:00    0
2012-06-01 09:31:00    1
2012-06-01 09:32:00    2
2012-06-01 09:33:00    3
...
2012-06-06 15:56:00    1556
2012-06-06 15:57:00    1557
2012-06-06 15:58:00    1558
2012-06-06 15:59:00    1559
Length: 1560
```

Indexing with a Python `datetime.time` object will extract values at those times:

```
In [48]: from datetime import time

In [49]: ts[time(10, 0)]
Out[49]:
2012-06-01 10:00:00      30
2012-06-04 10:00:00     420
2012-06-05 10:00:00     810
2012-06-06 10:00:00    1200
```

Under the hood, this uses an instance method `at_time` (available on individual time series and DataFrame objects alike):

```
In [50]: ts.at_time(time(10, 0))
Out[50]:
2012-06-01 10:00:00      30
2012-06-04 10:00:00     420
2012-06-05 10:00:00     810
2012-06-06 10:00:00    1200
```

You can select values between two times using the related `between_time` method:

```
In [51]: ts.between_time(time(10, 0), time(10, 1))
Out[51]:
2012-06-01 10:00:00      30
2012-06-01 10:01:00      31
2012-06-04 10:00:00     420
2012-06-04 10:01:00     421
2012-06-05 10:00:00     810
2012-06-05 10:01:00     811
2012-06-06 10:00:00    1200
2012-06-06 10:01:00    1201
```

As mentioned above, it might be the case that no data actually fall exactly at a time like 10 AM, but you might want to know the last known value at 10 AM:

```
# Set most of the time series randomly to NA
In [53]: indexer = np.sort(np.random.permutation(len(ts))[700:])
```

```
In [54]: irr_ts = ts.copy()

In [55]: irr_ts[indexer] = np.nan

In [56]: irr_ts['2012-06-01 09:50':'2012-06-01 10:00']
Out[56]:
2012-06-01 09:50:00    20
2012-06-01 09:51:00   NaN
2012-06-01 09:52:00    22
2012-06-01 09:53:00    23
2012-06-01 09:54:00   NaN
2012-06-01 09:55:00    25
2012-06-01 09:56:00   NaN
2012-06-01 09:57:00   NaN
2012-06-01 09:58:00   NaN
2012-06-01 09:59:00   NaN
2012-06-01 10:00:00   NaN
```

By passing an array of timestamps to the `asof` method, you will obtain an array of the last valid (non-NA) values at or before each timestamp. So we construct a date range at 10 AM for each day and pass that to `asof`:

```
In [57]: selection = pd.date_range('2012-06-01 10:00', periods=4, freq='B')

In [58]: irr_ts.asof(selection)
Out[58]:
2012-06-01 10:00:00      25
2012-06-04 10:00:00     420
2012-06-05 10:00:00     810
2012-06-06 10:00:00    1197
Freq: B
```

Splicing Together Data Sources

In Chapter 7, I described a number of strategies for merging together two related data sets. In a financial or economic context, there are a few widely occurring use cases:

- Switching from one data source (a time series or collection of time series) to another at a specific point in time
- "Patching" missing values in a time series at the beginning, middle, or end using another time series
- Completely replacing the data for a subset of symbols (countries, asset tickers, and so on)

In the first case, switching from one set of time series to another at a specific instant, it is a matter of splicing together two TimeSeries or DataFrame objects using `pandas.concat`:

```
In [59]: data1 = DataFrame(np.ones((6, 3), dtype=float),
   ....:                   columns=['a', 'b', 'c'],
   ....:                   index=pd.date_range('6/12/2012', periods=6))
```

```
In [60]: data2 = DataFrame(np.ones((6, 3), dtype=float) * 2,
   ....:                   columns=['a', 'b', 'c'],
   ....:                   index=pd.date_range('6/13/2012', periods=6))

In [61]: spliced = pd.concat([data1.ix[:'2012-06-14'], data2.ix['2012-06-15':]])

In [62]: spliced
Out[62]:
            a  b  c
2012-06-12  1  1  1
2012-06-13  1  1  1
2012-06-14  1  1  1
2012-06-15  2  2  2
2012-06-16  2  2  2
2012-06-17  2  2  2
2012-06-18  2  2  2
```

Suppose in a similar example that `data1` was missing a time series present in `data2`:

```
In [63]: data2 = DataFrame(np.ones((6, 4), dtype=float) * 2,
   ....:                   columns=['a', 'b', 'c', 'd'],
   ....:                   index=pd.date_range('6/13/2012', periods=6))

In [64]: spliced = pd.concat([data1.ix[:'2012-06-14'], data2.ix['2012-06-15':]])

In [65]: spliced
Out[65]:
            a  b  c   d
2012-06-12  1  1  1 NaN
2012-06-13  1  1  1 NaN
2012-06-14  1  1  1 NaN
2012-06-15  2  2  2   2
2012-06-16  2  2  2   2
2012-06-17  2  2  2   2
2012-06-18  2  2  2   2
```

Using `combine_first`, you can bring in data from before the splice point to extend the history for `'d'` item:

```
In [66]: spliced_filled = spliced.combine_first(data2)

In [67]: spliced_filled
Out[67]:
            a  b  c   d
2012-06-12  1  1  1 NaN
2012-06-13  1  1  1   2
2012-06-14  1  1  1   2
2012-06-15  2  2  2   2
2012-06-16  2  2  2   2
2012-06-17  2  2  2   2
2012-06-18  2  2  2   2
```

Since `data2` does not have any values for `2012-06-12`, no values are filled on that day.

DataFrame has a related method `update` for performing in-place updates. You have to pass `overwrite=False` to make it only fill the holes:

```
In [68]: spliced.update(data2, overwrite=False)

In [69]: spliced
Out[69]:
            a  b  c   d
2012-06-12  1  1  1 NaN
2012-06-13  1  1  1   2
2012-06-14  1  1  1   2
2012-06-15  2  2  2   2
2012-06-16  2  2  2   2
2012-06-17  2  2  2   2
2012-06-18  2  2  2   2
```

To replace the data for a subset of symbols, you can use any of the above techniques, but sometimes it's simpler to just set the columns directly with DataFrame indexing:

```
In [70]: cp_spliced = spliced.copy()

In [71]: cp_spliced[['a', 'c']] = data1[['a', 'c']]

In [72]: cp_spliced
Out[72]:
             a  b   c   d
2012-06-12   1  1   1 NaN
2012-06-13   1  1   1   2
2012-06-14   1  1   1   2
2012-06-15   1  2   1   2
2012-06-16   1  2   1   2
2012-06-17   1  2   1   2
2012-06-18 NaN  2 NaN   2
```

Return Indexes and Cumulative Returns

In a financial context, *returns* usually refer to percent changes in the price of an asset. Let's consider price data for Apple in 2011 and 2012:

```
In [73]: import pandas.io.data as web

In [74]: price = web.get_data_yahoo('AAPL', '2011-01-01')['Adj Close']

In [75]: price[-5:]
Out[75]:
Date
2012-07-23    603.83
2012-07-24    600.92
2012-07-25    574.97
2012-07-26    574.88
2012-07-27    585.16
Name: Adj Close
```

For Apple, which has no dividends, computing the cumulative percent return between two points in time requires computing only the percent change in the price:

```
In [76]: price['2011-10-03'] / price['2011-3-01'] - 1
Out[76]: 0.072399874037388123
```

For other stocks with dividend payouts, computing how much money you make from holding a stock can be more complicated. The adjusted close values used here have been adjusted for splits and dividends, however. In all cases, it's quite common to derive a *return index*, which is a time series indicating the value of a unit investment (one dollar, say). Many assumptions can underlie the return index; for example, some will choose to reinvest profit and others not. In the case of Apple, we can compute a simple return index using `cumprod`:

```
In [77]: returns = price.pct_change()

In [78]: ret_index = (1 + returns).cumprod()

In [79]: ret_index[0] = 1  # Set first value to 1

In [80]: ret_index
Out[80]:
Date
2011-01-03    1.000000
2011-01-04    1.005219
2011-01-05    1.013442
2011-01-06    1.012623
...
2012-07-24    1.823346
2012-07-25    1.744607
2012-07-26    1.744334
2012-07-27    1.775526
Length: 396
```

With a return index in hand, computing cumulative returns at a particular resolution is simple:

```
In [81]: m_returns = ret_index.resample('BM', how='last').pct_change()

In [82]: m_returns['2012']
Out[82]:
Date
2012-01-31    0.127111
2012-02-29    0.188311
2012-03-30    0.105284
2012-04-30   -0.025969
2012-05-31   -0.010702
2012-06-29    0.010853
2012-07-31    0.001986
Freq: BM
```

Of course, in this simple case (no dividends or other adjustments to take into account) these could have been computed from the daily percent changed by resampling with aggregation (here, to periods):

```
In [83]: m_rets = (1 + returns).resample('M', how='prod', kind='period') - 1

In [84]: m_rets['2012']
Out[84]:
Date
```

```
2012-01    0.127111
2012-02    0.188311
2012-03    0.105284
2012-04   -0.025969
2012-05   -0.010702
2012-06    0.010853
2012-07    0.001986
Freq: M
```

If you had dividend dates and percentages, including them in the total return per day would look like:

```
returns[dividend_dates] += dividend_pcts
```

Group Transforms and Analysis

In Chapter 9, you learned the basics of computing group statistics and applying your own transformations to groups in a dataset.

Let's consider a collection of hypothetical stock portfolios. I first randomly generate a broad *universe* of 2000 tickers:

```
import random; random.seed(0)
import string

N = 1000
def rands(n):
    choices = string.ascii_uppercase
    return ''.join([random.choice(choices) for _ in xrange(n)])
tickers = np.array([rands(5) for _ in xrange(N)])
```

I then create a DataFrame containing 3 columns representing hypothetical, but random portfolios for a subset of tickers:

```
M = 500
df = DataFrame({'Momentum' : np.random.randn(M) / 200 + 0.03,
                'Value' : np.random.randn(M) / 200 + 0.08,
                'ShortInterest' : np.random.randn(M) / 200 - 0.02},
                index=tickers[:M])
```

Next, let's create a random industry classification for the tickers. To keep things simple, I'll just keep it to 2 industries, storing the mapping in a Series:

```
ind_names = np.array(['FINANCIAL', 'TECH'])
sampler = np.random.randint(0, len(ind_names), N)
industries = Series(ind_names[sampler], index=tickers,
                    name='industry')
```

Now we can group by `industries` and carry out group aggregation and transformations:

```
In [90]: by_industry = df.groupby(industries)

In [91]: by_industry.mean()
Out[91]:
           Momentum  ShortInterest     Value
```

```
industry
FINANCIAL  0.029485      -0.020739  0.079929
TECH       0.030407      -0.019609  0.080113

In [92]: by_industry.describe()
Out[92]:
                    Momentum  ShortInterest       Value
industry
FINANCIAL count  246.000000     246.000000  246.000000
          mean     0.029485      -0.020739    0.079929
          std      0.004802       0.004986    0.004548
          min      0.017210      -0.036997    0.067025
          25%      0.026263      -0.024138    0.076638
          50%      0.029261      -0.020833    0.079804
          75%      0.032806      -0.017345    0.082718
          max      0.045884      -0.006322    0.093334
TECH      count  254.000000     254.000000  254.000000
          mean     0.030407      -0.019609    0.080113
          std      0.005303       0.005074    0.004886
          min      0.016778      -0.032682    0.065253
          25%      0.026456      -0.022779    0.076737
          50%      0.030650      -0.019829    0.080296
          75%      0.033602      -0.016923    0.083353
          max      0.049638      -0.003698    0.093081
```

By defining transformation functions, it's easy to transform these portfolios by industry. For example, standardizing within industry is widely used in equity portfolio construction:

```
# Within-Industry Standardize
def zscore(group):
    return (group - group.mean()) / group.std()

df_stand = by_industry.apply(zscore)
```

You can verify that each industry has mean 0 and standard deviation 1:

```
In [94]: df_stand.groupby(industries).agg(['mean', 'std'])
Out[94]:
           Momentum       ShortInterest       Value
               mean  std           mean  std   mean  std
industry
FINANCIAL         0    1              0    1      0    1
TECH             -0    1             -0    1     -0    1
```

Other, built-in kinds of transformations, like `rank`, can be used more concisely:

```
# Within-industry rank descending
In [95]: ind_rank = by_industry.rank(ascending=False)

In [96]: ind_rank.groupby(industries).agg(['min', 'max'])
Out[96]:
           Momentum       ShortInterest       Value
                min  max            min  max    min  max
industry
FINANCIAL         1  246              1  246      1  246
TECH              1  254              1  254      1  254
```

In quantitative equity, "rank and standardize" is a common sequence of transforms. You could do this by chaining together `rank` and `zscore` like so:

```
# Industry rank and standardize
In [97]: by_industry.apply(lambda x: zscore(x.rank()))
Out[97]:
<class 'pandas.core.frame.DataFrame'>
Index: 500 entries, VTKGN to PTDQE
Data columns:
Momentum         500  non-null values
ShortInterest    500  non-null values
Value            500  non-null values
dtypes: float64(3)
```

Group Factor Exposures

Factor analysis is a technique in quantitative portfolio management. Portfolio holdings and performance (profit and less) are decomposed using one or more *factors* (risk factors are one example) represented as a portfolio of weights. For example, a stock price's co-movement with a benchmark (like S&P 500 index) is known as its *beta*, a common risk factor. Let's consider a contrived example of a portfolio constructed from 3 randomly-generated factors (usually called the *factor loadings*) and some weights:

```
from numpy.random import rand
fac1, fac2, fac3 = np.random.rand(3, 1000)

ticker_subset = tickers.take(np.random.permutation(N)[:1000])

# Weighted sum of factors plus noise
port = Series(0.7 * fac1 - 1.2 * fac2 + 0.3 * fac3 + rand(1000),
              index=ticker_subset)
factors = DataFrame({'f1': fac1, 'f2': fac2, 'f3': fac3},
                    index=ticker_subset)
```

Vector correlations between each factor and the portfolio may not indicate too much:

```
In [99]: factors.corrwith(port)
Out[99]:
f1    0.402377
f2   -0.680980
f3    0.168083
```

The standard way to compute the factor exposures is by least squares regression; using `pandas.ols` with `factors` as the explanatory variables we can compute exposures over the entire set of tickers:

```
In [100]: pd.ols(y=port, x=factors).beta
Out[100]:
f1           0.761789
f2          -1.208760
f3           0.289865
intercept    0.484477
```

As you can see, the original factor weights can nearly be recovered since there was not too much additional random noise added to the portfolio. Using `groupby` you can compute exposures industry by industry. To do so, write a function like so:

```
def beta_exposure(chunk, factors=None):
    return pd.ols(y=chunk, x=factors).beta
```

Then, group by `industries` and apply that function, passing the DataFrame of factor loadings:

```
In [102]: by_ind = port.groupby(industries)

In [103]: exposures = by_ind.apply(beta_exposure, factors=factors)

In [104]: exposures.unstack()
Out[104]:
                 f1        f2        f3  intercept
industry
FINANCIAL  0.790329 -1.182970  0.275624   0.455569
TECH       0.740857 -1.232882  0.303811   0.508188
```

Decile and Quartile Analysis

Analyzing data based on sample quantiles is another important tool for financial analysts. For example, the performance of a stock portfolio could be broken down into quartiles (four equal-sized chunks) based on each stock's price-to-earnings. Using `pandas.qcut` combined with `groupby` makes quantile analysis reasonably straightforward.

As an example, let's consider a simple trend following or *momentum* strategy trading the S&P 500 index via the SPY exchange-traded fund. You can download the price history from Yahoo! Finance:

```
In [105]: import pandas.io.data as web

In [106]: data = web.get_data_yahoo('SPY', '2006-01-01')

In [107]: data
Out[107]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1655 entries, 2006-01-03 00:00:00 to 2012-07-27 00:00:00
Data columns:
Open         1655  non-null values
High         1655  non-null values
Low          1655  non-null values
Close        1655  non-null values
Volume       1655  non-null values
Adj Close    1655  non-null values
dtypes: float64(5), int64(1)
```

Now, we'll compute daily returns and a function for transforming the returns into a trend signal formed from a lagged moving sum:

```
px = data['Adj Close']
returns = px.pct_change()
```

```
def to_index(rets):
    index = (1 + rets).cumprod()
    first_loc = max(index.notnull().argmax() - 1, 0)
    index.values[first_loc] = 1
    return index

def trend_signal(rets, lookback, lag):
    signal = pd.rolling_sum(rets, lookback, min_periods=lookback - 5)
    return signal.shift(lag)
```

Using this function, we can (naively) create and test a trading strategy that trades this momentum signal every Friday:

```
In [109]: signal = trend_signal(returns, 100, 3)

In [110]: trade_friday = signal.resample('W-FRI').resample('B', fill_method='ffill')

In [111]: trade_rets = trade_friday.shift(1) * returns
```

We can then convert the strategy returns to a return index and plot them (see Figure 11-1):

```
In [112]: to_index(trade_rets).plot()
```

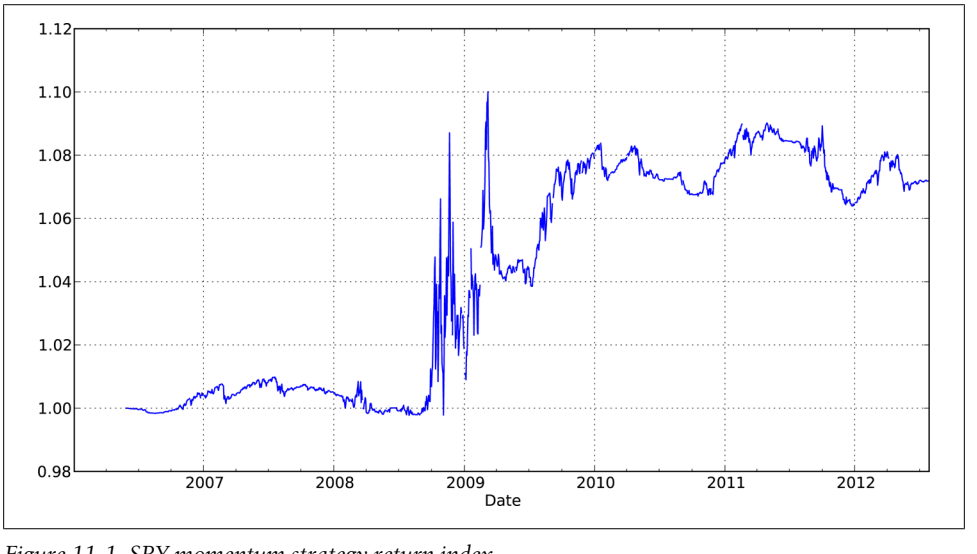


Figure 11-1. SPY momentum strategy return index

Suppose you wanted to decompose the strategy performance into more and less volatile periods of trading. Trailing one-year annualized standard deviation is a simple measure of volatility, and we can compute Sharpe ratios to assess the reward-to-risk ratio in various volatility regimes:

```
vol = pd.rolling_std(returns, 250, min_periods=200) * np.sqrt(250)
```

```
def sharpe(rets, ann=250):
    return rets.mean() / rets.std()  * np.sqrt(ann)
```

Now, dividing `vol` into quartiles with `qcut` and aggregating with `sharpe` we obtain:

```
In [114]: trade_rets.groupby(pd.qcut(vol, 4)).agg(sharpe)
Out[114]:
[0.0955, 0.16]    0.490051
(0.16, 0.188]     0.482788
(0.188, 0.231]   -0.731199
(0.231, 0.457]    0.570500
```

These results show that the strategy performed the best during the period when the volatility was the highest.

More Example Applications

Here is a small set of additional examples.

Signal Frontier Analysis

In this section, I'll describe a simplified cross-sectional momentum portfolio and show how you might explore a grid of model parameterizations. First, I'll load historical prices for a portfolio of financial and technology stocks:

```
names = ['AAPL', 'GOOG', 'MSFT', 'DELL', 'GS', 'MS', 'BAC', 'C']
def get_px(stock, start, end):
    return web.get_data_yahoo(stock, start, end)['Adj Close']
px = DataFrame({n: get_px(n, '1/1/2009', '6/1/2012') for n in names})
```

We can easily plot the cumulative returns of each stock (see Figure 11-2):

```
In [117]: px = px.asfreq('B').fillna(method='pad')

In [118]: rets = px.pct_change()

In [119]: ((1 + rets).cumprod() - 1).plot()
```

For the portfolio construction, we'll compute momentum over a certain lookback, then rank in descending order and standardize:

```
def calc_mom(price, lookback, lag):
    mom_ret = price.shift(lag).pct_change(lookback)
    ranks = mom_ret.rank(axis=1, ascending=False)
    demeaned = ranks - ranks.mean(axis=1)
    return demeaned / demeaned.std(axis=1)
```

With this transform function in hand, we can set up a strategy backtesting function that computes a portfolio for a particular lookback and holding period (days between trading), returning the overall Sharpe ratio:

```
compound = lambda x : (1 + x).prod() - 1
daily_sr = lambda x: x.mean() / x.std()
```

```
def strat_sr(prices, lb, hold):
    # Compute portfolio weights
    freq = '%dB' % hold
    port = calc_mom(prices, lb, lag=1)

    daily_rets = prices.pct_change()

    # Compute portfolio returns
    port = port.shift(1).resample(freq, how='first')
    returns = daily_rets.resample(freq, how=compound)
    port_rets = (port * returns).sum(axis=1)

    return daily_sr(port_rets) * np.sqrt(252 / hold)
```

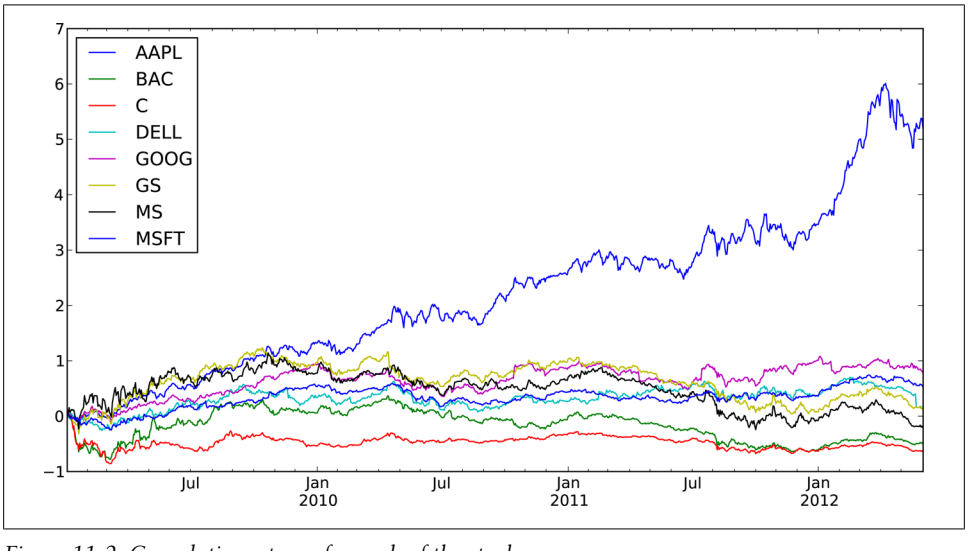


Figure 11-2. Cumulative returns for each of the stocks

When called with the prices and a parameter combination, this function returns a scalar value:

```
In [122]: strat_sr(px, 70, 30)
Out[122]: 0.27421582756800583
```

From there, you can evaluate the `strat_sr` function over a grid of parameters, storing them as you go in a `defaultdict` and finally putting the results in a DataFrame:

```
from collections import defaultdict

lookbacks = range(20, 90, 5)
holdings = range(20, 90, 5)
dd = defaultdict(dict)
for lb in lookbacks:
    for hold in holdings:
        dd[lb][hold] = strat_sr(px, lb, hold)
```

```
ddf = DataFrame(dd)
ddf.index.name = 'Holding Period'
ddf.columns.name = 'Lookback Period'
```

To visualize the results and get an idea of what's going on, here is a function that uses matplotlib to produce a heatmap with some adornments:

```
import matplotlib.pyplot as plt

def heatmap(df, cmap=plt.cm.gray_r):
    fig = plt.figure()
    ax = fig.add_subplot(111)
    axim = ax.imshow(df.values, cmap=cmap, interpolation='nearest')
    ax.set_xlabel(df.columns.name)
    ax.set_xticks(np.arange(len(df.columns)))
    ax.set_xticklabels(list(df.columns))
    ax.set_ylabel(df.index.name)
    ax.set_yticks(np.arange(len(df.index)))
    ax.set_yticklabels(list(df.index))
    plt.colorbar(axim)
```

Calling this function on the backtest results, we get Figure 11-3:

```
In [125]: heatmap(ddf)
```

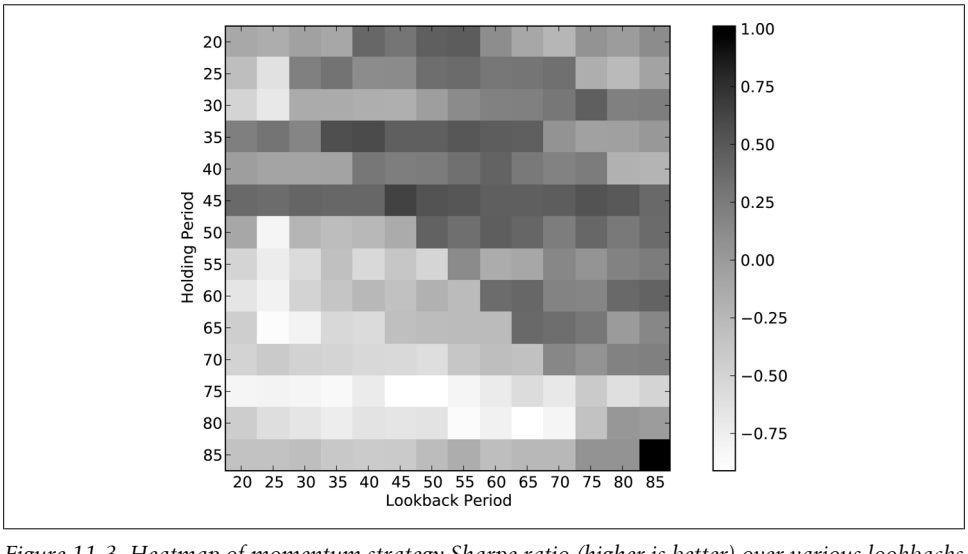


Figure 11-3. Heatmap of momentum strategy Sharpe ratio (higher is better) over various lookbacks and holding periods

Future Contract Rolling

A *future* is an ubiquitous form of derivative contract; it is an agreement to take delivery of a certain asset (such as oil, gold, or shares of the FTSE 100 index) on a particular date. In practice, modeling and trading futures contracts on equities, currencies,

commodities, bonds, and other asset classes is complicated by the time-limited nature of each contract. For example, at any given time for a type of future (say silver or copper futures) multiple contracts with different *expiration dates* may be traded. In many cases, the future contract expiring next (the *near* contract) will be the most liquid (highest volume and lowest bid-ask spread).

For the purposes of modeling and forecasting, it can be much easier to work with a *continuous* return index indicating the profit and loss associated with always holding the near contract. Transitioning from an expiring contract to the next (or *far*) contract is referred to as *rolling*. Computing a continuous future series from the individual contract data is not necessarily a straightforward exercise and typically requires a deeper understanding of the market and how the instruments are traded. For example, in practice when and how quickly would you trade out of an expiring contract and into the next contract? Here I describe one such process.

First, I'll use scaled prices for the SPY exchange-traded fund as a proxy for the S&P 500 index:

```
In [127]: import pandas.io.data as web

# Approximate price of S&P 500 index
In [128]: px = web.get_data_yahoo('SPY')['Adj Close'] * 10

In [129]: px
Out[129]:
Date
2011-08-01    1261.0
2011-08-02    1228.8
2011-08-03    1235.5
...
2012-07-25    1339.6
2012-07-26    1361.7
2012-07-27    1386.8
Name: Adj Close, Length: 251
```

Now, a little bit of setup. I put a couple of S&P 500 future contracts and expiry dates in a Series:

```
from datetime import datetime
expiry = {'ESU2': datetime(2012, 9, 21),
          'ESZ2': datetime(2012, 12, 21)}
expiry = Series(expiry).order()
```

`expiry` then looks like:

```
In [131]: expiry
Out[131]:
ESU2    2012-09-21 00:00:00
ESZ2    2012-12-21 00:00:00
```

Then, I use the Yahoo! Finance prices along with a random walk and some noise to simulate the two contracts into the future:

```
np.random.seed(12347)
N = 200
walk = (np.random.randint(0, 200, size=N) - 100) * 0.25
perturb = (np.random.randint(0, 20, size=N) - 10) * 0.25
walk = walk.cumsum()

rng = pd.date_range(px.index[0], periods=len(px) + N, freq='B')
near = np.concatenate([px.values, px.values[-1] + walk])
far = np.concatenate([px.values, px.values[-1] + walk + perturb])
prices = DataFrame({'ESU2': near, 'ESZ2': far}, index=rng)
```

`prices` then has two time series for the contracts that differ from each other by a random amount:

```
In [133]: prices.tail()
Out[133]:
                ESU2     ESZ2
2013-04-16  1416.05  1417.80
2013-04-17  1402.30  1404.55
2013-04-18  1410.30  1412.05
2013-04-19  1426.80  1426.05
2013-04-22  1406.80  1404.55
```

One way to splice time series together into a single continuous series is to construct a weighting matrix. Active contracts would have a weight of 1 until the expiry date approaches. At that point you have to decide on a roll convention. Here is a function that computes a weighting matrix with linear decay over a number of periods leading up to expiry:

```
def get_roll_weights(start, expiry, items, roll_periods=5):
    # start : first date to compute weighting DataFrame
    # expiry : Series of ticker -> expiration dates
    # items : sequence of contract names

    dates = pd.date_range(start, expiry[-1], freq='B')
    weights = DataFrame(np.zeros((len(dates), len(items))),
                        index=dates, columns=items)

    prev_date = weights.index[0]
    for i, (item, ex_date) in enumerate(expiry.iteritems()):
        if i < len(expiry) - 1:
            weights.ix[prev_date:ex_date - pd.offsets.BDay(), item] = 1
            roll_rng = pd.date_range(end=ex_date - pd.offsets.BDay(),
                                     periods=roll_periods + 1, freq='B')

            decay_weights = np.linspace(0, 1, roll_periods + 1)
            weights.ix[roll_rng, item] = 1 - decay_weights
            weights.ix[roll_rng, expiry.index[i + 1]] = decay_weights
        else:
            weights.ix[prev_date:, item] = 1

        prev_date = ex_date
```

```
    return weights
```

The weights look like this around the ESU2 expiry:

```
In [135]: weights = get_roll_weights('6/1/2012', expiry, prices.columns)

In [136]: weights.ix['2012-09-12':'2012-09-21']
Out[136]:
            ESU2  ESZ2
2012-09-12   1.0   0.0
2012-09-13   1.0   0.0
2012-09-14   0.8   0.2
2012-09-17   0.6   0.4
2012-09-18   0.4   0.6
2012-09-19   0.2   0.8
2012-09-20   0.0   1.0
2012-09-21   0.0   1.0
```

Finally, the rolled future returns are just a weighted sum of the contract returns:

```
In [137]: rolled_returns = (prices.pct_change() * weights).sum(1)
```

Rolling Correlation and Linear Regression

Dynamic models play an important role in financial modeling as they can be used to simulate trading decisions over a historical period. Moving window and exponentially-weighted time series functions are an example of tools that are used for dynamic models.

Correlation is one way to look at the co-movement between the changes in two asset time series. pandas's `rolling_corr` function can be called with two return series to compute the moving window correlation. First, I load some price series from Yahoo! Finance and compute daily returns:

```
aapl = web.get_data_yahoo('AAPL', '2000-01-01')['Adj Close']
msft = web.get_data_yahoo('MSFT', '2000-01-01')['Adj Close']

aapl_rets = aapl.pct_change()
msft_rets = msft.pct_change()
```

Then, I compute and plot the one-year moving correlation (see Figure 11-4):

```
In [140]: pd.rolling_corr(aapl_rets, msft_rets, 250).plot()
```

One issue with correlation between two assets is that it does not capture differences in volatility. Least-squares regression provides another means for modeling the dynamic relationship between a variable and one or more other predictor variables.

```
In [142]: model = pd.ols(y=aapl_rets, x={'MSFT': msft_rets}, window=250)

In [143]: model.beta
Out[143]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2913 entries, 2000-12-28 00:00:00 to 2012-07-27 00:00:00
Data columns:
```

```
MSFT         2913  non-null values
intercept    2913  non-null values
dtypes: float64(2)

In [144]: model.beta['MSFT'].plot()
```

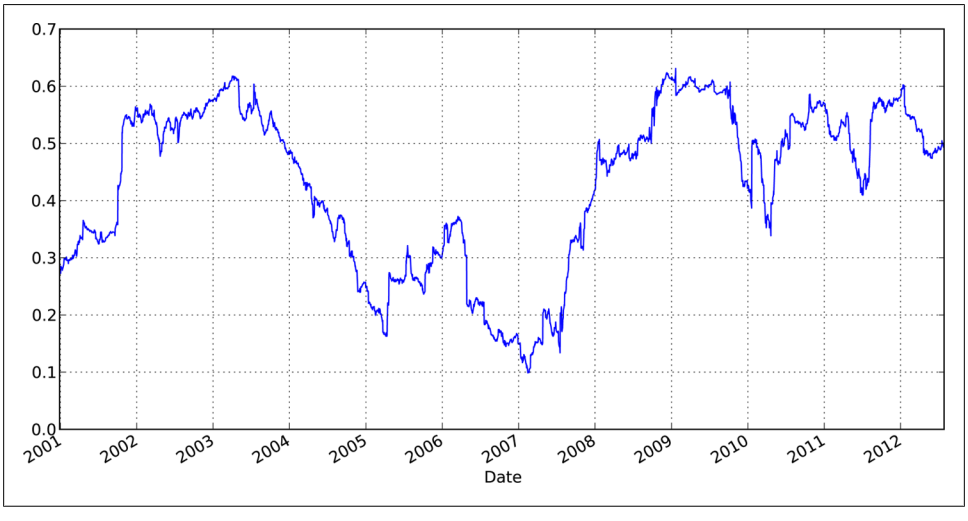


Figure 11-4. One-year correlation of Apple with Microsoft

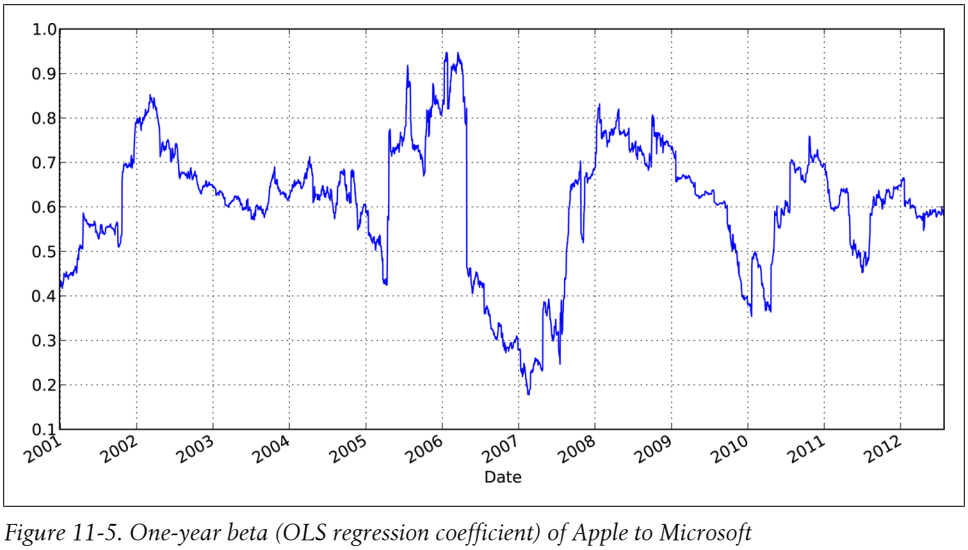


Figure 11-5. One-year beta (OLS regression coefficient) of Apple to Microsoft

pandas's `ols` function implements static and dynamic (expanding or rolling window) least squares regressions. For more sophisticated statistical and econometrics models, see the statsmodels project (*http://statsmodels.sourceforge.net*).

CHAPTER 12

Advanced NumPy

ndarray Object Internals

The NumPy ndarray provides a means to interpret a block of homogeneous data (either contiguous or strided, more on this later) as a multidimensional array object. As you've seen, the data type, or *dtype*, determines how the data is interpreted as being floating point, integer, boolean, or any of the other types we've been looking at.

Part of what makes ndarray powerful is that every array object is a *strided* view on a block of data. You might wonder, for example, how the array view `arr[::2, ::-1]` does not copy any data. Simply put, the ndarray is more than just a chunk of memory and a dtype; it also has striding information which enables the array to move through memory with varying step sizes. More precisely, the ndarray internally consists of the following:

- A *pointer to data*, that is a block of system memory
- The *data type* or dtype
- A tuple indicating the array's *shape*; For example, a 10 by 5 array would have shape `(10, 5)`

  ```
  In [8]: np.ones((10, 5)).shape
  Out[8]: (10, 5)
  ```

- A tuple of *strides*, integers indicating the number of bytes to "step" in order to advance one element along a dimension; For example, a typical (C order, more on this later) 3 x 4 x 5 array of `float64` (8-byte) values has strides `(160, 40, 8)`

  ```
  In [9]: np.ones((3, 4, 5), dtype=np.float64).strides
  Out[9]: (160, 40, 8)
  ```

  While it is rare that a typical NumPy user would be interested in the array strides, they are the critical ingredient in constructing copyless array views. Strides can even be negative which enables an array to move *backward* through memory, which would be the case in a slice like `obj[::-1]` or `obj[:, ::-1]`.

See Figure 12-1 for a simple mockup the ndarray innards.

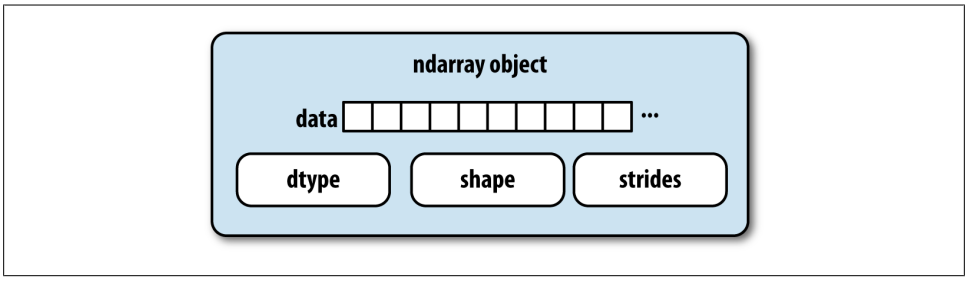


Figure 12-1. The NumPy ndarray object

NumPy dtype Hierarchy

You may occasionally have code which needs to check whether an array contains integers, floating point numbers, strings, or Python objects. Because there are many types of floating point numbers (`float16` through `float128`), checking that the dtype is among a list of types would be very verbose. Fortunately, the dtypes have superclasses such as `np.integer` and `np.floating` which can be used in conjunction with the `np.issubdtype` function:

```
In [10]: ints = np.ones(10, dtype=np.uint16)

In [11]: floats = np.ones(10, dtype=np.float32)

In [12]: np.issubdtype(ints.dtype, np.integer)
Out[12]: True

In [13]: np.issubdtype(floats.dtype, np.floating)
Out[13]: True
```

You can see all of the parent classes of a specific dtype by calling the type's `mro` method:

```
In [14]: np.float64.mro()
Out[14]:
[numpy.float64,
 numpy.floating,
 numpy.inexact,
 numpy.number,
 numpy.generic,
 float,
 object]
```

Most NumPy users will never have to know about this, but it occasionally comes in handy. See Figure 12-2 for a graph of the dtype hierarchy and parent-subclass relationships [1].

1. Some of the dtypes have trailing underscores in their names. These are there to avoid variable name conflicts between the NumPy-specific types and the Python built-in ones.

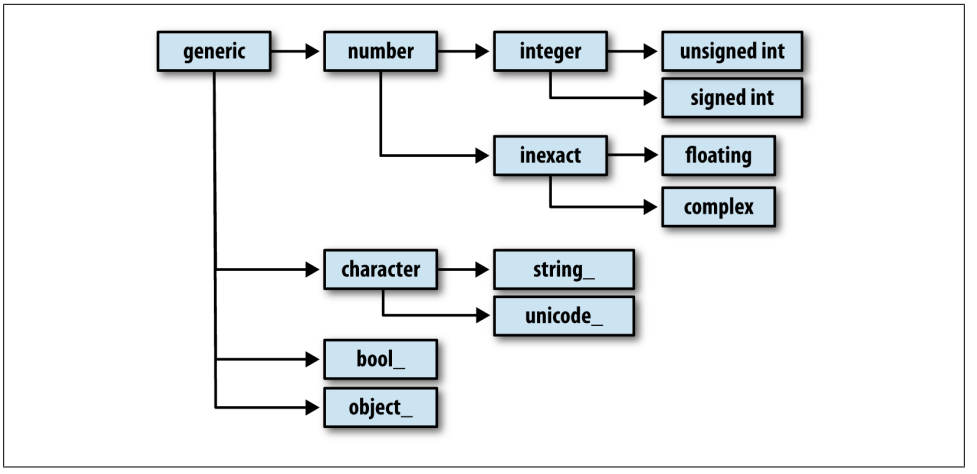


Figure 12-2. The NumPy dtype class hierarchy

Advanced Array Manipulation

There are many ways to work with arrays beyond fancy indexing, slicing, and boolean subsetting. While much of the heavy lifting for data analysis applications is handled by higher level functions in pandas, you may at some point need to write a data algorithm that is not found in one of the existing libraries.

Reshaping Arrays

Given what we know about NumPy arrays, it should come as little surprise that you can convert an array from one shape to another without copying any data. To do this, pass a tuple indicating the new shape to the `reshape` array instance method. For example, suppose we had a one-dimensional array of values that we wished to rearrange into a matrix:

```
In [15]: arr = np.arange(8)

In [16]: arr
Out[16]: array([0, 1, 2, 3, 4, 5, 6, 7])

In [17]: arr.reshape((4, 2))
Out[17]:
array([[0, 1],
       [2, 3],
       [4, 5],
       [6, 7]])
```

A multidimensional array can also be reshaped:

```
In [18]: arr.reshape((4, 2)).reshape((2, 4))
Out[18]:
```

```
array([[0, 1, 2, 3],
       [4, 5, 6, 7]])
```

One of the passed shape dimensions can be -1, in which case the value used for that dimension will be inferred from the data:

```
In [19]: arr = np.arange(15)
```

```
In [20]: arr.reshape((5, -1))
Out[20]:
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11],
       [12, 13, 14]])
```

Since an array's `shape` attribute is a tuple, it can be passed to `reshape`, too:

```
In [21]: other_arr = np.ones((3, 5))

In [22]: other_arr.shape
Out[22]: (3, 5)

In [23]: arr.reshape(other_arr.shape)
Out[23]:
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14]])
```

The opposite operation of `reshape` from one-dimensional to a higher dimension is typically known as *flattening* or *raveling*:

```
In [24]: arr = np.arange(15).reshape((5, 3))
```

```
In [25]: arr
Out[25]:
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11],
       [12, 13, 14]])
```

```
In [26]: arr.ravel()
Out[26]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14])
```

`ravel` does not produce a copy of the underlying data if it does not have to (more on this below). The `flatten` method behaves like `ravel` except it always returns a copy of the data:

```
In [27]: arr.flatten()
Out[27]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14])
```

The data can be reshaped or raveled in different orders. This is a slightly nuanced topic for new NumPy users and is therefore the next subtopic.

C versus Fortran Order

Contrary to some other scientific computing environments like R and MATLAB, NumPy gives you much more control and flexibility over the layout of your data in

memory. By default, NumPy arrays are created in *row major* order. Spatially this means that if you have a two-dimensional array of data, the items in each row of the array are stored in adjacent memory locations. The alternative to row major ordering is *column major* order, which means that (you guessed it) values within each column of data are stored in adjacent memory locations.

For historical reasons, row and column major order are also know as C and Fortran order, respectively. In FORTRAN 77, the language of our forebears, matrices were all column major.

Functions like `reshape` and `ravel`, accept an `order` argument indicating the order to use the data in the array. This can be `'C'` or `'F'` in most cases (there are also less commonly-used options `'A'` and `'K'`; see the NumPy documentation). These are illustrated in Figure 12-3.

```
In [28]: arr = np.arange(12).reshape((3, 4))

In [29]: arr
Out[29]:
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])

In [30]: arr.ravel()
Out[30]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])

In [31]: arr.ravel('F')
Out[31]: array([ 0,  4,  8,  1,  5,  9,  2,  6, 10,  3,  7, 11])
```

Reshaping arrays with more than two dimensions can be a bit mind-bending. The key difference between C and Fortran order is the order in which the dimensions are walked:

- *C / row major order:* traverse higher dimensions *first* (e.g. axis 1 before advancing on axis 0).
- *Fortran / column major order:* traverse higher dimensions *last* (e.g. axis 0 before advancing on axis 1).

Concatenating and Splitting Arrays

`numpy.concatenate` takes a sequence (tuple, list, etc.) of arrays and joins them together in order along the input axis.

```
In [32]: arr1 = np.array([[1, 2, 3], [4, 5, 6]])

In [33]: arr2 = np.array([[7, 8, 9], [10, 11, 12]])

In [34]: np.concatenate([arr1, arr2], axis=0)
Out[34]:
array([[ 1,  2,  3],
       [ 4,  5,  6],
```

```
       [ 7,  8,  9],
       [10, 11, 12]])

In [35]: np.concatenate([arr1, arr2], axis=1)
Out[35]:
array([[ 1,  2,  3,  7,  8,  9],
       [ 4,  5,  6, 10, 11, 12]])
```

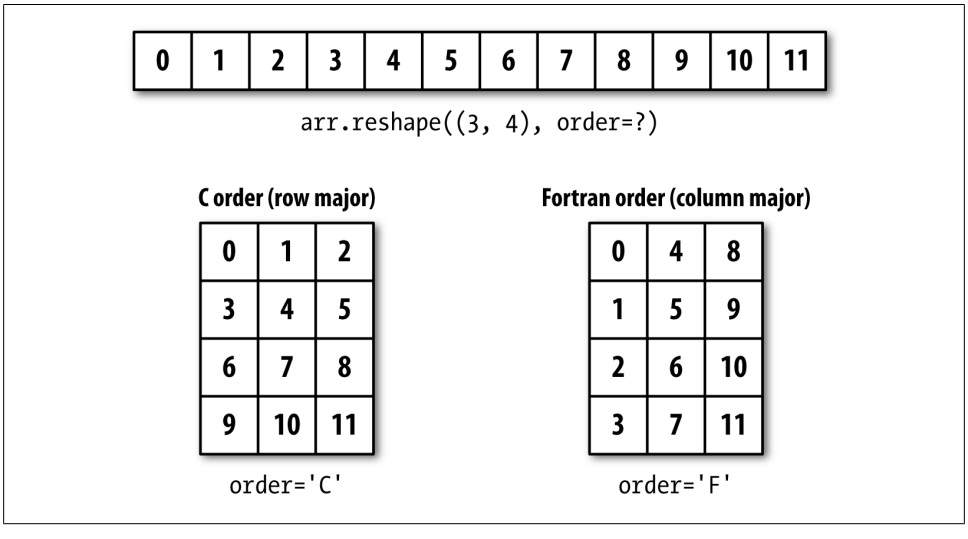


Figure 12-3. Reshaping in C (row major) or Fortran (column major) order

There are some convenience functions, like `vstack` and `hstack`, for common kinds of concatenation. The above operations could have been expressed as:

```
In [36]: np.vstack((arr1, arr2))
Out[36]:
array([[ 1,  2,  3],
       [ 4,  5,  6],
       [ 7,  8,  9],
       [10, 11, 12]])
```

```
In [37]: np.hstack((arr1, arr2))
Out[37]:
array([[ 1,  2,  3,  7,  8,  9],
       [ 4,  5,  6, 10, 11, 12]])
```

`split`, on the other hand, slices apart an array into multiple arrays along an axis:

```
In [38]: from numpy.random import randn

In [39]: arr = randn(5, 2)
```

```
In [40]: arr
Out[40]:
array([[ 0.1689,  0.3287],
       [ 0.4703,  0.8989],
       [ 0.1535,  0.0243],
       [-0.2832,  1.1536],
       [ 0.2707,  0.8075]])
```

```
In [41]: first, second, third = np.split(arr, [1, 3])

In [42]: first
```

```
Out[42]: array([[ 0.1689,  0.3287]])

In [43]: second
Out[43]:
array([[ 0.4703,  0.8989],
       [ 0.1535,  0.0243]])

In [44]: third
Out[44]:
array([[-0.2832,  1.1536],
       [ 0.2707,  0.8075]])
```

See Table 12-1 for a list of all relevant concatenation and splitting functions, some of which are provided only as a convenience of the very general purpose `concatenate`.

Table 12-1. Array concatenation functions

Function	Description
`concatenate`	Most general function, concatenates collection of arrays along one axis
`vstack, row_stack`	Stack arrays row-wise (along axis 0)
`hstack`	Stack arrays column-wise (along axis 1)
`column_stack`	Like hstack, but converts 1D arrays to 2D column vectors first
`dstack`	Stack arrays "depth"-wise (along axis 2)
`split`	Split array at passed locations along a particular axis
`hsplit / vsplit / dsplit`	Convenience functions for splitting on axis 0, 1, and 2, respectively.

Stacking helpers: r_ and c_

There are two special objects in the NumPy namespace, `r_` and `c_`, that make stacking arrays more concise:

```
In [45]: arr = np.arange(6)

In [46]: arr1 = arr.reshape((3, 2))

In [47]: arr2 = randn(3, 2)

In [48]: np.r_[arr1, arr2]
Out[48]:
array([[ 0.    ,  1.    ],
       [ 2.    ,  3.    ],
       [ 4.    ,  5.    ],
       [ 0.7258, -1.5325],
       [-0.4696, -0.2127],
       [-0.1072,  1.2871]])

In [49]: np.c_[np.r_[arr1, arr2], arr]
Out[49]:
array([[ 0.    ,  1.    ,  0.    ],
       [ 2.    ,  3.    ,  1.    ],
       [ 4.    ,  5.    ,  2.    ],
       [ 0.7258, -1.5325,  3.    ],
       [-0.4696, -0.2127,  4.    ],
       [-0.1072,  1.2871,  5.    ]])
```

These additionally can translate slices to arrays:

```
In [50]: np.c_[1:6, -10:-5]
Out[50]:
array([[  1, -10],
       [  2,  -9],
       [  3,  -8],
       [  4,  -7],
       [  5,  -6]])
```

See the docstring for more on what you can do with `c_` and `r_`.

Repeating Elements: Tile and Repeat

The need to replicate or repeat arrays is less common with NumPy than it is with other popular array programming languages like MATLAB. The main reason for this is that *broadcasting* fulfills this need better, which is the subject of the next section.

The two main tools for repeating or replicating arrays to produce larger arrays are the `repeat` and `tile` functions. `repeat` replicates each element in an array some number of times, producing a larger array:

```
In [51]: arr = np.arange(3)

In [52]: arr.repeat(3)
Out[52]: array([0, 0, 0, 1, 1, 1, 2, 2, 2])
```

By default, if you pass an integer, each element will be repeated that number of times. If you pass an array of integers, each element can be repeated a different number of times:

```
In [53]: arr.repeat([2, 3, 4])
Out[53]: array([0, 0, 1, 1, 1, 2, 2, 2, 2])
```

Multidimensional arrays can have their elements repeated along a particular axis.

```
In [54]: arr = randn(2, 2)

In [55]: arr
Out[55]:
array([[ 0.7157, -0.6387],
       [ 0.3626,  0.849 ]])
```

```
In [56]: arr.repeat(2, axis=0)
Out[56]:
array([[ 0.7157, -0.6387],
       [ 0.7157, -0.6387],
       [ 0.3626,  0.849 ],
       [ 0.3626,  0.849 ]])
```

Note that if no axis is passed, the array will be flattened first, which is likely not what you want. Similarly you can pass an array of integers when repeating a multidimensional array to repeat a given slice a different number of times:

```
In [57]: arr.repeat([2, 3], axis=0)
Out[57]:
array([[ 0.7157, -0.6387],
       [ 0.7157, -0.6387],
       [ 0.3626,  0.849 ],
       [ 0.3626,  0.849 ],
       [ 0.3626,  0.849 ]])

In [58]: arr.repeat([2, 3], axis=1)
Out[58]:
array([[ 0.7157,  0.7157, -0.6387, -0.6387, -0.6387],
       [ 0.3626,  0.3626,  0.849 ,  0.849 ,  0.849 ]])
```

`tile`, on the other hand, is a shortcut for stacking copies of an array along an axis. You can visually think about it as like "laying down tiles":

```
In [59]: arr
Out[59]:
array([[ 0.7157, -0.6387],
       [ 0.3626,  0.849 ]])

In [60]: np.tile(arr, 2)
Out[60]:
array([[ 0.7157, -0.6387,  0.7157, -0.6387],
       [ 0.3626,  0.849 ,  0.3626,  0.849 ]])
```

The second argument is the number of tiles; with a scalar, the tiling is made row-by-row, rather than column by column: The second argument to `tile` can be a tuple indicating the layout of the "tiling":

```
In [61]: arr
Out[61]:
array([[ 0.7157, -0.6387],
       [ 0.3626,  0.849 ]])

In [62]: np.tile(arr, (2, 1))
Out[62]:
array([[ 0.7157, -0.6387],
       [ 0.3626,  0.849 ],
       [ 0.7157, -0.6387],
       [ 0.3626,  0.849 ]])
```

```
In [63]: np.tile(arr, (3, 2))
Out[63]:
array([[ 0.7157, -0.6387,  0.7157, -0.6387],
       [ 0.3626,  0.849 ,  0.3626,  0.849 ],
       [ 0.7157, -0.6387,  0.7157, -0.6387],
       [ 0.3626,  0.849 ,  0.3626,  0.849 ],
       [ 0.7157, -0.6387,  0.7157, -0.6387],
       [ 0.3626,  0.849 ,  0.3626,  0.849 ]])
```

Fancy Indexing Equivalents: Take and Put

As you may recall from Chapter 4, one way to get and set subsets of arrays is by *fancy* indexing using integer arrays:

```
In [64]: arr = np.arange(10) * 100

In [65]: inds = [7, 1, 2, 6]
```

```
In [66]: arr[inds]
Out[66]: array([700, 100, 200, 600])
```

There are alternate ndarray methods that are useful in the special case of only making a selection on a single axis:

```
In [67]: arr.take(inds)
Out[67]: array([700, 100, 200, 600])

In [68]: arr.put(inds, 42)

In [69]: arr
Out[69]: array([  0,  42,  42, 300, 400, 500,  42,  42, 800, 900])

In [70]: arr.put(inds, [40, 41, 42, 43])
```

```
In [71]: arr
Out[71]: array([  0,  41,  42, 300, 400, 500,  43,  40, 800, 900])
```

To use `take` along other axes, you can pass the `axis` keyword:

```
In [72]: inds = [2, 0, 2, 1]

In [73]: arr = randn(2, 4)

In [74]: arr
Out[74]:
array([[-0.8237,  2.6047, -0.4578, -1.    ],
       [ 2.3198, -1.0792,  0.518 ,  0.2527]])

In [75]: arr.take(inds, axis=1)
Out[75]:
array([[-0.4578, -0.8237, -0.4578,  2.6047],
       [ 0.518 ,  2.3198,  0.518 , -1.0792]])
```

`put` does not accept an `axis` argument but rather indexes into the flattened (one-dimensional, C order) version of the array (this could be changed in principle). Thus, when you need to set elements using an index array on other axes, you will want to use fancy indexing.

As of this writing, the `take` and `put` functions in general have better performance than their fancy indexing equivalents by a significant margin. I regard this as a "bug" and something to be fixed in NumPy, but it's something worth keeping in mind if you're selecting subsets of large arrays using integer arrays:

```
In [76]: arr = randn(1000, 50)

# Random sample of 500 rows
In [77]: inds = np.random.permutation(1000)[:500]

In [78]: %timeit arr[inds]
1000 loops, best of 3: 356 us per loop

In [79]: %timeit arr.take(inds, axis=0)
10000 loops, best of 3: 34 us per loop
```

Broadcasting

Broadcasting describes how arithmetic works between arrays of different shapes. It is a very powerful feature, but one that can be easily misunderstood, even by experienced users. The simplest example of broadcasting occurs when combining a scalar value with an array:

```
In [80]: arr = np.arange(5)

In [81]: arr                          In [82]: arr * 4
Out[81]: array([0, 1, 2, 3, 4])       Out[82]: array([ 0,  4,  8, 12, 16])
```

Here we say that the scalar value 4 has been *broadcast* to all of the other elements in the multiplication operation.

For example, we can demean each column of an array by subtracting the column means. In this case, it is very simple:

```
In [83]: arr = randn(4, 3)

In [84]: arr.mean(0)
Out[84]: array([ 0.1321,  0.552 ,  0.8571])

In [85]: demeaned = arr - arr.mean(0)

In [86]: demeaned
Out[86]:
array([[ 0.1718, -0.1972, -1.3669],
       [-0.1292,  1.6529, -0.3429],
       [-0.2891, -0.0435,  1.2322],
       [ 0.2465, -1.4122,  0.4776]])

In [87]: demeaned.mean(0)
Out[87]: array([ 0., -0., -0.])
```

See Figure 12-4 for an illustration of this operation. Demeaning the rows as a broadcast operation requires a bit more care. Fortunately, broadcasting potentially lower dimensional values across any dimension of an array (like subtracting the row means from each column of a two-dimensional array) is possible as long as you follow the rules. This brings us to:

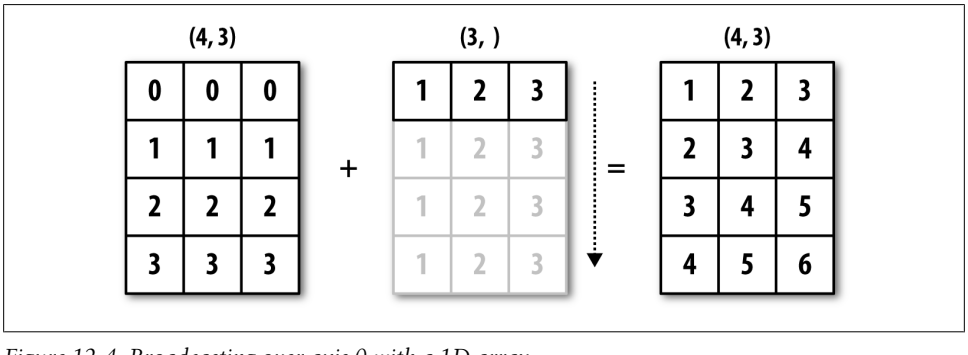


Figure 12-4. Broadcasting over axis 0 with a 1D array

The Broadcasting Ru

Two arrays are compatible for broadcasting if for each *trailing dimension* (that is, starting from the end), the axis lengths match or if either of the lengths is 1. Broadcasting is then performed over the missing and / or length 1 dimensions.

Even as an experienced NumPy user, I often must stop to draw pictures and think about the broadcasting rule. Consider the last example and suppose we wished instead to subtract the mean value from each row. Since `arr.mean(0)` has length 3, it is compatible

for broadcasting across axis 0 because the trailing dimension in `arr` is 3 and therefore matches. According to the rules, to subtract over axis 1 (that is, subtract the row mean from each row), the smaller array must have shape `(4, 1)`:

```
In [88]: arr
Out[88]:
array([[ 0.3039,  0.3548, -0.5097],
       [ 0.0029,  2.2049,  0.5142],
       [-0.1571,  0.5085,  2.0893],
       [ 0.3786, -0.8602,  1.3347]])

In [89]: row_means = arr.mean(1)
```

```
In [90]: row_means.reshape((4, 1))
Out[90]:
array([[ 0.0496],
       [ 0.9073],
       [ 0.8136],
       [ 0.2844]])
```

```
In [91]: demeaned = arr - row_means.reshape((4, 1))

In [92]: demeaned.mean(1)
Out[92]: array([ 0.,  0.,  0.,  0.])
```

Has your head exploded yet? See Figure 12-5 for an illustration of this operation.

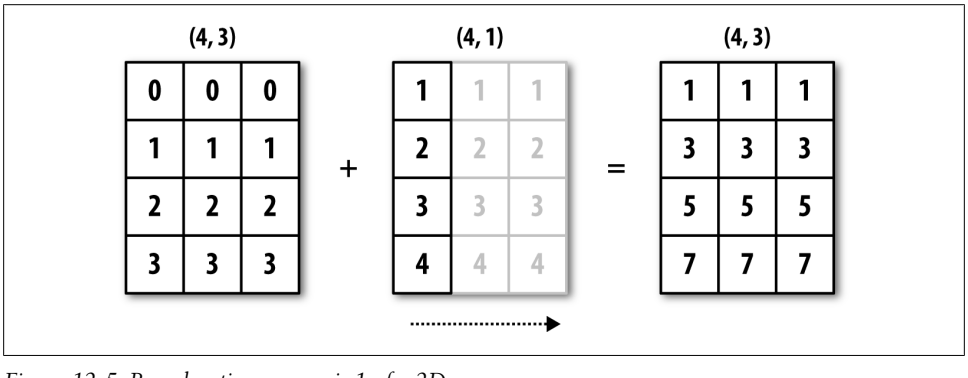


Figure 12-5. Broadcasting over axis 1 of a 2D array

See Figure 12-6 for another illustration, this time subtracting a two-dimensional array from a three-dimensional one across axis 0.

Broadcasting Over Other Axes

Broadcasting with higher dimensional arrays can seem even more mind-bending, but it is really a matter of following the rules. If you don't, you'll get an error like this:

```
In [93]: arr - arr.mean(1)
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-93-7b87b85a20b2> in <module>()
```

```
----> 1 arr - arr.mean(1)
ValueError: operands could not be broadcast together with shapes (4,3) (4)
```

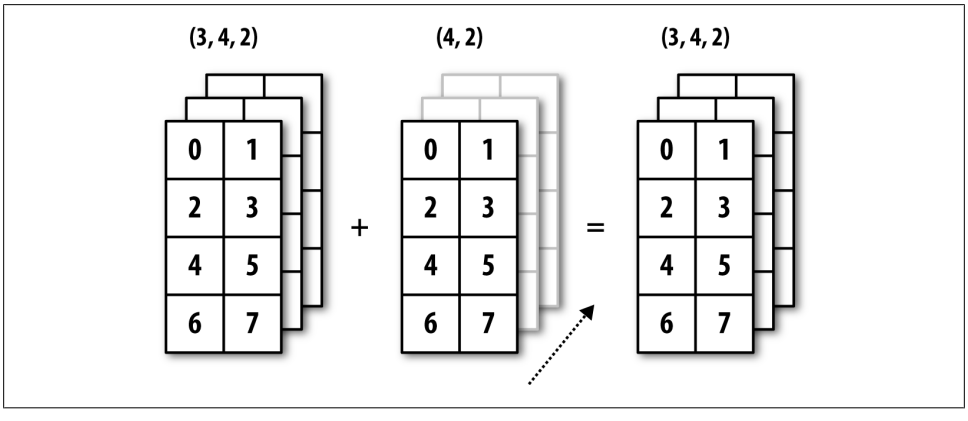


Figure 12-6. Broadcasting over axis 0 of a 3D array

It's quite common to want to perform an arithmetic operation with a lower dimensional array across axes other than axis 0. According to the broadcasting rule, the "broadcast dimensions" must be 1 in the smaller array. In the example of row demeaning above this meant reshaping the row means to be shape `(4, 1)` instead of `(4,)`:

```
In [94]: arr - arr.mean(1).reshape((4, 1))
Out[94]:
array([[ 0.2542,  0.3051, -0.5594],
       [-0.9044,  1.2976, -0.3931],
       [-0.9707, -0.3051,  1.2757],
       [ 0.0942, -1.1446,  1.0503]])
```

In the three-dimensional case, broadcasting over any of the three dimensions is only a matter of reshaping the data to be shape-compatible. See Figure 12-7 for a nice visualization of the shapes required to broadcast over each axis of a three-dimensional array.

A very common problem, therefore, is needing to add a new axis with length 1 specifically for broadcasting purposes, especially in generic algorithms. Using `reshape` is one option, but inserting an axis requires constructing a tuple indicating the new shape. This can often be a tedious exercise. Thus, NumPy arrays offer a special syntax for inserting new axes by indexing. We use the special `np.newaxis` attribute along with "full" slices to insert the new axis:

```
In [95]: arr = np.zeros((4, 4))

In [96]: arr_3d = arr[:, np.newaxis, :]      In [97]: arr_3d.shape
                                             Out[97]: (4, 1, 4)

In [98]: arr_1d = np.random.normal(size=3)

In [99]: arr_1d[:, np.newaxis]      In [100]: arr_1d[np.newaxis, :]
Out[99]:                            Out[100]: array([[-0.3899,  0.396 , -0.1852]])
```

```
array([[-0.3899],
       [ 0.396 ],
       [-0.1852]])
```

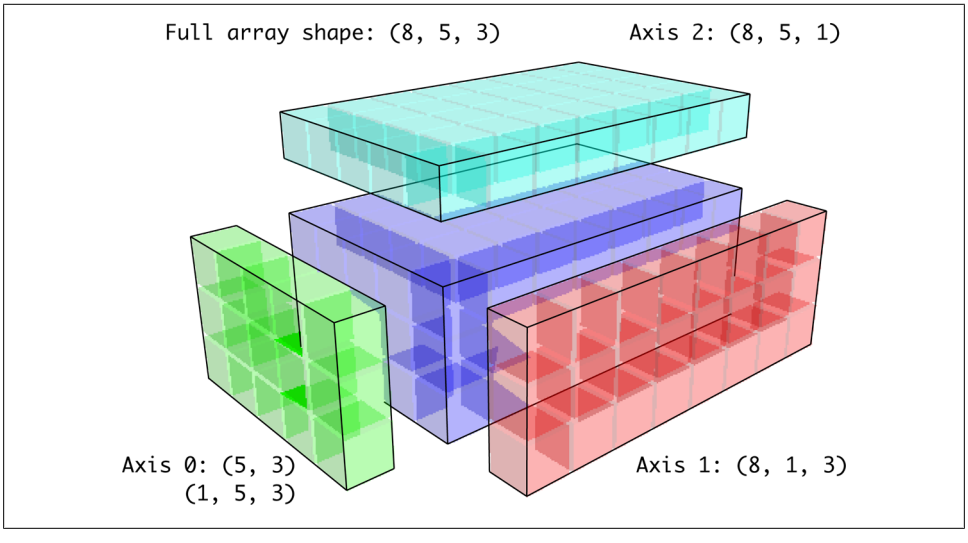


Figure 12-7. Compatible 2D array shapes for broadcasting over a 3D array

Thus, if we had a three-dimensional array and wanted to demean axis 2, say, we would only need to write:

```
In [101]: arr = randn(3, 4, 5)

In [102]: depth_means = arr.mean(2)

In [103]: depth_means
Out[103]:
array([[ 0.1097,  0.3118, -0.5473,  0.2663],
       [ 0.1747,  0.1379,  0.1146, -0.4224],
       [ 0.0217,  0.3686, -0.0468,  1.3026]])

In [104]: demeaned = arr - depth_means[:, :, np.newaxis]

In [105]: demeaned.mean(2)
Out[105]:
array([[ 0.,  0., -0.,  0.],
       [ 0., -0., -0.,  0.],
       [-0., -0.,  0.,  0.]])
```

If you're completely confused by this, don't worry. With practice you will get the hang of it!

Some readers might wonder if there's a way to generalize demeaning over an axis without sacrificing performance. There is, in fact, but it requires some indexing gymnastics:

```
def demean_axis(arr, axis=0):
    means = arr.mean(axis)

    # This generalized things like [:, :, np.newaxis] to N dimensions
    indexer = [slice(None)] * arr.ndim
    indexer[axis] = np.newaxis
    return arr - means[indexer]
```

Setting Array Values by Broadcasting

The same broadcasting rule governing arithmetic operations also applies to setting values via array indexing. In the simplest case, we can do things like:

```
In [106]: arr = np.zeros((4, 3))

In [107]: arr[:] = 5        In [108]: arr
                            Out[108]:
                            array([[ 5.,  5.,  5.],
                                   [ 5.,  5.,  5.],
                                   [ 5.,  5.,  5.],
                                   [ 5.,  5.,  5.]])
```

However, if we had a one-dimensional array of values we wanted to set into the columns of the array, we can do that as long as the shape is compatible:

```
In [109]: col = np.array([1.28, -0.42, 0.44, 1.6])

In [110]: arr[:] = col[:, np.newaxis]      In [111]: arr
                                           Out[111]:
                                           array([[ 1.28,  1.28,  1.28],
                                                  [-0.42, -0.42, -0.42],
                                                  [ 0.44,  0.44,  0.44],
                                                  [ 1.6 ,  1.6 ,  1.6 ]])

In [112]: arr[:2] = [[-1.37], [0.509]]     In [113]: arr
                                           Out[113]:
                                           array([[-1.37 , -1.37 , -1.37 ],
                                                  [ 0.509,  0.509,  0.509],
                                                  [ 0.44 ,  0.44 ,  0.44 ],
                                                  [ 1.6  ,  1.6  ,  1.6  ]])
```

Advanced ufunc Usage

While many NumPy users will only make use of the fast element-wise operations provided by the universal functions, there are a number of additional features that occasionally can help you write more concise code without loops.

ufunc Instance Methods

Each of NumPy's binary ufuncs has special methods for performing certain kinds of special vectorized operations. These are summarized in Table 12-2, but I'll give a few concrete examples to illustrate how they work.

`reduce` takes a single array and aggregates its values, optionally along an axis, by performing a sequence of binary operations. For example, an alternate way to sum elements in an array is to use `np.add.reduce`:

```
In [114]: arr = np.arange(10)

In [115]: np.add.reduce(arr)
Out[115]: 45

In [116]: arr.sum()
Out[116]: 45
```

The starting value (0 for `add`) depends on the ufunc. If an axis is passed, the reduction is performed along that axis. This allows you to answer certain kinds of questions in a concise way. As a less trivial example, we can use `np.logical_and` to check whether the values in each row of an array are sorted:

```
In [118]: arr = randn(5, 5)

In [119]: arr[::2].sort(1) # sort a few rows

In [120]: arr[:, :-1] < arr[:, 1:]
Out[120]:
array([[ True,  True,  True,  True],
       [False,  True, False, False],
       [ True,  True,  True,  True],
       [ True, False,  True,  True],
       [ True,  True,  True,  True]], dtype=bool)

In [121]: np.logical_and.reduce(arr[:, :-1] < arr[:, 1:], axis=1)
Out[121]: array([ True, False,  True, False,  True], dtype=bool)
```

Of course, `logical_and.reduce` is equivalent to the `all` method.

`accumulate` is related to `reduce` like `cumsum` is related to `sum`. It produces an array of the same size with the intermediate "accumulated" values:

```
In [122]: arr = np.arange(15).reshape((3, 5))

In [123]: np.add.accumulate(arr, axis=1)
Out[123]:
array([[ 0,  1,  3,  6, 10],
       [ 5, 11, 18, 26, 35],
       [10, 21, 33, 46, 60]])
```

`outer` performs a pairwise cross-product between two arrays:

```
In [124]: arr = np.arange(3).repeat([1, 2, 2])
```

```
In [125]: arr
Out[125]: array([0, 1, 1, 2, 2])

In [126]: np.multiply.outer(arr, np.arange(5))
Out[126]:
array([[0, 0, 0, 0, 0],
       [0, 1, 2, 3, 4],
       [0, 1, 2, 3, 4],
       [0, 2, 4, 6, 8],
       [0, 2, 4, 6, 8]])
```

The output of `outer` will have a dimension that is the sum of the dimensions of the inputs:

```
In [127]: result = np.subtract.outer(randn(3, 4), randn(5))

In [128]: result.shape
Out[128]: (3, 4, 5)
```

The last method, `reduceat`, performs a "local reduce", in essence an array `groupby` operation in which slices of the array are aggregated together. While it's less flexible than the GroupBy capabilities in pandas, it can be very fast and powerful in the right circumstances. It accepts a sequence of "bin edges" which indicate how to split and aggregate the values:

```
In [129]: arr = np.arange(10)

In [130]: np.add.reduceat(arr, [0, 5, 8])
Out[130]: array([10, 18, 17])
```

The results are the reductions (here, sums) performed over `arr[0:5]`, `arr[5:8]`, and `arr[8:]`. Like the other methods, you can pass an axis argument:

```
In [131]: arr = np.multiply.outer(np.arange(4), np.arange(5))

In [132]: arr
Out[132]:
array([[ 0,  0,  0,  0,  0],
       [ 0,  1,  2,  3,  4],
       [ 0,  2,  4,  6,  8],
       [ 0,  3,  6,  9, 12]])

In [133]: np.add.reduceat(arr, [0, 2, 4], axis=1)
Out[133]:
array([[ 0,  0,  0],
       [ 1,  5,  4],
       [ 2, 10,  8],
       [ 3, 15, 12]])
```

Table 12-2. ufunc methods

Method	Description
`reduce(x)`	Aggregate values by successive applications of the operation
`accumulate(x)`	Aggregate values, preserving all partial aggregates
`reduceat(x, bins)`	"Local" reduce or "group by". Reduce contiguous slices of data to produce aggregated array.
`outer(x, y)`	Apply operation to all pairs of elements in `x` and `y`. Result array has shape `x.shape + y.shape`

Custom ufuncs

There are a couple facilities for creating your own functions with ufunc-like semantics. `numpy.frompyfunc` accepts a Python function along with a specification for the number of inputs and outputs. For example, a simple function that adds element-wise would be specified as:

```
In [134]: def add_elements(x, y):
   .....:     return x + y

In [135]: add_them = np.frompyfunc(add_elements, 2, 1)

In [136]: add_them(np.arange(8), np.arange(8))
Out[136]: array([0, 2, 4, 6, 8, 10, 12, 14], dtype=object)
```

Functions created using `frompyfunc` always return arrays of Python objects which isn't very convenient. Fortunately, there is an alternate, but slightly less featureful function `numpy.vectorize` that is a bit more intelligent about type inference:

```
In [137]: add_them = np.vectorize(add_elements, otypes=[np.float64])

In [138]: add_them(np.arange(8), np.arange(8))
Out[138]: array([  0.,   2.,   4.,   6.,   8.,  10.,  12.,  14.])
```

These functions provide a way to create ufunc-like functions, but they are very slow because they require a Python function call to compute each element, which is a lot slower than NumPy's C-based ufunc loops:

```
In [139]: arr = randn(10000)

In [140]: %timeit add_them(arr, arr)
100 loops, best of 3: 2.12 ms per loop

In [141]: %timeit np.add(arr, arr)
100000 loops, best of 3: 11.6 us per loop
```

There are a number of projects under way in the scientific Python community to make it easier to define new ufuncs whose performance is closer to that of the built-in ones.

Structured and Record Arrays

You may have noticed up until now that ndarray is a *homogeneous* data container; that is, it represents a block of memory in which each element takes up the same number of bytes, determined by the dtype. On the surface, this would appear to not allow you to represent heterogeneous or tabular-like data. A *structured* array is an ndarray in which each element can be thought of as representing a *struct* in C (hence the "structured" name) or a row in a SQL table with multiple named fields:

```
In [142]: dtype = [('x', np.float64), ('y', np.int32)]

In [143]: sarr = np.array([(1.5, 6), (np.pi, -2)], dtype=dtype)
```

```
In [144]: sarr
Out[144]:
array([(1.5, 6), (3.141592653589793, -2)],
      dtype=[('x', '<f8'), ('y', '<i4')])
```

There are several ways to specify a structured dtype (see the online NumPy documentation). One typical way is as a list of tuples with `(field_name, field_data_type)`. Now, the elements of the array are tuple-like objects whose elements can be accessed like a dictionary:

```
In [145]: sarr[0]
Out[145]: (1.5, 6)

In [146]: sarr[0]['y']
Out[146]: 6
```

The field names are stored in the `dtype.names` attribute. On accessing a field on the structured array, a strided view on the data is returned thus copying nothing:

```
In [147]: sarr['x']
Out[147]: array([ 1.5   ,  3.1416])
```

Nested dtypes and Multidimensional Fields

When specifying a structured dtype, you can additionally pass a shape (as an int or tuple):

```
In [148]: dtype = [('x', np.int64, 3), ('y', np.int32)]

In [149]: arr = np.zeros(4, dtype=dtype)

In [150]: arr
Out[150]:
array([([0, 0, 0], 0), ([0, 0, 0], 0), ([0, 0, 0], 0), ([0, 0, 0], 0)],
      dtype=[('x', '<i8', (3,)), ('y', '<i4')])
```

In this case, the `x` field now refers to an array of length three for each record:

```
In [151]: arr[0]['x']
Out[151]: array([0, 0, 0])
```

Conveniently, accessing `arr['x']` then returns a two-dimensional array instead of a one-dimensional array as in prior examples:

```
In [152]: arr['x']
Out[152]:
array([[0, 0, 0],
       [0, 0, 0],
       [0, 0, 0],
       [0, 0, 0]])
```

This enables you to express more complicated, nested structures as a single block of memory in an array. Though, since dtypes can be arbitrarily complex, why not nested dtypes? Here is a simple example:

```
In [153]: dtype = [('x', [('a', 'f8'), ('b', 'f4')]), ('y', np.int32)]

In [154]: data = np.array([((1, 2), 5), ((3, 4), 6)], dtype=dtype)

In [155]: data['x']
Out[155]:
array([(1.0, 2.0), (3.0, 4.0)],
      dtype=[('a', '<f8'), ('b', '<f4')])

In [156]: data['y']
Out[156]: array([5, 6], dtype=int32)

In [157]: data['x']['a']
Out[157]: array([ 1.,  3.])
```

As you can see, variable-shape fields and nested records is a very rich feature that can be the right tool in certain circumstances. A DataFrame from pandas, by contrast, does not support this feature directly, though it is similar to hierarchical indexing.

Why Use Structured Arrays?

Compared with, say, a DataFrame from pandas, NumPy structured arrays are a comparatively low-level tool. They provide a means to interpreting a block of memory as a tabular structure with arbitrarily complex nested columns. Since each element in the array is represented in memory as a fixed number of bytes, structured arrays provide a very fast and efficient way of writing data to and from disk (including memory maps, more on this later), transporting it over the network, and other such use.

As another common use for structured arrays, writing data files as fixed length record byte streams is a common way to serialize data in C and C++ code, which is commonly found in legacy systems in industry. As long as the format of the file is known (the size of each record and the order, byte size, and data type of each element), the data can be read into memory using `np.fromfile`. Specialized uses like this are beyond the scope of this book, but it's worth knowing that such things are possible.

Structured Array Manipulations: numpy.lib.recfunctions

While there is not as much functionality available for structured arrays as for DataFrames, the NumPy module `numpy.lib.recfunctions` has some helpful tools for adding and dropping fields or doing basic join-like operations. The thing to remember with these tools is that it is typically necessary to create a new array to make any modifications to the dtype (like adding or dropping a column). These functions are left to the interested reader to explore as I do not use them anywhere in this book.

More About Sorting

Like Python's built-in list, the ndarray `sort` instance method is an *in-place* sort, meaning that the array contents are rearranged without producing a new array:

```
In [158]: arr = randn(6)

In [159]: arr.sort()

In [160]: arr
Out[160]: array([-1.082 ,  0.3759,  0.8014,  1.1397,  1.2888,  1.8413])
```

When sorting arrays in-place, remember that if the array is a view on a different ndarray, the original array will be modified:

```
In [161]: arr = randn(3, 5)

In [162]: arr
Out[162]:
array([[-0.3318, -1.4711,  0.8705, -0.0847, -1.1329],
       [-1.0111, -0.3436,  2.1714,  0.1234, -0.0189],
       [ 0.1773,  0.7424,  0.8548,  1.038 , -0.329 ]])

In [163]: arr[:, 0].sort()  # Sort first column values in-place

In [164]: arr
Out[164]:
array([[-1.0111, -1.4711,  0.8705, -0.0847, -1.1329],
       [-0.3318, -0.3436,  2.1714,  0.1234, -0.0189],
       [ 0.1773,  0.7424,  0.8548,  1.038 , -0.329 ]])
```

On the other hand, `numpy.sort` creates a new, sorted copy of an array. Otherwise it accepts the same arguments (such as `kind`, more on this below) as `ndarray.sort`:

```
In [165]: arr = randn(5)

In [166]: arr
Out[166]: array([-1.1181, -0.2415, -2.0051,  0.7379, -1.0614])

In [167]: np.sort(arr)
Out[167]: array([-2.0051, -1.1181, -1.0614, -0.2415,  0.7379])

In [168]: arr
Out[168]: array([-1.1181, -0.2415, -2.0051,  0.7379, -1.0614])
```

All of these sort methods take an axis argument for sorting the sections of data along the passed axis independently:

```
In [169]: arr = randn(3, 5)

In [170]: arr
Out[170]:
array([[ 0.5955, -0.2682,  1.3389, -0.1872,  0.9111],
       [-0.3215,  1.0054, -0.5168,  1.1925, -0.1989],
       [ 0.3969, -1.7638,  0.6071, -0.2222, -0.2171]])
```

```
In [171]: arr.sort(axis=1)

In [172]: arr
Out[172]:
array([[-0.2682, -0.1872,  0.5955,  0.9111,  1.3389],
       [-0.5168, -0.3215, -0.1989,  1.0054,  1.1925],
       [-1.7638, -0.2222, -0.2171,  0.3969,  0.6071]])
```

You may notice that none of the sort methods have an option to sort in descending order. This is not actually a big deal because array slicing produces views, thus not producing a copy or requiring any computational work. Many Python users are familiar with the "trick" that for a list `values`, `values[::-1]` returns a list in reverse order. The same is true for ndarrays:

```
In [173]: arr[:, ::-1]
Out[173]:
array([[ 1.3389,  0.9111,  0.5955, -0.1872, -0.2682],
       [ 1.1925,  1.0054, -0.1989, -0.3215, -0.5168],
       [ 0.6071,  0.3969, -0.2171, -0.2222, -1.7638]])
```

Indirect Sorts: argsort and lexsort

In data analysis it's very common to need to reorder data sets by one or more keys. For example, a table of data about some students might need to be sorted by last name then by first name. This is an example of an *indirect* sort, and if you've read the pandas-related chapters you have already seen many higher-level examples. Given a key or keys (an array or values or multiple arrays of values), you wish to obtain an array of integer *indices* (I refer to them colloquially as *indexers*) that tells you how to reorder the data to be in sorted order. The two main methods for this are `argsort` and `numpy.lexsort`. As a trivial example:

```
In [174]: values = np.array([5, 0, 1, 3, 2])

In [175]: indexer = values.argsort()

In [176]: indexer
Out[176]: array([1, 2, 4, 3, 0])

In [177]: values[indexer]
Out[177]: array([0, 1, 2, 3, 5])
```

As a less trivial example, this code reorders a 2D array by its first row:

```
In [178]: arr = randn(3, 5)

In [179]: arr[0] = values

In [180]: arr
Out[180]:
array([[ 5.    ,  0.    ,  1.    ,  3.    ,  2.    ],
       [-0.3636, -0.1378,  2.1777, -0.4728,  0.8356],
       [-0.2089,  0.2316,  0.728 , -1.3918,  1.9956]])
```

```
In [181]: arr[:, arr[0].argsort()]
Out[181]:
array([[ 0.    ,  1.    ,  2.    ,  3.    ,  5.    ],
       [-0.1378,  2.1777,  0.8356, -0.4728, -0.3636],
       [ 0.2316,  0.728 ,  1.9956, -1.3918, -0.2089]])
```

`lexsort` is similar to argsort, but it performs an indirect *lexicographical* sort on multiple key arrays. Suppose we wanted to sort some data identified by first and last names:

```
In [182]: first_name = np.array(['Bob', 'Jane', 'Steve', 'Bill', 'Barbara'])

In [183]: last_name = np.array(['Jones', 'Arnold', 'Arnold', 'Jones', 'Walters'])

In [184]: sorter = np.lexsort((first_name, last_name))

In [185]: zip(last_name[sorter], first_name[sorter])
Out[185]:
[('Arnold', 'Jane'),
 ('Arnold', 'Steve'),
 ('Jones', 'Bill'),
 ('Jones', 'Bob'),
 ('Walters', 'Barbara')]
```

`lexsort` can be a bit confusing the first time you use it because the order in which the keys are used to order the data starts with the *last* array passed. As you can see, `last_name` was used before `first_name`.

pandas methods like Series's and DataFrame's `sort_index` methods and the Series `order` method are implemented with variants of these functions (which also must take into account missing values)

Alternate Sort Algorithms

A *stable* sorting algorithm preserves the relative position of equal elements. This can be especially important in indirect sorts where the relative ordering is meaningful:

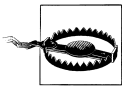
```
In [186]: values = np.array(['2:first', '2:second', '1:first', '1:second', '1:third'])

In [187]: key = np.array([2, 2, 1, 1, 1])

In [188]: indexer = key.argsort(kind='mergesort')

In [189]: indexer
Out[189]: array([2, 3, 4, 0, 1])

In [190]: values.take(indexer)
Out[190]:
array(['1:first', '1:second', '1:third', '2:first', '2:second'],
      dtype='|S8')
```

The only stable sort available is *mergesort* which has guaranteed O(n log n) performance (for complexity buffs), but its performance is on average worse than the default

quicksort method. See Table 12-3 for a summary of available methods and their relative performance (and performance guarantees). This is not something that most users will ever have to think about but useful to know that it's there.

Table 12-3. Array sorting methods

Kind	Speed	Stable	Work space	Worst-case
`'quicksort'`	1	No	0	$O(n^2)$
`'mergesort'`	2	Yes	n / 2	O(n log n)
`'heapsort'`	3	No	0	O(n log n)



At the time of this writing, sort algorithms other than quicksort are not available on arrays of Python objects (`dtype=object`). This means occasionally that algorithms requiring stable sorting will require workarounds when dealing with Python objects.

numpy.searchsorted: Finding elements in a Sorted Array

`searchsorted` is an array method that performs a binary search on a sorted array, returning the location in the array where the value would need to be inserted to maintain sortedness:

```
In [191]: arr = np.array([0, 1, 7, 12, 15])

In [192]: arr.searchsorted(9)
Out[192]: 3
```

As you might expect, you can also pass an array of values to get an array of indices back:

```
In [193]: arr.searchsorted([0, 8, 11, 16])
Out[193]: array([0, 3, 3, 5])
```

You might have noticed that `searchsorted` returned `0` for the `0` element. This is because the default behavior is to return the index at the left side of a group of equal values:

```
In [194]: arr = np.array([0, 0, 0, 1, 1, 1, 1])

In [195]: arr.searchsorted([0, 1])
Out[195]: array([0, 3])

In [196]: arr.searchsorted([0, 1], side='right')
Out[196]: array([3, 7])
```

As another application of `searchsorted`, suppose we had an array of values between 0 and 10,000) and a separate array of "bucket edges" that we wanted to use to bin the data:

```
In [197]: data = np.floor(np.random.uniform(0, 10000, size=50))

In [198]: bins = np.array([0, 100, 1000, 5000, 10000])

In [199]: data
```

```
Out[199]:
array([ 8304.,  4181.,  9352.,  4907.,  3250.,  8546.,  2673.,  6152.,
        2774.,  5130.,  9553.,  4997.,  1794.,  9688.,   426.,  1612.,
         651.,  8653.,  1695.,  4764.,  1052.,  4836.,  8020.,  3479.,
        1513.,  5872.,  8992.,  7656.,  4764.,  5383.,  2319.,  4280.,
        4150.,  8601.,  3946.,  9904.,  7286.,  9969.,  6032.,  4574.,
        8480.,  4298.,  2708.,  7358.,  6439.,  7916.,  3899.,  9182.,
         871.,  7973.])
```

To then get a labeling of which interval each data point belongs to (where 1 would mean the bucket `[0, 100)`), we can simply use `searchsorted`:

```
In [200]: labels = bins.searchsorted(data)

In [201]: labels
Out[201]:
array([4, 3, 4, 3, 3, 4, 3, 4, 3, 4, 4, 3, 3, 4, 2, 3, 2, 4, 3, 3, 3, 3, 4,
       3, 3, 4, 4, 4, 3, 4, 3, 3, 3, 4, 3, 4, 4, 4, 4, 3, 4, 3, 3, 4, 4, 4,
       3, 4, 2, 4])
```

This, combined with pandas's `groupby`, can be used to easily bin data:

```
In [202]: Series(data).groupby(labels).mean()
Out[202]:
2     649.333333
3    3411.521739
4    7935.041667
```

Note that NumPy actually has a function `digitize` that computes this bin labeling:

```
In [203]: np.digitize(data, bins)
Out[203]:
array([4, 3, 4, 3, 3, 4, 3, 4, 3, 4, 4, 3, 3, 4, 2, 3, 2, 4, 3, 3, 3, 3, 4,
       3, 3, 4, 4, 4, 3, 4, 3, 3, 3, 4, 3, 4, 4, 4, 4, 3, 4, 3, 3, 4, 4, 4,
       3, 4, 2, 4])
```

NumPy Matrix Class

Compared with other languages for matrix operations and linear algebra, like MATLAB, Julia, and GAUSS, NumPy's linear algebra syntax can often be quite verbose. One reason is that matrix multiplication requires using `numpy.dot`. Also NumPy's indexing semantics are different, which makes porting code to Python less straightforward at times. Selecting a single row (e.g. `X[1, :]`) or column (e.g. `X[:, 1]`) from a 2D array yields a 1D array compared with a 2D array as in, say, MATLAB.

```
In [204]: X =  np.array([[ 8.82768214,  3.82222409, -1.14276475,  2.04411587],
   .....:                [ 3.82222409,  6.75272284,  0.83909108,  2.08293758],
   .....:                [-1.14276475,  0.83909108,  5.01690521,  0.79573241],
   .....:                [ 2.04411587,  2.08293758,  0.79573241,  6.24095859]])

In [205]: X[:, 0]  # one-dimensional
Out[205]: array([ 8.8277,  3.8222, -1.1428,  2.0441])

In [206]: y = X[:, :1]  # two-dimensional by slicing
```

```
In [207]: X
Out[207]:
array([[ 8.8277,  3.8222, -1.1428,  2.0441],
       [ 3.8222,  6.7527,  0.8391,  2.0829],
       [-1.1428,  0.8391,  5.0169,  0.7957],
       [ 2.0441,  2.0829,  0.7957,  6.241 ]])

In [208]: y
Out[208]:
array([[ 8.8277],
       [ 3.8222],
       [-1.1428],
       [ 2.0441]])
```

In this case, the product $y^T X y$ would be expressed like so:

```
In [209]: np.dot(y.T, np.dot(X, y))
Out[209]: array([[ 1195.468]])
```

To aid in writing code with a lot of matrix operations, NumPy has a `matrix` class which has modified indexing behavior to make it more MATLAB-like: single rows and columns come back two-dimensional and multiplication with * is matrix multiplication. The above operation with `numpy.matrix` would look like:

```
In [210]: Xm = np.matrix(X)

In [211]: ym = Xm[:, 0]

In [212]: Xm
Out[212]:
matrix([[ 8.8277,  3.8222, -1.1428,  2.0441],
        [ 3.8222,  6.7527,  0.8391,  2.0829],
        [-1.1428,  0.8391,  5.0169,  0.7957],
        [ 2.0441,  2.0829,  0.7957,  6.241 ]])

In [213]: ym
Out[213]:
matrix([[ 8.8277],
        [ 3.8222],
        [-1.1428],
        [ 2.0441]])

In [214]: ym.T * Xm * ym
Out[214]: matrix([[ 1195.468]])
```

`matrix` also has a special attribute `I` which returns the matrix inverse:

```
In [215]: Xm.I * X
Out[215]:
matrix([[ 1., -0., -0., -0.],
        [ 0.,  1.,  0.,  0.],
        [ 0.,  0.,  1.,  0.],
        [ 0.,  0.,  0.,  1.]])
```

I do not recommend using `numpy.matrix` as a replacement for regular ndarrays because they are generally more seldom used. In individual functions with lots of linear algebra, it may be helpful to convert the function argument to `matrix` type, then cast back to regular arrays with `np.asarray` (which does not copy any data) before returning them.

Advanced Array Input and Output

In Chapter 4, I introduced you to `np.save` and `np.load` for storing arrays in binary format on disk. There are a number of additional options to consider for more sophisticated use. In particular, memory maps have the additional benefit of enabling you to work with data sets that do not fit into RAM.

Memory-mapped Files

A *memory-mapped* file is a method for treating potentially very large binary data on disk as an in-memory array. NumPy implements a `memmap` object that is ndarray-like, enabling small segments of a large file to be read and written without reading the whole array into memory. Additionally, a `memmap` has the same methods as an in-memory array and thus can be substituted into many algorithms where an ndarray would be expected.

To create a new `memmap`, use the function `np.memmap` and pass a file path, dtype, shape, and file mode:

```
In [216]: mmap = np.memmap('mymmap', dtype='float64', mode='w+', shape=(10000, 10000))

In [217]: mmap
Out[217]:
memmap([[ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       ...,
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.]])
```

Slicing a `memmap` returns views on the data on disk:

```
In [218]: section = mmap[:5]
```

If you assign data to these, it will be buffered in memory (like a Python file object), but can be written to disk by calling `flush`:

```
In [219]: section[:] = np.random.randn(5, 10000)

In [220]: mmap.flush()

In [221]: mmap
Out[221]:
memmap([[-0.1614, -0.1768,  0.422 , ..., -0.2195, -0.1256, -0.4012],
       [ 0.4898, -2.2219, -0.7684, ..., -2.3517, -1.0782,  1.3208],
       [-0.6875,  1.6901, -0.7444, ..., -1.4218, -0.0509,  1.2224],
```

```
       ...,
       [ 0.    ,  0.    ,  0.    , ...,  0.    ,  0.    ,  0.    ],
       [ 0.    ,  0.    ,  0.    , ...,  0.    ,  0.    ,  0.    ],
       [ 0.    ,  0.    ,  0.    , ...,  0.    ,  0.    ,  0.    ]])

In [222]: del mmap
```

Whenever a memory map falls out of scope and is garbage-collected, any changes will be flushed to disk also. When *opening an existing memory map*, you still have to specify the dtype and shape as the file is just a block of binary data with no metadata on disk:

```
In [223]: mmap = np.memmap('mymmap', dtype='float64', shape=(10000, 10000))

In [224]: mmap
Out[224]:
memmap([[-0.1614, -0.1768,  0.422 , ..., -0.2195, -0.1256, -0.4012],
       [ 0.4898, -2.2219, -0.7684, ..., -2.3517, -1.0782,  1.3208],
       [-0.6875,  1.6901, -0.7444, ..., -1.4218, -0.0509,  1.2224],
       ...,
       [ 0.    ,  0.    ,  0.    , ...,  0.    ,  0.    ,  0.    ],
       [ 0.    ,  0.    ,  0.    , ...,  0.    ,  0.    ,  0.    ],
       [ 0.    ,  0.    ,  0.    , ...,  0.    ,  0.    ,  0.    ]])
```

Since a memory map is just an on-disk ndarray, there are no issues using a structured dtype as described above.

HDF5 and Other Array Storage Options

PyTables and h5py are two Python projects providing NumPy-friendly interfaces for storing array data in the efficient and compressible HDF5 format (HDF stands for *hierarchical data format*). You can safely store hundreds of gigabytes or even terabytes of data in HDF5 format. The use of these libraries is unfortunately outside the scope of the book.

PyTables provides a rich facility for working with structured arrays with advanced querying features and the ability to add column indexes to accelerate queries. This is very similar to the table indexing capabilities provided by relational databases.

Performance Tips

Getting good performance out of code utilizing NumPy is often straightforward, as array operations typically replace otherwise comparatively extremely slow pure Python loops. Here is a brief list of some of the things to keep in mind:

- Convert Python loops and conditional logic to array operations and boolean array operations
- Use broadcasting whenever possible
- Avoid copying data using array views (slicing)
- Utilize ufuncs and ufunc methods

If you can't get the performance you require after exhausting the capabilities provided by NumPy alone, writing code in C, Fortran, or especially Cython (see a bit more on this below) may be in order. I personally use Cython (*http://cython.org*) heavily in my own work as an easy way to get C-like performance with minimal development.

The Importance of Contiguous Memory

While the full extent of this topic is a bit outside the scope of this book, in some applications the memory layout of an array can significantly affect the speed of computations. This is based partly on performance differences having to do with the cache hierarchy of the CPU; operations accessing contiguous blocks of memory (for example, summing the rows of a C order array) will generally be the fastest because the memory subsystem will buffer the appropriate blocks of memory into the ultrafast L1 or L2 CPU cache. Also, certain code paths inside NumPy's C codebase have been optimized for the contiguous case in which generic strided memory access can be avoided.

To say that an array's memory layout is *contiguous* means that the elements are stored in memory in the order that they appear in the array with respect to Fortran (column major) or C (row major) ordering. By default, NumPy arrays are created as *C-contiguous* or just simply contiguous. A column major array, such as the transpose of a C-contiguous array, is thus said to be Fortran-contiguous. These properties can be explicitly checked via the `flags` attribute on the `ndarray`:

```
In [227]: arr_c = np.ones((1000, 1000), order='C')

In [228]: arr_f = np.ones((1000, 1000), order='F')

In [229]: arr_c.flags
Out[229]:
  C_CONTIGUOUS : True
  F_CONTIGUOUS : False
  OWNDATA : True
  WRITEABLE : True
  ALIGNED : True
  UPDATEIFCOPY : False

In [230]: arr_f.flags
Out[230]:
  C_CONTIGUOUS : False
  F_CONTIGUOUS : True
  OWNDATA : True
  WRITEABLE : True
  ALIGNED : True
  UPDATEIFCOPY : False

In [231]: arr_f.flags.f_contiguous
Out[231]: True
```

In this example, summing the rows of these arrays should, in theory, be faster for `arr_c` than `arr_f` since the rows are contiguous in memory. Here I check for sure using `%timeit` in IPython:

```
In [232]: %timeit arr_c.sum(1)
1000 loops, best of 3: 1.33 ms per loop

In [233]: %timeit arr_f.sum(1)
100 loops, best of 3: 8.75 ms per loop
```

When looking to squeeze more performance out of NumPy, this is often a place to invest some effort. If you have an array that does not have the desired memory order, you can use `copy` and pass either `'C'` or `'F'`:

```
In [234]: arr_f.copy('C').flags
Out[234]:
  C_CONTIGUOUS : True
  F_CONTIGUOUS : False
  OWNDATA : True
  WRITEABLE : True
  ALIGNED : True
  UPDATEIFCOPY : False
```

When constructing a view on an array, keep in mind that the result is not guaranteed to be contiguous:

```
In [235]: arr_c[:50].flags.contiguous
Out[235]: True
```

```
In [236]: arr_c[:, :50].flags
Out[236]:
  C_CONTIGUOUS : False
  F_CONTIGUOUS : False
  OWNDATA : False
  WRITEABLE : True
  ALIGNED : True
  UPDATEIFCOPY : False
```

Other Speed Options: Cython, f2py, C

In recent years, the Cython project ((*http://cython.org*) has become the tool of choice for many scientific Python programmers for implementing fast code that may need to interact with C or C++ libraries, but without having to write pure C code. You can think of Cython as Python with static types and the ability to interleave functions implemented in C into Python-like code. For example, a simple Cython function to sum the elements of a one-dimensional array might look like:

```
from numpy cimport ndarray, float64_t

def sum_elements(ndarray[float64_t] arr):
    cdef Py_ssize_t i, n = len(arr)
    cdef float64_t result = 0

    for i in range(n):
        result += arr[i]

    return result
```

Cython takes this code, translates it to C, then compiles the generated C code to create a Python extension. Cython is an attractive option for performance computing because the code is only slightly more time-consuming to write than pure Python code and it integrates closely with NumPy. A common workflow is to get an algorithm working in Python, then translate it to Cython by adding type declarations and a handful of other tweaks. For more, see the project documentation.

Some other options for writing high performance code with NumPy include f2py, a wrapper generator for Fortran 77 and 90 code, and writing pure C extensions.

APPENDIX

Python Language Essentials

> Knowledge is a treasure, but practice is the key to it.
>
> —Thomas Fuller

People often ask me about good resources for learning Python for data-centric applications. While there are many excellent Python language books, I am usually hesitant to recommend some of them as they are intended for a general audience rather than tailored for someone who wants to load in some data sets, do some computations, and plot some of the results. There are actually a couple of books on "scientific programming in Python", but they are geared toward numerical computing and engineering applications: solving differential equations, computing integrals, doing Monte Carlo simulations, and various topics that are more mathematically-oriented rather than being about data analysis and statistics. As this is a book about becoming proficient at working with data in Python, I think it is valuable to spend some time highlighting the most important features of Python's built-in data structures and libraries from the perspective of processing and manipulating structured and unstructured data. As such, I will only present roughly enough information to enable you to follow along with the rest of the book.

This chapter is not intended to be an exhaustive introduction to the Python language but rather a biased, no-frills overview of features which are used repeatedly throughout this book. For new Python programmers, I recommend that you supplement this chapter with the official Python tutorial (*http://docs.python.org*) and potentially one of the many excellent (and much longer) books on general purpose Python programming. In my opinion, it is *not* necessary to become proficient at building good software in Python to be able to productively do data analysis. I encourage you to use IPython to experiment with the code examples and to explore the documentation for the various types, functions, and methods. Note that some of the code used in the examples may not necessarily be fully-introduced at this point.

Much of this book focuses on high performance array-based computing tools for working with large data sets. In order to use those tools you must often first do some munging to corral messy data into a more nicely structured form. Fortunately, Python is one of

the easiest-to-use languages for rapidly whipping your data into shape. The greater your facility with Python, the language, the easier it will be for you to prepare new data sets for analysis.

The Python Interpreter

Python is an *interpreted* language. The Python interpreter runs a program by executing one statement at a time. The standard interactive Python interpreter can be invoked on the command line with the `python` command:

```
$ python
Python 2.7.2 (default, Oct  4 2011, 20:06:09)
[GCC 4.6.1] on linux2
Type "help", "copyright", "credits" or "license" for more information.
>>> a = 5
>>> print a
5
```

The `>>>` you see is the *prompt* where you'll type expressions. To exit the Python interpreter and return to the command prompt, you can either type `exit()` or press `Ctrl-D`.

Running Python programs is as simple as calling `python` with a `.py` file as its first argument. Suppose we had created `hello_world.py` with these contents:

```
print 'Hello world'
```

This can be run from the terminal simply as:

```
$ python hello_world.py
Hello world
```

While many Python programmers execute all of their Python code in this way, many *scientific* Python programmers make use of IPython, an enhanced interactive Python interpreter. Chapter 3 is dedicated to the IPython system. By using the `%run` command, IPython executes the code in the specified file in the same process, enabling you to explore the results interactively when it's done.

```
$ ipython
Python 2.7.2 |EPD 7.1-2 (64-bit)| (default, Jul  3 2011, 15:17:51)
Type "copyright", "credits" or "license" for more information.

IPython 0.12 -- An enhanced Interactive Python.
?         -> Introduction and overview of IPython's features.
%quickref -> Quick reference.
help      -> Python's own help system.
object?   -> Details about 'object', use 'object??' for extra details.

In [1]: %run hello_world.py
Hello world

In [2]:
```

The default IPython prompt adopts the numbered `In [2]:` style compared with the standard >>> prompt.

The Basics

Language Semantics

The Python language design is distinguished by its emphasis on readability, simplicity, and explicitness. Some people go so far as to liken it to "executable pseudocode".

Indentation, not braces

Python uses whitespace (tabs or spaces) to structure code instead of using braces as in many other languages like R, C++, Java, and Perl. Take the for loop in the above quicksort algorithm:

```
for x in array:
    if x < pivot:
        less.append(x)
    else:
        greater.append(x)
```

A colon denotes the start of an indented code block after which all of the code must be indented by the same amount until the end of the block. In another language, you might instead have something like:

```
for x in array {
        if x < pivot {
            less.append(x)
        } else {
            greater.append(x)
        }
    }
```

One major reason that whitespace matters is that it results in most Python code looking cosmetically similar, which means less cognitive dissonance when you read a piece of code that you didn't write yourself (or wrote in a hurry a year ago!). In a language without significant whitespace, you might stumble on some differently formatted code like:

```
for x in array
    {
      if x < pivot
      {
        less.append(x)
      }
      else
      {
        greater.append(x)
```

```
    }
  }
```

Love it or hate it, significant whitespace is a fact of life for Python programmers, and in my experience it helps make Python code a lot more readable than other languages I've used. While it may seem foreign at first, I suspect that it will grow on you after a while.

I strongly recommend that you use *4 spaces* to as your default indentation and that your editor replace tabs with 4 spaces. Many text editors have a setting that will replace tab stops with spaces automatically (do this!). Some people use tabs or a different number of spaces, with 2 spaces not being terribly uncommon. 4 spaces is by and large the standard adopted by the vast majority of Python programmers, so I recommend doing that in the absence of a compelling reason otherwise.

As you can see by now, Python statements also do not need to be terminated by semicolons. Semicolons can be used, however, to separate multiple statements on a single line:

```
a = 5; b = 6; c = 7
```

Putting multiple statements on one line is generally discouraged in Python as it often makes code less readable.

Everything is an object

An important characteristic of the Python language is the consistency of its *object model*. Every number, string, data structure, function, class, module, and so on exists in the Python interpreter in its own "box" which is referred to as a *Python object*. Each object has an associated *type* (for example, *string* or *function*) and internal data. In practice this makes the language very flexible, as even functions can be treated just like any other object.

Comments

Any text preceded by the hash mark (pound sign) # is ignored by the Python interpreter. This is often used to add comments to code. At times you may also want to exclude certain blocks of code without deleting them. An easy solution is to *comment out* the code:

```
results = []
for line in file_handle:
    # keep the empty lines for now
    # if len(line) == 0:
    #   continue
    results.append(line.replace('foo', 'bar'))
```

Function and object method calls

Functions are called using parentheses and passing zero or more arguments, optionally assigning the returned value to a variable:

```
result = f(x, y, z)
g()
```

Almost every object in Python has attached functions, known as *methods*, that have access to the object's internal contents. They can be called using the syntax:

```
obj.some_method(x, y, z)
```

Functions can take both *positional* and *keyword* arguments:

```
result = f(a, b, c, d=5, e='foo')
```

More on this later.

Variables and pass-by-reference

When assigning a variable (or *name*) in Python, you are creating a *reference* to the object on the right hand side of the equals sign. In practical terms, consider a list of integers:

```
In [241]: a = [1, 2, 3]
```

Suppose we assign `a` to a new variable `b`:

```
In [242]: b = a
```

In some languages, this assignment would cause the data `[1, 2, 3]` to be copied. In Python, `a` and `b` actually now refer to the same object, the original list `[1, 2, 3]` (see Figure A-1 for a mockup). You can prove this to yourself by appending an element to `a` and then examining `b`:

```
In [243]: a.append(4)

In [244]: b
Out[244]: [1, 2, 3, 4]
```

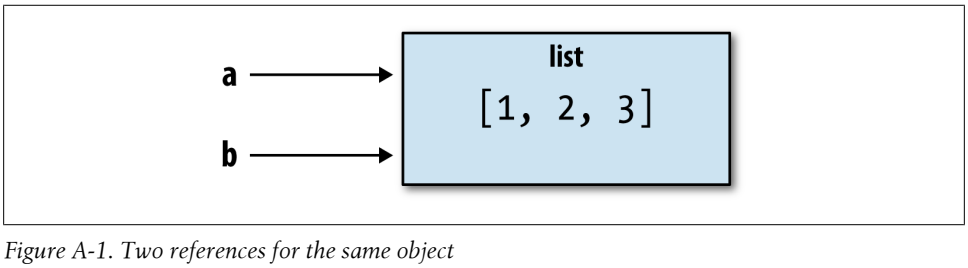


Figure A-1. Two references for the same object

Understanding the semantics of references in Python and when, how, and why data is copied is especially critical when working with larger data sets in Python.

Assignment is also referred to as *binding*, as we are binding a name to an object. Variables names that have been assigned may occasionally be referred to as bound variables.

When you pass objects as arguments to a function, you are only passing references; no copying occurs. Thus, Python is said to *pass by reference*, whereas some other languages support both pass by value (creating copies) and pass by reference. This means that a function can mutate the internals of its arguments. Suppose we had the following function:

```
def append_element(some_list, element):
    some_list.append(element)
```

Then given what's been said, this should not come as a surprise:

```
In [2]: data = [1, 2, 3]

In [3]: append_element(data, 4)

In [4]: data
Out[4]: [1, 2, 3, 4]
```

Dynamic references, strong types

In contrast with many compiled languages, such as Java and C++, object *references* in Python have no type associated with them. There is no problem with the following:

```
In [245]: a = 5        In [246]: type(a)
                       Out[246]: int

In [247]: a = 'foo'    In [248]: type(a)
                       Out[248]: str
```

Variables are names for objects within a particular namespace; the type information is stored in the object itself. Some observers might hastily conclude that Python is not a "typed language". This is not true; consider this example:

```
In [249]: '5' + 5
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-249-f9dbf5f0b234> in <module>()
----> 1 '5' + 5
TypeError: cannot concatenate 'str' and 'int' objects
```

In some languages, such as Visual Basic, the string `'5'` might get implicitly converted (or *casted*) to an integer, thus yielding 10. Yet in other languages, such as JavaScript, the integer `5` might be casted to a string, yielding the concatenated string `'55'`. In this regard Python is considered a *strongly-typed* language, which means that every object has a specific type (or *class*), and implicit conversions will occur only in certain obvious circumstances, such as the following:

```
In [250]: a = 4.5

In [251]: b = 2

# String formatting, to be visited later
In [252]: print 'a is %s, b is %s' % (type(a), type(b))
a is <type 'float'>, b is <type 'int'>

In [253]: a / b
Out[253]: 2.25
```

Knowing the type of an object is important, and it's useful to be able to write functions that can handle many different kinds of input. You can check that an object is an instance of a particular type using the `isinstance` function:

```
In [254]: a = 5        In [255]: isinstance(a, int)
                       Out[255]: True
```

`isinstance` can accept a tuple of types if you want to check that an object's type is among those present in the tuple:

```
In [256]: a = 5; b = 4.5

In [257]: isinstance(a, (int, float))      In [258]: isinstance(b, (int, float))
Out[257]: True                             Out[258]: True
```

Attributes and methods

Objects in Python typically have both attributes, other Python objects stored "inside" the object, and methods, functions associated with an object which can have access to the object's internal data. Both of them are accessed via the syntax *`obj.attribute_name`*:

```
In [1]: a = 'foo'

In [2]: a.<Tab>
a.capitalize  a.format      a.isupper     a.rindex      a.strip
a.center      a.index       a.join        a.rjust       a.swapcase
a.count       a.isalnum     a.ljust       a.rpartition  a.title
a.decode      a.isalpha     a.lower       a.rsplit      a.translate
a.encode      a.isdigit     a.lstrip      a.rstrip      a.upper
a.endswith    a.islower     a.partition   a.split       a.zfill
a.expandtabs  a.isspace     a.replace     a.splitlines
a.find        a.istitle     a.rfind       a.startswith
```

Attributes and methods can also be accessed by name using the `getattr` function:

```
>>> getattr(a, 'split')
<function split>
```

While we will not extensively use the functions `getattr` and related functions `hasattr` and `setattr` in this book, they can be used very effectively to write generic, reusable code.

"Duck" typing

Often you may not care about the type of an object but rather only whether it has certain methods or behavior. For example, you can verify that an object is iterable if it implemented the *iterator protocol*. For many objects, this means it has a `__iter__` "magic method", though an alternative and better way to check is to try using the `iter` function:

```
def isiterable(obj):
    try:
        iter(obj)
        return True
    except TypeError: # not iterable
        return False
```

This function would return `True` for strings as well as most Python collection types:

```
In [260]: isiterable('a string')
Out[260]: True

In [261]: isiterable([1, 2, 3])
Out[261]: True

In [262]: isiterable(5)
Out[262]: False
```

A place where I use this functionality all the time is to write functions that can accept multiple kinds of input. A common case is writing a function that can accept any kind of sequence (list, tuple, ndarray) or even an iterator. You can first check if the object is a list (or a NumPy array) and, if it is not, convert it to be one:

```
if not isinstance(x, list) and isiterable(x):
    x = list(x)
```

Imports

In Python a *module* is simply a `.py` file containing function and variable definitions along with such things imported from other `.py` files. Suppose that we had the following module:

```
# some_module.py
PI = 3.14159

def f(x):
    return x + 2

def g(a, b):
    return a + b
```

If we wanted to access the variables and functions defined in `some_module.py`, from another file in the same directory we could do:

```
import some_module
result = some_module.f(5)
pi = some_module.PI
```

Or equivalently:

```
from some_module import f, g, PI
result = g(5, PI)
```

By using the `as` keyword you can give imports different variable names:

```
import some_module as sm
from some_module import PI as pi, g as gf

r1 = sm.f(pi)
r2 = gf(6, pi)
```

Binary operators and comparisons

Most of the binary math operations and comparisons are as you might expect:

```
In [263]: 5 - 7          In [264]: 12 + 21.5
Out[263]: -2             Out[264]: 33.5

In [265]: 5 <= 2
Out[265]: False
```

See Table A-1 for all of the available binary operators.

To check if two references refer to the same object, use the `is` keyword. `is not` is also perfectly valid if you want to check that two objects are not the same:

```
In [266]: a = [1, 2, 3]

In [267]: b = a

# Note, the list function always creates a new list
In [268]: c = list(a)

In [269]: a is b          In [270]: a is not c
Out[269]: True            Out[270]: True
```

Note this is not the same thing is comparing with `==`, because in this case we have:

```
In [271]: a == c
Out[271]: True
```

A very common use of `is` and `is not` is to check if a variable is `None`, since there is only one instance of `None`:

```
In [272]: a = None

In [273]: a is None
Out[273]: True
```

Table A-1. Binary operators

Operation	Description
`a + b`	Add a and b
`a - b`	Subtract b from a
`a * b`	Multiply a by b
`a / b`	Divide a by b
`a // b`	Floor-divide a by b, dropping any fractional remainder

Operation	Description
`a ** b`	Raise a to the b power
`a & b`	`True` if both a and b are `True`. For integers, take the bitwise AND.
`a | b`	`True` if either a or b is `True`. For integers, take the bitwise OR.
`a ^ b`	For booleans, `True` if a or b is `True`, but not both. For integers, take the bitwise `EXCLUSIVE-OR`.
`a == b`	`True` if a equals b
`a != b`	`True` if a is not equal to b
`a <= b, a < b`	`True` if a is less than (less than or equal) to b
`a > b, a >= b`	`True` if a is greater than (greater than or equal) to b
`a is b`	`True` if a and b reference same Python object
`a is not b`	`True` if a and b reference different Python objects

Strictness versus laziness

When using any programming language, it's important to understand *when* expressions are evaluated. Consider the simple expression:

```
a = b = c = 5
d = a + b * c
```

In Python, once these statements are evaluated, the calculation is immediately (or *strictly*) carried out, setting the value of `d` to 30. In another programming paradigm, such as in a pure functional programming language like Haskell, the value of `d` might not be evaluated until it is actually used elsewhere. The idea of deferring computations in this way is commonly known as *lazy evaluation*. Python, on the other hand, is a very *strict* (or eager) language. Nearly all of the time, computations and expressions are evaluated immediately. Even in the above simple expression, the result of `b * c` is computed as a separate step before adding it to `a`.

There are Python techniques, especially using iterators and generators, which can be used to achieve laziness. When performing very expensive computations which are only necessary some of the time, this can be an important technique in data-intensive applications.

Mutable and immutable objects

Most objects in Python are mutable, such as lists, dicts, NumPy arrays, or most user-defined types (classes). This means that the object or values that they contain can be modified.

```
In [274]: a_list = ['foo', 2, [4, 5]]

In [275]: a_list[2] = (3, 4)

In [276]: a_list
Out[276]: ['foo', 2, (3, 4)]
```

Others, like strings and tuples, are immutable:

```
In [277]: a_tuple = (3, 5, (4, 5))

In [278]: a_tuple[1] = 'four'
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-278-b7966a9ae0f1> in <module>()
----> 1 a_tuple[1] = 'four'
TypeError: 'tuple' object does not support item assignment
```

Remember that just because you *can* mutate an object does not mean that you always *should*. Such actions are known in programming as *side effects*. For example, when writing a function, any side effects should be explicitly communicated to the user in the function's documentation or comments. If possible, I recommend trying to avoid side effects and *favor immutability*, even though there may be mutable objects involved.

Scalar Types

Python has a small set of built-in types for handling numerical data, strings, boolean (`True` or `False`) values, and dates and time. See Table A-2 for a list of the main scalar types. Date and time handling will be discussed separately as these are provided by the `datetime` module in the standard library.

Table A-2. Standard Python Scalar Types

Type	Description
None	The Python "null" value (only one instance of the None object exists)
`str`	String type. ASCII-valued only in Python 2.x and Unicode in Python 3
`unicode`	Unicode string type
`float`	Double-precision (64-bit) floating point number. Note there is no separate `double` type.
`bool`	A `True` or `False` value
`int`	Signed integer with maximum value determined by the platform.
`long`	Arbitrary precision signed integer. Large `int` values are automatically converted to `long`.

Numeric types

The primary Python types for numbers are `int` and `float`. The size of the integer which can be stored as an `int` is dependent on your platform (whether 32 or 64-bit), but Python will transparently convert a very large integer to `long`, which can store arbitrarily large integers.

```
In [279]: ival = 17239871

In [280]: ival ** 6
Out[280]: 26254519291092456596965462913230729701102721L
```

Floating point numbers are represented with the Python `float` type. Under the hood each one is a double-precision (64 bits) value. They can also be expressed using scientific notation:

```
In [281]: fval = 7.243

In [282]: fval2 = 6.78e-5
```

In Python 3, integer division not resulting in a whole number will always yield a floating point number:

```
In [284]: 3 / 2
Out[284]: 1.5
```

In Python 2.7 and below (which some readers will likely be using), you can enable this behavior by default by putting the following cryptic-looking statement at the top of your module:

```
from __future__ import division
```

Without this in place, you can always explicitly convert the denominator into a floating point number:

```
In [285]: 3 / float(2)
Out[285]: 1.5
```

To get C-style integer division (which drops the fractional part if the result is not a whole number), use the floor division operator `//`:

```
In [286]: 3 // 2
Out[286]: 1
```

Complex numbers are written using `j` for the imaginary part:

```
In [287]: cval = 1 + 2j

In [288]: cval * (1 - 2j)
Out[288]: (5+0j)
```

Strings

Many people use Python for its powerful and flexible built-in string processing capabilities. You can write *string literal* using either single quotes `'` or double quotes `"`:

```
a = 'one way of writing a string'
b = "another way"
```

For multiline strings with line breaks, you can use triple quotes, either `'''` or `"""`:

```
c = """
This is a longer string that
spans multiple lines
"""
```

Python strings are immutable; you cannot modify a string without creating a new string:

```
In [289]: a = 'this is a string'

In [290]: a[10] = 'f'
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-290-5ca625d1e504> in <module>()
----> 1 a[10] = 'f'
TypeError: 'str' object does not support item assignment

In [291]: b = a.replace('string', 'longer string')

In [292]: b
Out[292]: 'this is a longer string'
```

Many Python objects can be converted to a string using the `str` function:

```
In [293]: a = 5.6        In [294]: s = str(a)

In [295]: s
Out[295]: '5.6'
```

Strings are a sequence of characters and therefore can be treated like other sequences, such as lists and tuples:

```
In [296]: s = 'python'        In [297]: list(s)
                              Out[297]: ['p', 'y', 't', 'h', 'o', 'n']

In [298]: s[:3]
Out[298]: 'pyt'
```

The backslash character `\` is an *escape character*, meaning that it is used to specify special characters like newline `\n` or unicode characters. To write a string literal with backslashes, you need to escape them:

```
In [299]: s = '12\\34'

In [300]: print s
12\34
```

If you have a string with a lot of backslashes and no special characters, you might find this a bit annoying. Fortunately you can preface the leading quote of the string with `r` which means that the characters should be interpreted as is:

```
In [301]: s = r'this\has\no\special\characters'

In [302]: s
Out[302]: 'this\\has\\no\\special\\characters'
```

Adding two strings together concatenates them and produces a new string:

```
In [303]: a = 'this is the first half '

In [304]: b = 'and this is the second half'

In [305]: a + b
Out[305]: 'this is the first half and this is the second half'
```

String templating or formatting is another important topic. The number of ways to do so has expanded with the advent of Python 3, here I will briefly describe the mechanics of one of the main interfaces. Strings with a `%` followed by one or more format characters is a target for inserting a value into that string (this is quite similar to the `printf` function in C). As an example, consider this string:

```
In [306]: template = '%.2f %s are worth $%d'
```

In this string, `%s` means to format an argument as a string, `%.2f` a number with 2 decimal places, and `%d` an integer. To substitute arguments for these format parameters, use the binary operator `%` with a tuple of values:

```
In [307]: template % (4.5560, 'Argentine Pesos', 1)
Out[307]: '4.56 Argentine Pesos are worth $1'
```

String formatting is a broad topic; there are multiple methods and numerous options and tweaks available to control how values are formatted in the resulting string. To learn more, I recommend you seek out more information on the web.

I discuss general string processing as it relates to data analysis in more detail in Chapter 7.

Booleans

The two boolean values in Python are written as `True` and `False`. Comparisons and other conditional expressions evaluate to either `True` or `False`. Boolean values are combined with the `and` and `or` keywords:

```
In [308]: True and True
Out[308]: True

In [309]: False or True
Out[309]: True
```

Almost all built-in Python tops and any class defining the `__nonzero__` magic method have a `True` or `False` interpretation in an `if` statement:

```
In [310]: a = [1, 2, 3]
   .....: if a:
   .....:     print 'I found something!'
   .....:
I found something!

In [311]: b = []
   .....: if not b:
   .....:     print 'Empty!'
   .....:
Empty!
```

Most objects in Python have a notion of true- or falseness. For example, empty sequences (lists, dicts, tuples, etc.) are treated as `False` if used in control flow (as above with the empty list `b`). You can see exactly what boolean value an object coerces to by invoking `bool` on it:

```
In [312]: bool([]), bool([1, 2, 3])
Out[312]: (False, True)

In [313]: bool('Hello world!'), bool('')
Out[313]: (True, False)

In [314]: bool(0), bool(1)
Out[314]: (False, True)
```

Type casting

The `str`, `bool`, `int` and `float` types are also functions which can be used to cast values to those types:

```
In [315]: s = '3.14159'

In [316]: fval = float(s)        In [317]: type(fval)
                                 Out[317]: float

In [318]: int(fval)        In [319]: bool(fval)        In [320]: bool(0)
Out[318]: 3                Out[319]: True              Out[320]: False
```

None

`None` is the Python null value type. If a function does not explicitly return a value, it implicitly returns `None`.

```
In [321]: a = None      In [322]: a is None
                        Out[322]: True

In [323]: b = 5         In [324]: b is not None
                        Out[324]: True
```

`None` is also a common default value for optional function arguments:

```
def add_and_maybe_multiply(a, b, c=None):
    result = a + b

    if c is not None:
        result = result * c

    return result
```

While a technical point, it's worth bearing in mind that `None` is not a reserved keyword but rather a unique instance of `NoneType`.

Dates and times

The built-in Python `datetime` module provides `datetime`, `date`, and `time` types. The `datetime` type as you may imagine combines the information stored in `date` and `time` and is the most commonly used:

```
In [325]: from datetime import datetime, date, time

In [326]: dt = datetime(2011, 10, 29, 20, 30, 21)
```

```
In [327]: dt.day    In [328]: dt.minute
Out[327]: 29        Out[328]: 30
```

Given a `datetime` instance, you can extract the equivalent `date` and `time` objects by calling methods on the `datetime` of the same name:

```
In [329]: dt.date()                     In [330]: dt.time()
Out[329]: datetime.date(2011, 10, 29)   Out[330]: datetime.time(20, 30, 21)
```

The `strftime` method formats a datetime as a string:

```
In [331]: dt.strftime('%m/%d/%Y %H:%M')
Out[331]: '10/29/2011 20:30'
```

Strings can be converted (parsed) into datetime objects using the `strptime` function:

```
In [332]: datetime.strptime('20091031', '%Y%m%d')
Out[332]: datetime.datetime(2009, 10, 31, 0, 0)
```

See Table 10-2 for a full list of format specifications.

When aggregating of otherwise grouping time series data, it will occasionally be useful to replace fields of a series of datetimes, for example replacing the minute and second fields with zero, producing a new object:

```
In [333]: dt.replace(minute=0, second=0)
Out[333]: datetime.datetime(2011, 10, 29, 20, 0)
```

The difference of two datetime objects produces a `datetime.timedelta` type:

```
In [334]: dt2 = datetime(2011, 11, 15, 22, 30)

In [335]: delta = dt2 - dt

In [336]: delta                             In [337]: type(delta)
Out[336]: datetime.timedelta(17, 7179)      Out[337]: datetime.timedelta
```

Adding a `timedelta` to a `datetime` produces a new shifted `datetime`:

```
In [338]: dt
Out[338]: datetime.datetime(2011, 10, 29, 20, 30, 21)

In [339]: dt + delta
Out[339]: datetime.datetime(2011, 11, 15, 22, 30)
```

Control Flow

if, elif, and else

The `if` statement is one of the most well-known control flow statement types. It checks a condition which, if `True`, evaluates the code in the block that follows:

```
if x < 0:
    print 'It's negative'
```

An `if` statement can be optionally followed by one or more `elif` blocks and a catch-all `else` block if all of the conditions are `False`:

```
if x < 0:
    print 'It's negative'
elif x == 0:
    print 'Equal to zero'
elif 0 < x < 5:
    print 'Positive but smaller than 5'
else:
    print 'Positive and larger than or equal to 5'
```

If any of the conditions is `True`, no further `elif` or `else` blocks will be reached. With a compound condition using `and` or `or`, conditions are evaluated left-to-right and will short circuit:

```
In [340]: a = 5; b = 7

In [341]: c = 8; d = 4

In [342]: if a < b or c > d:
   .....:     print 'Made it'
Made it
```

In this example, the comparison `c > d` never gets evaluated because the first comparison was `True`.

for loops

`for` loops are for iterating over a collection (like a list or tuple) or an iterater. The standard syntax for a `for` loop is:

```
for value in collection:
    # do something with value
```

A `for` loop can be advanced to the next iteration, skipping the remainder of the block, using the `continue` keyword. Consider this code which sums up integers in a list and skips `None` values:

```
sequence = [1, 2, None, 4, None, 5]
total = 0
for value in sequence:
    if value is None:
        continue
    total += value
```

A `for` loop can be exited altogether using the `break` keyword. This code sums elements of the list until a 5 is reached:

```
sequence = [1, 2, 0, 4, 6, 5, 2, 1]
total_until_5 = 0
for value in sequence:
    if value == 5:
        break
    total_until_5 += value
```

As we will see in more detail, if the elements in the collection or iterator are sequences (tuples or lists, say), they can be conveniently *unpacked* into variables in the `for` loop statement:

```
for a, b, c in iterator:
    # do something
```

while loops

A `while` loop specifies a condition and a block of code that is to be executed until the condition evaluates to `False` or the loop is explicitly ended with `break`:

```
x = 256
total = 0
while x > 0:
    if total > 500:
        break
    total += x
    x = x // 2
```

pass

`pass` is the "no-op" statement in Python. It can be used in blocks where no action is to be taken; it is only required because Python uses whitespace to delimit blocks:

```
if x < 0:
    print 'negative!'
elif x == 0:
    # TODO: put something smart here
    pass
else:
    print 'positive!'
```

It's common to use `pass` as a place-holder in code while working on a new piece of functionality:

```
def f(x, y, z):
    # TODO: implement this function!
    pass
```

Exception handling

Handling Python errors or *exceptions* gracefully is an important part of building robust programs. In data analysis applications, many functions only work on certain kinds of input. As an example, Python's `float` function is capable of casting a string to a floating point number, but fails with `ValueError` on improper inputs:

```
In [343]: float('1.2345')
Out[343]: 1.2345

In [344]: float('something')
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-344-439904410854> in <module>()
```

```
----> 1 float('something')
ValueError: could not convert string to float: something
```

Suppose we wanted a version of `float` that fails gracefully, returning the input argument. We can do this by writing a function that encloses the call to `float` in a `try/except` block:

```
def attempt_float(x):
    try:
        return float(x)
    except:
        return x
```

The code in the `except` part of the block will only be executed if `float(x)` raises an exception:

```
In [346]: attempt_float('1.2345')
Out[346]: 1.2345

In [347]: attempt_float('something')
Out[347]: 'something'
```

You might notice that `float` can raise exceptions other than `ValueError`:

```
In [348]: float((1, 2))
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-348-842079ebb635> in <module>()
----> 1 float((1, 2))
TypeError: float() argument must be a string or a number
```

You might want to only suppress `ValueError`, since a `TypeError` (the input was not a string or numeric value) might indicate a legitimate bug in your program. To do that, write the exception type after `except`:

```
def attempt_float(x):
    try:
        return float(x)
    except ValueError:
        return x
```

We have then:

```
In [350]: attempt_float((1, 2))
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-350-9bdfd730cead> in <module>()
----> 1 attempt_float((1, 2))
<ipython-input-349-3e06b8379b6b> in attempt_float(x)
      1 def attempt_float(x):
      2     try:
----> 3         return float(x)
      4     except ValueError:
      5         return x
TypeError: float() argument must be a string or a number
```

You can catch multiple exception types by writing a tuple of exception types instead (the parentheses are required):

```
def attempt_float(x):
    try:
        return float(x)
    except (TypeError, ValueError):
        return x
```

In some cases, you may not want to suppress an exception, but you want some code to be executed regardless of whether the code in the `try` block succeeds or not. To do this, use `finally`:

```
f = open(path, 'w')

try:
    write_to_file(f)
finally:
    f.close()
```

Here, the file handle `f` will *always* get closed. Similarly, you can have code that executes only if the `try:` block succeeds using `else`:

```
f = open(path, 'w')

try:
    write_to_file(f)
except:
    print 'Failed'
else:
    print 'Succeeded'
finally:
    f.close()
```

range and xrange

The `range` function produces a list of evenly-spaced integers:

```
In [352]: range(10)
Out[352]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

Both a start, end, and step can be given:

```
In [353]: range(0, 20, 2)
Out[353]: [0, 2, 4, 6, 8, 10, 12, 14, 16, 18]
```

As you can see, `range` produces integers up to but not including the endpoint. A common use of `range` is for iterating through sequences by index:

```
seq = [1, 2, 3, 4]
for i in range(len(seq)):
    val = seq[i]
```

For very long ranges, it's recommended to use `xrange`, which takes the same arguments as `range` but returns an iterator that generates integers one by one rather than generating

all of them up-front and storing them in a (potentially very large) list. This snippet sums all numbers from 0 to 9999 that are multiples of 3 or 5:

```
sum = 0
for i in xrange(10000):
    # % is the modulo operator
    if x % 3 == 0 or x % 5 == 0:
        sum += i
```

In Python 3, `range` always returns an iterator, and thus it is not necessary to use the `xrange` function

Ternary Expressions

A *ternary expression* in Python allows you combine an `if-else` block which produces a value into a single line or expression. The syntax for this in Python is

```
value = true-expr if condition else
false-expr
```

Here, *`true-expr`* and *`false-expr`* can be any Python expressions. It has the identical effect as the more verbose

```
if condition:
    value = true-expr
else:
    value = false-expr
```

This is a more concrete example:

```
In [354]: x = 5

In [355]: 'Non-negative' if x >= 0 else 'Negative'
Out[355]: 'Non-negative'
```

As with `if-else` blocks, only one of the expressions will be evaluated. While it may be tempting to always use ternary expressions to condense your code, realize that you may sacrifice readability if the condition as well and the true and false expressions are very complex.

Data Structures and Sequences

Python's data structures are simple, but powerful. Mastering their use is a critical part of becoming a proficient Python programmer.

Tuple

A tuple is a one-dimensional, fixed-length, *immutable* sequence of Python objects. The easiest way to create one is with a comma-separated sequence of values:

```
In [356]: tup = 4, 5, 6

In [357]: tup
Out[357]: (4, 5, 6)
```

When defining tuples in more complicated expressions, it's often necessary to enclose the values in parentheses, as in this example of creating a tuple of tuples:

```
In [358]: nested_tup = (4, 5, 6), (7, 8)

In [359]: nested_tup
Out[359]: ((4, 5, 6), (7, 8))
```

Any sequence or iterator can be converted to a tuple by invoking `tuple`:

```
In [360]: tuple([4, 0, 2])
Out[360]: (4, 0, 2)

In [361]: tup = tuple('string')

In [362]: tup
Out[362]: ('s', 't', 'r', 'i', 'n', 'g')
```

Elements can be accessed with square brackets `[]` as with most other sequence types. Like C, C++, Java, and many other languages, sequences are 0-indexed in Python:

```
In [363]: tup[0]
Out[363]: 's'
```

While the objects stored in a tuple may be mutable themselves, once created it's not possible to modify which object is stored in each slot:

```
In [364]: tup = tuple(['foo', [1, 2], True])

In [365]: tup[2] = False
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-365-c7308343b841> in <module>()
----> 1 tup[2] = False
TypeError: 'tuple' object does not support item assignment

# however
In [366]: tup[1].append(3)

In [367]: tup
Out[367]: ('foo', [1, 2, 3], True)
```

Tuples can be concatenated using the `+` operator to produce longer tuples:

```
In [368]: (4, None, 'foo') + (6, 0) + ('bar',)
Out[368]: (4, None, 'foo', 6, 0, 'bar')
```

Multiplying a tuple by an integer, as with lists, has the effect of concatenating together that many copies of the tuple.

```
In [369]: ('foo', 'bar') * 4
Out[369]: ('foo', 'bar', 'foo', 'bar', 'foo', 'bar', 'foo', 'bar')
```

Note that the objects themselves are not copied, only the references to them.

Unpacking tuples

If you try to *assign* to a tuple-like expression of variables, Python will attempt to *unpack* the value on the right-hand side of the equals sign:

```
In [370]: tup = (4, 5, 6)

In [371]: a, b, c = tup

In [372]: b
Out[372]: 5
```

Even sequences with nested tuples can be unpacked:

```
In [373]: tup = 4, 5, (6, 7)

In [374]: a, b, (c, d) = tup

In [375]: d
Out[375]: 7
```

Using this functionality it's easy to swap variable names, a task which in many languages might look like:

```
tmp = a
a = b
b = tmp

b, a = a, b
```

One of the most common uses of variable unpacking when iterating over sequences of tuples or lists:

```
seq = [(1, 2, 3), (4, 5, 6), (7, 8, 9)]
for a, b, c in seq:
    pass
```

Another common use is for returning multiple values from a function. More on this later.

Tuple methods

Since the size and contents of a tuple cannot be modified, it is very light on instance methods. One particularly useful one (also available on lists) is `count`, which counts the number of occurrences of a value:

```
In [376]: a = (1, 2, 2, 2, 3, 4, 2)
```

```
In [377]: a.count(2)
Out[377]: 4
```

List

In contrast with tuples, lists are variable-length and their contents can be modified. They can be defined using square brackets `[]` or using the `list` type function:

```
In [378]: a_list = [2, 3, 7, None]

In [379]: tup = ('foo', 'bar', 'baz')

In [380]: b_list = list(tup)        In [381]: b_list
                                    Out[381]: ['foo', 'bar', 'baz']

In [382]: b_list[1] = 'peekaboo'    In [383]: b_list
                                    Out[383]: ['foo', 'peekaboo', 'baz']
```

Lists and tuples are semantically similar as one-dimensional sequences of objects and thus can be used interchangeably in many functions.

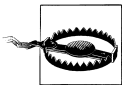
Adding and removing elements

Elements can be appended to the end of the list with the `append` method:

```
In [384]: b_list.append('dwarf')

In [385]: b_list
Out[385]: ['foo', 'peekaboo', 'baz', 'dwarf']
```

Using `insert` you can insert an element at a specific location in the list:

```
In [386]: b_list.insert(1, 'red')

In [387]: b_list
Out[387]: ['foo', 'red', 'peekaboo', 'baz', 'dwarf']
```



`insert` is computationally expensive compared with `append` as references to subsequent elements have to be shifted internally to make room for the new element.

The inverse operation to `insert` is `pop`, which removes and returns an element at a particular index:

```
In [388]: b_list.pop(2)
Out[388]: 'peekaboo'

In [389]: b_list
Out[389]: ['foo', 'red', 'baz', 'dwarf']
```

Elements can be removed by value using `remove`, which locates the first such value and removes it from the last:

```
In [390]: b_list.append('foo')

In [391]: b_list.remove('foo')

In [392]: b_list
Out[392]: ['red', 'baz', 'dwarf', 'foo']
```

If performance is not a concern, by using `append` and `remove`, a Python list can be used as a perfectly suitable "multi-set" data structure.

You can check if a list contains a value using the `in` keyword:

```
In [393]: 'dwarf' in b_list
Out[393]: True
```

Note that checking whether a list contains a value is a lot slower than dicts and sets as Python makes a linear scan across the values of the list, whereas the others (based on hash tables) can make the check in constant time.

Concatenating and combining lists

Similar to tuples, adding two lists together with `+` concatenates them:

```
In [394]: [4, None, 'foo'] + [7, 8, (2, 3)]
Out[394]: [4, None, 'foo', 7, 8, (2, 3)]
```

If you have a list already defined, you can append multiple elements to it using the `extend` method:

```
In [395]: x = [4, None, 'foo']

In [396]: x.extend([7, 8, (2, 3)])

In [397]: x
Out[397]: [4, None, 'foo', 7, 8, (2, 3)]
```

Note that list concatenation is a compartively expensive operation since a new list must be created and the objects copied over. Using `extend` to append elements to an existing list, especially if you are building up a large list, is usually preferable. Thus,

```
everything = []
for chunk in list_of_lists:
    everything.extend(chunk)
```

is faster than than the concatenative alternative

```
everything = []
for chunk in list_of_lists:
    everything = everything + chunk
```

Sorting

A list can be sorted in-place (without creating a new object) by calling its `sort` function:

```
In [398]: a = [7, 2, 5, 1, 3]
```

```
In [399]: a.sort()

In [400]: a
Out[400]: [1, 2, 3, 5, 7]
```

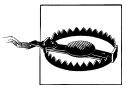
`sort` has a few options that will occasionally come in handy. One is the ability to pass a secondary *sort key*, i.e. a function that produces a value to use to sort the objects. For example, we could sort a collection of strings by their lengths:

```
In [401]: b = ['saw', 'small', 'He', 'foxes', 'six']

In [402]: b.sort(key=len)

In [403]: b
Out[403]: ['He', 'saw', 'six', 'small', 'foxes']
```

Binary search and maintaining a sorted list

The built-in `bisect` module implements binary-search and insertion into a sorted list. `bisect.bisect` finds the location where an element should be inserted to keep it sorted, while `bisect.insort` actually inserts the element into that location:

```
In [404]: import bisect

In [405]: c = [1, 2, 2, 2, 3, 4, 7]

In [406]: bisect.bisect(c, 2)        In [407]: bisect.bisect(c, 5)
Out[406]: 4                          Out[407]: 6

In [408]: bisect.insort(c, 6)

In [409]: c
Out[409]: [1, 2, 2, 2, 3, 4, 6, 7]
```



The `bisect` module functions do not check whether the list is sorted as doing so would be computationally expensive. Thus, using them with an unsorted list will succeed without error but may lead to incorrect results.

Slicing

You can select sections of list-like types (arrays, tuples, NumPy arrays) by using slice notation, which in its basic form consists of `start:stop` passed to the indexing operator `[]`:

```
In [410]: seq = [7, 2, 3, 7, 5, 6, 0, 1]

In [411]: seq[1:5]
Out[411]: [2, 3, 7, 5]
```

Slices can also be assigned to with a sequence:

```
In [412]: seq[3:4] = [6, 3]
```

```
In [413]: seq
Out[413]: [7, 2, 3, 6, 3, 5, 6, 0, 1]
```

While element at the `start` index is included, the `stop` index is not included, so that the number of elements in the result is `stop - start`.

Either the `start` or `stop` can be omitted in which case they default to the start of the sequence and the end of the sequence, respectively:

```
In [414]: seq[:5]
Out[414]: [7, 2, 3, 6, 3]
```

```
In [415]: seq[3:]
Out[415]: [6, 3, 5, 6, 0, 1]
```

Negative indices slice the sequence relative to the end:

```
In [416]: seq[-4:]
Out[416]: [5, 6, 0, 1]
```

```
In [417]: seq[-6:-2]
Out[417]: [6, 3, 5, 6]
```

Slicing semantics takes a bit of getting used to, especially if you're coming from R or MATLAB. See Figure A-2 for a helpful illustrating of slicing with positive and negative integers.

A `step` can also be used after a second colon to, say, take every other element:

```
In [418]: seq[::2]
Out[418]: [7, 3, 3, 6, 1]
```

A clever use of this is to pass `-1` which has the useful effect of reversing a list or tuple:

```
In [419]: seq[::-1]
Out[419]: [1, 0, 6, 5, 3, 6, 3, 2, 7]
```

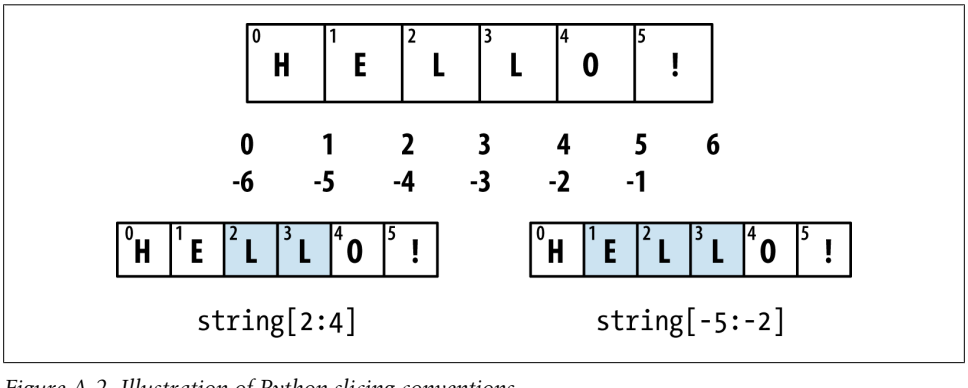


Figure A-2. Illustration of Python slicing conventions

Built-in Sequence Functions

Python has a handful of useful sequence functions that you should familiarize yourself with and use at any opportunity.

enumerate

It's common when iterating over a sequence to want to keep track of the index of the current item. A do-it-yourself approach would look like:

```
i = 0
for value in collection:
   # do something with value
   i += 1
```

Since this is so common, Python has a built-in function `enumerate` which returns a sequence of `(i, value)` tuples:

```
for i, value in enumerate(collection):
   # do something with value
```

When indexing data, a useful pattern that uses `enumerate` is computing a `dict` mapping the values of a sequence (which are assumed to be unique) to their locations in the sequence:

```
In [420]: some_list = ['foo', 'bar', 'baz']

In [421]: mapping = dict((v, i) for i, v in enumerate(some_list))

In [422]: mapping
Out[422]: {'bar': 1, 'baz': 2, 'foo': 0}
```

sorted

The `sorted` function returns a new sorted list from the elements of any sequence:

```
In [423]: sorted([7, 1, 2, 6, 0, 3, 2])
Out[423]: [0, 1, 2, 2, 3, 6, 7]

In [424]: sorted('horse race')
Out[424]: [' ', 'a', 'c', 'e', 'e', 'h', 'o', 'r', 'r', 's']
```

A common pattern for getting a sorted list of the unique elements in a sequence is to combine `sorted` with `set`:

```
In [425]: sorted(set('this is just some string'))
Out[425]: [' ', 'e', 'g', 'h', 'i', 'j', 'm', 'n', 'o', 'r', 's', 't', 'u']
```

zip

`zip` "pairs" up the elements of a number of lists, tuples, or other sequences, to create a list of tuples:

```
In [426]: seq1 = ['foo', 'bar', 'baz']

In [427]: seq2 = ['one', 'two', 'three']

In [428]: zip(seq1, seq2)
Out[428]: [('foo', 'one'), ('bar', 'two'), ('baz', 'three')]
```

`zip` can take an arbitrary number of sequences, and the number of elements it produces is determined by the *shortest* sequence:

```
In [429]: seq3 = [False, True]

In [430]: zip(seq1, seq2, seq3)
Out[430]: [('foo', 'one', False), ('bar', 'two', True)]
```

A very common use of `zip` is for simultaneously iterating over multiple sequences, possibly also combined with `enumerate`:

```
In [431]: for i, (a, b) in enumerate(zip(seq1, seq2)):
   .....:     print('%d: %s, %s' % (i, a, b))
   .....:
0: foo, one
1: bar, two
2: baz, three
```

Given a "zipped" sequence, `zip` can be applied in a clever way to "unzip" the sequence. Another way to think about this is converting a list of *rows* into a list of *columns*. The syntax, which looks a bit magical, is:

```
In [432]: pitchers = [('Nolan', 'Ryan'), ('Roger', 'Clemens'),
   .....:             ('Schilling', 'Curt')]

In [433]: first_names, last_names = zip(*pitchers)

In [434]: first_names
Out[434]: ('Nolan', 'Roger', 'Schilling')

In [435]: last_names
Out[435]: ('Ryan', 'Clemens', 'Curt')
```

We'll look in more detail at the use of * in a function call. It is equivalent to the following:

```
zip(seq[0], seq[1], ..., seq[len(seq) - 1])
```

reversed

`reversed` iterates over the elements of a sequence in reverse order:

```
In [436]: list(reversed(range(10)))
Out[436]: [9, 8, 7, 6, 5, 4, 3, 2, 1, 0]
```

Dict

`dict` is likely the most important built-in Python data structure. A more common name for it is *hash map* or *associative array*. It is a flexibly-sized collection of *key-value* pairs, where *key* and *value* are Python objects. One way to create one is by using curly braces {} and using colons to separate keys and values:

```
In [437]: empty_dict = {}

In [438]: d1 = {'a' : 'some value', 'b' : [1, 2, 3, 4]}
```

```
In [439]: d1
Out[439]: {'a': 'some value', 'b': [1, 2, 3, 4]}
```

Elements can be accessed and inserted or set using the same syntax as accessing elements of a list or tuple:

```
In [440]: d1[7] = 'an integer'

In [441]: d1
Out[441]: {7: 'an integer', 'a': 'some value', 'b': [1, 2, 3, 4]}

In [442]: d1['b']
Out[442]: [1, 2, 3, 4]
```

You can check if a dict contains a key using the same syntax as with checking whether a list or tuple contains a value:

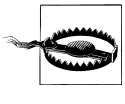
```
In [443]: 'b' in d1
Out[443]: True
```

Values can be deleted either using the `del` keyword or the `pop` method (which simultaneously returns the value and deletes the key):

```
In [444]: d1[5] = 'some value'

In [445]: d1['dummy'] = 'another value'

In [446]: del d1[5]

In [447]: ret = d1.pop('dummy')        In [448]: ret
                                       Out[448]: 'another value'
```

The `keys` and `values` method give you lists of the keys and values, respectively. While the key-value pairs are not in any particular order, these functions output the keys and values in the same order:

```
In [449]: d1.keys()            In [450]: d1.values()
Out[449]: ['a', 'b', 7]        Out[450]: ['some value', [1, 2, 3, 4], 'an integer']
```



If you're using Python 3, `dict.keys()` and `dict.values()` are iterators instead of lists.

One dict can be merged into another using the `update` method:

```
In [451]: d1.update({'b' : 'foo', 'c' : 12})

In [452]: d1
Out[452]: {7: 'an integer', 'a': 'some value', 'b': 'foo', 'c': 12}
```

Creating dicts from sequences

It's common to occasionally end up with two sequences that you want to pair up element-wise in a dict. As a first cut, you might write code like this:

```
mapping = {}
for key, value in zip(key_list, value_list):
    mapping[key] = value
```

Since a dict is essentially a collection of 2-tuples, it should be no shock that the `dict` type function accepts a list of 2-tuples:

```
In [453]: mapping = dict(zip(range(5), reversed(range(5))))

In [454]: mapping
Out[454]: {0: 4, 1: 3, 2: 2, 3: 1, 4: 0}
```

In a later section we'll talk about *dict comprehensions*, another elegant way to construct dicts.

Default values

It's very common to have logic like:

```
if key in some_dict:
    value = some_dict[key]
else:
    value = default_value
```

Thus, the dict methods `get` and `pop` can take a default value to be returned, so that the above `if-else` block can be written simply as:

```
value = some_dict.get(key, default_value)
```

`get` by default will return `None` if the key is not present, while `pop` will raise an exception. With *setting* values, a common case is for the values in a dict to be other collections, like lists. For example, you could imagine categorizing a list of words by their first letters as a dict of lists:

```
In [455]: words = ['apple', 'bat', 'bar', 'atom', 'book']

In [456]: by_letter = {}

In [457]: for word in words:
   .....:     letter = word[0]
   .....:     if letter not in by_letter:
   .....:         by_letter[letter] = [word]
   .....:     else:
   .....:         by_letter[letter].append(word)
   .....:

In [458]: by_letter
Out[458]: {'a': ['apple', 'atom'], 'b': ['bat', 'bar', 'book']}
```

The `setdefault` dict method is for precisely this purpose. The `if-else` block above can be rewritten as:

```
by_letter.setdefault(letter, []).append(word)
```

The built-in `collections` module has a useful class, `defaultdict`, which makes this even easier. One is created by passing a type or function for generating the default value for each slot in the dict:

```
from collections import defaultdict
by_letter = defaultdict(list)
for word in words:
    by_letter[word[0]].append(word)
```

The initializer to `defaultdict` only needs to be a callable object (e.g. any function), not necessarily a type. Thus, if you wanted the default value to be 4 you could pass a function returning 4

```
counts = defaultdict(lambda: 4)
```

Valid dict key types

While the values of a dict can be any Python object, the keys have to be immutable objects like scalar types (int, float, string) or tuples (all the objects in the tuple need to be immutable, too). The technical term here is *hashability*. You can check whether an object is hashable (can be used as a key in a dict) with the `hash` function:

```
In [459]: hash('string')
Out[459]: -9167918882415130555

In [460]: hash((1, 2, (2, 3)))
Out[460]: 1097636502276347782

In [461]: hash((1, 2, [2, 3])) # fails because lists are mutable
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-461-800cd14ba8be> in <module>()
----> 1 hash((1, 2, [2, 3])) # fails because lists are mutable
TypeError: unhashable type: 'list'
```

To use a list as a key, an easy fix is to convert it to a tuple:

```
In [462]: d = {}

In [463]: d[tuple([1, 2, 3])] = 5

In [464]: d
Out[464]: {(1, 2, 3): 5}
```

Set

A set is an unordered collection of unique elements. You can think of them like dicts, but keys only, no values. A set can be created in two ways: via the `set` function or using a *set literal* with curly braces:

```
In [465]: set([2, 2, 2, 1, 3, 3])
Out[465]: set([1, 2, 3])
```

```
In [466]: {2, 2, 2, 1, 3, 3}
Out[466]: set([1, 2, 3])
```

Sets support mathematical *set operations* like union, intersection, difference, and symmetric difference. See Table A-3 for a list of commonly used set methods.

```
In [467]: a = {1, 2, 3, 4, 5}

In [468]: b = {3, 4, 5, 6, 7, 8}

In [469]: a | b  # union (or)
Out[469]: set([1, 2, 3, 4, 5, 6, 7, 8])

In [470]: a & b  # intersection (and)
Out[470]: set([3, 4, 5])

In [471]: a - b  # difference
Out[471]: set([1, 2])

In [472]: a ^ b  # symmetric difference (xor)
Out[472]: set([1, 2, 6, 7, 8])
```

You can also check if a set is a subset of (is contained in) or a superset of (contains all elements of) another set:

```
In [473]: a_set = {1, 2, 3, 4, 5}

In [474]: {1, 2, 3}.issubset(a_set)
Out[474]: True

In [475]: a_set.issuperset({1, 2, 3})
Out[475]: True
```

As you might guess, sets are equal if their contents are equal:

```
In [476]: {1, 2, 3} == {3, 2, 1}
Out[476]: True
```

Table A-3. Python Set Operations

Function	Alternate Syntax	Description
`a.add(x)`	N/A	Add element x to the set a
`a.remove(x)`	N/A	Remove element x from the set a
`a.union(b)`	`a | b`	All of the unique elements in a and b.
`a.intersection(b)`	`a & b`	All of the elements in *both* a and b.
`a.difference(b)`	`a - b`	The elements in a that are not in b.
`a.symmetric_difference(b)`	`a ^ b`	All of the elements in a or b but *not both*.
`a.issubset(b)`	N/A	`True` if the elements of a are all contained in b.
`a.issuperset(b)`	N/A	`True` if the elements of b are all contained in a.
`a.isdisjoint(b)`	N/A	`True` if a and b have no elements in common.

List, Set, and Dict Comprehensions

List comprehensions are one of the most-loved Python language features. They allow you to concisely form a new list by filtering the elements of a collection and transforming the elements passing the filter in one conscise expression. They take the basic form:

```
[expr for val in collection if condition]
```

This is equivalent to the following `for` loop:

```
result = []
for val in collection:
    if condition:
        result.append(expr)
```

The filter condition can be omitted, leaving only the expression. For example, given a list of strings, we could filter out strings with length 2 or less and also convert them to uppercase like this:

```
In [477]: strings = ['a', 'as', 'bat', 'car', 'dove', 'python']

In [478]: [x.upper() for x in strings if len(x) > 2]
Out[478]: ['BAT', 'CAR', 'DOVE', 'PYTHON']
```

Set and dict comprehensions are a natural extension, producing sets and dicts in a idiomatically similar way instead of lists. A dict comprehension looks like this:

```
dict_comp = {key-expr : value-expr for value in collection
             if condition}
```

A set comprehension looks like the equivalent list comprehension except with curly braces instead of square brackets:

```
set_comp = {expr for value in collection if condition}
```

Like list comprehensions, set and dict comprehensions are just syntactic sugar, but they similarly can make code both easier to write and read. Consider the list of strings above. Suppose we wanted a set containing just the lengths of the strings contained in the collection; this could be easily computed using a set comprehension:

```
In [479]: unique_lengths = {len(x) for x in strings}

In [480]: unique_lengths
Out[480]: set([1, 2, 3, 4, 6])
```

As a simple dict comprehension example, we could create a lookup map of these strings to their locations in the list:

```
In [481]: loc_mapping = {val : index for index, val in enumerate(strings)}

In [482]: loc_mapping
Out[482]: {'a': 0, 'as': 1, 'bat': 2, 'car': 3, 'dove': 4, 'python': 5}
```

Note that this dict could be equivalently constructed by:

```
loc_mapping = dict((val, idx) for idx, val in enumerate(strings)}
```

The dict comprehension version is shorter and cleaner in my opinion.

Dict and set comprehensions were added to Python fairly recently in Python 2.7 and Python 3.1+.

Nested list comprehensions

Suppose we have a list of lists containing some boy and girl names:

```
In [483]: all_data = [['Tom', 'Billy', 'Jefferson', 'Andrew', 'Wesley', 'Steven', 'Joe'],
   .....:             ['Susie', 'Casey', 'Jill', 'Ana', 'Eva', 'Jennifer', 'Stephanie']]
```

You might have gotten these names from a couple of files and decided to keep the boy and girl names separate. Now, suppose we wanted to get a single list containing all names with two or more `e`'s in them. We could certainly do this with a simple `for` loop:

```
names_of_interest = []
for names in all_data:
    enough_es = [name for name in names if name.count('e') > 2]
    names_of_interest.extend(enough_es)
```

You can actually wrap this whole operation up in a single *nested list comprehension*, which will look like:

```
In [484]: result = [name for names in all_data for name in names
   .....:           if name.count('e') >= 2]

In [485]: result
Out[485]: ['Jefferson', 'Wesley', 'Steven', 'Jennifer', 'Stephanie']
```

At first, nested list comprehensions are a bit hard to wrap your head around. The `for` parts of the list comprehension are arranged according to the order of nesting, and any filter condition is put at the end as before. Here is another example where we "flatten" a list of tuples of integers into a simple list of integers:

```
In [486]: some_tuples = [(1, 2, 3), (4, 5, 6), (7, 8, 9)]

In [487]: flattened = [x for tup in some_tuples for x in tup]

In [488]: flattened
Out[488]: [1, 2, 3, 4, 5, 6, 7, 8, 9]
```

Keep in mind that the order of the `for` expressions would be the same if you wrote a nested `for` loop instead of a list comprehension:

```
flattened = []

for tup in some_tuples:
    for x in tup:
        flattened.append(x)
```

You can have arbitrarily many levels of nesting, though if you have more than two or three levels of nesting you should probably start to question your data structure design. It's important to distinguish the above syntax from a list comprehension inside a list comprehension, which is also perfectly valid:

```
In [229]: [[x for x in tup] for tup in some_tuples]
```

Functions

Functions are the primary and most important method of code organization and reuse in Python. There may not be such a thing as having too many functions. In fact, I would argue that most programmers doing data analysis don't write enough functions! As you have likely inferred from prior examples, functions are declared using the `def` keyword and returned from using the `return` keyword:

```
def my_function(x, y, z=1.5):
    if z > 1:
        return z * (x + y)
    else:
        return z / (x + y)
```

There is no issue with having multiple `return` statements. If the end of a function is reached without encountering a `return` statement, `None` is returned.

Each function can have some number of *positional* arguments and some number of *keyword* arguments. Keyword arguments are most commonly used to specify default values or optional arguments. In the above function, `x` and `y` are positional arguments while `z` is a keyword argument. This means that it can be called in either of these equivalent ways:

```
my_function(5, 6, z=0.7)
my_function(3.14, 7, 3.5)
```

The main restriction on function arguments it that the keyword arguments *must* follow the positional arguments (if any). You can specify keyword arguments in any order; this frees you from having to remember which order the function arguments were specified in and only what their names are.

Namespaces, Scope, and Local Functions

Functions can access variables in two different scopes: *global* and *local*. An alternate and more descriptive name describing a variable scope in Python is a *namespace*. Any variables that are assigned within a function by default are assigned to the local namespace. The local namespace is created when the function is called and immediately populated by the function's arguments. After the function is finished, the local namespace is destroyed (with some exceptions, see section on closures below). Consider the following function:

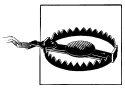
```
def func():
    a = []
    for i in range(5):
        a.append(i)
```

Upon calling `func()`, the empty list `a` is created, 5 elements are appended, then `a` is destroyed when the function exits. Suppose instead we had declared `a`

```
a = []
def func():
    for i in range(5):
        a.append(i)
```

Assigning global variables within a function is possible, but those variables must be declared as global using the `global` keyword:

```
In [489]: a = None

In [490]: def bind_a_variable():
   .....:     global a
   .....:     a = []
   .....: bind_a_variable()
   .....:

In [491]: print a
[]
```



I generally discourage people from using the `global` keyword frequently. Typically global variables are used to store some kind of state in a system. If you find yourself using a lot of them, it's probably a sign that some object-oriented programming (using classes) is in order.

Functions can be declared anywhere, and there is no problem with having *local* functions that are dynamically created when a function is called:

```
def outer_function(x, y, z):
    def inner_function(a, b, c):
        pass
    pass
```

In the above code, the `inner_function` will not exist until `outer_function` is called. As soon as `outer_function` is done executing, the `inner_function` is destroyed.

Nested inner functions can access the local namespace of the enclosing function, but they cannot bind new variables in it. I'll talk a bit more about this in the section on closures.

In a strict sense, all functions are local to some scope, that scope may just be the module level scope.

Returning Multiple Values

When I first programmed in Python after having programmed in Java and C++, one of my favorite features was the ability to return multiple values from a function. Here's a simple example:

```
def f():
    a = 5
    b = 6
    c = 7
    return a, b, c

a, b, c = f()
```

In data analysis and other scientific applications, you will likely find yourself doing this very often as many functions may have multiple outputs, whether those are data structures or other auxiliary data computed inside the function. If you think about tuple packing and unpacking from earlier in this chapter, you may realize that what's happening here is that the function is actually just returning *one* object, namely a tuple, which is then being unpacked into the result variables. In the above example, we could have done instead:

```
return_value = f()
```

In this case, `return_value` would be, as you may guess, a 3-tuple with the three returned variables. A potentially attractive alternative to returning multiple values like above might be to return a dict instead:

```
def f():
    a = 5
    b = 6
    c = 7
    return {'a' : a, 'b' : b, 'c' : c}
```

Functions Are Objects

Since Python functions are objects, many constructs can be easily expressed that are difficult to do in other languages. Suppose we were doing some data cleaning and needed to apply a bunch of transformations to the following list of strings:

```
states = ['   Alabama ', 'Georgia!', 'Georgia', 'georgia', 'FlOrIda',
          'south   carolina##', 'West virginia?']
```

Anyone who has ever worked with user-submitted survey data can expect messy results like these. Lots of things need to happen to make this list of strings uniform and ready for analysis: whitespace stripping, removing punctuation symbols, and proper capitalization. As a first pass, we might write some code like:

```
import re  # Regular expression module

def clean_strings(strings):
    result = []
```

```
    for value in strings:
        value = value.strip()
        value = re.sub('[!#?]', '', value) # remove punctuation
        value = value.title()
        result.append(value)
    return result
```

The result looks like this:

```
In [15]: clean_strings(states)
Out[15]:
['Alabama',
 'Georgia',
 'Georgia',
 'Georgia',
 'Florida',
 'South Carolina',
 'West Virginia']
```

An alternate approach that you may find useful is to make a list of the operations you want to apply to a particular set of strings:

```
def remove_punctuation(value):
    return re.sub('[!#?]', '', value)

clean_ops = [str.strip, remove_punctuation, str.title]

def clean_strings(strings, ops):
    result = []
    for value in strings:
        for function in ops:
            value = function(value)
        result.append(value)
    return result
```

Then we have

```
In [22]: clean_strings(states, clean_ops)
Out[22]:
['Alabama',
 'Georgia',
 'Georgia',
 'Georgia',
 'Florida',
 'South Carolina',
 'West Virginia']
```

A more *functional* pattern like this enables you to easily modify how the strings are transformed at a very high level. The `clean_strings` function is also now more reusable!

You can naturally use functions as arguments to other functions like the built-in `map` function, which applies a function to a collection of some kind:

```
In [23]: map(remove_punctuation, states)
Out[23]:
['   Alabama ',
 'Georgia',
```

```
 'Georgia',
 'georgia',
 'FlOrIda',
 'south   carolina',
 'West virginia']
```

Anonymous (lambda) Functions

Python has support for so-called *anonymous* or *lambda* functions, which are really just simple functions consisting of a single statement, the result of which is the return value. They are defined using the `lambda` keyword, which has no meaning other than "we are declaring an anonymous function."

```
def short_function(x):
    return x * 2

equiv_anon = lambda x: x * 2
```

I usually refer to these as lambda functions in the rest of the book. They are especially convenient in data analysis because, as you'll see, there are many cases where data transformation functions will take functions as arguments. It's often less typing (and clearer) to pass a lambda function as opposed to writing a full-out function declaration or even assigning the lambda function to a local variable. For example, consider this silly example:

```
def apply_to_list(some_list, f):
    return [f(x) for x in some_list]

ints = [4, 0, 1, 5, 6]
apply_to_list(ints, lambda x: x * 2)
```

You could also have written `[x * 2 for x in ints]`, but here we were able to succintly pass a custom operator to the `apply_to_list` function.

As another example, suppose you wanted to sort a collection of strings by the number of distinct letters in each string:

```
In [492]: strings = ['foo', 'card', 'bar', 'aaaa', 'abab']
```

Here we could pass a lambda function to the list's `sort` method:

```
In [493]: strings.sort(key=lambda x: len(set(list(x))))

In [494]: strings
Out[494]: ['aaaa', 'foo', 'abab', 'bar', 'card']
```

One reason lambda functions are called anonymous functions is that the function object itself is never given a name attribute.

Closures: Functions that Return Functions

Closures are nothing to fear. They can actually be a very useful and powerful tool in the right circumstance! In a nutshell, a closure is any *dynamically-generated* function returned by another function. The key property is that the returned function has access to the variables in the local namespace where it was created. Here is a very simple example:

```
def make_closure(a):
    def closure():
        print('I know the secret: %d' % a)
    return closure

closure = make_closure(5)
```

The difference between a closure and a regular Python function is that the closure continues to have access to the namespace (the function) where it was created, even though that function is done executing. So in the above case, the returned closure will always print `I know the secret: 5` whenever you call it. While it's common to create closures whose internal state (in this example, only the value of `a`) is static, you can just as easily have a mutable object like a dict, set, or list that can be modified. For example, here's a function that returns a function that keeps track of arguments it has been called with:

```
def make_watcher():
    have_seen = {}

    def has_been_seen(x):
        if x in have_seen:
            return True
        else:
            have_seen[x] = True
            return False

    return has_been_seen
```

Using this on a sequence of integers I obtain:

```
In [496]: watcher = make_watcher()

In [497]: vals = [5, 6, 1, 5, 1, 6, 3, 5]

In [498]: [watcher(x) for x in vals]
Out[498]: [False, False, False, True, True, True, False, True]
```

However, one technical limitation to keep in mind is that while you can mutate any internal state objects (like adding key-value pairs to a dict), you cannot *bind* variables in the enclosing function scope. One way to work around this is to modify a dict or list rather than binding variables:

```
def make_counter():
    count = [0]
    def counter():
```

```
        # increment and return the current count
        count[0] += 1
        return count[0]
    return counter

counter = make_counter()
```

You might be wondering why this is useful. In practice, you can write very general functions with lots of options, then fabricate simpler, more specialized functions. Here's an example of creating a string formatting function:

```
def format_and_pad(template, space):
    def formatter(x):
        return (template % x).rjust(space)

    return formatter
```

You could then create a floating point formatter that always returns a length-15 string like so:

```
In [500]: fmt = format_and_pad('%.4f', 15)

In [501]: fmt(1.756)
Out[501]: '         1.7560'
```

If you learn more about object-oriented programming in Python, you might observe that these patterns also could be implemented (albeit more verbosely) using classes.

Extended Call Syntax with *args, **kwargs

The way that function arguments work under the hood in Python is actually very simple. When you write `func(a, b, c, d=some, e=value)`, the positional and keyword arguments are actually packed up into a tuple and dict, respectively. So the internal function receives a tuple `args` and dict `kwargs` and internally does the equivalent of:

```
a, b, c = args
d = kwargs.get('d', d_default_value)
e = kwargs.get('e', e_default_value)
```

This all happens nicely behind the scenes. Of course, it also does some error checking and allows you to specify some of the positional arguments as keywords also (even if they aren't keyword in the function declaration!).

```
def say_hello_then_call_f(f, *args, **kwargs):
    print 'args is', args
    print 'kwargs is', kwargs
    print("Hello! Now I'm going to call %s" % f)
    return f(*args, **kwargs)

def g(x, y, z=1):
    return (x + y) / z
```

Then if we call `g` with `say_hello_then_call_f` we get:

```
In [8]:  say_hello_then_call_f(g, 1, 2, z=5.)
args is (1, 2)
kwargs is {'z': 5.0}
Hello! Now I'm going to call <function g at 0x2dd5cf8>
Out[8]: 0.6
```

Currying: Partial Argument Application

Currying is a fun computer science term which means deriving new functions from existing ones by *partial argument application*. For example, suppose we had a trivial function that adds two numbers together:

```
def add_numbers(x, y):
    return x + y
```

Using this function, we could derive a new function of one variable, `add_five`, that adds 5 to its argument:

```
add_five = lambda y: add_numbers(5, y)
```

The second argument to `add_numbers` is said to be *curried*. There's nothing very fancy here as we really only have defined a new function that calls an existing function. The built-in `functools` module can simplify this process using the `partial` function:

```
from functools import partial
add_five = partial(add_numbers, 5)
```

When discussing pandas and time series data, we'll use this technique to create specialized functions for transforming data series

```
# compute 60-day moving average of time series x
ma60 = lambda x: pandas.rolling_mean(x, 60)

# Take the 60-day moving average of of all time series in data
data.apply(ma60)
```

Generators

Having a consistent way to iterate over sequences, like objects in a list or lines in a file, is an important Python feature. This is accomplished by means of the *iterator protocol*, a generic way to make objects iterable. For example, iterating over a dict yields the dict keys:

```
In [502]: some_dict = {'a': 1, 'b': 2, 'c': 3}

In [503]: for key in some_dict:
   .....:     print key,
a c b
```

When you write `for key in some_dict`, the Python interpreter first attempts to create an iterator out of `some_dict`:

```
In [504]: dict_iterator = iter(some_dict)
```

```
In [505]: dict_iterator
Out[505]: <dictionary-keyiterator at 0x10a0a1578>
```

Any iterator is any object that will yield objects to the Python interpreter when used in a context like a `for` loop. Most methods expecting a list or list-like object will also accept any iterable object. This includes built-in methods such as `min`, `max`, and `sum`, and type constructors like `list` and `tuple`:

```
In [506]: list(dict_iterator)
Out[506]: ['a', 'c', 'b']
```

A *generator* is a simple way to construct a new iterable object. Whereas normal functions execute and return a single value, generators return a sequence of values lazily, pausing after each one until the next one is requested. To create a generator, use the `yield` keyword instead of `return` in a function:

```
def squares(n=10):
    for i in xrange(1, n + 1):
        print 'Generating squares from 1 to %d' % (n ** 2)
        yield i ** 2
```

When you actually call the generator, no code is immediately executed:

```
In [2]: gen = squares()

In [3]: gen
Out[3]: <generator object squares at 0x34c8280>
```

It is not until you request elements from the generator that it begins executing its code:

```
In [4]: for x in gen:
   ...:     print x,
   ...:
Generating squares from 0 to 100
1 4 9 16 25 36 49 64 81 100
```

As a less trivial example, suppose we wished to find all unique ways to make change for $1 (100 cents) using an arbitrary set of coins. You can probably think of various ways to implement this and how to store the unique combinations as you come up with them. One way is to write a generator that yields lists of coins (represented as integers):

```
def make_change(amount, coins=[1, 5, 10, 25], hand=None):
    hand = [] if hand is None else hand
    if amount == 0:
        yield hand
    for coin in coins:
        # ensures we don't give too much change, and combinations are unique
        if coin > amount or (len(hand) > 0 and hand[-1] < coin):
            continue

        for result in make_change(amount - coin, coins=coins,
                                  hand=hand + [coin]):
            yield result
```

The details of the algorithm are not that important (can you think of a shorter way?). Then we can write:

```
In [508]: for way in make_change(100, coins=[10, 25, 50]):
   .....:     print way
[10, 10, 10, 10, 10, 10, 10, 10, 10, 10]
[25, 25, 10, 10, 10, 10, 10]
[25, 25, 25, 25]
[50, 10, 10, 10, 10, 10]
[50, 25, 25]
[50, 50]

In [509]: len(list(make_change(100)))
Out[509]: 242
```

Generator expresssions

A simple way to make a generator is by using a *generator expression*. This is a generator analogue to list, dict and set comprehensions; to create one, enclose what would otherwise be a list comprehension with parenthesis instead of brackets:

```
In [510]: gen = (x ** 2 for x in xrange(100))

In [511]: gen
Out[511]: <generator object <genexpr> at 0x10a0a31e0>
```

This is completely equivalent to the following more verbose generator:

```
def _make_gen():
    for x in xrange(100):
        yield x ** 2
gen = _make_gen()
```

Generator expressions can be used inside any Python function that will accept a generator:

```
In [512]: sum(x ** 2 for x in xrange(100))
Out[512]: 328350

In [513]: dict((i, i **2) for i in xrange(5))
Out[513]: {0: 0, 1: 1, 2: 4, 3: 9, 4: 16}
```

itertools module

The standard library `itertools` module has a collection of generators for many common data algorithms. For example, `groupby` takes any sequence and a function; this groups consecutive elements in the sequence by return value of the function. Here's an example:

```
In [514]: import itertools

In [515]: first_letter = lambda x: x[0]

In [516]: names = ['Alan', 'Adam', 'Wes', 'Will', 'Albert', 'Steven']

In [517]: for letter, names in itertools.groupby(names, first_letter):
   .....:     print letter, list(names) # names is a generator
A ['Alan', 'Adam']
```

```
W ['Wes', 'Will']
A ['Albert']
S ['Steven']
```

See Table A-4 for a list of a few other itertools functions I've frequently found useful.

Table A-4. Some useful itertools functions

Function	Description
`imap(func, *iterables)`	Generator version of the built-in `map`; applies `func` to each zipped tuple of the passed sequences.
`ifilter(func, iterable)`	Generator version of the built-in `filter`; yields elements `x` for which `func(x)` is `True`.
`combinations(iterable, k)`	Generates a sequence of all possible `k`-tuples of elements in the iterable, ignoring order.
`permutations(iterable, k)`	Generates a sequence of all possible `k`-tuples of elements in the iterable, respecting order.
`groupby(iterable[, keyfunc])`	Generates `(key, sub-iterator)` for each unique key

In Python 3, several built-in functions (`zip, map, filter`) producing lists have been replaced by their generator versions found in `itertools` in Python 2.

Files and the operating system

Most of this book uses high-level tools like `pandas.read_csv` to read data files from disk into Python data structures. However, it's important to understand the basics of how to work with files in Python. Fortunately, it's very simple, which is part of why Python is so popular for text and file munging.

To open a file for reading or writing, use the built-in `open` function with either a relative or absolute file path:

```
In [518]: path = 'ch13/segismundo.txt'

In [519]: f = open(path)
```

By default, the file is opened in read-only mode `'r'`. We can then treat the file handle `f` like a list and iterate over the lines like so

```
for line in f:
    pass
```

The lines come out of the file with the end-of-line (EOL) markers intact, so you'll often see code to get an EOL-free list of lines in a file like

```
In [520]: lines = [x.rstrip() for x in open(path)]

In [521]: lines
```

```
Out[521]:
['Sue\xc3\xb1a el rico en su riqueza,',
 'que m\xc3\xa1s cuidados le ofrece;',
 '',
 'sue\xc3\xb1a el pobre que padece',
 'su miseria y su pobreza;',
 '',
 'sue\xc3\xb1a el que a medrar empieza,',
 'sue\xc3\xb1a el que afana y pretende,',
 'sue\xc3\xb1a el que agravia y ofende,',
 '',
 'y en el mundo, en conclusi\xc3\xb3n,',
 'todos sue\xc3\xb1an lo que son,',
 'aunque ninguno lo entiende.',
 '']
```

If we had typed `f = open(path, 'w')`, a *new file* at `ch13/segismundo.txt` would have been created, overwriting any one in its place. See below for a list of all valid file read/write modes.

Table A-5. Python file modes

Mode	Description
`r`	Read-only mode
`w`	Write-only mode. Creates a new file (deleting any file with the same name)
`a`	Append to existing file (create it if it does not exist)
`r+`	Read and write
`b`	Add to mode for binary files, that is `'rb'` or `'wb'`
`U`	Use universal newline mode. Pass by itself `'U'` or appended to one of the read modes like `'rU'`

To write text to a file, you can use either the file's `write` or `writelines` methods. For example, we could create a version of `prof_mod.py` with no blank lines like so:

```
In [522]: with open('tmp.txt', 'w') as handle:
   .....:     handle.writelines(x for x in open(path) if len(x) > 1)

In [523]: open('tmp.txt').readlines()
Out[523]:
['Sue\xc3\xb1a el rico en su riqueza,\n',
 'que m\xc3\xa1s cuidados le ofrece;\n',
 'sue\xc3\xb1a el pobre que padece\n',
 'su miseria y su pobreza;\n',
 'sue\xc3\xb1a el que a medrar empieza,\n',
 'sue\xc3\xb1a el que afana y pretende,\n',
 'sue\xc3\xb1a el que agravia y ofende,\n',
 'y en el mundo, en conclusi\xc3\xb3n,\n',
 'todos sue\xc3\xb1an lo que son,\n',
 'aunque ninguno lo entiende.\n']
```

See Table A-6 for many of the most commonly-used file methods.

Table A-6. Important Python file methods or attributes

Method	Description
`read([size])`	Return data from file as a string, with optional `size` argument indicating the number of bytes to read
`readlines([size])`	Return list of lines in the file, with optional `size` argument
`readlines([size])`	Return list of lines (as strings) in the file
`write(str)`	Write passed string to file.
`writelines(strings)`	Write passed sequence of strings to the file.
`close()`	Close the handle
`flush()`	Flush the internal I/O buffer to disk
`seek(pos)`	Move to indicated file position (integer).
`tell()`	Return current file position as integer.
`closed`	`True` is the file is closed.

Index

Symbols

! character, 60, 61, 64
!= operator, 91
!cmd command, 60
"two-language" problem, 2–3
(hash mark), 388
$PATH variable, 10
% character, 398
%a datetime format, 293
%A datetime format, 293
%alias magic function, 61
%automagic magic function, 55
%b datetime format, 293
%B datetime format, 293
%bookmark magic function, 60, 62
%c datetime format, 293
%cd magic function, 60
%cpaste magic function, 51–52, 55
%d datetime format, 292
%D datetime format, 293
%d format character, 398
%debug magic function, 54–55, 62
%dhist magic function, 60
%dirs magic function, 60
%env magic function, 60
%F datetime format, 293
%gui magic function, 57
%H datetime format, 292
%hist magic function, 55, 59
%I datetime format, 292
%logstart magic function, 60
%logstop magic function, 60
%lprun magic function, 70, 72
%m datetime format, 292
%M datetime format, 292
%magic magic function, 55
%p datetime format, 293
%page magic function, 55
%paste magic function, 51, 55
%pdb magic function, 54, 63
%popd magic function, 60
%prun magic function, 55, 70
%pushd magic function, 60
%pwd magic function, 60
%quickref magic function, 55
%reset magic function, 55, 59
%run magic function, 49–50, 55, 386
%S datetime format, 292
%s format character, 398
%time magic function, 55, 67
%timeit magic function, 54, 67, 68
%U datetime format, 293
%w datetime format, 292
%W datetime format, 293
%who magic function, 55
%whos magic function, 55
%who_ls magic function, 55
%x datetime format, 293
%X datetime format, 293
%xdel magic function, 55, 59
%xmode magic function, 54
%Y datetime format, 292
%y datetime format, 292
%z datetime format, 293
& operator, 91
* operator, 105
+ operator, 406, 409
2012 Federal Election Commission database example, 278–287

We'd like to hear your suggestions for improving our indexes. Send email to *index@oreilly.com*.

bucketing donation amounts, 283–285
donation statistics by occupation and employer, 280–283
donation statistics by state, 285–287
== operator, 393
>>> prompt, 386
? (question mark), 49
[] (brackets), 406, 408
\ (backslash), 397
_ (underscore), 48, 58
__ (two underscores), 58
{} (braces), 413
| operator, 91

A

a file mode, 431
abs function, 96
accumulate method, 368
add method, 95, 130, 417
add_patch method, 229
add_subplot method, 221
aggfunc option, 277
aggregate method, 260, 262
aggregations, 100
algorithms for sorting, 375–376
alignment of data, 330–331
all method, 101, 368
alpha argument, 233
and keyword, 398, 401
annotating in matplotlib, 228–230
anonymous functions, 424
any method, 101, 110, 201
append method, 122, 408
apply method, 39, 132, 142, 266–268, 270
apt package management tool, 10
arange function, 82
arccos function, 96
arccosh function, 96
arcsin function, 96
arcsinh function, 96
arctan function, 96
arctanh function, 96
argmax method, 101
argmin method, 101, 139
argsort method, 135, 374
arithmetic, 128–132
operations between DataFrame and Series, 130–132
with fill values, 129–130
arrays
boolean arrays, 101
boolean indexing for, 89–92
conditional logic as operation, 98–100
creating, 81–82
creating PeriodIndex from, 312
data types for, 83–85
fancy indexing, 92–93
file input and output with, 103–105
saving and loading text files, 104–105
storing on disk in binary format, 103–104
finding elements in sorted array, 376–377
in NumPy, 355–362
concatenating, 357–359
c_ object, 359
layout of in memory, 356–357
replicating, 360–361
reshaping, 355–356
r_ object, 359
saving to file, 379–380
splitting, 357–359
subsets for, 361–362
indexes for, 86–89
operations between, 85–86
setting values by broadcasting, 367
slicing, 86–89
sorting, 101–102
statistical methods for, 100
structured arrays, 370–372
benefits of, 372
mainpulating, 372
nested data types, 371–372
swapping axes in, 93–94
transposing, 93–94
unique function, 102–103
where function, 98–100
arrow function, 229
as keyword, 393
asarray function, 82, 379
asfreq method, 308, 318
asof method, 334–336
astype method, 84, 85
attributes
in Python, 391
starting with underscore, 48
average method, 136
ax argument, 233
axes

broadcasting over, 364–367
concatenating along, 185–188
labels for, 226–227
renaming indexes for, 197–198
swapping in arrays, 93–94
AxesSubplot object, 221
axis argument, 188
axis method, 138

B

b file mode, 431
backslash (\), 397
bar plots, 235–238
Basemap object, 245, 246
.bashrc file, 10
.bash_profile file, 9
bbox_inches option, 231
benefits
of Python, 2–3
glue for code, 2
solving "two-language" problem with, 2–3
of structured arrays, 372
beta function, 107
defined, 342
between_time method, 335
bfill method, 123
bin edges, 314
binary data formats, 171–172
HDF5, 171–172
Microsoft Excel files, 172
storing arrays in, 103–104
binary moving window functions, 324–325
binary search of lists, 410
binary universal functions, 96
binding
defined, 390
variables, 425
binomial function, 107
bisect module, 410
bookmarking directories in IPython, 62
Boolean
arrays, 101
data type, 84, 398
indexing for arrays, 89–92
bottleneck library, 324
braces ({}), 413
brackets ([]), 406, 408
break keyword, 401
broadcasting, 362–367
defined, 86, 360, 362
over other axes, 364–367
setting array values by, 367
bucketing, 283–285

C

calendar module, 290
casting, 84
cat method, 156, 212
Categorical object, 199
ceil function, 96
center method, 212
Chaco, 248
chisquare function, 107
chunksize argument, 160, 161
clearing screen shortcut, 53
clipboard, executing code from, 50–52
clock function, 67
close method, 220, 432
closures, 425–426
cmd.exe, 7
collections module, 416
colons, 387
cols option, 277
columns, grouping on, 256–257
column_stack function, 359
combinations function, 430
combine_first method, 177, 189
combining
data sources, 336–338
data sources, with overlap, 188–189
lists, 409
commands, 65
(see also magic commands)
debugger, 65
history in IPython, 58–60
input and output variables, 58–59
logging of, 59–60
reusing command history, 58
searching for, 53
comment argument, 160
comments in Python, 388
compile method, 208
complex128 data type, 84
complex256 data type, 84
complex64 data type, 84
concat function, 34, 177, 184, 185, 186, 267, 357, 359

concatenating
along axis, 185–188
arrays, 357–359
conditional logic as array operation, 98–100
conferences, 12
configuring matplotlib, 231–232
conforming, 122
contains method, 212
contiguous memory, 381–382
continue keyword, 401
continuous return, 348
convention argument, 314
converting
between string and datetime, 291–293
timestamps to periods, 311
coordinated universal time (UTC), 303
copy argument, 181
copy method, 118
copysign function, 96
corr method, 140
correlation, 139–141
corrwith method, 140
cos function, 96
cosh function, 96
count method, 139, 206, 212, 261, 407
Counter class, 21
cov method, 140
covariance, 139–141
CPython, 7
cross-section, 329
crosstab function, 277–278
crowdsourcing, 241
CSV files, 163–165, 242
Ctrl-A keyboard shortcut, 53
Ctrl-B keyboard shortcut, 53
Ctrl-C keyboard shortcut, 53
Ctrl-E keyboard shortcut, 53
Ctrl-F keyboard shortcut, 53
Ctrl-K keyboard shortcut, 53
Ctrl-L keyboard shortcut, 53
Ctrl-N keyboard shortcut, 53
Ctrl-P keyboard shortcut, 53
Ctrl-R keyboard shortcut, 53
Ctrl-Shift-V keyboard shortcut, 53
Ctrl-U keyboard shortcut, 53
cummax method, 139
cummin method, 139
cumprod method, 100, 139
cumsum method, 100, 139
cumulative returns, 338–340
currying, 427
cursor, moving with keyboard, 53
custom universal functions, 370
cut function, 199, 200, 201, 268, 283
Cython project, 2, 382–383
c_ object, 359

D

data aggregation, 259–264
returning data in unindexed form, 264
using multiple functions, 262–264
data alignment, 128–132
arithmetic methods with fill values, 129–130
operations between DataFrame and Series, 130–132
data munging, 329–340
asof method, 334–336
combining data, 336–338
for data alignment, 330–331
for specialized frequencies, 332–334
data structures for pandas, 112–121
DataFrame, 115–120
Index objects, 120–121
Panel, 152–154
Series, 112–115
data types
for arrays, 83–85
for ndarray, 83–85
for NumPy, 353–354
hierarchy of, 354
for Python, 395–400
boolean data type, 398
dates and times, 399–400
None data type, 399
numeric data types, 395–396
str data type, 396–398
type casting in, 399
for time series data, 290–293
converting between string and datetime, 291–293
nested, 371–372
data wrangling
manipulating strings, 205–211
methods for, 206–207
vectorized string methods, 210–211
with regular expressions, 207–210
merging data, 177–189

combining data with overlap, 188–189
concatenating along axis, 185–188
DataFrame merges, 178–181
on index, 182–184
pivoting, 192–193
reshaping, 190–191
transforming data, 194–205
discretization, 199–201
dummy variables, 203–205
filtering outliers, 201–202
mapping, 195–196
permutation, 202
removing duplicates, 194–195
renaming axis indexes, 197–198
replacing values, 196–197
USDA food database example, 212–217
databases
reading and writing to, 174–176
DataFrame data structure, 22, 27, 112, 115–120
arithmetic operations between Series and, 130–132
hierarchical indexing using, 150–151
merging data with, 178–181
dates and times, 291
(see also time series data)
data types for, 291, 399–400
date ranges, 298
datetime type, 291–293, 395, 399
DatetimeIndex Index object, 121
dateutil package, 291
date_parser argument, 160
date_range function, 298
dayfirst argument, 160
debug function, 66
debugger, IPython
in IPython, 62–66
def keyword, 420
defaults
profiles, 77
values for dicts, 415–416
del keyword, 59, 118, 414
delete method, 122
delimited formats, 163–165
density plots, 238–239
describe method, 138, 243, 267
design tips, 74–76
flat is better than nested, 75
keeping relevant objects and data alive, 75
overcoming fear of longer files, 75–76
det function, 106
development tools in IPython, 62–72
debugger, 62–66
profiling code, 68–70
profiling function line-by-line, 70–72
timing code, 67–68
diag function, 106
dicts, 413–416
creating, 415
default values for, 415–416
dict comprehensions, 418–420
grouping on, 257–258
keys for, 416
returning system environment variables as, 60
diff method, 122, 139
difference method, 417
digitize function, 377
directories
bookmarking in IPython, 62
changing, commands for, 60
discretization, 199–201
div method, 130
divide function, 96
.dmg file, 9
donation statistics
by occupation and employer, 280–283
by state, 285–287
dot function, 105, 106, 377
doublequote option, 165
downsampling, 312
dpi (dots-per-inch) option, 231
dreload function, 74
drop method, 122, 125
dropna method, 143
drop_duplicates method, 194
dsplit function, 359
dstack function, 359
dtype object (see data types)
“duck” typing in Python, 392
dummy variables, 203–205
dumps function, 165
duplicated method, 194
duplicates
indices, 296–297
removing from data, 194–195
dynamically-generated functions, 425

E

edgecolo option, 231
edit-compile-run workflow, 45
eig function, 106
elif blocks (see if statements)
else block (see if statements)
empty function, 82, 83
empty namespace, 50
encoding argument, 160
endswith method, 207, 212
enumerate function, 412
environment variables, 8, 60
EPD (Enthought Python Distribution), 7–9
equal function, 96
escapechar option, 165
ewma function, 323
ewmcorr function, 323
ewmcov function, 323
ewmstd function, 323
ewmvar function, 323
ExcelFile class, 172
except block, 403
exceptions
    automatically entering debugger after, 55
    defined, 402
    handling in Python, 402–404
exec keyword, 59
execute-explore workflow, 45
execution time
    of code, 55
    of single statement, 55
exit command, 386
exp function, 96
expanding window mean, 322
exponentially-weighted functions, 324
extend method, 409
extensible markup language (XML) files, 169–170
eye function, 83

F

fabs function, 96
facecolor option, 231
factor analysis, 342–343
Factor object, 269
factors, 342
fancy indexing
    defined, 361
    for arrays, 92–93
ffill method, 123
figsize argument, 234
Figure object, 220, 223
file input/output
    binary data formats for, 171–172
        HDF5, 171–172
        Microsoft Excel files, 172
    for arrays, 103–105
        HDF5, 380
        memory-mapped files, 379–380
        saving and loading text files, 104–105
        storing on disk in binary format, 103–104
    in Python, 430–431
    saving plot to file, 231
    text files, 155–170
        delimited formats, 163–165
        HTML files, 166–170
        JSON data, 165–166
        lxml library, 166–170
        reading in pieces, 160–162
        writing to, 162–163
        XML files, 169–170
    with databases, 174–176
    with Web APIs, 173–174
filling in missing data, 145–146, 270–271
fillna method, 22, 143, 145, 146, 196, 270, 317
fill_method argument, 313
fill_value option, 277
filtering
    in pandas, 125–128
    missing data, 143–144
    outliers, 201–202
financial applications
    cumulative returns, 338–340
    data munging, 329–340
        asof method, 334–336
        combining data, 336–338
        for data alignment, 330–331
        for specialized frequencies, 332–334
    future contract rolling, 347–350
    grouping for, 340–345
        factor analysis with, 342–343
        quartile analysis, 343–345
    linear regression, 350–351
    return indexes, 338–340
    rolling correlation, 350–351

signal frontier analysis, 345–347
find method, 206, 207
findall method, 167, 208, 210, 212
finditer method, 210
first crossing time, 109
first method, 136, 261
flat is better than nested, 75
flattening, 356
float data type, 83, 354, 395, 396, 399
float function, 402
float128 data type, 84
float16 data type, 84
float32 data type, 84
float64 data type, 84
floor function, 96
floor_divide function, 96
flow control, 400–405
exception handling, 402–404
for loops, 401–402
if statements, 400–401
pass statements, 402
range function, 404–405
ternary expressions, 405
while loops, 402
xrange function, 404–405
flush method, 432
fmax function, 96
fmin function, 96
fname option, 231
for loops, 85, 100, 401–402, 418, 419
format option, 231
frequencies, 299–301
converting, 308
specialized frequencies, 332–334
week of month dates, 301
frompyfunc function, 370
from_csv method, 163
functions, 389, 420–430
anonymous functions, 424
are objects, 422–423
closures, 425–426
currying of, 427
extended call syntax for, 426
lambda functions, 424
namespaces for, 420–421
parsing in pandas, 155
returning multiple values from, 422
scope of, 420–421
functools module, 427
future contract rolling, 347–350
futures, 347

G

gamma function, 107
gcc command, 9, 11
generators, 427–430
defined, 428
generator expressions, 429
itertools module for, 429–430
get method, 167, 172, 212, 415
getattr function, 391
get_chunk method, 162
get_dummies function, 203, 205
get_value method, 128
get_xlim method, 226
GIL (global interpreter lock), 3
global scope, 420, 421
glue for code
Python as, 2
.gov domain, 17
Granger, Brian, 72
graphics
Chaco, 248
mayavi, 248
greater function, 96
greater_equal function, 96
grid argument, 234
group keys, 268
groupby method, 39, 252–259, 297, 316, 343, 377, 429
iterating over groups, 255–256
on column, 256–257
on dict, 257–258
on levels, 259
resampling with, 316
using functions with, 258–259
with Series, 257–258
grouping
2012 Federal Election Commission database example, 278–287
bucketing donation amounts, 283–285
donation statistics by occupation and employer, 280–283
donation statistics by state, 285–287
apply method, 266–268
data aggregation, 259–264
returning data in unindexed form, 264
using multiple functions, 262–264

filling missing values with group-specific values, 270–271
for financial applications, 340–345
factor analysis with, 342–343
quartile analysis, 343–345
group weighted average, 273–274
groupby method, 252–259
iterating over groups, 255–256
on column, 256–257
on dict, 257–258
on levels, 259
using functions with, 258–259
with Series, 257–258
linear regression for, 274–275
pivot tables, 275–278
cross-tabulation, 277–278
quantile analysis with, 268–269
random sampling with, 271–272

H

Haiti earthquake crisis data example, 241–247
half-open, 314
hasattr function, 391
hash mark (#), 388
hashability, 416
HDF5 (hierarchical data format), 171–172, 380
HDFStore class, 171
header argument, 160
heapsort sorting method, 376
hierarchical data format (HDF5), 171–172, 380
hierarchical indexing
in pandas, 147–151
sorting levels, 149–150
summary statistics by level, 150
with DataFrame columns, 150–151
reshaping data with, 190–191
hist method, 238
histograms, 238–239
history of commands, searching, 53
homogeneous data container, 370
how argument, 181, 313, 316
hsplit function, 359
hstack function, 358
HTML files, 166–170
HTML Notebook in IPython, 72
Hunter, John D., 5, 219
hyperbolic trigonometric functions, 96

I

icol method, 128, 152
IDEs (Integrated Development Environments), 11, 52
idxmax method, 138
idxmin method, 138
if statements, 400–401, 415
ifilter function, 430
iget_value method, 152
ignore_index argument, 188
imap function, 430
import directive
in Python, 392–393
usage of in this book, 13
imshow function, 98
in keyword, 409
in-place sort, 373
in1d method, 103
indentation
in Python, 387–388
IndentationError event, 51
index method, 206, 207
Index objects data structure, 120–121
indexes
defined, 112
for arrays, 86–89
for axis, 197–198
for TimeSeries class, 294–296
hierarchical indexing, 147–151
reshaping data with, 190–191
sorting levels, 149–150
summary statistics by level, 150
with DataFrame columns, 150–151
in pandas, 136
integer indexing, 151–152
merging data on, 182–184
index_col argument, 160
indirect sorts, 374–375, 374
input variables, 58–59
insert method, 122, 408
insort method, 410
int data type, 83, 395, 399
int16 data type, 84
int32 data type, 84
int64 data type, 84
Int64Index Index object, 121
int8 data type, 84
integer arrays, indexing using (see fancy indexing)

integer indexing, 151–152
Integrated Development Environments (IDEs), 11, 52
interpreted languages
  defined, 386
  Python interpreter, 386
interrupting code, 50, 53
intersect1d method, 103
intersection method, 122, 417
intervals of time, 289
inv function, 106
inverse trigonometric functions, 96
.ipynb files, 72
IPython, 5
  bookmarking directories, 62
  command history in, 58–60
    input and output variables, 58–59
    logging of, 59–60
    reusing command history, 58
  design tips, 74–76
    flat is better than nested, 75
    keeping relevant objects and data alive, 75
    overcoming fear of longer files, 75–76
  development tools, 62–72
    debugger, 62–66
    profiling code, 68–70
    profiling function line-by-line, 70–72
    timing code, 67–68
  executing code from clipboard, 50–52
  HTML Notebook in, 72
  integration with IDEs and editors, 52
  integration with mathplotlib, 56–57
  keyboard shortcuts for, 52
  magic commands in, 54–55
  making classes output correctly, 76
  object introspection in, 48–49
  profiles for, 77–78
  Qt console for, 55
  Quick Reference Card for, 55
  reloading module dependencies, 74
  %run command in, 49–50
  shell commands in, 60–61
  tab completion in, 47–48
  tracebacks in, 53–54
ipython_config.py file, 77
irow method, 128, 152
is keyword, 393
isdisjoint method, 417
isfinite function, 96
isin method, 141–142
isinf function, 96
isinstance function, 391
isnull method, 96, 114, 143
issubdtype function, 354
issubset method, 417
issuperset method, 417
is_monotonic method, 122
is_unique method, 122
iter function, 392
iterating over groups, 255–256
iterator argument, 160
iterator protocol, 392, 427
itertools module, 429–430, 429
ix_ function, 93

J

join method, 184, 206, 212
JSON (JavaScript Object Notation), 18, 165–166, 213

K

KDE (kernel density estimate) plots, 239
keep_date_col argument, 160
kernels, 239
key-value pairs, 413
keyboard shortcuts, 53
  for deleting text, 53
  for IPython, 52
KeyboardInterrupt event, 50
keys
  argument, 188
  for dicts, 416
  method, 414
keyword arguments, 389, 420
kind argument, 234, 314
kurt method, 139

L

label argument, 233, 313, 315
lambda functions, 211, 262, 424
last method, 261
layout of arrays in memory, 356–357
left argument, 181
left_index argument, 181
left_on argument, 181
legends in matplotlib, 228

len function, 212, 258
less function, 96
less_equal function, 96
level keyword, 259
levels
    defined, 147
    grouping on, 259
    sorting, 149–150
    summary statistics by, 150
lexicographical sort
    defined, 375
    lexsort method, 374
libraries, 3–6
    IPython, 5
    matplotlib, 5
    NumPy, 4
    pandas, 4–5
    SciPy, 6
limit argument, 313
linalg function, 105
line plots, 232–235
linear algebra, 105–106
linear regression, 274–275, 350–351
lineterminator option, 164
line_profiler extension, 70
Linux, setting up on, 10–11
list comprehensions, 418–420
    nested list comprehensions, 419–420
list function, 408
lists, 408–411
    adding elements to, 408–409
    binary search of, 410
    combining, 409
    insertion into sorted, 410
    list comprehensions, 418–420
    removing elements from, 408–409
    slicing, 410–411
    sorting, 409–410
ljust method, 207
load function, 103, 379
load method, 171
loads function, 18
local scope, 420
localizing time series data, 304–305
loffset argument, 313, 316
log function, 96
log1p function, 96
log2 function, 96
logging command history in IPython, 59–60
logical_and function, 96
logical_not function, 96
logical_or function, 96
logical_xor function, 96
logy argument, 234
long format, 192
long type, 395
longer files overcoming fear of, 75–76
lower method, 207, 212
lstrip method, 207, 212
lstsq function, 106
lxml library, 166–170

M

mad method, 139
magic methods, 48, 54–55
main function, 75
mainpulating structured arrays, 372
many-to-many merge, 179
many-to-one merge, 178
map method, 133, 195–196, 211, 280, 423
margins, 275
markers, 224
match method, 208–212
matplotlib, 5, 219–232
    annotating in, 228–230
    axis labels in, 226–227
    configuring, 231–232
    integrating with IPython, 56–57
    legends in, 228
    saving to file, 231
    styling for, 224–225
    subplots in, 220–224
    ticks in, 226–227
    title in, 226–227
matplotlibrc file, 232
matrix operations in NumPy, 377–379
max method, 101, 136, 139, 261, 428
maximum function, 95, 96
mayavi, 248
mean method, 100, 139, 253, 259, 261, 265
median method, 139, 261
memmap object, 379
memory, layout of arrays in, 356–357
memory-mapped files
    defined, 379
    saving arrays to file, 379–380
mergesort sorting method, 375, 376
merging data, 177–189

combining data with overlap, 188–189
concatenating along axis, 185–188
DataFrame merges, 178–181
on index, 182–184
meshgrid function, 97
methods
defined, 389
for tuples, 407
in Python, 389
starting with underscore, 48
Microsoft Excel files, 172
.mil domain, 17
min method, 101, 136, 139, 261, 428
minimum function, 96
missing data, 142–146
filling in, 145–146
filtering out, 143–144
mod function, 96
modf function, 95
modules, 392
momentum, 343
MongoDB, 176
MovieLens 1M data set example, 26–31
moving window functions, 320–326
binary moving window functions, 324–325
exponentially-weighted functions, 324
user-defined, 326
.mpkg file, 9
mro method, 354
mul method, 130
MultiIndex Index object, 121, 147, 149
multiple profiles, 77
multiply function, 96
munging, 13
mutable objects, 394–395

N

NA data type, 143
names argument, 160, 188
namespaces
defined, 420
in Python, 420–421
naming trends
in US baby names 1880-2010 example, 36–43
boy names that became girl names, 42–43
measuring increase in diversity, 37–40
revolution of last letter, 40–41
NaN (not a number), 101, 114, 143
na_values argument, 160
ncols option, 223
ndarray, 80
Boolean indexing, 89–92
creating arrays, 81–82
data types for, 83–85
fancy indexing, 92–93
indexes for, 86–89
operations between arrays, 85–86
slicing arrays, 86–89
swapping axes in, 93–94
transposing, 93–94
nested code, 75
nested data types, 371–372
nested list comprehensions, 419–420
New York MTA (Metropolitan Transportation Authority), 169
None data type, 395, 399
normal function, 107, 110
normalized timestamps, 298
NoSQL databases, 176
not a number (NaN), 101, 114, 143
NotebookCloud, 72
notnull method, 114, 143
not_equal function, 96
.npy files, 103
.npz files, 104
nrows argument, 160, 223
nuisance column, 254
numeric data types, 395–396
NumPy, 4
arrays in, 355–362
concatenating, 357–359
c_ object, 359
layout of in memory, 356–357
replicating, 360–361
reshaping, 355–356
r_ object, 359
saving to file, 379–380
splitting, 357–359
subsets for, 361–362
broadcasting, 362–367
over other axes, 364–367
setting array values by, 367
data processing using
where function, 98–100
data processing using arrays, 97–103

conditional logic as array operation, 98–100
methods for boolean arrays, 101
sorting arrays, 101–102
statistical methods, 100
unique function, 102–103
data types for, 353–354
file input and output with arrays, 103–105
saving and loading text files, 104–105
storing on disk in binary format, 103–104
linear algebra, 105–106
matrix operations in, 377–379
ndarray arrays, 80
Boolean indexing, 89–92
creating, 81–82
data types for, 83–85
fancy indexing, 92–93
indexes for, 86–89
operations between arrays, 85–86
slicing arrays, 86–89
swapping axes in, 93–94
transposing, 93–94
numpy-discussion (mailing list), 12
performance of, 380–383
contiguous memory, 381–382
Cython project, 382–383
random number generation, 106–107
random walks example, 108–110
sorting, 373–377
algorithms for, 375–376
finding elements in sorted array, 376–377
indirect sorts, 374–375
structured arrays in, 370–372
benefits of, 372
mainpulating, 372
nested data types, 371–372
universal functions for, 95–96, 367–370
custom, 370
in pandas, 132–133
instance methods for, 368–369

O

object introspection, 48–49
object model, 388
object type, 84
objectify function, 166, 169
objs argument, 188
offsets for time series data, 302–303
OHLC (Open-High-Low-Close) resampling, 316
ols function, 351
Olson database, 303
on argument, 181
ones function, 82
open function, 430
Open-High-Low-Close (OHLC) resampling, 316
operators in Python, 393
or keyword, 401
order method, 375
OS X, setting up Python on, 9–10
outer method, 368, 369
outliers, filtering, 201–202
output variables, 58–59

P

pad method, 212
pairs plot, 241
pandas, 4–5
arithmetic and data alignment, 128–132
arithmetic methods with fill values, 129–130
operations between DataFrame and Series, 130–132
data structures for, 112–121
DataFrame, 115–120
Index objects, 120–121
Panel, 152–154
Series, 112–115
drop function, 125
filtering in, 125–128
handling missing data, 142–146
filling in, 145–146
filtering out, 143–144
hierarchical indexing in, 147–151
sorting levels, 149–150
summary statistics by level, 150
with DataFrame columns, 150–151
indexes in, 136
indexing options, 125–128
integer indexing, 151–152
NumPy universal functions with, 132–133
plotting with, 232
bar plots, 235–238
density plots, 238–239
histograms, 238–239

line plots, 232–235
scatter plots, 239–241
ranking data in, 133–135
reductions in, 137–142
reindex function, 122–124
selecting in objects, 125–128
sorting in, 133–135
summary statistics in
correlation and covariance, 139–141
isin function, 141–142
unique function, 141–142
value_counts function, 141–142
usa.gov data from bit.ly example with, 21–26
Panel data structure, 152–154
panels, 329
parse method, 291
parse_dates argument, 160
partial function, 427
partial indexing, 147
pass statements, 402
passing by reference, 390
pasting
keyboard shortcut for, 53
magic command for, 55
patches, 229
path argument, 160
Path variable, 8
pct_change method, 139
pdb debugger, 62
.pdf files, 231
percentileofscore function, 326
Pérez, Fernando, 45, 219
performance
and time series data, 327–328
of NumPy, 380–383
contiguous memory, 381–382
Cython project, 382–383
Period class, 307
PeriodIndex Index object, 121, 311, 312
periods, 307–312
converting timestamps to, 311
creating PeriodIndex from arrays, 312
defined, 289, 307
frequency conversion for, 308
instead of timestamps, 333–334
quarterly periods, 309–310
resampling with, 318–319
period_range function, 307, 310
permutation, 202
pickle serialization, 170
pinv function, 106
pivoting data
cross-tabulation, 277–278
defined, 189
pivot method, 192–193
pivot_table method, 29, 275–278
pivot_table aggregation type, 275
plot method, 23, 36, 41, 220, 224, 232, 239, 246, 319
plotting
Haiti earthquake crisis data example, 241–247
time series data, 319–320
with matplotlib, 219–232
annotating in, 228–230
axis labels in, 226–227
configuring, 231–232
legends in, 228
saving to file, 231
styling for, 224–225
subplots in, 220–224
ticks in, 226–227
title in, 226–227
with pandas, 232
bar plots, 235–238
density plots, 238–239
histograms, 238–239
line plots, 232–235
scatter plots, 239–241
.png files, 231
pop method, 408, 414
positional arguments, 389
power function, 96
pprint module, 76
pretty printing
and displaying through pager, 55
defined, 47
private attributes, 48
private methods, 48
prod method, 261
profiles
defined, 77
for IPython, 77–78
profile_default directory, 77
profiling code
in IPython, 68–70
pseudocode, 14

put function, 362
put method, 362
.py files, 50, 386, 392
pydata (Google group), 12
pylab mode, 219
pymongo driver, 175
pyplot module, 220
pystatsmodels (mailing list), 12
Python
  benefits of using, 2–3
    glue for code, 2
    solving "two-language" problem with, 2–3
  data types for, 395–400
    boolean data type, 398
    dates and times, 399–400
    None data type, 399
    numeric data types, 395–396
    str data type, 396–398
    type casting in, 399
  dict comprehensions in, 418–420
  dicts in, 413–416
    creating, 415
    default values for, 415–416
    keys for, 416
  file input/output in, 430–431
  flow control in, 400–405
    exception handling, 402–404
    for loops, 401–402
    if statements, 400–401
    pass statements, 402
    range function, 404–405
    ternary expressions, 405
    while loops, 402
    xrange function, 404–405
  functions in, 420–430
    anonymous functions, 424
    are objects, 422–423
    closures, 425–426
    currying of, 427
    extended call syntax for, 426
    lambda functions, 424
    namespaces for, 420–421
    returning multiple values from, 422
    scope of, 420–421
  generators in, 427–430
    generator expressions, 429
    itertools module for, 429–430
  IDEs for, 11
  interpreter for, 386
  list comprehensions in, 418–420
  lists in, 408–411
    adding elements to, 408–409
    binary search of, 410
    combining, 409
    insertion into sorted, 410
    removing elements from, 408–409
    slicing, 410–411
    sorting, 409–410
  Python 2 vs. Python 3, 11
  required libraries, 3–6
    IPython, 5
    matplotlib, 5
    NumPy, 4
    pandas, 4–5
    SciPy, 6
  semantics of, 387–395
    attributes in, 391
    comments in, 388
    functions in, 389
    import directive, 392–393
    indentation, 387–388
    methods in, 389
    mutable objects in, 394–395
    object model, 388
    operators for, 393
    references in, 389–390
    strict evaluation, 394
    strongly-typed language, 390–391
    variables in, 389–390
    “duck” typing, 392
  sequence functions in, 411–413
    enumerate function, 412
    reversed function, 413
    sorted function, 412
    zip function, 412–413
  set comprehensions in, 418–420
  sets in, 416–417
  setting up, 6–11
    on Linux, 10–11
    on OS X, 9–10
    on Windows, 7–9
  tuples in, 406–407
    methods for, 407
    unpacking, 407
pytz library, 303

Q

qcut method, 200, 201, 268, 269, 343
qr function, 106
Qt console for IPython, 55
quantile analysis, 268–269
quarterly periods, 309–310
quartile analysis, 343–345
question mark (?), 49
quicksort sorting method, 376
quotechar option, 164
quoting option, 164

R

r file mode, 431
r+ file mode, 431
Ramachandran, Prabhu, 248
rand function, 107
randint function, 107, 202
randn function, 89, 107
random number generation, 106–107
random sampling with grouping, 271–272
random walks example, 108–110
range function, 82, 404–405
ranking data
    defined, 135
    in pandas, 133–135
ravel method, 356, 357
rc method, 231, 232
re module, 207
read method, 432
read-only mode, 431
reading
    from databases, 174–176
    from text files in pieces, 160–162
readline functionality, 58
readlines method, 432
readshapefile method, 246
read_clipboard function, 155
read_csv function, 104, 155, 161, 163, 261, 430
read_frame function, 175
read_fwf function, 155
read_table function, 104, 155, 158, 163
recfunctions module, 372
reduce method, 368, 369
reduceat method, 369
reductions, 137
    (see also aggregations)
    defined, 137
    in pandas, 137–142
references
    defined, 389, 390
    in Python, 389–390
regress function, 274
regular expressions (regex)
    defined, 207
    manipulating strings with, 207–210
reindex method, 122–124, 317, 332
reload function, 74
remove method, 408, 417
rename method, 198
renaming axis indexes, 197–198
repeat method, 212, 360
replace method, 196, 206, 212
replicating arrays, 360–361
resampling, 312–319, 332
    defined, 312
    OHLC (Open-High-Low-Close) resampling, 316
    upsampling, 316–317
    with groupby method, 316
    with periods, 318–319
reset_index function, 151
reshape method, 190–191, 355, 365
reshaping
    arrays, 355–356
    defined, 189
    with hierarchical indexing, 190–191
resources, 12
return statements, 420
returns
    cumulative returns, 338–340
    defined, 338
    return indexes, 338–340
reversed function, 413
rfind method, 207
right argument, 181
right_index argument, 181
right_on argument, 181
rint function, 96
rjust method, 207
rollback method, 302
rollforward method, 302
rolling, 348
rolling correlation, 350–351
rolling_apply function, 323, 326
rolling_corr function, 323, 350

rolling_count function, 323
rolling_cov function, 323
rolling_kurt function, 323
rolling_mean function, 321, 323
rolling_median function, 323
rolling_min function, 323
rolling_mint function, 323
rolling_quantile function, 323, 326
rolling_skew function, 323
rolling_std function, 323
rolling_sum function, 323
rolling_var function, 323
rot argument, 234
rows option, 277
row_stack function, 359
rstrip method, 207, 212
r_ object, 359

S

save function, 103, 379
save method, 171, 176
savefig method, 231
savez function, 104
saving text files, 104–105
scatter method, 239
scatter plots, 239–241
scatter_matrix function, 241
Scientific Python base, 7
SciPy library, 6
scipy-user (mailing list), 12
scope, 420–421
screen, clearing, 53
scripting languages, 2
scripts, 2
search method, 208, 210
searchsorted method, 376
seed function, 107
seek method, 432
semantics, 387–395
    attributes in, 391
    comments in, 388
    “duck” typing, 392
    functions in, 389
    import directive, 392–393
    indentation, 387–388
    methods in, 389
    mutable objects in, 394–395
    object model, 388
    operators for, 393
    references in, 389–390
    strict evaluation, 394
    strongly-typed language, 390–391
    variables in, 389–390
semicolons, 388
sentinels, 143, 159
sep argument, 160
sequence functions, 411–413
    enumerate function, 412
    reversed function, 413
    sorted function, 412
    zip function, 412–413
Series data structure, 112–115
    arithmetic operations between DataFrame and, 130–132
    grouping with, 257–258
set comprehensions, 418–420
set function, 416
setattr function, 391
setdefault method, 415
setdiff1d method, 103
sets/set comprehensions, 416–417
setxor1d method, 103
set_index function, 151
set_index method, 193
set_title method, 226
set_trace function, 65
set_value method, 128
set_xlabel method, 226
set_xlim method, 226
set_xticklabels method, 226
set_xticks method, 226
shapefiles, 246
shapes, 80, 353
sharex option, 223, 234
sharey option, 223, 234
shell commands in IPython, 60–61
shifting in time series data, 301–303
shortcuts, keyboard, 53
    for deleting text, 53
    for IPython, 52
shuffle function, 107
sign function, 96, 202
signal frontier analysis, 345–347
sin function, 96
sinh function, 96
size method, 255
skew method, 139
skipinitialspace option, 165

skipna method, 138
skipna option, 137
skiprows argument, 160
skip_footer argument, 160
slice method, 212
slicing
  arrays, 86–89
  lists, 410–411
Social Security Administration (SSA), 32
solve function, 106
sort argument, 181
sort method, 101, 373, 409, 424
sorted function, 412
sorting
  arrays, 101–102
  finding elements in sorted array, 376–377
  in NumPy, 373–377
    algorithms for, 375–376
    finding elements in sorted array, 376–377
    indirect sorts, 374–375
  in pandas, 133–135
  levels, 149–150
  lists, 409–410
sortlevel function, 149
sort_columns argument, 235
sort_index method, 133, 150, 375
spaces, structuring code with, 387–388
spacing around subplots, 223–224
span, 324
specialized frequencies
  data munging for, 332–334
split method, 165, 206, 210, 212, 358
split-apply-combine, 252
splitting arrays, 357–359
SQL databases, 175
sql module, 175
SQLite databases, 174
sqrt function, 95, 96
square function, 96
squeeze argument, 160
SSA (Social Security Administration), 32
stable sorting, 375
stacked format, 192
start index, 411
startswith method, 207, 212
statistical methods, 100
std method, 101, 139, 261
stdout, 162
step index, 411
stop index, 411
strftime method, 291, 400
strict evaluation/language, 394
strides/strided view, 353
strings
  converting to datetime, 291–293
  data types for, 84, 396–398
  manipulating, 205–211
    methods for, 206–207
    vectorized string methods, 210–211
    with regular expressions, 207–210
strip method, 207, 212
strongly-typed languages, 390–391, 390
strptime method, 291, 400
structs, 370
structured arrays, 370–372
  benefits of, 372
  defined, 370
  mainpulating, 372
  nested data types, 371–372
style argument, 233
styling for matplotlib, 224–225
sub method, 130, 209
subn method, 210
subperiod, 319
subplots, 220–224
subplots method, 222
subplots_adjust method, 223
subplot_kw option, 223
subsets for arrays, 361–362
subtract function, 96
sudo command, 11
suffixes argument, 181
sum method, 100, 132, 137, 139, 259, 261, 330, 428
summary statistics, 137
  by level, 150
  correlation and covariance, 139–141
  isin function, 141–142
  unique function, 141–142
  value_counts function, 141–142
superperiod, 319
svd function, 106
swapaxes method, 94
swaplevel function, 149
swapping axes in arrays, 93–94
symmetric_difference method, 417
syntactic sugar, 14

system commands, defining alias for, 60

T

tab completion in IPython, 47–48
tabs, structuring code with, 387–388
take method, 202, 362
tan function, 96
tanh function, 96
tell method, 432
terminology, 13–14
ternary expressions, 405
text editors, integrating with IPython, 52
text files, 155–170
    delimited formats, 163–165
    HTML files, 166–170
    JSON data, 165–166
    lxml library, 166–170
    reading in pieces, 160–162
    saving and loading, 104–105
    writing to, 162–163
    XML files, 169–170
TextParser class, 160, 162, 168
text_content method, 167
thousands argument, 160
thresh argument, 144
ticks, 226–227
tile function, 360, 361
time series data
    and performance, 327–328
    data types for, 290–293
        converting between string and datetime, 291–293
    date ranges, 298
    frequencies, 299–301
        week of month dates, 301
    moving window functions, 320–326
        binary moving window functions, 324–325
        exponentially-weighted functions, 324
        user-defined, 326
    periods, 307–312
        converting timestamps to, 311
        creating PeriodIndex from arrays, 312
        frequency conversion for, 308
        quarterly periods, 309–310
    plotting, 319–320
    resampling, 312–319
        OHLC (Open-High-Low-Close) resampling, 316
        upsampling, 316–317
        with groupby method, 316
        with periods, 318–319
    shifting in, 301–303
        with offsets, 302–303
    time zones in, 303–306
        localizing objects, 304–305
        methods for time zone-aware objects, 305–306
    TimeSeries class, 293–297
        duplicate indices with, 296–297
        indexes for, 294–296
        selecting data in, 294–296
timestamps
    converting to periods, 311
    defined, 289
    using periods instead of, 333–334
timing code, 67–68
title in matplotlib, 226–227
top method, 267, 282
to_csv method, 162, 163
to_datetime method, 292
to_panel method, 154
to_period method, 311
trace function, 106
tracebacks, 53–54
transform method, 264–266
transforming data, 194–205
    discretization, 199–201
    dummy variables, 203–205
    filtering outliers, 201–202
    mapping, 195–196
    permutation, 202
    removing duplicates, 194–195
    renaming axis indexes, 197–198
    replacing values, 196–197
transpose method, 93, 94
transposing arrays, 93–94
trellis package, 247
trigonometric functions, 96
truncate method, 296
try/except block, 403, 404
tuples, 406–407
    methods for, 407
    unpacking, 407
type casting, 399
type command, 156
TypeError event, 84, 403
types, 388

tz_convert method, 305
tz_localize method, 304, 305

U

U file mode, 431
uint16 data type, 84
uint32 data type, 84
uint64 data type, 84
uint8 data type, 84
unary functions, 95
underscore (_), 48, 58
unicode type, 19, 84, 395
uniform function, 107
union method, 103, 122, 204, 417
unique method, 102–103, 122, 141–142, 279
universal functions, 95–96, 367–370
    custom, 370
    in pandas, 132–133
    instance methods for, 368–369
universal newline mode, 431
unpacking tuples, 407
unstack function, 148
update method, 337
upper method, 207, 212
upsampling, 312, 316–317
US baby names 1880-2010 example, 32–43
    boy names that became girl names, 42–43
    measuring increase in diversity, 37–40
    revolution of last letter, 40–41
usa.gov data from bit.ly example, 17–26
USDA (US Department of Agriculture) food database example, 212–217
use_index argument, 234
UTC (coordinated universal time), 303

V

ValueError event, 402, 403
values method, 414
value_counts method, 141–142
var method, 101, 139, 261
variables, 55
    (see also environment variables)
    deleting, 55
    displaying, 55
    in Python, 389–390
Varoquaux, Gaël, 248
vectorization, 85
    defined, 97
vectorize function, 370
vectorized string methods, 210–211
verbose argument, 160
verify_integrity argument, 188
views, 86, 118
visualization tools
    Chaco, 248
    mayavi, 248
vsplit function, 359
vstack function, 358

W

w file mode, 431
Wattenberg, Laura, 40
Web APIs, file input/output with, 173–174
week of month dates, 301
when expressions, 394
where function, 98–100, 188
while loops, 402
whitespace, structuring code with, 387–388
Wickham, Hadley, 252
Williams, Ashley, 212
Windows, setting up Python on, 7–9
working directory
    changing to passed directory, 60
    of current system, returning, 60
wrangling (see data wrangling)
write method, 431
write-only mode, 431
writelines method, 431
writer method, 165
writing
    to databases, 174–176
    to text files, 162–163

X

Xcode, 9
xlim method, 225, 226
XML (extensible markup language) files, 169–170
xrange function, 404–405
xs method, 128
xticklabels method, 225

Y

yield keyword, 428
ylim argument, 234
yticks argument, 234

Z

zeros function, 82
zip function, 412–413

About the Author

Wes McKinney is a New York–based data hacker and entrepreneur. After finishing his undergraduate degree in mathematics at MIT in 2007, he went on to do quantitative finance work at AQR Capital Management in Greenwich, CT. Frustrated by cumbersome data analysis tools, he learned Python and in 2008, started building what would later become the pandas project. He's now an active member of the scientific Python community and is an advocate for the use of Python in data analysis, finance, and statistical computing applications.

Colophon

The animal on the cover of *Python for Data Analysis* is a golden-tailed, or pen-tailed, tree shrew (*Ptilocercus lowii*). The golden-tailed tree shrew is the only one of its species in the genus *Ptilocercus* and family *Ptilocercidae*; all the other tree shrews are of the family *Tupaiidae*. Tree shrews are identified by their long tails and soft red-brown fur. As nicknamed, the golden-tailed tree shrew has a tail that resembles the feather on a quill pen. Tree shrews are omnivores, feeding primarily on insects, fruit, seeds, and small vertebrates.

Found predominantly in Indonesia, Malaysia, and Thailand, these wild mammals are known for their chronic consumption of alcohol. Malaysian tree shrews were found to spend several hours consuming the naturally fermented nectar of the bertam palm, equalling about 10 to 12 glasses of wine with 3.8% alcohol content. Despite this, no golden-tailed tree shrew has ever been intoxicated, thanks largely to their impressive ethanol breakdown, which includes metabolizing the alcohol in a way not used by humans. Also more impressive than any of their mammal counterparts, including humans? Brain to body mass ratio.

Despite these mammals' name, the golden-tailed shrew is not a true shrew, instead more closely related to primates. Because of their close relation, tree shrews have become an alternative to primates in medical experimentation for myopia, psychosocial stress, and hepatitis.

The cover image is from *Cassel's Natural History*. The cover font is Adobe ITC Garamond. The text font is Linotype Birka; the heading font is Adobe Myriad Condensed; and the code font is LucasFont's TheSansMonoCondensed.