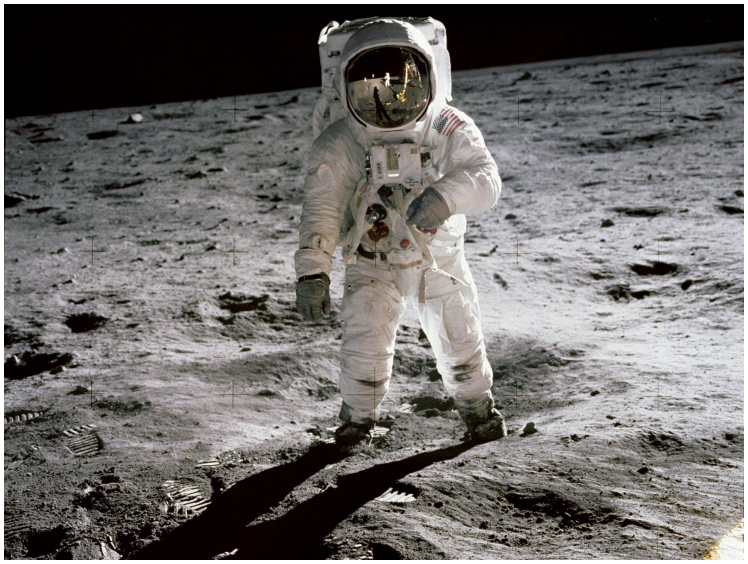
Labs for Foundations of Applied Mathematics

Data Science Essentials

Jeffrey Humpherys & Tyler J. Jarvis, managing editors



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Preface

This lab manual is designed to accompany the textbook *Foundations of Applied Mathematics* by Humpherys and Jarvis. While the Volume 3 text focuses on statistics and rigorous data analysis, these labs aim to introduce experienced Python programmers to common tools for obtaining, cleaning, organizing, and presenting data.

Contents

1 SQL 1: Introduction

Lab Objective: *Being able to store and manipulate large data sets quickly is a fundamental part of data science. The SQL language is the classic database management system for working with tabular data. In this lab we introduce the basics of SQL, including creating, reading, updating, and deleting SQL tables, all via Python's standard SQL interaction modules.*

Relational Databases

A *relational database* is a collection of tables called *relations*. A single row in a table, called a *tuple*, corresponds to an individual instance of data. The columns, called *attributes* or *features*, are data values of a particular category. The collection of column headings is called the *schema* of the table, which describes the kind of information stored in each entry of the tuples.

For example, suppose a database contains demographic information for M individuals. If a table had the schema `(Name, Gender, Age)`, then each row of the table would be a 3-tuple corresponding to a single individual, such as `(Jane Doe, F, 20)` or `(Samuel Clemens, M, 74.4)`. The table would therefore be $M \times 3$ in shape. Another table with the schema `(Name, Income)` would be $M \times 2$ if it included all M individuals.

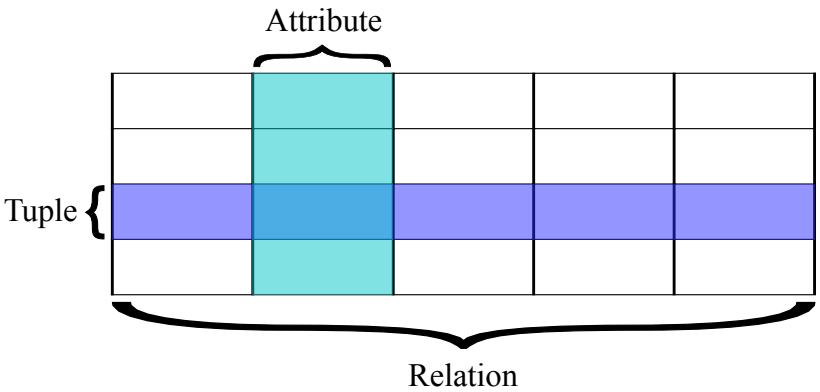


Figure 1.1: See `https://en.wikipedia.org/wiki/Relational_database`.

SQLite

The most common database management systems (DBMS) for relational databases are based on *Structured Query Language*, commonly called *SQL* (pronounced[1] "sequel"). Though SQL is a language in and of itself, most programming languages have tools for executing SQL routines. In Python, the most common variant of SQL is *SQLite*, implemented as the `sqlite3` module in the standard library.

A SQL database is stored in an external file, usually marked with the file extension `db` or `mdf`. These files should **not** be opened in Python with `open()` like text files; instead, any interactions with the database—creating, reading, updating, or deleting data—should occur as follows.

1. Create a connection to the database with `sqlite3.connect()`. This creates a database file if one does not already exist.
2. Get a *cursor*, an object that manages the actual traversal of the database, with the connection's `cursor()` method.
3. Alter or read data with the cursor's `execute()` method, which accepts an actual SQL command as a string.
4. Save any changes with the cursor's `commit()` method, or revert changes with `rollback()`.
5. Close the connection.

```
>>> import sqlite3 as sql

# Establish a connection to a database file or create one if it doesn't exist.
>>> conn = sql.connect("my_database.db")
>>> try:
...     cur = conn.cursor()                          # Get a cursor object.
...     cur.execute("SELECT * FROM MyTable")         # Execute a SQL command.
... except sql.Error:                                # If there is an error,
...     conn.rollback()                              #  revert the changes
...     raise                                        #  and raise the error.
... else:                                            # If there are no errors,
...     conn.commit()                                #  save the changes.
... finally:
...     conn.close()                                 # Close the connection.
```

Achtung!

Some changes, such as creating and deleting tables, are automatically committed to the database as part of the cursor's `execute()` method. Be **extremely cautious** when deleting tables, as the action is immediate and permanent. Most changes, however, do not take effect in the database file until the connection's `commit()` method is called. Be careful not to close the connection before committing desired changes, or those changes will not be recorded.

[1] See `https://english.stackexchange.com/questions/7231/how-is-sql-pronounced` for a brief history of the somewhat controversial pronunciation of SQL.

The `with` statement can be used with `open()` so that file streams are automatically closed, even in the event of an error. Likewise, combining the `with` statement with `sql.connect()` automatically rolls back changes if there is an error and commits them otherwise. However, the actual database connection is **not** closed automatically. With this strategy, the previous code block can be reduced to the following.

```
>>> try:
...     with sql.connect("my_database.db") as conn:
...         cur = conn.cursor()                     # Get the cursor.
...         cur.execute("SELECT * FROM MyTable")    # Execute a SQL command.
... finally:                                        # Commit or revert, then
...     conn.close()                                #  close the connection.
```

Managing Database Tables

SQLite uses five native data types (relatively few compared to other SQL systems) that correspond neatly to native Python data types.

Python Type	SQLite Type
None	NULL
int	INTEGER
float	REAL
str	TEXT
bytes	BLOB

The `CREATE TABLE` command, together with a table name and a schema, adds a new table to a database. The schema is a comma-separated list where each entry specifies the column name, the column data type,[2] and other optional parameters. For example, the following code adds a table called `MyTable` with the schema `(Name, ID, Age)` with appropriate data types.

```
>>> with sql.connect("my_database.db") as conn:
...     cur = conn.cursor()
...     cur.execute("CREATE TABLE MyTable (Name TEXT, ID INTEGER, Age REAL)")
...
>>> conn.close()
```

The `DROP TABLE` command deletes a table. However, using `CREATE TABLE` to try to create a table that already exists or using `DROP TABLE` to remove a nonexistent table raises an error. Use `DROP TABLE IF EXISTS` to remove a table without raising an error if the table doesn't exist. See Table 1.1 for more table management commands.

[2]Though SQLite does not force the data in a single column to be of the same type, most other SQL systems enforce uniform column types, so it is good practice to specify data types in the schema.

Operation	SQLite Command
Create a new table	`CREATE TABLE <table> (<schema>);`
Delete a table	`DROP TABLE <table>;`
Delete a table if it exists	`DROP TABLE IF EXISTS <table>;`
Add a new column to a table	`ALTER TABLE <table> ADD <column> <dtype>`
Remove an existing column	`ALTER TABLE <table> DROP COLUMN <column>;`
Rename an existing column	`ALTER TABLE <table> ALTER COLUMN <column> <dtype>;`

Table 1.1: SQLite commands for managing tables and columns.

Note

SQL commands like `CREATE TABLE` are often written in all caps to distinguish them from other parts of the query, like the table name. This is only a matter of style: SQLite, along with most other versions of SQL, is case insensitive. In Python's SQLite interface, the trailing semicolon is also unnecessary. However, most other database systems require it, so it's good practice to include the semicolon in Python.

Problem 1. Write a function that accepts the name of a database file. Connect to the database (and create it if it doesn't exist). Drop the tables `MajorInfo`, `CourseInfo`, `StudentInfo`, and `StudentGrades` from the database **if** they exist. Next, add the following tables to the database with the specified column names and types.

- `MajorInfo`: `MajorID` (integers) and `MajorName` (strings).
- `CourseInfo`: `CourseID` (integers) and `CourseName` (strings).
- `StudentInfo`: `StudentID` (integers), `StudentName` (strings), and `MajorID` (integers).
- `StudentGrades`: `StudentID` (integers), `CourseID` (integers), and `Grade` (strings).

Remember to commit and close the database. You should be able to execute your function more than once with the same input without raising an error.

To check the database, use the following commands to get the column names of a specified table. Assume here that the database file is called `students.db`.

```
>>> with sql.connect("students.db") as conn:
...     cur = conn.cursor()
...     cur.execute("SELECT * FROM StudentInfo;")
...     print([d[0] for d in cur.description])
...
['StudentID', 'StudentName', 'MajorID']
```

Inserting, Removing, and Altering Data

Tuples are added to SQLite database tables with the `INSERT INTO` command.

```
# Add the tuple (Samuel Clemens, 1910421, 74.4) to MyTable in my_database.db.
>>> with sql.connect("my_database.db") as conn:
...     cur = conn.cursor()
...     cur.execute("INSERT INTO MyTable "
...                 "VALUES('Samuel Clemens', 1910421, 74.4);")
```

With this syntax, SQLite assumes that values match sequentially with the schema of the table. The schema of the table can also be written explicitly for clarity.

```
>>> with sql.connect("my_database.db") as conn:
...     cur = conn.cursor()
...     cur.execute("INSERT INTO MyTable(Name, ID, Age) "
...                 "VALUES('Samuel Clemens', 1910421, 74.4);")
```

Achtung!

Never use Python's string operations to construct a SQL query from variables. Doing so makes the program susceptible to a *SQL injection attack*.[a] Instead, use parameter substitution to construct dynamic commands: use a `?` character within the command, then provide the sequence of values as a second argument to `execute()`.

```
>>> with sql.connect("my_database.db") as conn:
...     cur = conn.cursor()
...     values = ('Samuel Clemens', 1910421, 74.4)
...     # Don't piece the command together with string operations!
...     # cur.execute("INSERT INTO MyTable VALUES " + str(values)) # BAD!
...     # Instead, use parameter substitution.
...     cur.execute("INSERT INTO MyTable VALUES(?,?,?);", values)  # Good.
```

[a] See `https://xkcd.com/327/` for an example.

To insert several rows at a time to the same table, use the cursor object's `executemany()` method and parameter substitution with a list of tuples. This is typically much faster than using `execute()` repeatedly.

```
# Insert (Samuel Clemens, 1910421, 74.4) and (Jane Doe, 123, 20) to MyTable.
>>> with sql.connect("my_database.db") as conn:
...     cur = conn.cursor()
...     rows = [('John Smith', 456, 40.5), ('Jane Doe', 123, 20)]
...     cur.executemany("INSERT INTO MyTable VALUES(?,?,?);", rows)
```

Problem 2. Expand your function from Problem 1 so that it populates the tables with the data given in Tables 2.1a–2.1d.

MajorID	MajorName
1	Math
2	Science
3	Writing
4	Art

(a) MajorInfo

CourseID	CourseName
1	Calculus
2	English
3	Pottery
4	History

(b) CourseInfo

StudentID	StudentName	MajorID
401767594	Michelle Fernandez	1
678665086	Gilbert Chapman	NULL
553725811	Roberta Cook	2
886308195	Rene Cross	3
103066521	Cameron Kim	4
821568627	Mercedes Hall	NULL
206208438	Kristopher Tran	2
341324754	Cassandra Holland	1
262019426	Alfonso Phelps	NULL
622665098	Sammy Burke	2

(c) StudentInfo

StudentID	CourseID	Grade
401767594	4	C
401767594	3	B–
678665086	4	A+
678665086	3	A+
553725811	2	C
678665086	1	B
886308195	1	A
103066521	2	C
103066521	3	C–
821568627	4	D
821568627	2	A+
821568627	1	B
206208438	2	A
206208438	1	C+
341324754	2	D–
341324754	1	A–
103066521	4	A
262019426	2	B
262019426	3	C
622665098	1	A
622665098	2	A–

(d) StudentGrades

Table 1.2: Student database.

The `StudentInfo` and `StudentGrades` tables are also recorded in `student_info.csv` and `student_grades.csv`, respectively, with `NULL` values represented as -1. A CSV (**c**omma-**s**eparated **v**alues) file can be read like a normal text file or with the `csv` module.

```
>>> import csv
>>> with open("student_info.csv", 'r') as infile:
...     rows = list(csv.reader(infile))
```

To validate your database, use the following command to retrieve the rows from a table.

```
>>> with sql.connect("students.db") as conn:
...     cur = conn.cursor()
...     for row in cur.execute("SELECT * FROM MajorInfo;"):
...         print(row)
(1, 'Math')
(2, 'Science')
(3, 'Writing')
(4, 'Art')
```

Problem 3. The data file `us_earthquakes.csv`[a] contains data from about 3,500 earthquakes in the United States since the 1769. Each row records the year, month, day, hour, minute, second, latitude, longitude, and magnitude of a single earthquake (in that order). Note that latitude, longitude, and magnitude are floats, while the remaining columns are integers.

Write a function that accepts the name of a database file. Drop the table `USEarthquakes` if it already exists, then create a new `USEarthquakes` table with schema `(Year, Month, Day, Hour, Minute, Second, Latitude, Longitude, Magnitude)`. Populate the table with the data from `us_earthquakes.csv`. Remember to commit the changes and close the connection. (Hint: using `executemany()` is much faster than using `execute()` in a loop.)

[a]Retrieved from `https://datarepository.wolframcloud.com/resources/Sample-Data-US-Earthquakes`.

The WHERE Clause

Deleting or altering existing data in a database requires some searching for the desired row or rows. The `WHERE` clause is a *predicate* that filters the rows based on a boolean condition. The operators `==`, `!=`, `<`, `>`, `<=`, `>=`, `AND`, `OR`, and `NOT` all work as expected to create search conditions.

```
>>> with sql.connect("my_database.db") as conn:
...     cur = conn.cursor()
...     # Delete any rows where the Age column has a value less than 30.
...     cur.execute("DELETE FROM MyTable WHERE Age < 30;")
...     # Change the Name of "Samuel Clemens" to "Mark Twain".
...     cur.execute("UPDATE MyTable SET Name='Mark Twain' WHERE ID==1910421;")
```

If the `WHERE` clause were omitted from either of the previous commands, every record in `MyTable` would be affected. **Always** use a very specific `WHERE` clause when removing or updating data.

Operation	SQLite Command
Add a new row to a table	`INSERT INTO table VALUES(<values>);`
Remove rows from a table	`DELETE FROM <table> WHERE <condition>;`
Change values in existing rows	`UPDATE <table> SET <column1>=<value1>, ... WHERE <condition>;`

Table 1.3: SQLite commands for inserting, removing, and updating rows.

Problem 4. Modify your function from Problems 1 and 2 so that in the `StudentInfo` table, values of -1 in the `MajorID` column are replaced with `NULL` values.

Also modify your function from Problem 3 in the following ways.

1. Remove rows from `USEarthquakes` that have a value of 0 for the `Magnitude`.
2. Replace 0 values in the `Day`, `Hour`, `Minute`, and `Second` columns with `NULL` values.

Reading and Analyzing Data

Constructing and managing databases is fundamental, but most time in SQL is spent analyzing existing data. A *query* is a SQL command that reads all or part of a database without actually modifying the data. Queries start with the `SELECT` command, followed by column and table names and additional (optional) conditions. The results of a query, called the *result set*, are accessed through the cursor object. After calling `execute()` with a SQL query, use `fetchall()` or another cursor method from Table 1.4 to get the list of matching tuples.

Method	Description
`execute()`	Execute a single SQL command
`executemany()`	Execute a single SQL command over different values
`executescript()`	Execute a SQL script (multiple SQL commands)
`fetchone()`	Return a single tuple from the result set
`fetchmany(n)`	Return the next n rows from the result set as a list of tuples
`fetchall()`	Return the entire result set as a list of tuples

Table 1.4: Methods of database cursor objects.

```
>>> conn = sql.connect("students.db")
>>> cur = conn.cursor()

# Get tuples of the form (StudentID, StudentName) from the StudentInfo table.
>>> cur.execute("SELECT StudentID, StudentName FROM StudentInfo;")
>>> cur.fetchone()          # List the first match (a tuple).
(401767594, 'Michelle Fernandez')

>>> cur.fetchmany(3)        # List the next three matches (a list of tuples).
[(678665086, 'Gilbert Chapman'),
 (553725811, 'Roberta Cook'),
 (886308195, 'Rene Cross')]

>>> cur.fetchall()          # List the remaining matches.
[(103066521, 'Cameron Kim'),
 (821568627, 'Mercedes Hall'),
 (206208438, 'Kristopher Tran'),
 (341324754, 'Cassandra Holland'),
 (262019426, 'Alfonso Phelps'),
 (622665098, 'Sammy Burke')]

# Use * in place of column names to get all of the columns.
>>> cur.execute("SELECT * FROM MajorInfo;").fetchall()
[(1, 'Math'), (2, 'Science'), (3, 'Writing'), (4, 'Art')]

>>> conn.close()
```

The `WHERE` predicate can also refine a `SELECT` command. If the condition depends on a column in a different table from the data that is being a selected, create a *table alias* with the `AS` command to specify columns in the form `table.column`.

```
>>> conn = sql.connect("students.db")
>>> cur = conn.cursor()

# Get the names of all math majors.
>>> cur.execute("SELECT SI.StudentName "
...             "FROM StudentInfo AS SI, MajorInfo AS MI "
...             "WHERE SI.MajorID == MI.MajorID AND MI.MajorName == 'Math'")
# The result set is a list of 1-tuples; extract the entry from each tuple.
>>> [t[0] for t in cur.fetchall()]
['Cassandra Holland', 'Michelle Fernandez']

# Get the names and grades of everyone in English class.
>>> cur.execute("SELECT SI.StudentName, SG.Grade "
                "FROM StudentInfo AS SI, StudentGrades AS SG "
                "WHERE SI.StudentID == SG.StudentID AND CourseID == 2;")
>>> cur.fetchall()
[('Roberta Cook', 'C'),
 ('Cameron Kim', 'C'),
 ('Mercedes Hall', 'A+'),
 ('Kristopher Tran', 'A'),
 ('Cassandra Holland', 'D-'),
 ('Alfonso Phelps', 'B'),
 ('Sammy Burke', 'A-')]

>>> conn.close()
```

Problem 5. Write a function that accepts the name of a database file. Assuming the database to be in the format of the one created in Problems 1 and 2, query the database for all tuples of the form (`StudentName`, `CourseName`) where that student has an "A" or "A+" grade in that course. Return the list of tuples.

Aggregate Functions

A result set can be analyzed in Python using tools like NumPy, but SQL itself provides a few tools for computing a few very basic statistics: `AVG()`, `MIN()`, `MAX()`, `SUM()`, and `COUNT()` are *aggregate functions* that compress the columns of a result set into the desired quantity.

```
>>> conn = sql.connect("students.db")
>>> cur = conn.cursor()

# Get the number of students and the lowest ID number in StudentInfo.
>>> cur.execute("SELECT COUNT(StudentName), MIN(StudentID) FROM StudentInfo;")
>>> cur.fetchall()
[(10, 103066521)]
```

Problem 6. Write a function that accepts the name of a database file. Assuming the database to be in the format of the one created in Problem 3, query the `USEarthquakes` table for the following information.

- The magnitudes of the earthquakes during the 19th century (1800–1899).
- The magnitudes of the earthquakes during the 20th century (1900–1999).
- The average magnitude of all earthquakes in the database.

Create a single figure with two subplots: a histogram of the magnitudes of the earthquakes in the 19th century, and a histogram of the magnitudes of the earthquakes in the 20th century. Show the figure, then return the average magnitude of all of the earthquakes in the database. Be sure to return an actual number, not a list or a tuple.
(Hint: use `np.ravel()` to convert a result set of 1-tuples to a 1-D array.)

Note

Problem 6 raises an interesting question: are the number of earthquakes in the United States increasing with time, and if so, how drastically? A closer look shows that only 3 earthquakes were recorded (in this data set) from 1700–1799, 208 from 1800–1899, and a whopping 3049 from 1900–1999. Is the increase in earthquakes due to there actually being more earthquakes, or to the improvement of earthquake detection technology? The best answer without conducting additional research is "probably both." Be careful to question the nature of your data—how it was gathered, what it may be lacking, what biases or lurking variables might be present—before jumping to strong conclusions.

See the following for more info on the `sqlite3` and SQL in general.

- `https://docs.python.org/3/library/sqlite3.html`
- `https://www.w3schools.com/sql/`
- `https://en.wikipedia.org/wiki/SQL_injection`

Additional Material

Shortcuts for WHERE Conditions

Complicated `WHERE` conditions can be simplified with the following commands.

- `IN`: check for equality to one of several values quickly, similar to Python's `in` operator. In other words, the following SQL commands are equivalent.

```
SELECT * FROM StudentInfo WHERE MajorID == 1 OR MajorID == 2;
SELECT * FROM StudentInfo WHERE MajorID IN (1,2);
```

- `BETWEEN`: check two (inclusive) inequalities quickly. The following are equivalent.

```
SELECT * FROM MyTable WHERE AGE >= 20 AND AGE <= 60;
SELECT * FROM MyTable WHERE AGE BETWEEN 20 AND 60;
```

2 SQL 2 (The Sequel)

Lab Objective: *Since SQL databases contain multiple tables, retrieving information about the data can be complicated. In this lab we discuss joins, grouping, and other advanced SQL query concepts to facilitate rapid data retrieval.*

We will use the following database as an example throughout this lab, found in `students.db`.

MajorID	MajorName
1	Math
2	Science
3	Writing
4	Art

(a) MajorInfo

CourseID	CourseName
1	Calculus
2	English
3	Pottery
4	History

(b) CourseInfo

StudentID	StudentName	MajorID
401767594	Michelle Fernandez	1
678665086	Gilbert Chapman	NULL
553725811	Roberta Cook	2
886308195	Rene Cross	3
103066521	Cameron Kim	4
821568627	Mercedes Hall	NULL
206208438	Kristopher Tran	2
341324754	Cassandra Holland	1
262019426	Alfonso Phelps	NULL
622665098	Sammy Burke	2

(c) StudentInfo

StudentID	CourseID	Grade
401767594	4	C
401767594	3	B–
678665086	4	A+
678665086	3	A+
553725811	2	C
678665086	1	B
886308195	1	A
103066521	2	C
103066521	3	C–
821568627	4	D
821568627	2	A+
821568627	1	B
206208438	2	A
206208438	1	C+
341324754	2	D–
341324754	1	A–
103066521	4	A
262019426	2	B
262019426	3	C
622665098	1	A
622665098	2	A–

(d) StudentGrades

Table 2.1: Student database.

Joining Tables

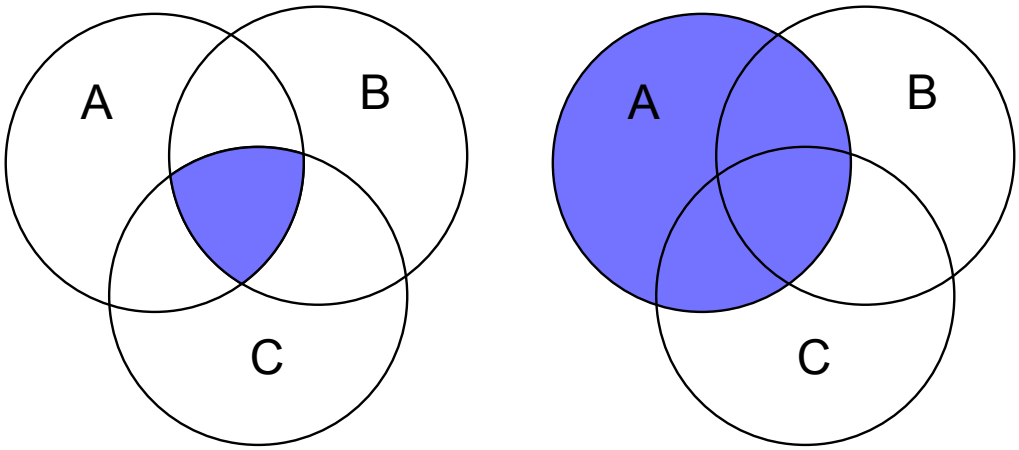
A *join* combines rows from different tables in a database based on common attributes. In other words, a join operation creates a new, temporary table containing data from 2 or more existing tables. Join commands in SQLite have the following general syntax.

```
SELECT <alias.column, ...>
    FROM <table> AS <alias> JOIN <table> AS <alias>, ...
    ON <alias.column> == <alias.column>, ...
    WHERE <condition>
```

The `ON` clause tells the query how to join tables together. Typically if there are N tables being joined together, there should be $N - 1$ conditions in the `ON` clause.

Inner Joins

An *inner join* creates a temporary table with the rows that have exact matches on the attribute(s) specified in the `ON` clause. Inner joins **intersect** two or more tables, as in Figure 2.1a.



(a) An inner join of A, B, and C.

(b) A left outer join of A with B and C.

Figure 2.1

For example, Table 2.1c (`StudentInfo`) and Table 2.1a (`MajorInfo`) both have a `MajorID` column, so the tables can be joined by pairing rows that have the same `MajorID`. Such a join temporarily creates the following table.

StudentID	StudentName	MajorID	MajorID	MajorName
401767594	Michelle Fernandez	1	1	Math
553725811	Roberta Cook	2	2	Science
886308195	Rene Cross	3	3	Writing
103066521	Cameron Kim	4	4	Art
206208438	Kristopher Tran	2	2	Science
341324754	Cassandra Holland	1	1	Math
622665098	Sammy Burke	2	2	Science

Table 2.2: An inner join of `StudentInfo` and `MajorInfo` on `MajorID`.

Notice that this table is missing the rows where `MajorID` was `NULL` in the `StudentInfo` table. This is because there was no match for `NULL` in the `MajorID` column of the `MajorInfo` table, so the inner join throws those rows away.

Because joins deal with multiple tables at once, it is important to assign table aliases with the `AS` command. Join statements can also be supplemented with `WHERE` clauses like regular queries.

```
>>> import sqlite3 as sql
>>> conn = sql.connect("students.db")
>>> cur = conn.cursor()

>>> cur.execute("SELECT * "
...             "FROM StudentInfo AS SI INNER JOIN MajorInfo AS MI "
...             "ON SI.MajorID = MI.MajorID;").fetchall()
[(401767594, 'Michelle Fernandez', 1, 1, 'Math'),
 (553725811, 'Roberta Cook', 2, 2, 'Science'),
 (886308195, 'Rene Cross', 3, 3, 'Writing'),
 (103066521, 'Cameron Kim', 4, 4, 'Art'),
 (206208438, 'Kristopher Tran', 2, 2, 'Science'),
 (341324754, 'Cassandra Holland', 1, 1, 'Math'),
 (622665098, 'Sammy Burke', 2, 2, 'Science')]

# Select the names and ID numbers of the math majors.
>>> cur.execute("SELECT SI.StudentName, SI.StudentID "
...             "FROM StudentInfo AS SI INNER JOIN MajorInfo AS MI "
...             "ON SI.MajorID = MI.MajorID "
...             "WHERE MI.MajorName == 'Math';").fetchall()
[('Cassandra Holland', 341324754), ('Michelle Fernandez', 401767594)]
```

Problem 1. Write a function that accepts the name of a database file. Assuming the database to be in the format of Tables 2.1a–2.1d, query the database for the list of the names of students who have a B grade in any course (not a B– or a B+).

Outer Joins

A *left outer join*, sometimes called a *left join*, creates a temporary table with **all** of the rows from the first (left-most) table, and all the "matched" rows on the given attribute(s) from the other relations. Rows from the left table that don't match up with the columns from the other tables are supplemented with `NULL` values to fill extra columns. Compare the following table and code to Table 2.2.

StudentID	StudentName	MajorID	MajorID	MajorName
401767594	Michelle Fernandez	1	1	Math
678665086	Gilbert Chapman	NULL	NULL	NULL
553725811	Roberta Cook	2	2	Science
886308195	Rene Cross	3	3	Writing
103066521	Cameron Kim	4	4	Art
821568627	Mercedes Hall	NULL	NULL	NULL
206208438	Kristopher Tran	2	2	Science
341324754	Cassandra Holland	1	1	Math
262019426	Alfonso Phelps	NULL	NULL	NULL
622665098	Sammy Burke	2	2	Science

Table 2.3: A left outer join of `StudentInfo` and `MajorInfo` on `MajorID`.

```
>>> cur.execute("SELECT * "
...             "FROM StudentInfo AS SI LEFT OUTER JOIN MajorInfo AS MI "
...             "ON SI.MajorID = MI.MajorID;").fetchall()
[(401767594, 'Michelle Fernandez', 1, 1, 'Math'),
 (678665086, 'Gilbert Chapman', None, None, None),
 (553725811, 'Roberta Cook', 2, 2, 'Science'),
 (886308195, 'Rene Cross', 3, 3, 'Writing'),
 (103066521, 'Cameron Kim', 4, 4, 'Art'),
 (821568627, 'Mercedes Hall', None, None, None),
 (206208438, 'Kristopher Tran', 2, 2, 'Science'),
 (341324754, 'Cassandra Holland', 1, 1, 'Math'),
 (262019426, 'Alfonso Phelps', None, None, None),
 (622665098, 'Sammy Burke', 2, 2, 'Science')]
```

Some flavors of SQL also support the `RIGHT OUTER JOIN` command, but `sqlite3` does not recognize the command since `T1 RIGHT OUTER JOIN T2` is equivalent to `T2 LEFT OUTER JOIN T1`.

Joining Multiple Tables

Complicated queries often join several different relations. If the same kind join is being used, the relations and conditional statements can be put in list form. For example, the following code selects courses that Kristopher Tran has taken, and the grades that he got in those courses, by joining three tables together. Note that 2 conditions are required in the `ON` clause in this case.

```
>>> cur.execute("SELECT CI.CourseName, SG.Grade "
...             "FROM StudentInfo AS SI "           # Join 3 tables.
...                 "INNER JOIN CourseInfo AS CI, StudentGrades SG "
...             "ON SI.StudentID==SG.StudentID AND CI.CourseID==SG.CourseID "
...             "WHERE SI.StudentName == 'Kristopher Tran';").fetchall()
[('Calculus', 'C+'), ('English', 'A')]
```

To use different kinds of joins in a single query, append one join statement after another. The join closest to the beginning of the statement is executed first, creating a temporary table, and the next join attempts to operate on that table. The following example performs an additional join on Table 2.3 to find the name and major of every student who got a C in a class.

```
# Do an inner join on the results of the left outer join.
>>> cur.execute("SELECT SI.StudentName, MI.MajorName "
...             "FROM StudentInfo AS SI LEFT OUTER JOIN MajorInfo AS MI "
...             "ON SI.MajorID == MI.MajorID "
...             "INNER JOIN StudentGrades AS SG "
...             "ON SI.StudentID = SG.StudentID "
...             "WHERE SG.Grade = 'C';").fetchall()
[('Michelle Fernandez', 'Math'),
 ('Roberta Cook', 'Science'),
 ('Cameron Kim', 'Art'),
 ('Alfonso Phelps', None)]
```

In this last example, note carefully that Alfonso Phelps would have been excluded from the result set if an inner join was performed first instead of an outer join (since he lacks a major).

Problem 2. Write a function that accepts the name of a database file. Query the database for all tuples of the form `(Name, MajorName, Grade)` where `Name` is a student's name and `Grade` is their grade in Calculus. Only include results for students that are actually taking Calculus, but be careful not to exclude students who haven't declared a major.

Grouping Data

Many data sets can be naturally sorted into groups. The `GROUP BY` command gathers rows from a table and groups them by a certain attribute. The groups must are then combined by one of the *aggregate functions* `AVG()`, `MIN()`, `MAX()`, `SUM()`, or `COUNT()`. The following code groups the rows in Table 2.1d by `studentID` and counts the number of entries in each group.

```
>>> cur.execute("SELECT StudentID, COUNT(*) "   # * means "all of the rows".
...             "FROM StudentGrades "
...             "GROUP BY StudentID").fetchall()
[(103066521, 3),
 (206208438, 2),
 (262019426, 2),
 (341324754, 2),
 (401767594, 2),
 (553725811, 1),
 (622665098, 2),
 (678665086, 3),
 (821568627, 3),
 (886308195, 1)]
```

`GROUP BY` can also be used in conjunction with joins. The join creates a temporary table like Tables 2.2 or 2.3, the results of which can then be grouped.

```
>>> cur.execute("SELECT SI.StudentName, COUNT(*) "
...             "FROM StudentGrades AS SG INNER JOIN StudentInfo AS SI "
...             "ON SG.StudentID == SI.StudentID "
...             "GROUP BY SG.StudentID").fetchall()
[('Cameron Kim', 3),
 ('Kristopher Tran', 2),
 ('Alfonso Phelps', 2),
 ('Cassandra Holland', 2),
 ('Michelle Fernandez', 2),
 ('Roberta Cook', 1),
 ('Sammy Burke', 2),
 ('Gilbert Chapman', 3),
 ('Mercedes Hall', 3),
 ('Rene Cross', 1)]
```

Just like the `WHERE` clause chooses rows in a relation, the `HAVING` clause chooses groups from the result of a `GROUP BY` based on some criteria related to the groupings. For this particular command, it is often useful (but not always necessary) to create an alias for the columns of the result set with the `AS` operator. For instance, the result set of the previous example can be filtered down to only contain students who are taking 3 courses.

```
>>> cur.execute("SELECT SI.StudentName, COUNT(*) as num_courses "   # Alias.
...             "FROM StudentGrades AS SG INNER JOIN StudentInfo AS SI "
...             "ON SG.StudentID == SI.StudentID "
...             "GROUP BY SG.StudentID "
...             "HAVING num_courses == 3").fetchall()   # Refer to alias later.
[('Cameron Kim', 3), ('Gilbert Chapman', 3), ('Mercedes Hall', 3)]

# Alternatively, get just the student names.
>>> cur.execute("SELECT SI.StudentName "                             # No alias.
...             "FROM StudentGrades AS SG INNER JOIN StudentInfo AS SI "
...             "ON SG.StudentID == SI.StudentID "
...             "GROUP BY SG.StudentID "
...             "HAVING COUNT(*) == 3").fetchall()
[('Cameron Kim',), ('Gilbert Chapman',), ('Mercedes Hall',)]
```

Problem 3. Write a function that accepts a database file. Query the database for the list of the names of courses that have at least 5 student enrolled in them.

Other Miscellaneous Commands

Ordering Result Sets

The `ORDER BY` command sorts a result set by one or more attributes. Sorting can be done in ascending or descending order with `ASC` or `DESC`, respectively. This is always the very last statement in a query.

```
>>> cur.execute("SELECT SI.StudentName, COUNT(*) AS num_courses "   # Alias.
...             "FROM StudentGrades AS SG INNER JOIN StudentInfo AS SI "
...             "ON SG.StudentID == SI.StudentID "
...             "GROUP BY SG.StudentID "
...             "ORDER BY num_courses DESC, SI.StudentName ASC").fetchall()
[('Cameron Kim', 3),                # The results are now ordered by the
 ('Gilbert Chapman', 3),            # number of courses each student is in,
 ('Mercedes Hall', 3),              # then alphabetically by student name.
 ('Alfonso Phelps', 2),
 ('Cassandra Holland', 2),
 ('Kristopher Tran', 2),
 ('Michelle Fernandez', 2),
 ('Sammy Burke', 2),
 ('Rene Cross', 1),
 ('Roberta Cook', 1)]
```

Problem 4. Write a function that accepts a database file. Query the given database for tuples of the form `(MajorName, N)` where `N` is the number of students in the specified major. Sort the results in ascending order by the count `N`.

Searching Text with Wildcards

The `LIKE` operator within a `WHERE` clause matches patterns in a `TEXT` column. The special characters `%` and `_` and called *wildcards* that match any number of characters or a single character, respectively. For instance, `%Z_` matches any string of characters ending in a Z then another character, and `%i%` matches any string containing the letter i.

```
>>> results = cur.execute("SELECT StudentName FROM StudentInfo "
...                       "WHERE StudentName LIKE '%i%';").fetchall()
>>> [r[0] for r in results]
['Michelle Fernandez', 'Gilbert Chapman', 'Cameron Kim', 'Kristopher Tran']
```

Problem 5. Write a function that accepts a database file. Query the database for tuples of the form `(StudentName, MajorName)` where the last name of the specified student begins with the letter C.

Case Expressions

A case expression maps the values in a column using boolean logic. There are two forms of a case expression: simple and searched. A *simple case expression* matches and replaces specified attributes.

```
# Replace the values MajorID with new custom values.
>>> cur.execute("SELECT StudentName, CASE MajorID "
...                 "WHEN 1 THEN 'Mathematics' "
...                 "WHEN 2 THEN 'Soft Science' "
...                 "WHEN 3 THEN 'Writing and Editing' "
...                 "WHEN 4 THEN 'Fine Arts' "
...                 "ELSE 'Undeclared' END "
...             "FROM StudentInfo "
...             "ORDER BY StudentName ASC;").fetchall()
[('Alfonso Phelps', 'Undeclared'),
 ('Cameron Kim', 'Fine Arts'),
 ('Cassandra Holland', 'Mathematics'),
 ('Gilbert Chapman', 'Undeclared'),
 ('Kristopher Tran', 'Soft Science'),
 ('Mercedes Hall', 'Undeclared'),
 ('Michelle Fernandez', 'Mathematics'),
 ('Rene Cross', 'Writing and Editing'),
 ('Roberta Cook', 'Soft Science'),
 ('Sammy Burke', 'Soft Science')]
```

A *searched case expression* involves using a boolean expression at each step, instead of listing all of the possible values for an attribute.

```
# Change NULL values in MajorID to 'Undeclared' and non-NULL to 'Declared'.
>>> cur.execute("SELECT StudentName, CASE "
...                 "WHEN MajorID IS NULL THEN 'Undeclared' "
...                 "ELSE 'Declared' END "
...             "FROM StudentInfo "
...             "ORDER BY StudentName ASC;").fetchall()
[('Alfonso Phelps', 'Undeclared'),
 ('Cameron Kim', 'Declared'),
 ('Cassandra Holland', 'Declared'),
 ('Gilbert Chapman', 'Undeclared'),
 ('Kristopher Tran', 'Declared'),
 ('Mercedes Hall', 'Undeclared'),
 ('Michelle Fernandez', 'Declared'),
 ('Rene Cross', 'Declared'),
 ('Roberta Cook', 'Declared'),
 ('Sammy Burke', 'Declared')]
```

Chaining Queries

The result set of any SQL query is really just another table with data from the original database. Separate queries can be made from result sets by enclosing the entire query in parentheses. For these sorts of operations, it is very important to carefully label the columns resulting from a subquery.

```
>>> cur.execute("SELECT majorstatus, COUNT(*) AS majorcount "
...             "FROM ( "                                    # Begin subquery.
...                 "SELECT StudentName, CASE "
...                 "WHEN MajorID IS NULL THEN 'Undeclared' "
...                 "ELSE 'Declared' END AS majorstatus "
...                 "FROM StudentInfo) "                     # End subquery.
...             "GROUP BY majorstatus "
...             "ORDER BY majorcount DESC;").fetchall()
[('Declared', 7), ('Undeclared', 3)]
```

Problem 6. Write a function that accepts the name of a database file. Query the database for tuples of the form `(StudentName, N, GPA)` where `N` is the number of courses that the specified student is enrolled in and `GPA` is their grade point average based on the following point system.

A+, A = 4.0	B = 3.0	C = 2.0	D = 1.0
A– = 3.7	B– = 2.7	C– = 1.7	D– = 0.7
B+ = 3.4	C+ = 2.4	D+ = 1.4	

Order the results from greatest GPA to least.

3 Regular Expressions

Lab Objective: *Cleaning and formatting data are fundamental problems in data science. Regular expressions are an important tool for working with text carefully and efficiently, and are useful for both gathering and cleaning data. This lab introduces regular expression syntax and common practices, including an application to a data cleaning problem.*

A *regular expression* or *regex* is a string of characters that follows a certain syntax to specify a pattern. Strings that follow the pattern are said to *match* the expression (and vice versa). A single regular expression can match a large set of strings, such as the set all valid email addresses.

> ACHTUNG!
>
> There are some universal standards for regular expression syntax, but the exact syntax varies slightly depending on the program or language. However, the syntax presented in this lab (for Python) is sufficiently similar to any other regex system. Consider learning to use regular expressions in vim or your favorite text editor, keeping in mind that there are bound to be slight syntactic differences from what is presented here.

Regular Expression Syntax in Python

The `re` module implements regular expressions in Python. The function `re.compile()` takes in a regular expression string and returns a corresponding *pattern* object, which has methods for determining if and how other strings match the pattern. For example, the `search()` method returns `None` for a string that doesn't match, and a *match* object for a string that does (more on these later).

```
>>> import re
>>> pattern = re.compile("cat")      # Make a pattern for finding 'cat'.
>>> bool(pattern.search("cat"))      # 'cat' matches 'cat', of course.
True
>>> bool(pattern.search("catfish")) # 'catfish' also contains 'cat'.
True
>>> bool(pattern.search("hat"))      # 'hat' does not contain 'cat'.
False
```

Achtung!

The poorly named `match()` method for pattern objects only matches strings that satisfy the pattern **at the beginning** of the string. To answer the question "does any part of my target string match this regular expression?" always use the `search()` method.

```
>>> pattern = re.compile("cat")
>>> bool(pattern.match("catfish"))
True
>>> bool(pattern.match("fishcat"))
False
>>> bool(pattern.search("fishcat"))
True
```

Note

Most of the functions in the `re` module are shortcuts for compiling a pattern object and calling one of its methods. For example, the following lines of code are equivalent.

```
>>> bool(re.compile("cat").search("catfish"))
True
>>> bool(re.search("cat", "catfish"))
True
```

Using `re.compile()` is good practice because the resulting object is reusable, while each call to `re.search()` compiles a new (but redundant) pattern object.

Problem 1. Write a function that compiles and returns a regular expression pattern object with the pattern string `"python"`.

Construct positive and negative test cases to test your object. Having good test cases will be important later, so be thorough. Your verification process might start as follows.

```
>>> pattern = re.compile("cat")
>>> positive = ["cat", "catfish", "fish cat", "your cat ran away"]
>>> assert all(pattern.search(p) for p in positive)
```

Literal Characters and Metacharacters

The following string characters (separated by spaces) are *metacharacters* in Python's regular expressions, meaning they have special significance in a pattern string: `. ^ $ * + ? { } [ ] \ | ( )`.

To construct a regular expression that matches strings with one or more metacharacters in them requires two things. First, use *raw strings* instead of regular Python strings by prefacing the string with an `r`, such as `r"cat"`. The resulting string interprets backslashes as actual backslash characters, rather than the start of an escape sequence like `\n` or `\t`. Second, preface any metacharacters with a backslash to indicate a literal character. For example, the following code constructs a regular expression to match the string `"$3.99? Thanks."`.

```
>>> dollar = re.compile(r"\$3\.99\? Thanks\.")
>>> bool(dollar.search("$3.99? Thanks."))
True
>>> bool(dollar.search("$3\.99? Thanks."))
False
>>> bool(dollar.search("$3.99?"))   # Doesn't contain the entire pattern.
False
```

Without raw strings, every backslash in has to be written as a double backslash, which makes many regular expression patterns hard to read (`"\\$3\\.99\\? Thanks\\."`). Readability counts.

Problem 2. Write a function that compiles and returns a regular expression pattern object that matches the string `"^{@}(?)[%]{.}(*)[_]{&}$"`.

The regular expressions of Problems 1 and 2 only match strings that are or include the exact pattern. The metacharacters allow regular expressions to have much more flexibility and control so that a single pattern could match a wide variety of strings, or a very specific set of strings.

To begin, the *line anchor* metacharacters `^` and `$` are used to match the **start** and the **end** of a line of text, respectively. This shrinks the matching set, even when using the `search()` method instead of the `match()` method. For example, the only single-line string that the expression `^x$` matches is `'x'`, whereas the expression `x` can match any string with an `x` in it.

```
>>> has_x, just_x = re.compile(r"x"), re.compile(r"^x$")
>>> for test in ["x", "xabc", "abcx"]:
...     print(test + ':', bool(has_x.search(test)), bool(just_x.search(test)))
...
x: True True
xabc: True False                    # Starts with 'x', but doesn't end with it.
abcx: True False                    # Ends with 'x', but doesn't start with it.
```

The *pipe* character `|` is like a logical `OR` in a regular expression: `A|B` matches `A` or `B`.

```
>>> rb, rbg = re.compile(r"^red$|^blue$"), re.compile(r"^red$|^blue$|^green$")
>>> for test in ["red", "blue", "green", "redblue"]:
...     print(test + ":", bool(rb.search(test)), bool(rbg.search(test)))
red: True True
blue: True True
green: False True
redblue: False False                # The line anchors prevent matching here.
```

The parentheses `()` create a *group* in a regular expression. Among other things, a group establishes an order of operations in an expression, much like how parentheses work in an arithmetic expression such as $3 \cdot (4 + 5)$.

```
>>> fish = re.compile(r"^(one|two) fish$")
>>> for test in ["one fish", "two fish", "red fish", "one two fish"]:
...     print(test + ':', bool(fish.search(test)))
...
one fish: True
two fish: True
red fish: False
one two fish: False
```

Problem 3. Write a function that compiles and returns a regular expression pattern object that matches the following strings (and no other strings, even with `re.search()`).

```
"Book store"      "Mattress store"      "Grocery store"
"Book supplier"   "Mattress supplier"   "Grocery supplier"
```

Character Classes

The hard bracket metacharacters `[` and `]` are used to create *character classes*, a part of a regular expression that can match a variety of characters. For example, the pattern `[abc]` matches any of the characters `a`, `b`, or `c`. This is different than a group delimited by parentheses: a group can match multiple characters, while a character class matches only one character. For instance, `[abc]` does not match `ab` or `abc`, and `(abc)` matches `abc` but not `ab` or even `a`.

Within character classes, there are two additional metacharacters. When `^` appears **as the first character** in a character class, right after the opening bracket `[`, the character class matches anything **not** specified instead. In other words, `^` is the set complement operation on the character class. Additionally, the dash `-` specifies a range of values. For instance, `[0-9]` matches any digit, and `[a-z]` matches any lowercase letter. Thus `[^0-9]` matches any character **except** for a digit, and `[^a-z]` matches any character **except** for a lowercase letters

```
>>> p1, p2 = re.compile(r"^[a-z][^0-7]$"), re.compile(r"^[^abcA-C][0-27-9]$")
>>> for test in ["d8", "aa", "E9", "EE", "d88"]:
...     print(test + ':', bool(p1.search(test)), bool(p2.search(test)))
...
d8: True True
aa: True False                    # a is not in [^abcA-C] or [0-27-9].
E9: False True                    # E is not in [a-z].
EE: False False                   # E is not in [a-z] or [0-27-9].
d88: False False                  # Too many characters.
```

Note that `[0-27-9]` acts like `[(0-2)|(7-9)]`.

There are also a variety of shortcuts that represent common character classes, listed in Table 3.1. Familiarity with these shortcuts makes some regular expressions significantly more readable.

Character	Description
`\b`	Matches the empty string, but only at the start or end of a word.
`\d`	Matches any decimal digit; equivalent to `[0-9]`.
`\D`	Matches any non-digit character; equivalent to `[^\d]`.
`\s`	Matches any whitespace character; equivalent to `[ \t\n\r\f\v]`.
`\S`	Matches any non-whitespace character; equivalent to `[^\s]`.
`\w`	Matches any alphanumeric character; equivalent to `[a-zA-Z0-9_]`.
`\W`	Matches any non-alphanumeric character; equivalent to `[^\w]`.

Table 3.1: Character class shortcuts.

Any of the character class shortcuts can be used within other custom character classes. For example, `[_A-Z\s]` matches an underscore, capital letter, or whitespace character.

Finally, a period `.` matches **any** character except for a line break, and is therefore equivalent to `[^\n]` on UNIX machines and `[^\r\n]` on Windows machines. This is a very powerful metacharacter; be careful to only use it when part of the regular expression really should match **any** character.

```
# Match any three-character string with a digit in the middle.
>>> pattern = re.compile(r"^.\d.$")
>>> for test in ["a0b", "888", "n2%", "abc", "cat"]:
...     print(test + ':', bool(pattern.search(test)))
...
a0b: True
888: True
n2%: True
abc: False
cat: False

# Match two letters followed by a number and two non-newline characters.
>>> pattern = re.compile(r"^[a-zA-Z][a-zA-Z]\d..$")
>>> for test in ["tk421", "bb8!?", "JB007", "Boba?"]:
...     print(test + ':', bool(pattern.search(test)))
..
tk421: True
bb8!?: True
JB007: True
Boba?: False
```

Character	Description
`.`	Matches any character except a newline.
`^`	Matches the start of the string.
`$`	Matches the end of the string or just before the newline at the end of the string.
`|`	`A|B` creates an regular expression that will match either `A` or `B`.
`[...]`	Indicates a set of characters. A `^` as the first character indicates a complementing set.
`(...)`	Matches the regular expression inside the parentheses. The contents can be retrieved or matched later in the string.

Table 3.2: Standard regular expression metacharacters in Python.

Repetition

The remaining metacharacters are for matching a specified number of characters. This allows a single regular expression to match strings of varying lengths.

Character	Description
`*`	Matches 0 or more repetitions of the preceding regular expression.
`+`	Matches 1 or more repetitions of the preceding regular expression.
`?`	Matches 0 or 1 of the preceding regular expression.
`{m,n}`	Matches from m to n repetitions of the preceding regular expression.
`*?`, `+?`, `??`, `{m,n}?`	Non-greedy versions of the previous four special characters.

Table 3.3: Repetition metacharacters for regular expressions in Python.

```
# Match 0 or more 'a' characters, ending in a 'b'.
>>> pattern = re.compile(r"^a*b$")
>>> for test in ["b", "ab", "aaaaaaaaaab", "aba"]:
...     print(test + ':', bool(pattern.search(test)))
...
b: True                             # 0 'a' characters, then 1 'b'.
ab: True
aaaaaaaaaab: True                   # Several 'a' characters, then 1 'b'.
aba: False                          # 'b' must be the last character.

# Match an 'h' followed by at least one 'i' or 'a' characters.
>>> pattern = re.compile(r"^h[ia]+$")
>>> for test in ["ha", "hii", "hiaiaa", "h", "hah"]:
...     print(test + ':', bool(pattern.search(test)))
...
ha: True
hii: True
hiaiaa: True                        # [ia] matches 'i' or 'a'.
h: False                            # Need at least one 'i' or 'a'
hah: False                          # 'i' or 'a' must be the last character.

# Match an 'a' followed by 'b' followed by 0 or 1 'c' characters.
>>> pattern = re.compile(r"^abc?$")
>>> for test in ["ab", "abc", "abcc", "ac"]:
...     print(test + ':', bool(pattern.search(test)))
...
ab: True
abc: True
abcc: False                         # Only up to one 'c' is allowed.
ac: False                           # Missing the 'b'.
```

Each of the repetition operators acts on the expression immediately preceding it. This could be a single character, a group, or a character class. For instance, `(abc)+` matches `abc`, `abcabc`, `abcabcabc`, and so on, but not `aba` or `cba`. On the other hand, `[abc]*` matches any sequence of `a`, `b`, and `c`, including `abcabc` and `aabbcc`.

The curly braces `{}` specify a custom number of repetitions allowed. `{,n}` matches **up to** n instances, `{m,}` matches **at least** m instances, `{k}` matches **exactly** k instances, and `{m,n}` matches from m to n instances. Thus the `?` operator is equivalent to `{,1}` and `+` is equivalent to `{1,}`.

```
# Match exactly 3 'a' characters.
>>> pattern = re.compile(r"^a{3}$")
>>> for test in ["aa", "aaa", "aaaa", "aba"]:
...     print(test + ':', bool(pattern.search(test)))
...
aa: False                           # Too few.
aaa: True
aaaa: False                         # Too many.
aba: False
```

Achtung!

Line anchors are especially important when using repetition operators. Consider the following (bad) example and compare it to the previous example.

```
# Match exactly 3 'a' characters, hopefully.
>>> pattern = re.compile(r"a{3}")
>>> for test in ["aaa", "aaaa", "aaaaa", "aaaab"]:
...     print(test + ':', bool(pattern.search(test)))
...
aaa: True
aaaa: True                          # Should be too many!
aaaaa: True                         # Should be too many!
aaaab: True                         # Too many, and even with the 'b'?
```

The unexpected matches occur because `"aaa"` is at the beginning of each of the test strings. With the line anchors `^` and `$`, the search truly only matches the exact string `"aaa"`.

Problem 4. A *valid Python identifier* (a valid variable name) is any string staring with an alphabetic character or an underscore, followed by any (possibly empty) sequence of alphanumeric characters and underscores.

Define a function that compiles and returns a regular expression pattern object that matches any valid Python identifier.
(Hint: Use the `\w` character class shortcut to keep your regular expression clean.)

Check your regular expression against the following words. These test cases are a good start, but are not exhaustive.

Matches:	`"Mouse"`	`"compile"`	`"_123456789"`	`"__x__"`	`"while"`
Non-matches:	`"3rats"`	`"err*r"`	`"sq(x)"`	`"sleep()"`	`" x"`

Manipulating Text with Regular Expressions

So far we have been solely concerned with whether or not a regular expression and a string match, but the power of regular expressions comes with what can be done with a match. In addition to the `search()` method, regular expression pattern objects have the following useful methods.

Method	Description
`match()`	Match a regular expression pattern to the beginning of a string.
`fullmatch()`	Match a regular expression pattern to all of a string.
`search()`	Search a string for the presence of a pattern.
`sub()`	Substitute occurrences of a pattern found in a string.
`subn()`	Same as sub, but also return the number of substitutions made.
`split()`	Split a string by the occurrences of a pattern.
`findall()`	Find all occurrences of a pattern in a string.
`finditer()`	Return an iterator yielding a match object for each match.

Table 3.4: Methods of regular expression pattern objects.

```
# Find words that start with 'cat'.
>>> expr = re.compile(r"\bcat\w*")  # \b is the shortcut for a word boundary.

>>> target = "Let's catch some catfish for the cat"
>>> bool(expr.search(target))       # Check to see if there is a match.
True

>>> expr.findall(target)            # Get all matching substrings.
['catch' 'catfish', 'cat']

>>> expr.sub("DOG", target)         # Substitute 'DOG' for the matches.
"Let's DOG some DOG for the DOG"

>>> expr.split(target)              # Split the target by the matches.
["Let's ", ' some ', ' for the ', '']
```

Some substitutions require remembering part of the text that the regular expression matches. Groups are useful here: each group in the regular expression can be represented in the substitution string by `\n`, where n is an integer (starting at 1) specifying which group to use.

```
# Find words that start with 'cat', remembering what comes after the 'cat'.
>>> pig_latin = re.compile(r"\bcat(\w*)")
>>> target = "Let's catch some catfish for the cat"

>>> pig_latin.sub(r"at\1clay", target)  # \1 = (\w*) from the expression.
"Let's atchclay some atfishclay for the atclay"
```

Note

The repetition operators `?`, `+`, `*`, and `{m,n}` are *greedy*, meaning that they match the largest string possible. On the other hand, the operators `??`, `+?`, `*?`, and `{m,n}?` are *non-greedy*, meaning they match the smallest strings possible. This is very often the desired behavior for a regular expression.

```
>>> target = "<abc> <def> <ghi>"

# Match angle brackets and anything in between.
>>> greedy = re.compile(r"^<.*>$")  # Greedy *
>>> greedy.findall(target)
['<abc> <def> <ghi>']               # The entire string matched!

# Try again, using the non-greedy version.
>>> nongreedy = re.compile(r"<.*?>")# Non-greedy *?
>>> nongreedy.findall(target)
['<abc>', '<def>', '<ghi>']         # Each <> set is an individual match.
```

Finally, there are a few customizations that make searching larger texts manageable. Each of these *flags* can be used as keyword arguments to `re.compile()`.

Flag	Description
`re.DOTALL`	`.` matches any character at all, including the newline.
`re.IGNORECASE`	Perform case-insensitive matching.
`re.MULTILINE`	`^` matches the beginning of lines (after a newline) as well as the string; `$` matches the end of lines (before a newline) as well as the end of the string.

Table 3.5: Regular expression flags.

```
# Match any line with 3 consecutive 'a' characters somewhere.
>>> pattern = re.compile("^.*a{3}.*$", re.MULTILINE)    # Search each line.
>>> pattern.findall("""
This is aaan example.
This is not an example.
Actually, it's an example, but it doesn't match.
This example does maaatch though.""")
['This is aaan example.', 'This example does maaatch though.']

# Match anything instance of 'cat', ignoring case.
>>> catfinder = re.compile("cat", re.IGNORECASE)
>>> catfinder.findall("cat CAT cAt TAC ctacATT")
['cat', 'CAT', 'cAt', 'cAT']
```

Problem 5. A Python *block* is composed of several lines of code with the same indentation level. Blocks are delimited by key words and expressions, followed by a colon. Possible key words are `if`, `elif`, `else`, `for`, `while`, `try`, `except`, `finally`, `with`, `def`, and `class`. Some of these keywords require an expression of some sort to follow before the colon (`if`, `elif`, `for`, etc.), some require no expressions to follow before the colon (`else`, `finally`), and `except` may or may not have an expression following before the colon.

Write a function that accepts a string of Python code and uses regular expressions to place colons in the appropriate spots. You may assume that every colon is missing in the input string. See the following for an example.

```
"""
k, i, p = 999, 1, 0
while k > i
    i *= 2
    p += 1
    if k != 999
        print("k should not have changed")
    else
        pass
print(p)
"""

# The string given above should become this string.
"""
k, i, p = 999, 1, 0
while k > i:
    i *= 2
    p += 1
    if k != 999:
        print("k should not have changed")
    else:
        pass
print(p)
"""
```

Problem 6. The file `fake_contacts.txt` contains poorly formatted contact data for 2000 fictitious individuals. Each line of the file contains data for one person, including their name and possibly their birthday, email address, and/or phone number. The formatting of the data is not consistent, and much of it is missing. For example, not everyone has their birthday listed, and those who do may have it listed in the form `1/1/11`, `1/01/2011`, or some other format.

Use regular expressions to parse the data and format it uniformly, writing birthdays as `mm/dd/yyyy` and phone numbers as `(xxx)xxx-xxxx`. Return a dictionary where the key is the name of an individual and the value is another dictionary containing their information. Each of these inner dictionaries should have the keys `"birthday"`, `"email"`, and `"phone"`. In the

case of missing data, map the key to `None`. The first two entries of the completed dictionary are given below.

```
{
    "John Doe": {
        "birthday": "01/01/1990",
        "email": "john_doe90@hopefullynotarealaddress.com",
        "phone": "(123)456-7890"
        },
    "Jane Smith": {
        "birthday": None,
        "email": None,
        "phone": "(222)111-3333"
        },
# ...
}
```

4 Web Technologies

Lab Objective: *The Internet is an umbrella term for the collective grouping of all publicly accessible computer networks in the world. This collective network can be traversed to access services such as social communication, maps, video streaming, and accessibility to large datasets, all of which are hosted on computers across the world. Using these technologies requires an understanding of data serialization, data transportation protocols, and how programs such as servers, clients, and APIs are created to facilitate this communication.*

Data Serialization

Serialization is the process of packaging data in a form that makes it easy to transmit the data and quickly reconstruct it on another computer or in a different programming language. One of the most prevalent serialization metalanguages is *JSON*, which stands for *JavaScript Object Notation*.[1] It stores information about objects as a specially formatted string that is easy for both humans and machines to read and write. *Deserialization* is the process of reconstructing an object from the string.

JSON is built on two types of data structures: a collection of key/value pairs and an ordered list of values, similar to Python's built-in `dict` and `list` structures, respectively.

```
{                                   # A family's info written in JSON format.
    "lastname": "Smith",            # The outer dictionary has two keys:
    "children": [                   # "lastname" and "children".
        {                           # The "children" key maps to a list of
            "name": "Timmy",        # two dictionaries, one for each of the
            "age": 8                # two children.
        },
        {
            "name": "Missy",
            "age": 5
        }
    ]
}
```

[1] Despite having "JavaScript" in its name, JSON is a language-independent format. In fact, JSON is frequently used for transmitting data between different programming languages.

> **Note**
>
> To see a longer example of what JSON looks like, try opening a Jupyter Notebook (a `.ipynb` file) in a plain text editor. The file lists the Notebook cells, each of which has attributes like `"cell_type"` (usually code or markdown) and `"source"` (the actual code in the cell).

The JSON libraries of various languages have a fairly standard interface. The Python standard library module for JSON is called `json`; if performance speed is critical, consider using the `ujson` or `simplejson` modules that are written in C.

A string written in JSON format that represents a piece of data is called a *JSON message*. To generate the JSON message for a single Python object, use `json.dumps()`. Alternatively, the function `json.dump()` generates the JSON message of an object and writes it to an open file. To load a JSON string or file, use `json.loads()` or `json.load()`, respectively.

```
>>> import json

# Store info about a car in a nested dictionary.
>>> my_car = {
...     "car": {
...         "make": "Ford",
...         "color": [255, 30, 30]  },
...     "owner": "me" }

# Get the JSON message corresponding to my_car.
>>> car_str = json.dumps(my_car)
>>> car_str
'{"car": {"make": "Ford", "color": [255, 30, 30]}, "owner": "me"}'

# Load the JSON message into a Python object, reconstructing my_car.
>>> car_object = json.loads(car_str)
>>> for key in car_object:          # The loaded object is a dictionary.
...     print(key + ':', car_object[key])
...
car: {'make': 'Ford', 'color': [255, 30, 30]}
owner: me

# Write the car info to an external file.
>>> with open("my_car.json", 'w') as outfile:
...     json.dump(my_car, outfile)
...
# Read the file to check that it saved correctly.
>>> with open("my_car.json", 'r') as infile:
...     new_car = json.load(infile)
...
>>> print(new_car.keys())           # This loaded object is also a dictionary.
dict_keys(['car', 'owner'])
```

Problem 1. The file `nyc_traffic.json` contains information about 1000 traffic accidents in New York City during the summer of 2017.[a] Each entry lists one or more reasons for the accident, such as "Unsafe Speed" or "Fell Asleep."

Write a function that loads the data from the JSON file. Look at the first few entries of the dataset and decide how to gather information about the cause(s) of each accident. Make a readable, sorted bar chart showing the total number of times that each of the 7 most common reasons for accidents are listed in the data set.
(Hint: the `collections.Counter` data structure may be useful here.)

To check your work, the 6th most common reason is "Backing Unsafely," listed 59 times.

[a] See `https://opendata.cityofnewyork.us/`.

Custom Encoders and Decoders for JSON

The default JSON encoder and decoder do not support serialization for every kind of data structure. For example, a `set` cannot be serialized using only `json` functions. However, the default JSON encoder can be subclassed to handle sets or custom data structures. A custom encoder must organize the information in an object as nested lists and dictionaries. The corresponding custom decoder uses the way that the encoder organizes the information to reconstruct the original object.

For example, one way to serialize a `set` is to express it as a dictionary with one key that indicates its data type, and another key mapping to the actual data.

```
>>> class SetEncoder(json.JSONEncoder):
...     """A custom JSON encoder for Python sets."""
...     def default(self, obj):
...         if not isinstance(obj, set):
...             raise TypeError("expected a set for encoding")
...         return {"dtype": "set", "data": list(obj)}
...
# Use the custom encoder to convert a set to its custom JSON message.
>>> set_message = json.dumps(set('abca'), cls=SetEncoder)
>>> set_message
'{"dtype": "set", "data": ["a", "b", "c"]}'

# Define a custom decoder for JSON messages generated by the SetEncoder.
>>> def set_decoder(item):
...     if "dtype" in item:
...         if item["dtype"] != "set" or "data" not in item:
...             raise ValueError("expected a JSON message from SetEncoder")
...         return set(item["data"]
...     raise ValueError("expected a JSON message from SetEncoder")
...
# Use the custom decoder to convert a JSON message to the original object.
>>> json.loads(set_message, object_hook=set_decoder)
{'a', 'b', 'c'}
```

Checks for errors like in the previous example are good practice to ensure that custom encoders and decoders are only used when intended.

Problem 2. The following class facilitates a regular 3×3 game of tic-tac-toe, where the boxes in the board have the following coordinates.

$(0,0)$	$(0,1)$	$(0,2)$
$(1,0)$	$(1,1)$	$(1,2)$
$(2,0)$	$(2,1)$	$(2,2)$

```
class TicTacToe:
    def __init__(self):
        """Initialize an empty board. The O's go first."""
        self.board = [[' ']*3 for _ in range(3)]
        self.turn, self.winner = "O", None

    def move(self, i, j):
        """Mark an O or X in the (i,j)th box and check for a winner."""
        if self.winner is not None:
            raise ValueError("the game is over!")
        elif self.board[i][j] != ' ':
            raise ValueError("space ({},{}) already taken".format(i,j))
        self.board[i][j] = self.turn

        # Determine if the game is over.
        b = self.board
        if any(sum(s == self.turn for s in r)==3 for r in b):
            self.winner = self.turn     # 3 in a row.
        elif any(sum(r[i] == self.turn for r in b)==3 for i in range(3)):
            self.winner = self.turn     # 3 in a column.
        elif b[0][0] == b[1][1] == b[2][2] == self.turn:
            self.winner = self.turn     # 3 in a diagonal.
        elif b[0][2] == b[1][1] == b[2][0] == self.turn:
            self.winner = self.turn     # 3 in a diagonal.
        else:
            self.turn = "O" if self.turn == "X" else "X"

    def empty_spaces(self):
        """Return the list of coordinates for the empty boxes."""
        return [(i,j) for i in range(3) for j in range(3)
                                        if self.board[i][j] == ' ' ]
    def __str__(self):
        return "\n---------\n".join(" | ".join(r) for r in self.board)
```

Write a custom encoder and decoder for the `TicTacToe` class. If the custom encoder receives anything other than a `TicTacToe` object, raise a `TypeError`.

NOTE

JSON is a good option for transferring data between two different languages. Python's `pickle` module is particularly good for serialization when the stored object will only be unpacked in Python. The main functions are almost identical to `json.dumps()` and its companions.

```
>>> import pickle

>>> item = pickle.dumps([1, 2, 3, 4, 5, 6])
>>> item
b'\x80\x03]q\x00(K\x01K\x02K\x03K\x04K\x05K\x06e.'

>>> pickle.loads(item)
[1, 2, 3, 4, 5, 6]
```

In addition, there are many other serialization formats such as YAML and XML. However, JSON is the dominant format for serialization in web applications.

Servers and Clients

The Internet is like a network of roads connecting the buildings of a city where each building represents a computer and each road represents the physical wires or wireless pathways that allow for intercommunication. Navigating the road properly, requires using the correct kinds of vehicles and following the established laws for road travel. There are also various kinds of vehicles for different purposes and with different capabilities that are used to transport items from building to building. In a similar fashion, the Internet has specific protocols that allow for standardized communication within and between computers.

The most common communication protocols in computer networks are contained in the Internet Protocol Suite. Among these is *Transmission Control Protocol* (TCP), used to establish a connection between two computers, exchange bits of information called *packets*, and then close the connection. More specifically, TCP creates network *socket* objects that are used to send and receive data packets from a computer. A socket is basically an address within a computer on which a program can send or receive data, like a P.O. box within a post office. The post office is the computer that receives mail, but the mail is distributed to individual programs that check the P.O. box for their personal communications.

Creating a Server

A *server* is a program that interacts with and provides functionality to *client* programs. A client program contacts a server to receive some sort of response that assists it in fulfilling its function. Servers are fundamental to modern networks and provide services such as file sharing, authentication, webpage information, databases, etc.

One simple way to create a server in Python is via the `socket` module. The server socket must first be initialized by specifying the type of connection and the address that clients can find the server at. The server socket then listens and waits for a connection from a client, receives and processes data, then eventually sends a response back to the client. After exchanges between the server and the client are finished, the server closes the connection to the client.

```
def mirror_server(server_address=("0.0.0.0", 33333)):
    """A server for reflecting strings back to clients in reverse order."""
    print("Starting mirror server on {}".format(server_address))

    # Specify the socket type, which determines how clients will connect.
    server_sock = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
    server_sock.bind(server_address)    # Assign this socket to an address.
    server_sock.listen(1)               # Start listening for clients.

    while True:
        # Wait for a client to connect to the server.
        print("\nWaiting for a connection...")
        connection, client_address = server_sock.accept()
        try:
            # Receive data from the client.
            print("Connection accepted from {}.".format(client_address))
            in_data = connection.recv(1024).decode()    # Receive data.
            print("Received '{}' from client".format(in_data))

            # Process the received data and send something back to the client.
            out_data = in_data[::-1]
            print("Sending '{}' back to the client".format(out_data))
            connection.sendall(out_data.encode())       # Send data.

        finally:    # Make sure the connection is closed securely.
            connection.close()
            print("Closing connection from {}".format(client_address))
```

The two parameters for `socket.socket()` specify the socket type.[2] The server address is a tuple (host, port). The host is the IP address, which in this case is `"localhost"` or `"0.0.0.0"`—the default address that specifies the local machine and allows connections on all interfaces. The port number is an integer from 0 to 65535. About 250 port numbers are commonly used, and certain ports have pre-defined uses.

> **Achtung!**
>
> Only use port numbers greater than 1023 to avoid interrupting standard system services.

After setting up the server socket, it waits for a client to connect. The `accept()` method returns a new socket object (`connection`) and the client's address. Data is received through the connection socket's `recv()` method, which takes an integer specifying the number of bits of data to receive. The data is transferred as a raw byte stream (of type `bytes`), so the `decode()` method is necessary to translate the data into a string. Likewise, data that is sent back to the client through the connection socket's `sendall()` method must be encoded into a byte stream via the `encode()` method.

Finally, the `try-finally` blocks ensure that the connection is always closed securely. To stop a server, raise a `KeyBoardInterrupt` (press `ctrl+c`) in the terminal where it is running.

[2] See `https://docs.python.org/3/library/socket.html` for details on these parameters.

NOTE

When running `mirror_server()`, the program hangs on the following line.

```
connection, client_address = server_sock.accept()
```

This is because the `accept()` method does not return until a connection is made with a client. Therefore, this server program cannot be executed in its entirety without a client. Client creation is addressed in the next section.

ACHTUNG!

It often takes some time for a computer to reopen a port after closing a server connection. This is due to the timeout functionality of specific protocols that check connections for errors and disruptions. While testing code, wait a few seconds before running the program again, or use different ports for each test.

Problem 3. Write a function that accepts a (host, port) tuple and starts up a tic-tac-toe server at the specified location. Wait to accept a connection, then while the connection is open, repeat the following operations.

1. Receive a JSON serialized `TicTacToe` object (serialized with your custom encoder from Problem 2) from the client.
2. Deserialize the `TicTacToe` object using your custom decoder from Problem 2.
3. If the client has just won the game, send `"WIN"` back to the client and close the connection.
4. If there is no winner but board is full, send `"DRAW"` to the client and close the connection.
5. If the game still isn't over, make a random move on the tic-tac-toe board and serialize the updated `TicTacToe` object. If this move wins the game, send `"LOSE"` to the client, then send the serialized object separately (as proof), and close the connection. Otherwise, send only the updated `TicTacToe` object back to the client but keep the connection open.

(Hint: print information at each step so you can see what the server is doing.)

Ensure that the connection closes securely even if an exception is raised. Note that you will not be able to fully test your server until you have written a client (see Problem 4).

Creating a Client

The `socket` module also has tools for writing client programs. First, create a socket object with the same settings as the server socket, then call the `connect()` method with the server address as a parameter. Once the client socket is connected to the server socket, the two sockets can transfer information between themselves.

```
def mirror_client(server_address=("0.0.0.0", 33333)):
    """A client program for mirror_server()."""
    print("Attempting to connect to server at {}...".format(server_address))

    # Set up the socket to be the same type as the server.
    client_sock = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
    client_sock.connect(server_address)    # Attempt to connect to the server.

    # Send some data from the client user to the server.
    out_data = input("Type a message to send to the server: ")
    client_sock.sendall(out_data.encode())              # Send data.

    # Wait to receive a response back from the server.
    in_data = client_sock.recv(1024).decode()           # Receive data.
    print("Received '{}' from the server".format(in_data))

    # Close the client socket.
    client_sock.close()
```

Note that unlike the server socket, the client socket sends and reads the data itself instead of creating a new connection socket. When the client program is complete, close the client socket. The server will keep running, waiting for another client to serve.

To see a client and server communicate, open a terminal and run the server, then run the client in a separate terminal.

```
# TERMINAL 1
>>> mirror_server()                 # First start up the server.
Starting mirror server on ('0.0.0.0', 33333)

Waiting for a connection...         # At this point, start the client.
Connection accepted from ('127.0.0.1', 50679).
Received 'racecars and lollipops' from client
Sending 'spopillol dna sracecar' back to the client
Closing connection from ('127.0.0.1', 50679)

Waiting for a connection...
# The client program is over, but the server waits to keep serving clients.
```

```
# TERMINAL 2
>>> mirror_client()                 # Start the client after the server.
Attempting to connect to server at ('0.0.0.0', 33333)...
Connected!
Type a message to send: racecars and lollipops
Received 'spopillol dna sracecar' from the server
```

Problem 4. Write a function that accepts a (host, port) tuple and connects to the tic-tac-toe server at the specified location. Start by initializing a new `TicTacToe` object, then repeat the following steps until the game is over.

1. Print the board and prompt the player for a move. Continue prompting the player until they provide valid input.
2. Update the board with the player's move, then serialize it using your custom encoder from Problem 2, and send the serialized version to the server.
3. Receive a response from the server. If the game is over, congratulate or mock the player appropriately. If the player lost, receive a second response from the server (the final game board), deserialize it, and print it out.

Close the connection once the game ends.

APIs

An *Application Program Interface* (API) is a particular kind of server that listens for requests from authorized users and responds with data. For example, a list of twenty different locations can be sent with the proper request syntax to a Google Maps API, and it will respond with the calculated driving time from each location to every other. Every API has *endpoints* where clients send their requests. Though standards exist for creating and communicating with APIs, most APIs have a unique syntax for authentication and requests that is documented by the organization providing the service.

Achtung!

Each website and API has a policy that specifies appropriate behavior for automated data retrieval and usage. If data is requested without complying with these requirements, there can be severe legal consequences. Most websites detail their policies in a file called *robots.txt* on their main page. See, for example, `https://www.google.com/robots.txt`.

Problem 5. The `requests` module is the standard way to send a download request to an API.

```
>>> import requests
>>> requests.get(endpoint).json()   # Download and extract the data.
```

Write a function that makes requests to download data from the following API endpoints managed by New York City.

- Recycling bin locations: https://data.cityofnewyork.us/api/views/sxx4-xhzg/rows.json?accessType=DOWNLOAD
- Residential addresses: https://data.cityofnewyork.us/api/views/7823-25a9/rows.json?accessType=DOWNLOAD

Save the recycling data as `nyc_recycling.json` and the address data as `nyc_addresses.json`.

Problem 6. Write a function that loads the data files generated in Problem 5 but **does not** call the actual function from Problem 5. Determine how close the residential addresses in New York City are to the nearest recycling bin.

1. Retrieve the latitude and longitude of each recycling bin and, separately, the latitude and longitude of each residential address (ignore entries without these coordinates). Note carefully that the coordinates for the recycling data are in (latitude, longitude) format, but the coordinates for the address data are in (longitude, latitude) format.
   (Hint: Both datasets are, at the highest level, dictionaries with two keys: `"meta"`, which has information about the data; and `"data"`, which has the actual data. All of the information needed is contained in the `"data"` key value.)
2. Load the recycling bin data into a k-d tree.
3. For each address, query the tree to find the distance to the nearest recycling bin, in terms of the coordinates.
4. Plot a histogram of the distances.

For steps 2–3, recall the following syntax for using a k-d tree in SciPy.

```
from scipy.spatial import KDTree

tree = KDTree(data)                          # Initialize the tree.
min_distance, index = tree.query(target)     # Query for a point.
```

5 Web Scraping I: Introduction to BeautifulSoup

Lab Objective: *Web Scraping is the process of gathering data from websites on the internet. Since almost everything rendered by an internet browser as a web page uses HTML, the first step in web scraping is being able to extract information from HTML. In this lab, we introduce BeautifulSoup, Python's canonical tool for efficiently and cleanly navigating and parsing HTML.*

HTML

Hyper Text Markup Language, or *HTML*, is the standard *markup language*—a language designed for the processing, definition, and presentation of text—for creating webpages. It provides a document with structure and is composed of pairs of *tags* to surround and define various types of content. Opening tags have a tag name surrounded by angle brackets (`<tag-name>`). The companion closing tag looks the same, but with a forward slash before the tag name (`</tag-name>`). A list of all current HTML tags can be found at `http://htmldog.com/reference/htmltags`.

Most tags can be combined with *attributes* to include more data about the content, help identify individual tags, and make navigating the document much simpler. In the following example, the `<a>` tag has `id` and `href` attributes.

```
<html>                                  <!-- Opening tags -->
   <body>
       <p>
           Click <a id='info' href='http://www.example.com'>here</a>
           for more information.
       </p>                             <!-- Closing tags -->
   </body>
</html>
```

In HTML, `href` stands for *hypertext reference*, a link to another website. Thus the above example would be rendered by a browser as a single line of text, with `here` being a clickable link to `http://www.example.com`:

Click here for more information.

Unlike Python, HTML does not enforce indentation (or any whitespace rules), though indentation generally makes HTML more readable. The previous example can even be written equivalently in a single line.

```
<html><body><p>Click <a id='info' href='http://www.example.com/info'>here</a>
  for more information.</p></body></html>
```

Special tags, which don't contain any text or other tags, are written without a closing tag and in a single pair of brackets. A forward slash is included between the name and the closing bracket. Examples of these include `<hr/>`, which describes a horizontal line, and `<img/>`, the tag for representing an image.

Problem 1. The HTML of a website is easy to view in most browsers. In Google Chrome, go to `http://www.example.com`, right click anywhere on the page that isn't a picture or a link, and select `View Page Source`. This will open the HTML source code that defines the page. Examine the source code. What tags are used? What is the value of the `type` attribute associated with the `style` tag?

Write a function that returns the set of names of tags used in the website, and the value of the `type` attribute of the `style` tag (as a string).
(Hint: there are ten unique tag names.)

BeautifulSoup

BeautifulSoup (`bs4`) is a package[1] that makes it simple to navigate and extract data from HTML documents. See `http://www.crummy.com/software/BeautifulSoup/bs4/doc/index.html` for the full documentation.

The `bs4.BeautifulSoup` class accepts two parameters to its constructor: a string of HTML code, and an HTML parser to use under the hood. The HTML parser is technically a keyword argument, but the constructor prints a warning if one is not specified. The standard choice for the parser is `"html.parser"`, which means the object uses the standard library's `html.parser` module as the engine behind the scenes.

Note

Depending on project demands, a parser other than `"html.parser"` may be useful. A couple of other options are `"lxml"`, an extremely fast parser written in C, and `"html5lib"`, a slower parser that treats HTML in much the same way a web browser does, allowing for irregularities. Both must be installed independently; see `https://www.crummy.com/software/BeautifulSoup/bs4/doc/#installing-a-parser` for more information.

A `BeautifulSoup` object represents an HTML document as a tree. In the tree, each tag is a *node* with nested tags and strings as its *children*. The `prettify()` method returns a string that can be printed to represent the BeautifulSoup object in a readable format that reflects the tree structure.

[1] BeautifulSoup is not part of the standard library; install it with `conda install beautifulsoup4` or with `pip install beautifulsoup4`.

```
>>> from bs4 import BeautifulSoup

>>> small_example_html = """
<html><body><p>
    Click <a id='info' href='http://www.example.com'>here</a>
    for more information.
</p></body></html>
"""

>>> small_soup = BeautifulSoup(small_example_html, 'html.parser')
>>> print(small_soup.prettify())
<html>
 <body>
  <p>
   Click
   <a href="http://www.example.com" id="info">
    here
   </a>
   for more information.
  </p>
 </body>
</html>
```

Each tag in a `BeautifulSoup` object's HTML code is stored as a `bs4.element.Tag` object, with actual text stored as a `bs4.element.NavigableString` object. Tags are accessible directly through the `BeautifulSoup` object.

```
# Get the <p> tag (and everything inside of it).
>>> small_soup.p
<p>
    Click <a href="http://www.example.com" id="info">here</a>
    for more information.
</p>

# Get the <a> sub-tag of the <p> tag.
>>> a_tag = small_soup.p.a
>>> print(a_tag, type(a_tag), sep='\n')
<a href="http://www.example.com" id="info">here</a>
<class 'bs4.element.Tag'>

# Get just the name, attributes, and text of the <a> tag.
>>> print(a_tag.name, a_tag.attrs, a_tag.string, sep="\n")
a
{'id': 'info', 'href': 'http://www.example.com'}
here
```

Attribute	Description
`name`	The name of the tag
`attrs`	A dictionary of the attributes
`string`	The single string contained in the tag
`strings`	Generator for strings of children tags
`stripped_strings`	Generator for strings of children tags, stripping whitespace
`text`	Concatenation of strings from all children tags

Table 5.1: Data attributes of the `bs4.element.Tag` class.

Problem 2. The `BeautifulSoup` class has a `find_all()` method that, when called with `True` as the only argument, returns a list of all tags in the HTML source code.

Write a function that accepts a string of HTML code as an argument. Use BeautifulSoup to return a list of the **names** of the tags in the code. Use your function and the source code from `http://www.example.com` (see `example.html`) to check your answers from Problem 1.

Navigating the Tree Structure

Not all tags are easily accessible from a `BeautifulSoup` object. Consider the following example.

```
>>> pig_html = """
<html><head><title>Three Little Pigs</title></head>
<body>
<p class="title"><b>The Three Little Pigs</b></p>
<p class="story">Once upon a time, there were three little pigs named
<a href="http://example.com/larry" class="pig" id="link1">Larry,</a>
<a href="http://example.com/mo" class="pig" id="link2">Mo</a>, and
<a href="http://example.com/curly" class="pig" id="link3">Curly.</a>
<p>The three pigs had an odd fascination with experimental construction.</p>
<p>...</p>
</body></html>
"""

>>> pig_soup = BeautifulSoup(pig_html, "html.parser")
>>> pig_soup.p
<p class="title"><b>The Three Little Pigs</b></p>

>>> pig_soup.a
<a class="pig" href="http://example.com/larry" id="link1">Larry,</a>
```

Since the HTML in this example has several `<p>` and `<a>` tags, only the **first** tag of each name is accessible directly from `pig_soup`. The other tags can be accessed by manually navigating through the HTML tree.

Every HTML tag (except for the topmost tag, which is usually `<html>`) has a *parent* tag. Each tag also has and zero or more *sibling* and *children* tags or text. Following a true tree structure, every `bs4.element.Tag` in a soup has multiple attributes for accessing or iterating through parent, sibling, or child tags.

Attribute	Description
`parent`	The parent tag
`parents`	Generator for the parent tags up to the top level
`next_sibling`	The tag immediately after to the current tag
`next_siblings`	Generator for sibling tags after the current tag
`previous_sibling`	The tag immediately before to the current tag
`previous_siblings`	Generator for sibling tags before the current tag
`contents`	A list of the immediate children tags
`children`	Generator for immediate children tags
`descendants`	Generator for all children tags (recursively)

Table 5.2: Navigation attributes of the `bs4.element.Tag` class.

```
>>> print(pig_soup.prettify())
<html>
 <head>                     # <head> is the parent of the <title>
  <title>
   Three Little Pigs
  </title>
 </head>
 <body>                     # <body> is the sibling of <head>
  <p class="title">         # and the parent of two <p> tags (title and story).
   <b>
    The Three Little Pigs
   </b>
  </p>
  <p class="story">
   Once upon a time, there were three little pigs named
   <a class="pig" href="http://example.com/larry" id="link1">
    Larry,
   </a>
   <a class="pig" href="http://example.com/mo" id="link2">
    Mo
   </a>
   , and
   <a class="pig" href="http://example.com/curly" id="link3">
    Curly.                  # The preceding <a> tags are siblings with each
   </a>                     # other and the following two <p> tags.
   <p>
    The three pigs had an odd fascination with experimental construction.
   </p>
   <p>
    ...
   </p>
  </p>
 </body>
</html>
```

```
# Start at the first <a> tag in the soup.
>>> a_tag = pig_soup.a
>>> a_tag
<a class="pig" href="http://example.com/larry" id="link1">Larry,</a>

# Get the names of all of <a>'s parent tags, traveling up to the top.
# The name '[document]' means it is the top of the HTML code.
>>> [par.name for par in a_tag.parents]     # <a>'s parent is <p>, whose
['p', 'body', 'html', '[document]']         # parent is <body>, and so on.

# Get the next siblings of <a>.
>>> a_tag.next_sibling
'\n'                                        # The first sibling is just text.
>>> a_tag.next_sibling.next_sibling         # The second sibling is a tag.
<a class="pig" href="http://example.com/mo" id="link2">Mo</a>

# Alternatively, get all siblings past <a> at once.
>>> list(a_tag.next_siblings)
['\n',
 <a class="pig" href="http://example.com/mo" id="link2">Mo</a>,
 ', and\n',
 <a class="pig" href="http://example.com/curly" id="link3">Curly.</a>,
 '\n',
 <p>The three pigs had an odd fascination with experimental construction.</p>,
 '\n',
 <p>...</p>,
 '\n']
```

Note carefully that newline characters are considered to be children of a parent tag. Therefore iterating through children or siblings often requires checking which entries are tags and which are just text.

```
# Get to the <p> tag that has class="story".
>>> p_tag = pig_soup.body.p.next_sibling.next_sibling
>>> p_tag.attrs["class"]                # Make sure it's the right tag.
['story']

# Iterate through the child tags of <p> and print hrefs whenever they exist.
>>> for child in p_tag.children:
...     if hasattr(child, "attrs") and "href" in child.attrs:
...         print(child.attrs["href"])
http://example.com/larry
http://example.com/mo
http://example.com/curly
```

Note that the `"class"` attribute of the `<p>` tag is a list. This is because the `"class"` attribute can take on several values at once; for example, the tag `<p class="story book">` is of class `'story'` and of class `'book'`.

Note

The behavior of the `string` attribute of a `bs4.element.Tag` object depends on the structure of the corresponding HTML tag.

1. If the tag has a string of text and no other child elements, then `string` is just that text.
2. If the tag has exactly one child tag and the child tag has only a string of text, then the tag has the same `string` as its child tag.
3. If the tag has more than one child, then `string` is `None`. In this case, use `strings` to iterate through the child strings. Alternatively, the `get_text()` method returns all text belonging to a tag and to all of its descendants. In other words, it returns anything inside a tag that isn't another tag.

```
>>> pig_soup.head
<head><title>Three Little Pigs</title></head>

# Case 1: the <title> tag's only child is a string.
>>> pig_soup.head.title.string
'Three Little Pigs'

# Case 2: The <head> tag's only child is the <title> tag.
>>> pig_soup.head.string
'Three Little Pigs'

# Case 3: the <body> tag has several children.
>>> pig_soup.body.string is None
True
>>> print(pig_soup.body.get_text().strip())
The Three Little Pigs
Once upon a time, there were three little pigs named
Larry,
Mo, and
Curly.
The three pigs had an odd fascination with experimental construction.
...
```

Problem 3. The file `example.html` contains the HTML source for `http://www.example.com`. Write a function that reads the file and loads the code into BeautifulSoup. Find the only `<a>` tag with a hyperlink and return its text.

Searching for Tags

Navigating the HTML tree manually can be helpful for gathering data out of lists or tables, but these kinds of structures are usually buried deep in the tree. The `find()` and `find_all()` methods of the `BeautifulSoup` class identify tags that have distinctive characteristics, making it much easier to jump straight to a desired location in the HTML code. The `find()` method only returns the **first** tag that matches a given criteria, while `find_all()` returns a list of all matching tags. Tags can be matched by name, attributes, and/or text.

```
# Find the first <b> tag in the soup.
>>> pig_soup.find(name='b')
<b>The Three Little Pigs</b>

# Find all tags with a class attribute of 'pig'.
# Since 'class' is a Python keyword, use 'class_' as the argument.
>>> pig_soup.find_all(class_="pig")
[<a class="pig" href="http://example.com/larry" id="link1">Larry,</a>,
 <a class="pig" href="http://example.com/mo" id="link2">Mo</a>,
 <a class="pig" href="http://example.com/curly" id="link3">Curly.</a>]

# Find the first tag that matches several attributes.
>>> pig_soup.find(attrs={"class": "pig", "href": "http://example.com/mo"})
<a class="pig" href="http://example.com/mo" id="link2">Mo</a>

# Find the first tag whose text is 'Mo'.
>>> pig_soup.find(string='Mo')
'Mo'                                  # The result is the actual string,
>>> soup.find(string='Mo').parent       # so go up one level to get the tag.
<a class="pig" href="http://example.com/mo" id="link2">Mo</a>
```

Problem 4. The file `san_diego_weather.html` contains the HTML source for an old page from Weather Underground.[a]. Write a function that reads the file and loads it into BeautifulSoup. Return a list of the following tags:

1. The tag containing the date "Thursday, January 1, 2015".
2. The tags which contain the **links** "Previous Day" and "Next Day."
3. The tag which contains the number associated with the Actual Max Temperature.

This HTML tree is significantly larger than the previous examples. To get started, consider opening the file in a web browser. Find the element that you are searching for on the page, right click it, and select `Inspect`. This opens the HTML source at the element that the mouse clicked on.

[a] See `http://www.wunderground.com/history/airport/KSAN/2015/1/1/DailyHistory.html?req_city=San+Diego&req_state=CA&req_statename=California&reqdb.zip=92101&reqdb.magic=1&reqdb.wmo=99999&MR=1`

Advanced Search Techniques

Consider the problem of finding the tag that is a link the URL `http://example.com/curly`.

```
>>> pig_soup.find(href="http://example.com/curly")
<a class="pig" href="http://example.com/curly" id="link3">Curly.</a>
```

This approach works, but it requires entering in the entire URL. To perform generalized searches, the `find()` and `find_all()` method also accept compile regular expressions from the `re` module. This way, the methods locate tags whose name, attributes, and/or string matches a pattern.

```
>>> import re

# Find the first tag with an href attribute containing 'curly'.
>>> pig_soup.find(href=re.compile(r"curly"))
<a class="pig" href="http://example.com/curly" id="link3">Curly.</a

# Find the first tag with a string that starts with 'Cu'.
>>> pig_soup.find(string=re.compile(r"^Cu")).parent
<a class="pig" href="http://example.com/curly" id="link3">Curly.</a>

# Find all tags with text containing 'Three'.
>>> [tag.parent for tag in pig_soup.find_all(string=re.compile(r"Three"))]
[<title>Three Little Pigs</title>, <b>The Three Little Pigs</b>]
```

Finally, to find a tag that has a particular attribute, regardless of the actual value of the attribute, use `True` in place of search values.

```
# Find all tags with an 'id' attribute.
>>> pig_soup.find_all(id=True)
[<a class="pig" href="http://example.com/larry" id="link1">Larry,</a>,
 <a class="pig" href="http://example.com/mo" id="link2">Mo</a>,
 <a class="pig" href="http://example.com/curly" id="link3">Curly.</a>]

# Final the names all tags WITHOUT an 'id' attribute.
>>> [tag.name for tag in pig_soup.find_all(id=False)]
['html', 'head', 'title', 'body', 'p', 'b', 'p', 'p', 'p']
```

Problem 5. The file `large_banks_index.html` is an index of data about large banks, as recorded by the Federal Reserve.[a] Write a function that reads the file and loads the source into BeautifulSoup. Return a list of the tags containing the links to bank data from September 30, 2003 to December 31, 2014, where the dates are in reverse chronological order.

[a] See `https://www.federalreserve.gov/releases/lbr/`.

Problem 6. The file `large_banks_data.html` is one of the pages from the index in Problem 5.[a] Write a function that reads the file and loads the source into BeautifulSoup. Create a single figure with two subplots:

1. A sorted bar chart of the seven banks with the most domestic branches.
2. A sorted bar chart of the seven banks with the most foreign branches.

In the case of a tie, sort the banks alphabetically by name.

[a] See `http://www.federalreserve.gov/releases/lbr/20030930/default.htm`.

6 Web Scraping II: Advanced Web Scraping Techniques

Lab Objective: *Gathering data from the internet often requires information from several web pages. In this lab, we present two methods for crawling through multiple web pages without violating copyright laws or straining the load a server. We also demonstrate how to scrape data from asynchronously loaded web pages, and how to interact programmatically with web pages when needed.*

Scraping Etiquette

There are two main ways that web scraping can be problematic for a website owner. First, if the scraper doesn't respect the website's terms and conditions or gathers private or proprietary data. Second, if the scraper imposes too much extra server load by making requests too often or in quick succession. These are extremely important considerations in any web scraping program.

Achtung!

Scraping copyrighted information without the consent of the copyright owner can have severe legal consequences. Many websites, in their terms and conditions, prohibit scraping parts or all of the site. Websites that do allow scraping usually have a file called `robots.txt` (for example, `www.google.com/robots.txt`) that specifies which parts of the website are off-limits and how often requests can be made according to the *robots exclusion standard.*[a]

Be careful and considerate when doing any sort of scraping, and take care when writing and testing code to avoid unintended behavior. It is up to the programmer to create a scraper that respects the rules found in the terms and conditions and in `robots.txt`.[b]

[a] See `www.robotstxt.org/orig.html` and `en.wikipedia.org/wiki/Robots_exclusion_standard`.

[b] Python provides a parsing library called `urllib.robotparser` for reading `robot.txt` files. For more information, see `https://docs.python.org/3/library/urllib.robotparser.html`.

The standard way to get the HTML source code of a website using Python is via the `requests` library.[1] Calling `requests.get()` sends an HTTP GET request to a specified website; the result is an object with a response code to indicate whether or not the request was responded to, and access to the website source code.

[1] Though `requests` is not part of the standard library, it is recognized as a standard tool in the data science community. See `http://docs.python-requests.org/`.

```
>>> import requests

# Make a request and check the result. A status code of 200 is good.
>>> response = requests.get("http://www.example.com")
>>> print(response.status_code, response.ok, response.reason)
200 True OK

# The HTML of the website is stored in the 'text' attribute.
>>> print(response.text)
<!doctype html>
<html>
<head>
    <title>Example Domain</title>

    <meta charset="utf-8" />
    <meta http-equiv="Content-type" content="text/html; charset=utf-8" />
# ...
```

ACHTUNG!

Consecutive GET requests without pauses can strain a website's server and provoke retaliation. Most servers are designed to identify such scrapers, block their access, and sometimes even blacklist the user. This is especially common in smaller websites that aren't built to handle enormous amounts of traffic. To briefly pause the program between requests, use `time.sleep()`.

```
>>> import time
>>> time.sleep(3)                    # Pause execution for 3 seconds.
```

The amount of necessary wait time depends on the website. Sometimes, `robots.txt` contains a `Request-rate` directive which gives a ratio of the form `<requests>/<seconds>`. If this doesn't exist, pausing for a half-second to a second between requests is typically sufficient. An email to the site's webmaster is always the safest approach, and may be necessary for large scraping operations.

Crawling Through Multiple Pages

While web *scraping* refers to the actual gathering of web-based data, web *crawling* refers to the navigation of a program between webpages. Web crawling allows a program to gather related data from multiple web pages and websites.

Consider `www.wunderground.com`, a site that records weather data in various cities. The page `https://www.wunderground.com/history/airport/KSAN/2012/7/1/DailyHistory.html` records the weather in San Diego on July 1, 2012. Data for previous or subsequent days can be accessed by clicking on the `Previous Day` and `Next Day` links, so gathering data for an entire month or year requires crawling through several pages. The following example gathers temperature data for July 1 through July 4 of 2012.

```
import re
import time
import requests
from bs4 import BeautifulSoup


def wunder_temp(day="/history/airport/KSAN/2012/7/1/DailyHistory.html"):
    """Crawl through Weather Underground and extract temperature data."""
    # Initialize variables, including a regex for finding the 'Next Day' link.
    actual_mean_temp = []
    next_day_finder = re.compile(r"Next Day")
    base_url = "https://www.wunderground.com"       # Web page base URL.
    page = base_url + day                           # Complete page URL.
    current = None

    for _ in range(4):
        while current is None:  # Try downloading until it works.
            # Download the page source and PAUSE before continuing.
            page_source = requests.get(page).text
            time.sleep(1)           # PAUSE before continuing.
            soup = BeautifulSoup(page_source, "html.parser")
            current = soup.find(string="Mean Temperature")

        # Navigate to the relevant tag, then extract the temperature data.
        temp_tag = current.parent.parent.next_sibling.next_sibling.span.span
        actual_mean_temp.append(int(temp_tag.string))

        # Find the URL for the page with the next day's data.
        new_day = soup.find(string=next_day_finder).parent["href"]
        page = base_url + new_day                   # New complete page URL.
        current = None

    return actual_mean_temp
```

In this example, the `for` loop cycles through the days, and the `while` loop ensures that each website page loads properly: if the downloaded `page_source` doesn't have a tag whose string is "Mean Temperature", the request is sent again. Later, after locating and recording the Actual Mean Temperature, the function locates the link to the next day's page. This link is stored in the HTML as a relative website path (`/history/airport/...`); the complete URL to the next day's page is the concatenation of the base URL `https://www.wunderground.com` with this relative link.

Problem 1. Modify `wunder_temp()` so that it gathers the Actual Mean Temperature, Actual Max Temperature, and Actual Min Temperature for every day in July of 2012. Plot these three measurements against time on the same plot.

Consider printing information at each iteration of the outer loop to keep track of the program's progress.

An alternative approach that is often useful is to first identify the links to relevant pages, then scrape each of these page in succession. For example, the Federal Reserve releases quarterly data on large banks in the United States at `http://www.federalreserve.gov/releases/lbr`. The following function extracts the four measurements of total consolidated assets for JPMorgan Chase during 2004.

```
def bank_data():
    """Crawl through the Federal Reserve site and extract bank data."""
    # Compile regular expressions for finding certain tags.
    link_finder = re.compile(r"2004$")
    chase_bank_finder = re.compile(r"^JPMORGAN CHASE BK")

    # Get the base page and find the URLs to all other relevant pages.
    base_url="https://www.federalreserve.gov/releases/lbr/"
    base_page_source = requests.get(base_url).text
    base_soup = BeautifulSoup(base_page_source, "html.parser")
    link_tags = base_soup.find_all(name='a', href=True, string=link_finder)
    pages = [base_url + tag.attrs["href"] for tag in link_tags]

    # Crawl through the individual pages and record the data.
    chase_assets = []
    for page in pages:
        time.sleep(1)               # PAUSE, then request the page.
        soup = BeautifulSoup(requests.get(page).text, "html.parser")

        # Find the tag corresponding to Chase Banks's consolidated assets.
        temp_tag = soup.find(name="td", string=chase_bank_finder)
        for _ in range(10):
            temp_tag = temp_tag.next_sibling
        # Extract the data, removing commas.
        chase_assets.append(int(temp_tag.string.replace(',', '')))

    return chase_assets
```

Problem 2. Modify `bank_data()` so that it extracts the total consolidated assets ("Consol Assets") for JPMorgan Chase, Bank of America, and Wells Fargo recorded each December from 2004 to the present. In a single figure, plot each bank's assets against time. Be careful to keep the data sorted by date.

Problem 3. ESPN hosts data on NBA athletes at `http://www.espn.go.com/nba/statistics`. Each player has their own page with detailed performance statistics. For each of the five offensive leaders in points and each of the five defensive leaders in rebounds, extract the player's career minutes per game (MPG) and career points per game (PPG). Make a scatter plot of MPG against PPG for these ten players.

Asynchronously Loaded Content and User Interaction

Web crawling with the methods presented in the previous section fails under a few circumstances. First, many webpages use *JavaScript*, the standard client-side scripting language for the web, to load portions of their content *asynchronously*. This means that at least some of the content isn't initially accessible through the page's source code. Second, some pages require user interaction, such as clicking buttons which aren't links (`<a>` tags which contain a URL that can be loaded) or entering text into form fields (like search bars).

The *Selenium* framework provides a solution to both of these problems. Originally developed for writing unit tests for web applications, Selenium allows a program to open a web browser and interact with it in the same way that a human user would, including clicking and typing. It also has BeautifulSoup-esque tools for searching the HTML source of the current page.

> **Note**
>
> Selenium requires an executable *driver* file for each kind of browser. The following examples use Google Chrome, but Selenium supports Firefox, Internet Explorer, Safari, Opera, and PhantomJS (a special browser without a user interface). See `https://seleniumhq.github.io/selenium/docs/api/py` or `http://selenium-python.readthedocs.io/installation.html` for installation instructions.

To use Selenium, start up a browser using one of the drivers in `selenium.webdriver`. The browser has a `get()` method for going to different web pages, a `page_source` attribute containing the HTML source of the current page, and a `close()` method to exit the browser.

```
>>> from selenium import webdriver

# Start up a browser and go to example.com.
>>> browser = webdriver.Chrome()
>>> browser.get("https://www.example.com")

# Feed the HTML source code for the page into BeautifulSoup for processing.
>>> soup = BeautifulSoup(browser.page_source, "html.parser")
>>> print(soup.prettify())
<!DOCTYPE html>
<html xmlns="http://www.w3.org/1999/xhtml">
 <head>
  <title>
   Example Domain
  </title>
  <meta charset="utf-8"/>
  <meta content="text/html; charset=utf-8" http-equiv="Content-type"/>
# ...

>>> browser.close()                # Close the browser.
```

Selenium can deliver the HTML page source to BeautifulSoup, but it also has its own tools for finding tags in the HTML.

Method	Returns
`find_element_by_tag_name()`	The first tag with the given name
`find_element_by_name()`	The first tag with the specified `name` attribute
`find_element_by_class_name()`	The first tag with the given `class` attribute
`find_element_by_id()`	The first tag with the given `id` attribute
`find_element_by_link_text()`	The first tag with a matching `href` attribute
`find_element_by_partial_link_text()`	The first tag with a partially matching `href` attribute

Table 6.1: Methods of the `selenium.webdriver.Chrome` class.

Each of the `find_element_by_*()` methods returns a single object representing a *web element* (of type `selenium.webdriver.remote.webelement.WebElement`), much like a BeautifulSoup tag (of type `bs4.element.Tag`). If no such element can be found, a Selenium `NoSuchElementException` is raised. Each webdriver also has several `find_elements_by_*()` methods (elements, plural) that return a list of all matching elements, or an empty list if there are no matches.

Web element objects have methods that allow the program to interact with them: `click()` sends a click, `send_keys()` enters in text, and `clear()` deletes existing text. This functionality makes it possible for Selenium to interact with a website in the same way that a human would. For example, the following code opens up `https://www.google.com`, types "Python Selenium Docs" into the search bar, and hits enter.

```
>>> from selenium.webdriver.common.keys import Keys
>>> from selenium.common.exceptions import NoSuchElementException

>>> browser = webdriver.Chrome()
>>> try:
...     browser.get("https://www.google.com")
...     try:
...         # Get the search bar, type in some text, and press Enter.
...         search_bar = browser.find_element_by_name('q')
...         search_bar.clear()                  # Clear any pre-set text.
...         search_bar.send_keys("Python Selenium Docs")
...         search_bar.send_keys(Keys.RETURN)   # Press Enter.
...     except NoSuchElementException:
...         print("Could not find the search bar!")
...         raise
... finally:
...     browser.close()
...
```

Problem 4. The arXiv (pronounced "archive") is an online repository of scientific publications, hosted by Cornell University. Write a function that accepts a string to serve as a search query. Use Selenium to enter the query into the search bar of `https://arxiv.org` and press Enter. The resulting page has up to 25 links to the PDFs of technical papers that match the query. Gather these URLs, then continue to the next page (if there are more results) and continue gathering links until obtaining at most 100 URLs. Return the list of URLs.

Note

Using Selenium to access a page's source code is typically much safer, though slower, than using `requests.get()`, since Selenium waits for each web page to load before proceeding. For instance, the arXiv is a somewhat defensive about scrapers (`https://arxiv.org/help/robots`), but Selenium makes it possible to gather info from the website without offending the administrators.

Problem 5. *Project Euler* (`https://projecteuler.net`) is a collection of mathematical computing problems. Each problem is listed with an ID, a description/title, and the number of users that have solved the problem.

Using Selenium, BeautifulSoup, or both, for each of the (at least) 600 problems in the archive at `https://projecteuler.net/archives`, record the problem ID and the number of people who have solved it. Return a list of IDs, sorted from largest to smallest by the number of people who have solved them. That is, the first entry in the list should be the ID of the **most solved** problem, and the last entry in the list should be the ID of the **least solved** problem. (Hint: start by identifying the URLs to each archive page.)

7 Pandas 1: Introduction

Lab Objective: *Though NumPy and SciPy are powerful tools for numerical computing, they lack some of the high-level functionality necessary for many data science applications. Python's* pandas *library, built on NumPy, is designed specifically for data management and analysis. In this lab, we introduce pandas data structures, syntax, and explore its capabilities for quickly analyzing and presenting data.*

Series

A pandas `Series` is generalization of a one-dimensional NumPy array. Like a NumPy array, every `Series` has a data type (`dtype`), and the entries of the `Series` are all of that type. Unlike a NumPy array, every `Series` has an *index* that labels each entry, and a `Series` object can also be given a name to label the entire data set.

```
>>> import numpy as np
>>> import pandas as pd

# Initialize a Series of random entries with an index of letters.
>>> pd.Series(np.random.random(4), index=['a', 'b', 'c', 'd'])
a    0.474170
b    0.106878
c    0.420631
d    0.279713
dtype: float64

# The default index is integers from 0 to the length of the data.
>>> pd.Series(np.random.random(4), name="uniform draws")
0    0.767501
1    0.614208
2    0.470877
3    0.335885
Name: uniform draws, dtype: float64
```

The index in a `Series` is a pandas object of type `Index` and is stored as the `index` attribute of the `Series`. The plain entries in the `Series` are stored as a NumPy array and can be accessed as such via the `values` attribute.

```
>>> s1 = pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'], name="some ints")

>>> s1.values                           # Get the entries as a NumPy array.
array([1, 2, 3, 4])

>>> print(s1.name, s1.dtype, sep=", ")  # Get the name and dtype.
some ints, int64

>>> s1.index                            # Get the pd.Index object.
Index(['a', 'b', 'c', 'd'], dtype='object')
```

The elements of a `Series` can be accessed by either the regular position-based integer index, or by the corresponding label in the index. New entries can be added dynamically as long as a valid index label is provided, similar to adding a new key-value pair to a dictionary. A `Series` can also be initialize from a dictionary: the keys become the index labels, and the values become the entries.

```
>>> s2 = pd.Series([10, 20, 30], index=["apple", "banana", "carrot"])
>>> s2
apple     10
banana    20
carrot    30
dtype: int64

# s2[0] and s2["apple"] refer to the same entry.
>>> print(s2[0], s2["apple"], s2["carrot"])
10 10 30

>>> s2[0] += 5              # Change the value of the first entry.
>>> s2["dewberry"] = 0      # Add a new value with label 'dewberry'.
>>> s2
apple       15
banana      20
carrot      30
dewberry     0
dtype: int64

# Initialize a Series from a dictionary.
>>> pd.Series({"eggplant":3, "fig":5, "grape":7}, name="more foods")
eggplant    3
fig         5
grape       7
Name: more foods, dtype: int64
```

Slicing and fancy indexing also work the same way in `Series` as in NumPy arrays. In addition, multiple entries of a `Series` can be selected by indexing a list of labels in the index.

```
>>> s3 = pd.Series({"lions":2, "tigers":1, "bears":3}, name="oh my")
>>> s3
bears     3
lions     2
tigers    1
Name: oh my, dtype: int64

# Get a subset of the data by regular slicing.
>>> s3[1:]
lions     2
tigers    1
Name: oh my, dtype: int64

# Get a subset of the data with fancy indexing.
>>> s3[np.array([len(i) == 5 for i in s3.index])]
bears    3
lions    2
Name: oh my, dtype: int64

# Get a subset of the data by providing several index labels.
>>> s3[ ["tigers", "bears"] ]
tigers    1                    # Note that the entries are reordered,
bears     3                    # and the name stays the same.
Name: oh my, dtype: int64
```

Problem 1. Create a pandas `Series` where the index labels are the even integers $0, 2, \ldots, 50$, and the entries are $n^2 - 1$, where n is the entry's label. Set all of the entries equal to zero whose labels are divisible by 3.

Operations with Series

A `Series` object has all of the advantages of a NumPy array, including entry-wise arithmetic, plus a few additional features (see Table 7.1). Operations between a `Series` S_1 with index I_1 and a `Series` S_2 with index I_2 results in a new `Series` with index $I_1 \cup I_2$. In other words, the index dictates how two `Series` can interact with each other.

```
>>> s4 = pd.Series([1, 2, 4], index=['a', 'c', 'd'])
>>> s5 = pd.Series([10, 20, 40], index=['a', 'b', 'd'])
>>> 2*s4 + s5
a    12.0
b     NaN                        # s4 doesn't have an entry for b, and
c     NaN                        # s5 doesn't have an entry for c, so
d    48.0                        # the combination is Nan (np.nan / None).
dtype: float64
```

Method	Returns
`abs()`	Object with absolute values taken (of numerical data)
`argmax()`	The index label of the maximum value
`argmin()`	The index label of the minimum value
`count()`	The number of non-null entries
`cumprod()`	The cumulative product over an axis
`cumsum()`	The cumulative sum over an axis
`max()`	The maximum of the entries
`mean()`	The average of the entries
`median()`	The median of the entries
`min()`	The minimum of the entries
`mode()`	The most common element(s)
`prod()`	The product of the elements
`sum()`	The sum of the elements
`var()`	The variance of the elements

Table 7.1: Numerical methods of the `Series` and `DataFrame` pandas classes.

Many `Series` are more useful than NumPy arrays primarily because of their index. For example, a `Series` can be indexed by time with a pandas `DatetimeIndex`, an index with date and/or time values. The usual way to create this kind of index is with `pd.date_range()`.

```
# Make an index of the first three days in July 2000.
>>> pd.date_range("7/1/2000", "7/3/2000", freq='D')
DatetimeIndex(['2000-07-01', '2000-07-02', '2000-07-03'],
              dtype='datetime64[ns]', freq='D')
```

Problem 2. Suppose you make an investment of d dollars in a particularly volatile stock. Every day the value of your stock goes up by \$1 with probability p, or down by \$1 with probability $1-p$ (this is an example of a *random walk*).

Write a function that accepts a probability parameter p and an initial amount of money d, defaulting to 100. Use `pd.date_range()` to create an index of the days from 1 January 2000 to 31 December 2000. Simulate the daily change of the stock by making one draw from a Bernoulli distribution with parameter p (a binomial distribution with one draw) for each day. Store the draws in a pandas `Series` with the date index and set the first draw to the initial amount d. Sum the entries cumulatively to get the stock value by day. Set any negative values to 0, then plot the series using the `plot()` method of the `Series` object.

Call your function with a few different values of p and d to observe the different possible kinds of behavior.

Note

The `Series` in Problem 2 is an example of a *time series*, since it is indexed by time. Time series show up often in data science; we will explore them in more depth in another lab.

Method	Description
`append()`	Concatenate two or more `Series`.
`drop()`	Remove the entries with the specified label or labels
`drop_duplicates()`	Remove duplicate values
`dropna()`	Drop null entries
`fillna()`	Replace null entries with a specified value or strategy
`reindex()`	Replace the index
`sample()`	Draw a random entry
`shift()`	Shift the index
`unique()`	Return unique values

Table 7.2: Methods for managing or modifying data in a pandas `Series` or `DataFrame`.

Data Frames

A `DataFrame` is a collection of `Series` that share the same index, and is therefore a two-dimensional generalization of a NumPy array. The row labels are collectively called the *index*, and the column labels are collectively called the *columns*. An individual column in a `DataFrame` object is one `Series`.

There are many ways to initialize a `DataFrame`. In the following code, we build a `DataFrame` out of a dictionary of `Series`.

```
>>> x = pd.Series(np.random.randn(4), ['a', 'b', 'c', 'd'])
>>> y = pd.Series(np.random.randn(5), ['a', 'b', 'd', 'e', 'f'])
>>> df1 = pd.DataFrame({"series 1": x, "series 2": y})
>>> df1
   series 1  series 2
a -0.365542  1.227960
b  0.080133  0.683523
c  0.737970       NaN
d  0.097878 -1.102835
e       NaN  1.345004
f       NaN  0.217523
```

Note that the index of this `DataFrame` is the union of the index of `Series` `x` and that of `Series` `y`. The columns are given by the keys of the dictionary `d`. Since `x` doesn't have a label `e`, the value in row `e`, column `1` is `NaN`. This same reasoning explains the other missing values as well. Note that if we take the first column of the `DataFrame` and drop the missing values, we recover the `Series` `x`:

```
>>> df1["series1"].dropna()
a   -0.365542
b    0.080133
c    0.737970
d    0.097878
Name: series 1, dtype: float64
```

Achtung!

A pandas `DataFrame` cannot be sliced in exactly the same way as a NumPy array. Notice how we just used `df1["series 1"]` to access a *column* of the the `DataFrame` `df1`. We will discuss this in more detail later on.

We can also initialize a `DataFrame` using a NumPy array, creating custom row and column labels.

```
>>> data = np.random.random((3, 4))
>>> pd.DataFrame(data, index=['A', 'B', 'C'], columns=np.arange(1, 5))

          1         2         3         4
A  0.065646  0.968593  0.593394  0.750110
B  0.803829  0.662237  0.200592  0.137713
C  0.288801  0.956662  0.817915  0.951016
3 rows     4 columns
```

As with Series, if we don't specify the index or columns, the default is `np.arange(n)`, where `n` is either the number of rows or columns.

Viewing and Accessing Data

In this section we will explore some elementary accessing and querying techniques that enable us to maneuver through and gain insight into our data. Try using the `describe()` and `head()` methods for quick data summaries.

Basic Data Access

We can slice the rows of a `DataFrame` much as with a NumPy array.

```
>>> df = pd.DataFrame(np.random.randn(4, 2), index=['a', 'b', 'c', 'd'],
                      columns = ['I', 'II'])
>>> df[:2]

          I        II
a  0.758867  1.231330
b  0.402484 -0.955039

[2 rows x 2 columns]
```

More generally, we can select subsets of the data using the `iloc` and `loc` indexers. The `loc` index selects rows and columns based on their *labels*, while the `iloc` method selects them based on their integer *position*. Accessing `Series` and `DataFrame` objects using these indexing operations is more efficient than using bracket indexing, because the bracket indexing has to check many cases before it can determine how to slice the data structure. Using `loc`/`iloc` explicitly, bypasses the extra checks.

```
>>> # select rows a and c, column II
>>> df.loc[['a','c'], 'II']

a    1.231330
c    0.556121
Name: II, dtype: float64

>>> # select last two rows, first column
>>> df.iloc[-2:, 0]

c   -0.475952
d   -0.518989
Name: I, dtype: float64
```

Finally, a column of a `DataFrame` may be accessed using simple square brackets and the name of the column, or alternatively by treating the label as an object:

```
>>> # get second column of df
>>> df['II']        # or, equivalently, df.II

a    1.231330
b   -0.955039
c    0.556121
d    0.173165
Name: II, dtype: float64
```

All of these techniques for getting subsets of the data may also be used to set subsets of the data:

```
>>> # set second columns to zeros
>>> df['II'] = 0
>>> df['II']
a    0
b    0
c    0
d    0
Name: II, dtype: int64

>>> # add additional column of ones
>>> df['III'] = 1
>>> df
            I  II  III
a   -0.460457   0    1
b    0.973422   0    1
c   -0.475952   0    1
d   -0.518989   0    1
```

SQL Operations in pandas

The `DataFrame`, being a tabular data structure, bears an obvious resemblance to a typical relational database table. SQL is the standard for working with relational databases, and in this section we will explore how pandas accomplishes some of the same tasks as SQL. The SQL-like functionality of pandas is one of its biggest advantages, since it can eliminate the need to switch between programming languages for different tasks. Within pandas we can handle both the querying *and* data analysis.

For the following examples, we will use the following data:

```
>>> #build toy data for SQL operations
>>> name = ['Mylan', 'Regan', 'Justin', 'Jess', 'Jason', 'Remi', 'Matt', '↩
    Alexander', 'JeanMarie']
>>> sex = ['M', 'F', 'M', 'F', 'M', 'F', 'M', 'M', 'F']
>>> age = [20, 21, 18, 22, 19, 20, 20, 19, 20]
>>> rank = ['Sp', 'Se', 'Fr', 'Se', 'Sp', 'J', 'J', 'J', 'Se']
>>> ID = range(9)
>>> aid = ['y', 'n', 'n', 'y', 'n', 'n', 'n', 'y', 'n']
>>> GPA = [3.8, 3.5, 3.0, 3.9, 2.8, 2.9, 3.8, 3.4, 3.7]
>>> mathID = [0, 1, 5, 6, 3]
>>> mathGd = [4.0, 3.0, 3.5, 3.0, 4.0]
>>> major = ['y', 'n', 'y', 'n', 'n']
>>> studentInfo = pd.DataFrame({'ID': ID, 'Name': name, 'Sex': sex, 'Age': age,↩
     'Class': rank})
>>> otherInfo = pd.DataFrame({'ID': ID, 'GPA': GPA, 'Financial_Aid': aid})
>>> mathInfo = pd.DataFrame({'ID': mathID, 'Grade': mathGd, 'Math_Major': major↩
    })
```

Before querying our data, it is important to know some of its basic properties, such as number of columns, number of rows, and the datatypes of the columns. This can be done by simply calling the `info()` method on the desired `DataFrame`:

```
>>> mathInfo.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5 entries, 0 to 4
Data columns (total 3 columns):
Grade         5 non-null float64
ID            5 non-null int64
Math_Major    5 non-null object
dtypes: float64(1), int64(1), object(1)
```

We can also get some basic information about the structure of the `DataFrame` using the `head()` or `tail()` methods.

```
>>> mathInfo.head()
   Grade  ID Math_Major  ID  Age  GPA
0    4.0   0          y   0   20  3.8
1    3.0   1          n   2   18  3.0
2    3.5   5          y   4   19  2.8
3    3.0   6          n   6   20  3.8
```

```
4    4.0   3          n   7   19  3.4
```

The method `isin()` is a useful way to find certain values in a `DataFrame`. It compares the input (a list, dictionary, or `Series`) to the `DataFrame` and returns a boolean `Series` showing whether or not the values match. You can then use this boolean array to select appropriate locations. Now let's look at the pandas equivalent of some SQL SELECT statements.

```
>>> # SELECT ID, Age FROM studentInfo
>>> studentInfo[['ID', 'Age']]

>>> # SELECT ID, GPA FROM otherInfo WHERE Financial_Aid = 'y'
>>> otherInfo[otherInfo['Financial_Aid']=='y'][['ID', 'GPA']]

>>> # SELECT Name FROM studentInfo WHERE Class = 'J' OR Class = 'Sp'
>>>  studentInfo[studentInfo['Class'].isin(['J','Sp'])]['Name']
```

Problem 3. The example above shows how to implement a simple WHERE condition, and it is easy to have a more complex expression. Simply enclose each condition by parentheses, and use the standard boolean operators `&` (AND), `|` (OR), and `~` (NOT) to connect the conditions appropriately. Use pandas to execute the following query:

```
SELECT ID, Name from studentInfo WHERE Age > 19 AND Sex = 'M'
```

Next, let's look at JOIN statements. In pandas, this is done with the `merge` function, which takes as arguments the two `DataFrame` objects to join, as well as keyword arguments specifying the column on which to join, along with the type (left, right, inner, outer).

```
>>> # SELECT * FROM studentInfo INNER JOIN mathInfo ON studentInfo.ID = ↩
    mathInfo.ID
>>> pd.merge(studentInfo, mathInfo, on='ID') # INNER JOIN is the default
   Age Class  ID    Name Sex  Grade Math_Major
0   20    Sp   0   Mylan   M    4.0          y
1   21    Se   1   Regan   F    3.0          n
2   22    Se   3    Jess   F    4.0          n
3   20     J   5    Remi   F    3.5          y
4   20     J   6    Matt   M    3.0          n
[5 rows x 7 columns]

>>> # SELECT GPA, Grade FROM otherInfo FULL OUTER JOIN mathInfo ON otherInfo.ID↩
     = mathInfo.ID
>>> pd.merge(otherInfo, mathInfo, on='ID', how='outer')[['GPA', 'Grade']]
   GPA  Grade
0  3.8    4.0
1  3.5    3.0
2  3.0    NaN
3  3.9    4.0
```

```
4  2.8    NaN
5  2.9    3.5
6  3.8    3.0
7  3.4    NaN
8  3.7    NaN
[9 rows x 2 columns]
```

Problem 4. Using a join operation, create a `DataFrame` containing the ID, age, and GPA of all male individuals. You ought to be able to accomplish this in one line of code.

Be aware that other types of SQL-like operations are also possible, such as UNION. When you find yourself unsure of how to carry out a more involved SQL-like operation, the online pandas documentation will be of great service.

Analyzing Data

Although pandas does not provide built-in support for heavy-duty statistical analysis of data, there are nevertheless many features and functions that facilitate basic data manipulation and computation, even when the data is in a somewhat messy state. We will now explore some of these features.

Basic Data Manipulation

Because the primary pandas data structures are subclasses of the `ndarray`, they are valid input to most NumPy functions, and can often be treated simply as NumPy arrays. For example, basic vectorized operations work just fine:

```
>>> x = pd.Series(np.random.randn(4), index=['a', 'b', 'c', 'd'])
>>> y = pd.Series(np.random.randn(5), index=['a', 'b', 'd', 'e', 'f'])
>>> x**2
a    1.710289
b    0.157482
c    0.540136
d    0.202580
dtype: float64
>>> z = x + y
>>> z
a    0.123877
b    0.278435
c         NaN
d   -1.318713
e         NaN
f         NaN
dtype: float64
>>> np.log(z)
a   -2.088469
b   -1.278570
```

```
c         NaN
d         NaN
e         NaN
f         NaN
dtype: float64
```

Notice that pandas automatically aligns the indexes when adding two `Series` (or `DataFrames`), so that the the index of the output is simply the union of the indexes of the two inputs. The default missing value `NaN` is given for labels that are not shared by both inputs.

It may also be useful to transpose `DataFrames`, re-order the columns or rows, or sort according to a given column. Here we demonstrate these capabilities:

```
>>> df = pd.DataFrame(np.random.randn(4,2), index=['a', 'b', 'c', 'd'], columns↩
    =['I', 'II'])
>>> df
          I        II
a -0.154878 -1.097156
b -0.948226  0.585780
c  0.433197 -0.493048
d -0.168612  0.999194

[4 rows x 2 columns]

>>> df.transpose()
           a         b         c         d
I  -0.154878 -0.948226  0.433197 -0.168612
II -1.097156  0.585780 -0.493048  0.999194

[2 rows x 4 columns]

>>> # switch order of columns, keep only rows 'a' and 'c'
>>> df.reindex(index=['a', 'c'], columns=['II', 'I'])
         II         I
a -1.097156 -0.154878
c -0.493048  0.433197

[2 rows x 2 columns]

>>> # sort descending according to column 'II'
>>> df.sort_values('II', ascending=False)
          I        II
d -0.168612  0.999194
b -0.948226  0.585780
c  0.433197 -0.493048
a -0.154878 -1.097156

[4 rows x 2 columns]
```

Dealing with Missing Data

Missing data is a ubiquitous problem in data science. Fortunately, pandas is particularly well-suited to handling missing and anomalous data. As we have already seen, the pandas default for a missing value is `NaN`. In basic arithmetic operations, if one of the operands is `NaN`, then the output is also `NaN`. The following example illustrates this concept:

```
>>> x = pd.Series(np.arange(5))
>>> y = pd.Series(np.random.randn(5))
>>> x.iloc[3] = np.nan
>>> x + y
0    0.731521
1    0.623651
2    2.396344
3         NaN
4    3.351182
dtype: float64
```

If we are not interested in the missing values, we can simply drop them from the data altogether:

```
>>> (x + y).dropna()
0    0.731521
1    0.623651
2    2.396344
4    3.351182
dtype: float64
```

This is not always the desired behavior, however. It may well be the case that missing data actually corresponds to some default value, such as zero. In this case, we can replace all instances of `NaN` with a specified value:

```
>>> # fill missing data with 0, add
>>> x.fillna(0) + y
0    0.731521
1    0.623651
2    2.396344
3    1.829400
4    3.351182
dtype: float64
```

Other functions, such as `sum()` and `mean()` ignore NaN values in the computation. When dealing with missing data, make sure you are aware of the behavior of the pandas functions you are using.

Data I/O

Being able to import and export data is a fundamental skill in data science. Unfortunately, with the multitude of data formats and conventions, importing data can often be a painful task. The pandas

library seeks to reduce some of the difficulty by providing file readers for various types of formats, including CSV, Excel, HDF5, SQL, JSON, HTML, and pickle files.

Method	Description
`describe()`	Return a `Series` describing the data structure
`head()`	Return the first n rows, defaulting to 5
`tail()`	Return the last n rows, defaulting to 5
`to_csv()`	Write the index and entries to a CSV file
`to_json()`	Convert the object to a JSON string
`to_pickle()`	Serialize the object and store it in an external file
`to_sql()`	Write the object data to an open SQL database

Table 7.3: Methods for viewing or exporting data in a pandas `Series` or `DataFrame`.

The CSV (comma separated values) format is a simple way of storing tabular data in plain text. Because CSV files are one of the most popular file formats for exchanging data, we will explore the `read_csv()` function in more detail. To learn to read other types of file formats, see the online pandas documentation. To read a CSV data file into a `DataFrame`, call the `read_csv()` function with the path to the CSV file, along with the appropriate keyword arguments. Below we list some of the most important keyword arguments:

- `delimiter`: This argument specifies the character that separates data fields, often a comma or a whitespace character.
- `header`: The row number (starting at 0) in the CSV file that contains the column names.
- `index_col`: If you want to use one of the columns in the CSV file as the index for the `DataFrame`, set this argument to the desired column number.
- `skiprows`: If an integer n, skip the first n rows of the file, and then start reading in the data. If a list of integers, skip the specified rows.
- `names`: If the CSV file does not contain the column names, or you wish to use other column names, specify them in a list assigned to this argument.

There are several other keyword arguments, but this should be enough to get you started.

When you need to save your data, pandas allows you to write to several different file formats. A typical example is the `to_csv()` function method attached to `Series` and `DataFrame` objects, which writes the data to a CSV file. Keyword arguments allow you to specify the separator character, omit writing the columns names or index, and specify many other options. The code below demonstrates its typical usage:

```
>>> df.to_csv("my_df.csv")
```

Problem 5. The file `crime_data.csv` contains data on types of crimes committed in the United States from 1960 to 2016.

- Load the data into a pandas `DataFrame`, using the column names in the file and the column titled "Year" as the index. Make sure to skip lines that don't contain data.

- Insert a new column into the data frame that contains the crime rate by year (the ratio of "Total" column to the "Population" column).
- Plot the crime rate as a function of the year.
- List the 5 years with the highest crime rate in descending order.
- Calculate the average number of total crimes as well as burglary crimes between 1960 and 2012.
- Find the years for which the total number of crimes was below average, but the number of burglaries was above average.
- Plot the number of murders as a function of the population.
- Select the Population, Violent, and Robbery columns for all years in the 1980s, and save this smaller data frame to a CSV file `crime_subset.csv`.

Problem 6. In 1912 the RMS *Titanic* sank after colliding with an iceberg. The file `titanic.csv` contains data on the incident. Each row represents a different passenger, and the columns describe various features of the passengers (age, sex, whether or not they survived, etc.)

Start by cleaning the data.

- Read the data into a `DataFrame`. Use the first row of the file as the column labels, but do not use any of the columns as the index.
- Drop the columns `"Sibsp"`, `"Parch"`, `"Cabin"`, `"Boat"`, `"Body"`, and `"home.dest"`.
- Drop any entries without data in the `"Survived"` column, then change the remaining entries to `True` or `False` (they start as 1 or 0).
- Replace null entries in the `"Age"` column with the average age.
- Save the new `DataFrame` as `titanic_clean.csv`.

Next, answer the following questions.

- How many people survived? What percentage of passengers survived?
- What was the average price of a ticket? How much did the most expensive ticket cost?
- How old was the oldest survivor? How young was the youngest survivor? What about non-survivors?

8 Pandas 2: Plotting

Lab Objective: *Clear, insightful visualizations are a crucial part of data analysis. To facilitate quick data visualization, pandas includes several tools that wrap around matplotlib. These tools make it easy to compare different parts of a data set and explore the data as a whole.*

Overview of Plotting Tools

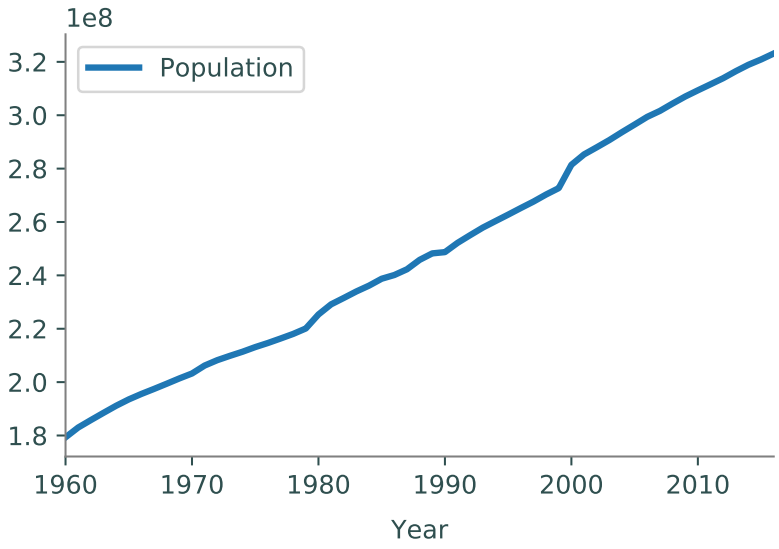
The main tool for visualization in pandas is the `plot()` method of the `Series` and `DataFrame`. The method has a keyword argument `kind` that specifies the type of plot to draw. The valid options for `kind` are detailed below.

Plot Type	`plot()` ID	Uses and Advantages
Line plot	`"line"`	Show trends ordered in data; easy to compare multiple data sets
Scatter plot	`"scatter"`	Compare exactly two data sets, independent of ordering
Bar plot	`"bar"`, `"barh"`	Compare categorical or sequential data
Histogram	`"hist"`	Show frequencies of one set of values, independent of ordering
Box plot	`"box"`	Display min, median, max, and quartiles; compare data distributions
Hexbin plot	`"hexbin"`	2D histogram; reveal density of cluttered scatter plots

Table 8.1: Uses for the `plot()` method of the pandas `Series` and `DataFrame`. The plot ID is the value of the keyword argument `kind`. That is, `df.plot(kind="scatter")` creates a scatter plot. The default `kind` is `"line"`.

The `plot()` method calls `plt.plot()`, `plt.hist()`, `plt.scatter()`, or another matplotlib plotting function, but it also assigns axis labels, tick marks, legends, and a few other things based on the index and the data. Most calls to `plot()` specify the `kind` of plot and which `Series` to use as the `x` and `y` axes. By default, the `index` of the `Series` or `DataFrame` is used for the `x` axis.

```
>>> import pandas as pd
>>> from matplotlib import pyplot as plt

>>> crime = pd.read_csv("crime_data.csv", index_col="Year")
>>> crime.plot(y="Population")  # Plot population against the index (years).
```



In this case, the call to the `plot()` method is essentially equivalent to the following code.

```
>>> plt.plot(crime.index, crime["Population"], label="Population")
>>> plt.xlabel(crime.index.name)
>>> plt.xlim(min(crime.index), max(crime.index))
>>> plt.legend(loc="best")
```

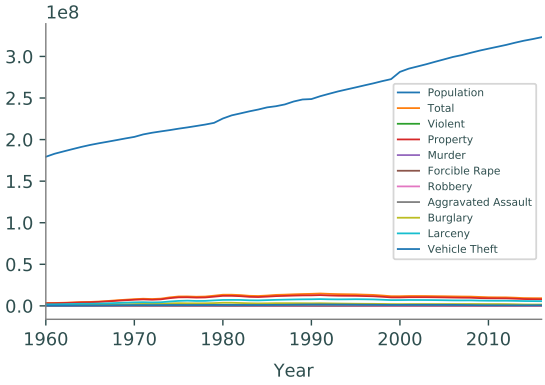
The `plot()` method also takes in many keyword arguments for matplotlib plotting and annotation functions. For example, setting `legend=False` disables the legend, providing a value for `title` sets the figure title, `grid=True` turns a grid on, and so on. For more customizations, see `https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.plot.html`.

Visualizing an Entire Data Set

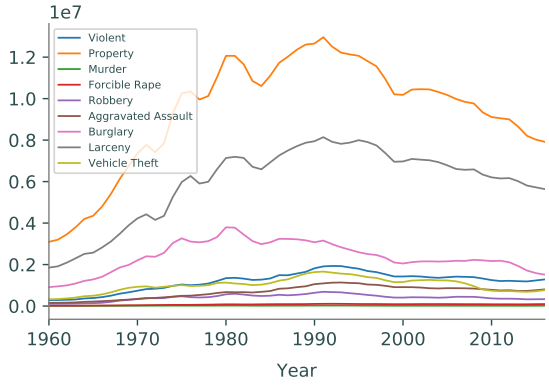
A good way to start analyzing an unfamiliar data set is to visualize as much of the data as possible to determine which parts are most important or interesting. For example, since the columns in a `DataFrame` share the same index, the columns can all be graphed together using the index as the x-axis. In fact, the `plot()` method attempts by default to plot **every** `Series` (column) in the `DataFrame`. This is especially useful with sequential data, like the crime data set.

The crime data set has 11 columns, so the resulting figure, Figure 8.1a, is fairly cluttered. However, it does shows that the `"Population"` column is on a completely different scale than the others. Dropping a few columns gives a better overview of the data, shown in Figure 8.1b.

```
# Plot all columns together against the index.
>>> crime.plot(linewidth=1)

# Plot all columns together except for 'Population' and 'Total'.
>>> crime.drop(["Population", "Total"], axis=1).plot(linewidth=1)
```



(a) All columns of the crime data set on the same figure, using the index as the x-axis.



(b) All columns of the crime data set except `"Population"` and `"Total"`.

Figure 8.1

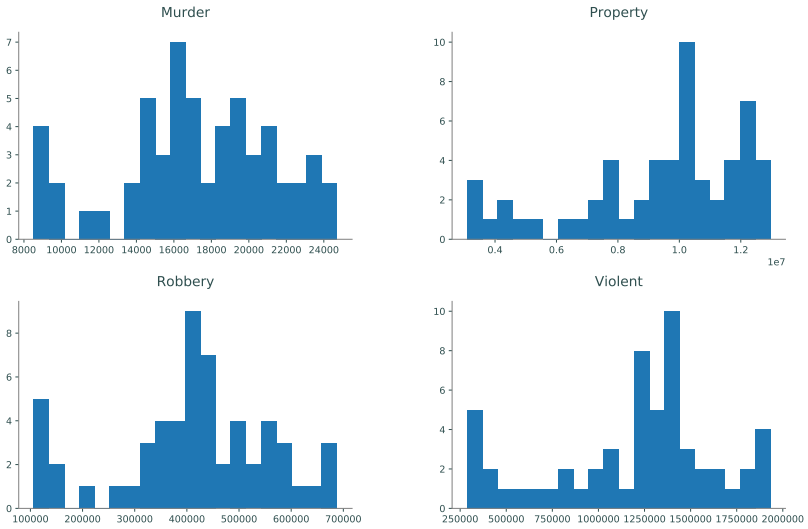
> **Achtung!**
>
> The `"Population"` column differs from the other columns because it is has **different units of measure**: population is measured by "number of people," but all other columns are measured in "number of crimes." Be careful not to plot parts of a data set together if those parts don't have the same units or are otherwise incomparable.

To quickly plot several columns in separate subplots, use `subplots=True` and specify a shape tuple as the `layout` for the plots. Subplots automatically share the same x-axis; set `sharey=True` to force them to share the same y-axis as well.

```
>>> crime.plot(y=["Property", "Larceny", "Burglary", "Violent"],
...            subplots=True, layout=(2,2), sharey=True,
...            style=['-', '--', '-.', ':'])
```

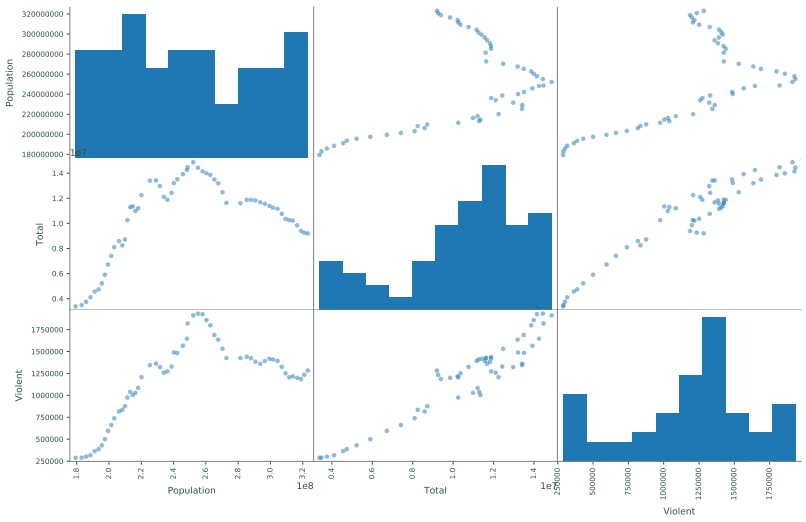
The `plot()` method can generate subplots of any kind of plot. However, since subplots share an x-axis by default, histograms turn out poorly whenever there are columns with very different data ranges. For histograms, use the `hist()` method of the `DataFrame` instead of the `plot()` method. Specify the number of bins with the `bins` parameter.

```
>>> crime[["Violent","Murder","Robbery","Property"]].hist(grid=False, bins=20)
```



Finally, the function `pd.plotting.scatter_matrix()` produces a table of plots where each column is plotted against each other column in separate scatter plots. The plots on the diagonal, instead of plotting a column against itself, displays a histogram of that column. This provides a way to very quickly do an initial analysis of the correlation between different columns.

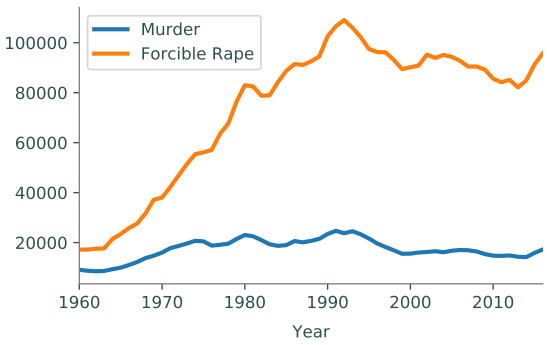
```
>>> pd.plotting.scatter_matrix(crime[["Population", "Total", "Violent"]])
```

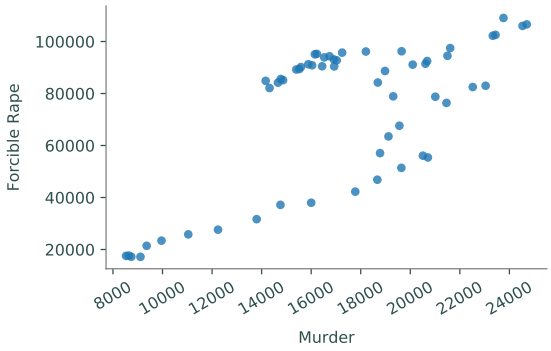


Patterns and Correlations

After visualizing the entire data set initially, the next step is usually to closely compare related parts of the data. For example, Figure 8.1b suggests that the `"Murder"` and `"Forcible Rape"` columns are roughly on the same scale. Since this data is sequential (indexed by time), start by plotting these two columns against the index. Next, create a scatter plot of one of the columns versus the other to investigate correlations that are independent of the index. Unlike other types of plots, using `kind="scatter"` requires both an `x` and a `y` column as arguments.

```
# Plot 'Murder' and 'Forcible Rape' as lines against the index.
>>> crime.plot(y=["Murder", "Forcible Rape"])

# Make a scatter plot of 'Murder' against 'Forcible Rape', ignoring the index.
>>> crime.plot(kind="scatter", x="Murder", y="Forcible Rape", alpha=.8, rot=30)
```





What does these graphs show about the data? First of all, rape is more common than murder. Second, rates of rape appear to be steadily increased from the mid 1960's to the mid 1990's before leveling out, while murder rates stay relatively constant. The disparity between rape and murder is confirmed in the scatter plot: the clump of data points at about 15,000 murders and 90,000 rapes shows that there have been many years where rape was relatively high while murder was somewhat low.

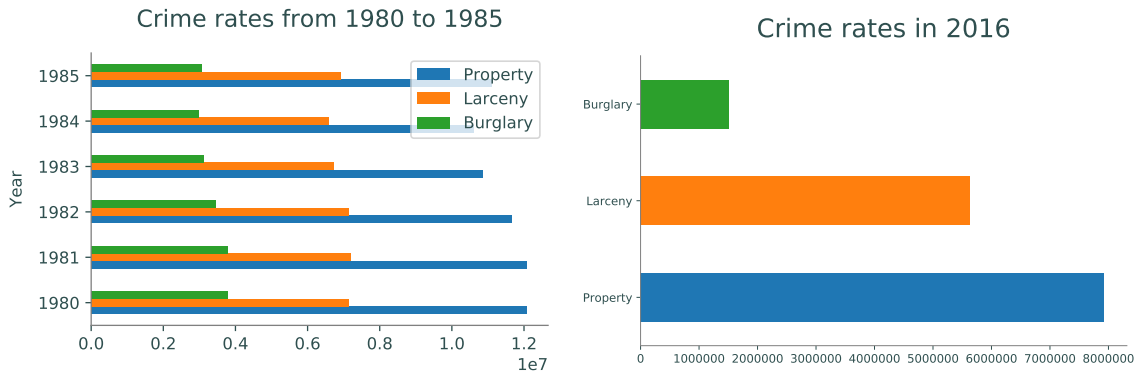
Achtung!

While analyzing data, especially while searching for patterns and correlations, **always** ask yourself if the data makes sense and is trustworthy. What lurking variables could have influenced the data measurements as they were being gathered?

The crime data set is somewhat suspect in this regard. The murder rate is likely accurate, since murder is conspicuous and highly reported, but what about the rape rate? Are the number of rapes increasing, or is the percentage of rapes being reported increasing? (It's probably both!) Be careful about drawing conclusions for sensitive or questionable data.

Figure 8.1b also reveals some general patterns relative to time. For instance, there seems to be a small bump in each type of crime in the early 1980's. Slicing the entries from 1980 to 1985 provides a closer look. Since there are only a few entries, we can treat the data as categorical and make a bar chart.

```
# Plot 'Property' and 'Larceny' rates from 1980 to 1985.
>>> crime.loc[1980:1985, ["Property", "Larceny", "Burglary"]].plot(kind="barh",
...                       title="Crime rates from 1980 to 1985")

# Plot the most recent year's crime rates for comparison.
>>> crime.iloc[-1][["Property", "Larceny", "Burglary"]].plot(kind="barh",
...                       title="Crime rates in 2016", color=["C0", "C1", "C2"])
>>> plt.tight_layout()
```

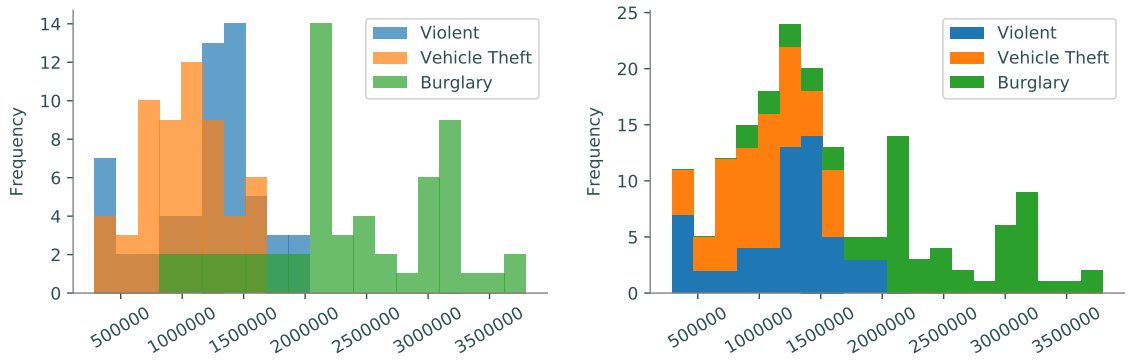


> **Note**
>
> As a general rule, horizontal bar charts (`kind="hbar"`) are better than the default vertical bar charts (`kind="bar"`) because most humans can detect horizontal differences more easily than vertical differences. If the labels are too long to fit on a normal figure, use `plt.tight_layout()` to adjust the plot boundaries to fit the labels in.

Distributional Visualizations

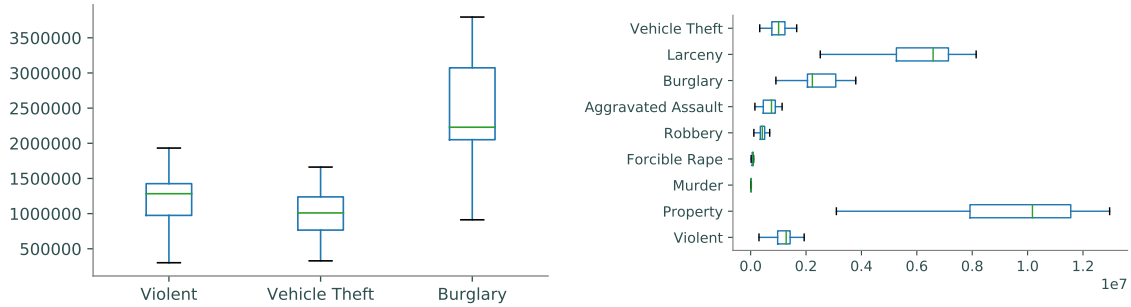
Histograms are good for examining the distribution of a **single** column in a data set. While pandas is capable of plotting several histograms on the same plot, the results are usually hard to read.

```
# Plot three histograms together.
>>> crime.plot(kind="hist", y=["Violent", "Vehicle Theft", "Burglary"],
...            bins=20, alpha=.7, rot=30)

# Plot three histograms, stacking one on top of the other.
>>> crime.plot(kind="hist", y=["Violent", "Vehicle Theft", "Burglary"],
...            bins=20, stacked=True, rot=30)
```



Instead of using histograms to compare distributions of data, use box plots. A *box plot* (sometimes called a "cat-and-whisker" plot) shows the five number summary: the minimum, first quartile, median, third quartile, and maximum of the data. While not quite the same as a histogram, box plots are much better suited to quickly compare relatable distributions.

```
# Compare the distributions of three columns.
>>> crime.plot(kind="box", y=["Violent", "Vehicle Theft", "Burglary"])

# Compare the distributions of all columns but 'Population' and 'Total'.
>>> crime.drop(["Population", "Total"], axis=1).plot(kind="box", vert=False)
```

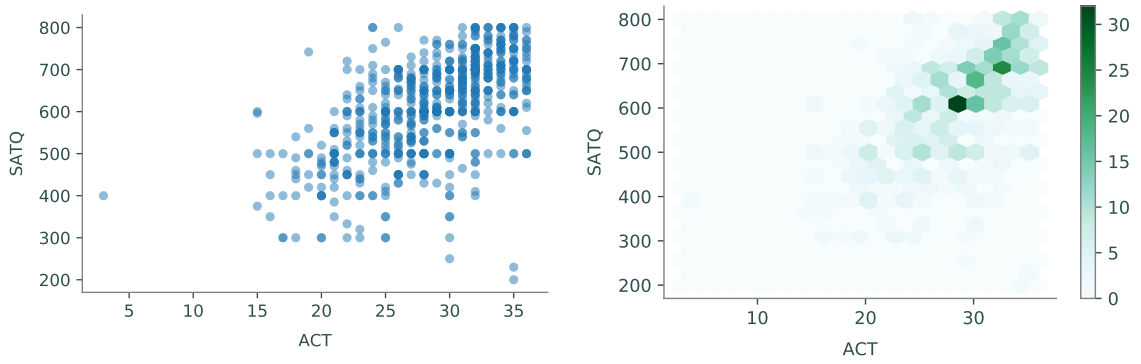


Hexbin Plots

A scatter plot is essentially a plot of samples from the joint distribution of two columns. However, scatter plots can be uninformative for large data sets when the points in a scatter plot are closely clustered. *Hexbin plots* solve this problem by plotting point density in hexagonal bins—essentially creating a 2-dimensional histogram.

The file `sat_act.csv` contains 700 self reported scores on the SAT Verbal, SAT Quantitative and ACT, collected as part of the Synthetic Aperture Personality Assessment (SAPA) web based personality assessment project. The obvious question with this data set is "how correlated are ACT and SAT scores?" The scatter plot of ACT scores versus SAT Quantitative scores, Figure 8.6a, is highly cluttered, even though the points have some transparency. A hexbin plot of the same data, Figure 8.6b, reveals the **frequency** of points in binned regions.

```
>>> satact = pd.read_csv("sat_act.csv", index_col="ID")
>>> list(satact.columns)
['gender', 'education', 'age', 'ACT', 'SATV', 'SATQ']

# Plot the ACT scores against the SAT Quant scores in a regular scatter plot.
>>> satact.plot(kind="scatter", x="ACT", y="SATQ", alpha=.8)

# Plot the densities of the ACT vs. SATQ scores with a hexbin plot.
>>> satact.plot(kind="Hexbin", x="ACT", y="SATQ", gridsize=20)
```



(a) ACT vs. SAT Quant scores.

(b) Frequency of ACT vs. SAT Quant scores.

Figure 8.6

Just as choosing a good number of `bins` is important for a good histogram, choosing a good `gridsize` is crucial for an informative hexbin plot. A large `gridsize` creates many small bins and a small `gridsize` creates fewer, larger bins.

See `http://pandas.pydata.org/pandas-docs/stable/visualization.html` for more types of plots available in Pandas and further examples.

Principles of Good Data Visualization

Visualization is much more than a set of pretty pictures scattered throughout a paper for the sole purpose of providing contrast to the text. When properly implemented, data visualization is a powerful tool for analysis and communication. When writing a paper or report, the author must make many decisions about how to use graphics effectively to convey useful information to the reader. Here we will go over a simple process for making deliberate, effective, and efficient design decisions.

Attention to Detail

Consider the plot in Figure 8.7. What does it depict? We can tell from a simple glance that it is a scatter plot of positively correlated data of some kind, with `temp`–likely temperature–on the x axis and `cons` on the y axis. However, the picture is not really communicating anything about the dataset. We have not specified the units for the x or the y axis, we have no idea what `cons` is, there is no title, and we don't even know where the data came from in the first place.

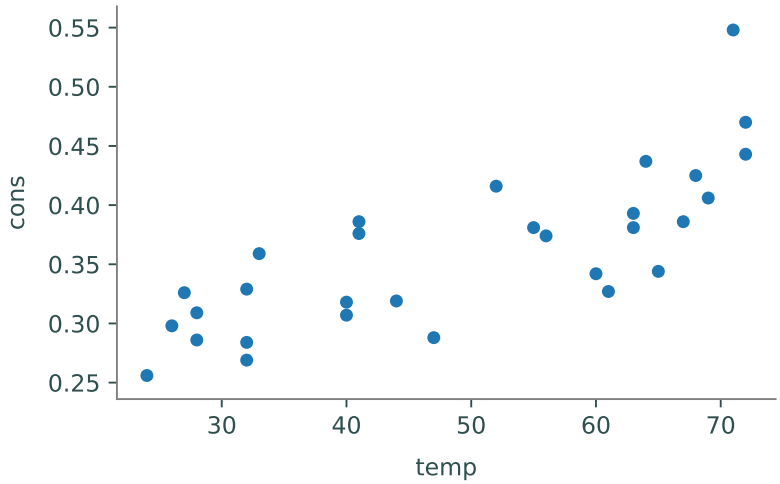


Figure 8.7: Non-specific data.

Labels and Citations

In a homework or lab setting, we sometimes (mistakenly) think that it is acceptable to leave off appropriate labels, legends, titles, and sourcing. In a published report or presentation, this kind of carelessness is confusing at best and, when the source is not included, even plagiaristic. Clearly, we need to explain our data in a useful manner that includes all of the vital information.

Consider again Figure 8.7. This figure comes from the `Icecream` dataset within the `pydataset` package, which we store here in a dataframe and then plot:

```
>>> from pydataset import data
>>> icecream = data("Icecream")
>>> icecream.plot(kind="scatter", x="temp", y="cons")
```

We have at this point reproduced the rather substandard plot in Figure 8.7. Using `data('Icecream', show_doc=True)` we find the following information:

1. The dataset details ice cream consumption via four-weekly observations from March 1951 to July 1953 in the United States.

2. `cons` corresponds to "consumption of ice cream per head" and is measured in pints.

3. `temp` corresponds to temperature, degrees Fahrenheit.

4. The listed source is: "Hildreth, C. and J. Lu (1960) *Demand relations with autocorrelated disturbances*, Technical Bulletin No 2765, Michigan State University."

We add these important details using the following code. As we have seen in previous examples, pandas automatically generates legends when appropriate. However, although pandas also automatically labels the x and y axes, our data frame column titles may be insufficient. Appropriate titles for the x and y axes must also list appropriate units. For example, the y axis should specify that the consumption is in units of *pints per head*, in place of the ambiguous label `cons`.

```
>>> icecream = data("Icecream")
# Set title via the title keyword argument
>>> icecream.plot(kind="scatter", x="temp", y="cons", title="Ice Cream ↩
    Consumption in the U.S., 1951-1953",)
# Override pandas automatic labelling using xlabel and ylabel
>>> plt.xlabel("Temp (Farenheit)")
>>> plt.ylabel("Consumption per head (pints)")
```

To arbitrarily add the necessary text to the figure, use either `plt.annotate()` or `plt.text()`. Alternatively, add text immediately below wherever the figure is displayed.

```
>>> plt.text(20, .1, r"Source: Hildreth, C. and J. Lu (1960) \emph{Demand"
...      "relations with autocorrelated disturbances}\nTechnical Bulletin No"
...      "2765, Michigan State University.", fontsize=7)
```

Both of these methods are imperfect, however, and can normally be just as easily replaced by a caption attached to the figure in your presentation or document setting. We again reiterate how important it is that you source any data you use. Failing to do so is plagiarism.

Finally, we have a clear and demonstrative graphic in Figure 8.8.

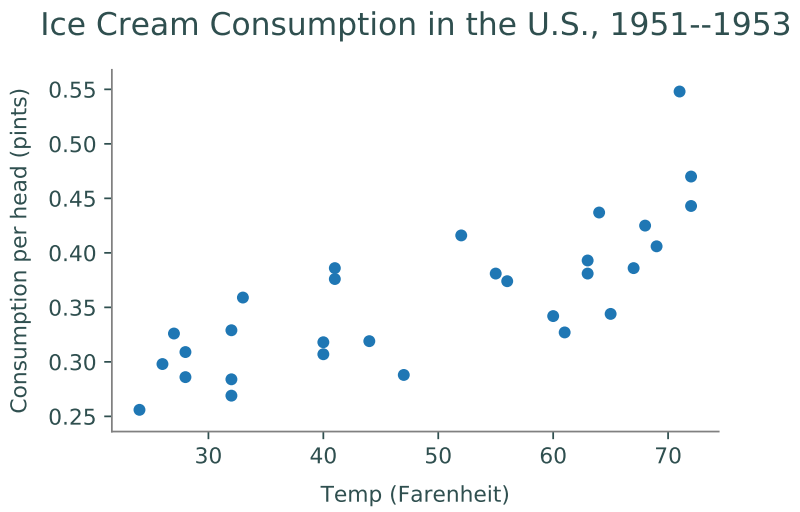


Figure 8.8: Source: Hildreth, C. and J. Lu (1960) *Demand relations with autocorrelated disturbances*, Technical Bulletin No 2765, Michigan State University.

Problem 1. The `pydataset` module[a] contains numerous data sets, each stored as a pandas `DataFrame`.

```
>>> from pydataset import data

# Call data() to see the entire list of data sets.
```

```
# To load a particular data set, enter its ID as an argument to data().
>>> titanic = data("Titanic")
# To see the information about a data set, call data() with show_doc=True.
>>> data("Titanic", show_doc=True)
Titanic

PyDataset Documentation (adopted from R Documentation. The displayed
examples are in R)

## Survival of passengers on the Titanic
```

Visualize and describe at least 5 of the following data sets with 2 or 3 figures each. Comment on the implications and significance of each visualization and give a comprehensive summary of the data set.

- `"Arbuthnot"`: Ratios of male to female births in London from 1629-1710
- `"trees"`: Girth, height and volume for black cherry trees
- `"road"`: Road accident deaths in the United States
- `"birthdeathrates"`: Birth and death rates by country
- `"bfeed"`: Child breast feeding records
- `"heart"`: Survival of patients on the waiting list for the Stanford heart transplant program
- `"lung"`: Survival in patients with advanced lung cancer from the North Central Cancer Treatment group
- `"birthwt"`: Risk factors associated with low infant birth weight
- A data set of your choice

Include each of the following in each visualization.

- A clear title, with relevant information for the period or region the data was collected in.
- Axis labels that specify units.
- A legend (if appropriate).
- The source. You may include the source information in your plot or print it after the plot.

[a] Run `pip install pydataset` if needed.

9 Pandas 3: Grouping

Lab Objective: *Many data sets contain categorical values that naturally sort the data into groups. Analyzing and comparing such groups is an important part of data analysis. In this lab we explore pandas tools for grouping data and presenting tabular data more compactly, primarily through grouby and pivot tables.*

Groupby

The file `mammal_sleep.csv`[1] contains data on the sleep cycles of different mammals, classified by order, genus, species, and diet (carnivore, herbivore, omnivore, or insectivore). The `"sleep_total"` column gives the total number of hours that each animal sleeps (on average) every 24 hours. To get an idea of how many animals sleep for how long, we start off with a histogram of the `"sleep_total"` column.

```
>>> import pandas as pd
>>> from matplotlib import pyplot as plt

# Read in the data and print a few random entries.
>>> msleep = pd.read_csv("mammal_sleep.csv")
>>> msleep.sample(5)
      name     genus   vore         order  sleep_total  sleep_rem  sleep_cycle
51  Jaguar  Panthera  carni     Carnivora         10.4        NaN          NaN
77  Tenrec    Tenrec   omni  Afrosoricida         15.6        2.3          NaN
10    Goat     Capri  herbi  Artiodactyla          5.3        0.6          NaN
80   Genet   Genetta  carni     Carnivora          6.3        1.3          NaN
33   Human      Homo   omni      Primates          8.0        1.9          1.5

# Plot the distribution of the sleep_total variable.
>>> msleep.plot(kind="hist", y="sleep_total", title="Mammalian Sleep Data")
>>> plt.xlabel("Hours")
```

[1] Proceedings of the National Academy of Sciences, 104 (3):1051–1056, 2007. Updates from V. M. Savage and G. B. West, with additional variables supplemented by Wikipedia. Available in `pydataset` (with a few more columns) under the key `"msleep"`.

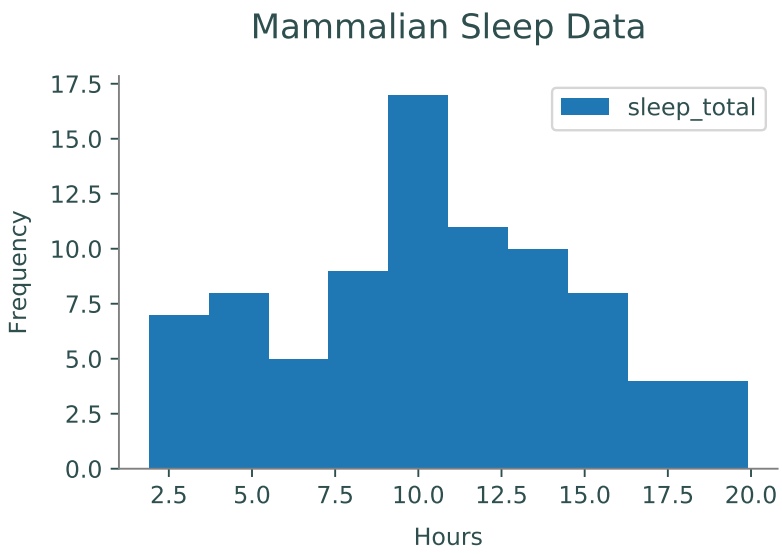


Figure 9.1: `"sleep_total"` frequencies from the mammalian sleep data set.

While this visualization is a good start, it doesn't provide any information about how different kinds of animals have different sleeping habits. How long do carnivores sleep compared to herbivores? Do mammals of the same genus have similar sleep patterns?

A powerful tool for answering these kinds of questions is the `groupby()` method of the pandas `DataFrame` class, which partitions the original `DataFrame` into groups based on the values in one or more columns. The `groupby()` method does **not** return a new `DataFrame`; it returns a pandas `GroupBy` object, an interface for analyzing the original `DataFrame` by groups.

For example, the columns `"genus"`, `"vore"`, and `"order"` in the mammal sleep data all have a discrete number of categorical values that could be used to group the data. Since the `"vore"` column has only a few unique values, we start by grouping the animals by diet.

```
# List all of the unique values in the 'vore' column.
>>> set(msleep["vore"])
{nan, 'herbi', 'omni', 'carni', 'insecti'}

# Group the data by the 'vore' column.
>>> vores = msleep.groupby("vore")
>>> list(vores.groups)
['carni', 'herbi', 'insecti', 'omni']       # NaN values for vore were dropped.

# Get a single group and sample a few rows. Note vore='carni' in each entry.
>>> vores.get_group("carni").sample(5)
       name     genus   vore      order  sleep_total  sleep_rem  sleep_cycle
80    Genet   Genetta  carni  Carnivora          6.3        1.3          NaN
50    Tiger  Panthera  carni  Carnivora         15.8        NaN          NaN
8       Dog     Canis  carni  Carnivora         10.1        2.9        0.333
0   Cheetah  Acinonyx  carni  Carnivora         12.1        NaN          NaN
82  Red fox    Vulpes  carni  Carnivora          9.8        2.4        0.350
```

For starters, `groupby()` is useful for filtering a `DataFrame` by column values: the command `df.groupby(col).get_group(value)` returns the rows of `df` where the entry of the `col` column is `value`. The real advantage of `groupby()`, however, is how easy it makes it to compare groups of data. Standard `DataFrame` methods like `describe()`, `mean()`, `std()`, `min()`, and `max()` all work on `GroupBy` objects to produce a new data frame that describes the statistics of each group.

```
# Get averages of the numerical columns for each group.
>>> vores.mean()
         sleep_total  sleep_rem  sleep_cycle
vore
carni         10.379      2.290        0.373
herbi          9.509      1.367        0.418
insecti       14.940      3.525        0.161
omni          10.925      1.956        0.592

# Get more detailed statistics for 'sleep_total' by group.
>>> vores["sleep_total"].describe()
         count    mean    std  min   25%   50%     75%   max
vore
carni     19.0  10.379  4.669  2.7  6.25  10.4  13.000  19.4
herbi     32.0   9.509  4.879  1.9  4.30  10.3  14.225  16.6
insecti    5.0  14.940  5.921  8.4  8.60  18.1  19.700  19.9
omni      20.0  10.925  2.949  8.0  9.10   9.9  10.925  18.0
```

Multiple columns can be used simultaneously for grouping. In this case, the `get_group()` method of the `GroupBy` object requires a tuple specifying the values for each of the grouping columns.

```
>>> msleep_small = msleep.drop(["sleep_rem", "sleep_cycle"], axis=1)
>>> vores_orders = msleep_small.groupby(["vore", "order"])
>>> vores_orders.get_group(("carni", "Cetacea"))
                    name          genus   vore    order  sleep_total
30           Pilot whale  Globicephalus  carni  Cetacea          2.7
59       Common porpoise       Phocoena  carni  Cetacea          5.6
79  Bottle-nosed dolphin       Tursiops  carni  Cetacea          5.2
```

Visualizing Groups

There are a few ways that `groupby()` or similar techniques can simplify the process of visualizing groups of data. First of all, `groupby()` makes it easy to visualize one group at a time. The following visualization improve on Figure 9.1 by grouping mammals by their diets.

```
# Plot histograms of 'sleep_total' for two separate groups.
>>> vores.get_group("carni").plot(kind="hist", y="sleep_total", legend="False",
                                  title="Carnivore Sleep Data")
>>> plt.xlabel("Hours")
>>> vores.get_group("herbi").plot(kind="hist", y="sleep_total", legend="False",
                                  title="Herbivore Sleep Data")
>>> plt.xlabel("Hours")
```

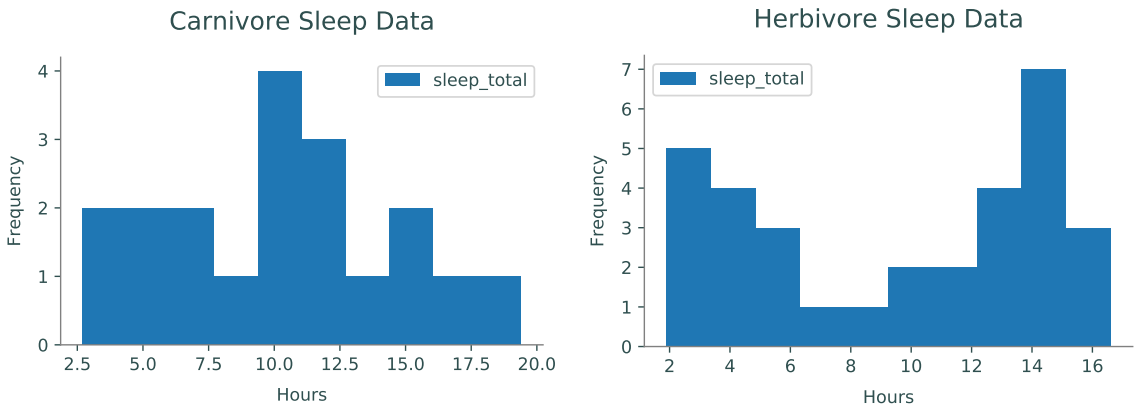
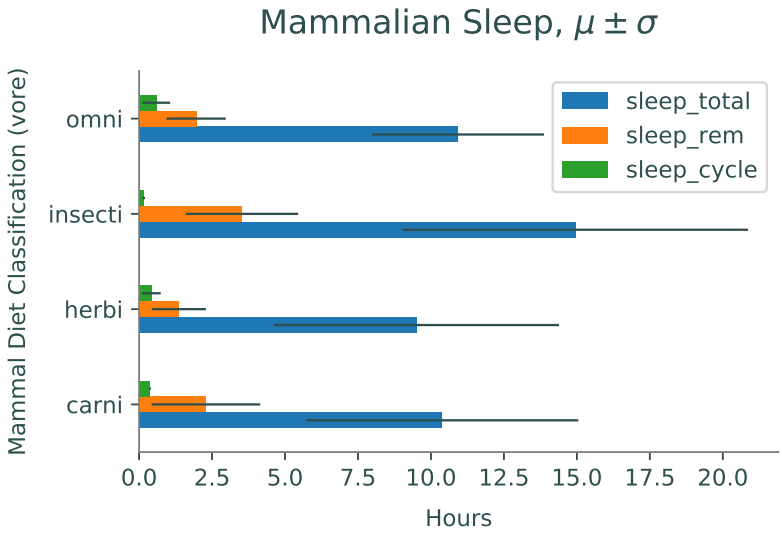


Figure 9.2: `"sleep_total"` histograms for two groups in the mammalian sleep data set.

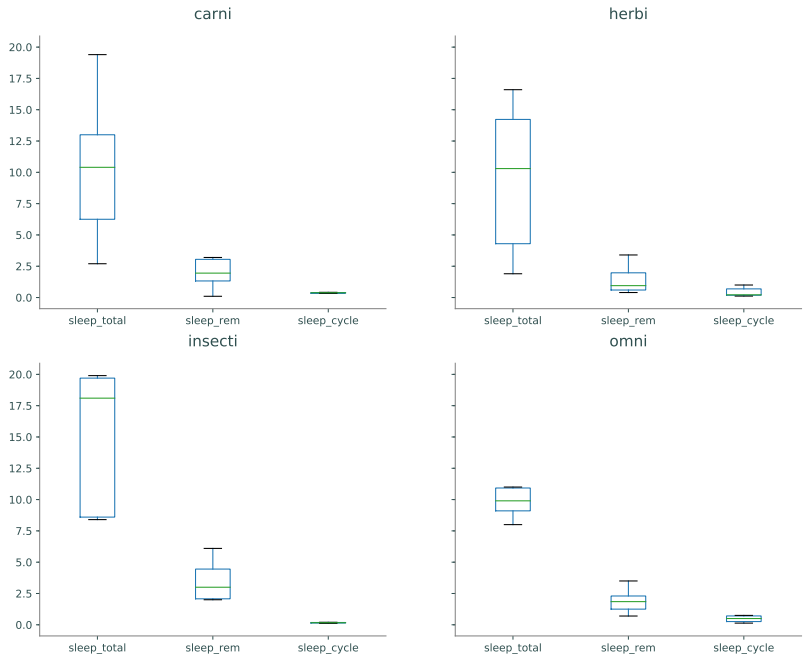
The statistical summaries from the `GroupBy` object's `mean()`, `std()`, or `describe()` methods also lend themselves well to certain visualizations for comparing groups.

```
>>> vores[["sleep_total", "sleep_rem", "sleep_cycle"]].mean().plot(kind="barh",
                xerr=vores.std(), title=r"Mammallian Sleep, $\mu\pm\sigma$")
>>> plt.xlabel("Hours")
>>> plt.ylabel("Mammal Diet Classification (vore)")
```



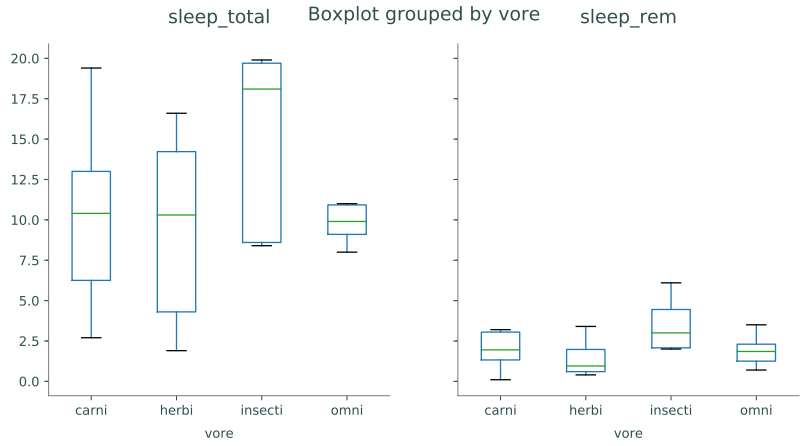
Box plots are well suited for comparing similar distributions. The `boxplot()` method of the `GroupBy` class creates one subplot **per group**, plotting each of the columns as a box plot.

```
# Use GroupBy.boxplot() to generate one box plot per group.
>>> vores.boxplot(grid=False)
>>> plt.tight_layout()
```



Alternatively, the `boxplot()` method of the `DataFrame` class creates one subplot **per column**, plotting each of the columns as a box plot. Specify the `by` keyword to group the data appropriately.

```
# Use DataFrame.boxplot() to generate one box plot per column.
>>> msleep.boxplot(["sleep_total", "sleep_rem"], by="vore", grid=False)
```



Like `groupby()`, the `by` argument can be a single column label or a list of column labels. Similar methods exist for creating histograms (`GroupBy.hist()` and `DataFrame.hist()` with `by` keyword), but generally box plots are better for comparing multiple distributions.

Problem 1. Examine the following data sets from `pydataset` and answer the corresponding questions. Use visualizations to support your conclusions.

- `"iris"`, measurements of various species of iris flowers.
  1. Which species is easiest to distinguish from the others? How?
  2. Given iris data without a species label, what strategies could you use to identify the flower's species?
- `"poisons"`, experimental results of three different poisons and four different treatments.
  1. In general, which poison is most deadly? Which treatment is most effective?
  2. If you were poisoned, how would you choose the treatment if you did not know which poison it was? What if you did know which poison it was?
     (Hint: group the data by poison, then group each subset by treatment.)
- `"diamonds"`, prices and characteristics of almost 54,000 round-cut diamonds.
  1. How does the color and cut of a diamond affect its price?
  2. Of the diamonds with color `"H"`, those with a `"Fair"` cut sell, on average, for a **higher** price than those with an `"Ideal"` (superior) cut. What other factors could explain this unintuitive statistic?

Pivot Tables

One of the downfalls of `groupby()` is that a typical `GroupBy` object has too much information to display coherently. A *pivot table* intelligently summarizes the results of a `groupby()` operation by aggregating the data in a specified way. The standard tool for making a pivot table is the `pivot_table()` method of the `DataFrame` class. As an example, consider the `"HairEyeColor"` data set from `pydataset`.

```
>>> from pydataset import data
>>> hec = data("HairEyeColor")              # Load and preview the data.
>>> hec.sample(5)
     Hair    Eye     Sex  Freq
3     Red  Brown    Male    10
1   Black  Brown    Male    32
14  Brown  Green    Male    15
31    Red  Green  Female     7
21  Black   Blue  Female     9

>>> for col in ["Hair", "Eye", "Sex"]:      # Get unique values per column.
...     print("{}: {}".format(col, ", ".join(set(str(x) for x in hec[col]))))
...
Hair: Brown, Black, Blond, Red
Eye: Brown, Blue, Hazel, Green
Sex: Male, Female
```

There are several ways to group this data with `groupby()`. However, since there is only one entry per unique hair-eye-sex combination, the data can be completely presented in a pivot table.

```
>>> hec.pivot_table(values="Freq", index=["Hair", "Eye"], columns="Sex")
Sex          Female  Male
Hair  Eye
Black Blue        9    11
      Brown      36    32
      Green       2     3
      Hazel       5    10
Blond Blue       64    30
      Brown       4     3
      Green       8     8
      Hazel       5     5
Brown Blue       34    50
      Brown      66    53
      Green      14    15
      Hazel      29    25
Red   Blue        7    10
      Brown      16    10
      Green       7     7
      Hazel       7     7
```

Listing the data in this way makes it easy to locate data and compare the female and male groups. For example, it is easy to see that brown hair is more common than red hair and that about twice as many females have blond hair and blue eyes than males.

Unlike `"HairEyeColor"`, many data sets have more than one entry in the data for each grouping (for example, if there were two or more rows in the original data for females with blond hair and blue eyes). To construct a pivot table, data of similar groups must be *aggregated* together in some way. By default entries are aggregated by averaging the non-null values. Other options include taking the min, max, standard deviation, or just counting the number of occurrences.

As an example, consider again the Titanic data set found in `titanic.csv`[2]. For this analysis, take only the `"Survived"`, `"Pclass"`, `"Sex"`, `"Age"`, `"Fare"`, and `"Embarked"` columns, replace null age values with the average age, then drop any rows that are missing data. To begin, we examine the average survival rate grouped by sex and passenger class.

```
>>> titanic = pd.read_csv("titanic.csv")
>>> titanic = titanic[["Survived", "Pclass", "Sex", "Age", "Fare", "Embarked"]]
>>> titanic["Age"].fillna(titanic["Age"].mean(), inplace=True)
>>> titanic.dropna(inplace=True)

>>> titanic.pivot_table(values="Survived", index="Sex", columns="Pclass")
Pclass     1.0    2.0    3.0
Sex
female   0.965  0.887  0.491
male     0.341  0.146  0.152
```

[2]There is a `"Titanic"` data set in `pydataset`, but it does not contain as much information as the data in `titanic.csv`.

NOTE

The `pivot_table()` method is just a convenient way of performing a potentially complicated `groupby()` operation with aggregation and some reshaping. For example, the following code is equivalent to the previous example.

```
>>> titanic.groupby(["Sex", "Pclass"])["Survived"].mean().unstack()
Pclass    1.0    2.0    3.0
Sex
female  0.965  0.887  0.491
male    0.341  0.146  0.152
```

The `stack()`, `unstack()`, and `pivot()` methods provide more advanced shaping options.

Among other things, this pivot table clearly shows how much more likely females were to survive than males. To see how many entries fall into each category, or how many survived in each category, aggregate by counting or summing instead of taking the mean.

```
# See how many entries are in each category.
>>> titanic.pivot_table(values="Survived", index="Sex", columns="Pclass",
...                     aggfunc="count")
Pclass  1.0  2.0  3.0
Sex
female  144  106  216
male    179  171  493

# See how many people from each category survived.
>>> titanic.pivot_table(values="Survived", index="Sex", columns="Pclass",
...                     aggfunc="sum")
Pclass    1.0   2.0    3.0
Sex
female  137.0  94.0  106.0
male     61.0  25.0   75.0
```

Discretizing Continuous Data

So far we have examined survival rates based on sex and passenger class. Another factor that could have played into survival is age. Were male children as likely to die as females in general? We can investigate this question by *multi-indexing*, or pivoting on more than just two variables, by adding in another index.

In the original dataset, the `"Age"` column has a floating point value for the age of each passenger. If we just added `"Age"` as another pivot, then the table would create a new row for **each** age present. Instead, we partition the `"Age"` column into intervals with `pd.cut()`, thus creating a categorical that can be used for grouping.

```
# pd.cut() maps continuous entries to discrete intervals.
>>> pd.cut([6, 1, 2, 3, 4, 5, 6, 7], [0, 4, 8])
[(0, 4], (0, 4], (0, 4], (0, 4], (4, 8], (4, 8], (4, 8], (0, 4]]
Categories (2, interval[int64]): [(0, 4] < (4, 8]]

# Partition the passengers into 3 categories based on age.
>>> age = pd.cut(titanic['Age'], [0, 12, 18, 80])

>>> titanic.pivot_table(values="Survived", index=["Sex", age],
                        columns="Pclass", aggfunc="mean")
Pclass              1.0    2.0    3.0
Sex    Age
female (0, 12]   0.000  1.000  0.467
       (12, 18]  1.000  0.875  0.607
       (18, 80]  0.969  0.871  0.475
male   (0, 12]   1.000  1.000  0.343
       (12, 18]  0.500  0.000  0.081
       (18, 80]  0.322  0.093  0.143
```

From this table, it appears that male children (ages 0 to 12) in the 1st and 2nd class were very likely to survive, whereas those in 3rd class were much less likely to. This clarifies the claim that males were less likely to survive than females. However, there are a few oddities in this table: zero percent of the female children in 1st class survived, and zero percent of teenage males in second class survived. To further investigate, count the number of entries in each group.

```
>>> titanic.pivot_table(values="Survived", index=["Sex", age],
                        columns="Pclass", aggfunc="count")
Pclass           1.0  2.0  3.0
Sex    Age
female (0, 12]     1   13   30
       (12, 18]   12    8   28
       (18, 80]  129   85  158
male   (0, 12]     4   11   35
       (12, 18]    4   10   37
       (18, 80]  171  150  420
```

This table shows that there was only 1 female child in first class and only 10 male teenagers in second class, which sheds light on the previous table.

Achtung!

The previous pivot table brings up an important point about partitioning datasets. The Titanic dataset includes data for about 1300 passengers, which is a somewhat reasonable sample size, but half of the groupings include less than 30 entries, which is **not** a healthy sample size for statistical analysis. Always carefully question the numbers from pivot tables before making any conclusions.

Pandas also supports multi-indexing on the columns. As an example, consider the price of a passenger tickets. This is another continuous feature that can be discretized with `pd.cut()`. Instead, we use `pd.qcut()` to split the prices into 2 equal quantiles. Some of the resulting groups are empty; to improve readability, specify `fill_value` as the empty string or a dash.

```
# pd.qcut() partitions entries into equally populated intervals.
>>> pd.qcut([1, 2, 5, 6, 8, 3], 2)
[(0.999, 4.0], (0.999, 4.0], (4.0, 8.0], (4.0, 8.0], (4.0, 8.0], (0.999, 4.0]]
Categories (2, interval[float64]): [(0.999, 4.0] < (4.0, 8.0]]

# Cut the ticket price into two intervals (cheap vs expensive).
>>> fare = pd.qcut(titanic["Fare"], 2)
>>> titanic.pivot_table(values="Survived",
                        index=["Sex", age], columns=[fare, "Pclass"],
                        aggfunc="count", fill_value='-')
Fare            (-0.001, 14.454]          (14.454, 512.329]
Pclass                       1.0 2.0  3.0               1.0 2.0 3.0
Sex    Age
female (0, 12]                 -   -    7                 1  13  23
       (12, 18]                -   4   23                12   4   5
       (18, 80]                -  31  101               129  54  57
male   (0, 12]                 -   -    8                 4  11  27
       (12, 18]                -   5   26                 4   5  11
       (18, 80]                8  94  350               163  56  70
```

Not surprisingly, most of the cheap tickets went to passengers in 3rd class.

Problem 2. Suppose that someone claims that the city from which a passenger embarked had a strong influence on the passenger's survival rate. Investigate this claim.

1. Check the survival rates of the passengers based on where they embarked from (given in the `"Embarked"` column).
2. Create a pivot table to examine survival rates based on both place of embarkment and gender.
3. What do these tables suggest to you about the significance of where people embarked in influencing their survival rate? Examine the context of the problem, and explain what you think this really means.
4. Investigate the claim further with at least two more pivot tables, exploring other criteria (e.g., class, age, etc.). Carefully explain your conclusions.

Problem 3. Examine the following data sets from `pydataset` and answer the corresponding questions. Use visualizations and/or pivot tables as appropriate to support your conclusions.

- `"npk"`, an experiment on the effects of nitrogen (N), phosphate (P), and potassium (K) on the growth of peas.
  1. Which element is most effective in general for simulating growth? Which is the least effective?
  2. What combination of N, P, and K is optimal? What combination is the worst?
- `"swiss"`, standardized fertility measures and socio-economic indicators for French-speaking provinces of Switzerland at about 1888.
  1. What is the relationship in the data between fertility rates and infant mortality?
  2. How are provinces that are predominantly Catholic different from non-Catholic provinces, if at all?
  3. What factors in the data are the most important for predicting fertility?
- Examine a data set of your choice. Formulate simple questions about the data and hypothesize the answers to those questions. Demonstrate the correctness of incorrectness of each hypothesis. Explain your conclusions.

10 Pandas 4: Time Series

Lab Objective: *Many real world data sets—stock market measurements, ocean tide levels, website traffic, seismograph data, audio signals, fluid simulations, quarterly dividends, and so on—are time series, meaning they come with time-based labels. There is no universal format for such labels, and indexing by time is often difficult with raw data. Fortunately, pandas has tools for cleaning and analyzing time series. In this lab we use pandas to clean and manipulate time-stamped data and introduce some basic tools for time series analysis.*

Working with Dates and Times

The `datetime` module in the standard library provides a few tools for representing and operating on dates and times. The `datetime.datetime` object represents a *time stamp*: a specific time of day on a certain day. Its constructor accepts a four-digit year, a month (starting at 1 for January), a day, and, optionally, an hour, minute, second, and microsecond. Each of these arguments must be an integer, with the hour ranging from 0 to 23 (military time).

```
>>> from datetime import datetime

# Represent November 18th, 1991, at 2:01 PM.
>>> bday = datetime(1991, 11, 18, 14, 1)
>>> print(bday)
1991-11-18 14:01:00

# Find the number of days between 11/18/1991 and 11/9/2017.
>>> dt = datetime(2017, 11, 9) - bday
>>> dt.days
9487
```

The `datetime.datetime` object has a parser method, `strptime()`, that converts a string into a new `datetime.datetime` object. The parser is flexible because the user must specify the format that the dates are in. For example, if the dates are in the format `"Month/Day//Year::Hour"`, specify `format="%m/%d//%Y::%H"` to parse the string appropriately. See Table 10.1 for formatting options.

Pattern	Description
`%Y`	4-digit year
`%y`	2-digit year
`%m`	1- or 2-digit month
`%d`	1- or 2-digit day
`%H`	Hour (24-hour)
`%I`	Hour (12-hour)
`%M`	2-digit minute
`%S`	2-digit second

Table 10.1: Formats recognized by `datetime.strptime()`

```
>>> print(datetime.strptime("1991-11-18 / 14:01", "%Y-%m-%d / %H:%M"),
...       datetime.strptime("1/22/1996", "%m/%d/%Y"),
...       datetime.strptime("19-8, 1998", "%d-%m, %Y"), sep='\n')
1991-11-18 14:01:00                 # The date formats are now standardized.
1996-01-22 00:00:00                 # If no hour/minute/seconds data is given,
1998-08-19 00:00:00                 #  the default is midnight.
```

Converting Dates to an Index

The `TimeStamp` class is the pandas equivalent to a `datetime.datetime` object. An pandas index for composed of `TimeStamp` objects is a `DatetimeIndex`, and a `Series` or `DataFrame` with such an index is called a *time series*. The function `pd.to_datetime()` converts a collection of dates in a parsable format to a `DatetimeIndex`. The format of the dates is inferred if possible, but it can be specified explicitly with the same syntax as `datetime.strptime()`.

```
>>> import pandas as pd

# Convert some dates (as strings) into a DatetimeIndex.
>>> dates = ["2010-1-1", "2010-2-1", "2012-1-1", "2012-1-2"]
>>> pd.to_datetime(dates)
DatetimeIndex(['2010-01-01', '2010-02-01', '2012-01-01', '2012-01-02'],
              dtype='datetime64[ns]', freq=None)

# Create a time series, specifying the format for the dates.
>>> dates = ["1/1, 2010", "1/2, 2010", "1/1, 2012", "1/2, 2012"]
>>> date_index = pd.to_datetime(dates, format="%m/%d, %Y")
>>> pd.Series([x**2 for x in range(4)], index=date_index)
2010-01-01    0
2010-01-02    1
2012-01-01    4
2012-01-02    9
dtype: int64
```

Problem 1. The file `DJIA.csv` contains daily closing values of the Dow Jones Industrial Average from 2006–2016. Read the data into a `Series` or `DataFrame` with a `DatetimeIndex` as the index. Drop rows with missing values, cast the `"VALUES"` column to floats, then plot the data. (Hint: Use `lw=.5` to make the line thin enough for the data.)

Generating Time-based Indices

Some time series datasets come without explicit labels, but still have instructions for deriving timestamps. For example, a list of bank account balances might have records from the beginning of every month, or heart rate readings could be recorded by an app every 10 minutes. Use `pd.date_range()` to generate a `DatetimeIndex` where the timestamps are equally spaced. The function is analogous to `np.arange()` and has the following parameters.

Parameter	Description
`start`	Starting date
`end`	End date
`periods`	Number of dates to include
`freq`	Amount of time between consecutive dates
`normalize`	Whether or not to trim the time to midnight

Table 10.2: Parameters for `pd.date_range()`.

Exactly two of the parameters `start`, `end`, and `periods` must be specified to generate a range of dates. The `freq` parameter accepts a variety of string representations, referred to as *offset aliases*. See Table 10.3 for a sampling of some of the options. For a complete list of the options, see `http://pandas.pydata.org/pandas-docs/stable/timeseries.html#offset-aliases`.

Parameter	Description
`"D"`	calendar daily (default)
`"B"`	business daily
`"H"`	hourly
`"T"`	minutely
`"S"`	secondly
`"MS"`	first day of the month
`"BMS"`	first weekday of the month
`"W-MON"`	every Monday
`"WOM-3FRI"`	every 3rd Friday of the month

Table 10.3: Options for the `freq` parameter to `pd.date_range()`.

```
# 5 consecutive days staring with September 28, 2016.
>>> pd.date_range(start='9/28/2016 16:00', periods=5)
DatetimeIndex(['2016-09-28 16:00:00', '2016-09-29 16:00:00',
               '2016-09-30 16:00:00', '2016-10-01 16:00:00',
               '2016-10-02 16:00:00'],
```

```
               dtype='datetime64[ns]', freq='D')

# The first weekday of every other month in 2016.
>>> pd.date_range(start='1/1/2016', end='1/1/2017', freq="2BMS" )
DatetimeIndex(['2016-01-01', '2016-03-01', '2016-05-02', '2016-07-01',
               '2016-09-01', '2016-11-01'],
               dtype='datetime64[ns]', freq='2BMS')


# 10 minute intervals between 4:00 PM and 4:30 PM on September 9, 2016.
>>> pd.date_range(start='9/28/2016 16:00',
            end='9/28/2016 16:30', freq="10T")
DatetimeIndex(['2016-09-28 16:00:00', '2016-09-28 16:10:00',
               '2016-09-28 16:20:00', '2016-09-28 16:30:00'],
               dtype='datetime64[ns]', freq='10T')
```

The `freq` parameter also supports more flexible string representations.

```
>>> pd.date_range(start='9/28/2016 16:30', periods=5, freq="2h30min")
DatetimeIndex(['2016-09-28 16:30:00', '2016-09-28 19:00:00',
               '2016-09-28 21:30:00', '2016-09-29 00:00:00',
               '2016-09-29 02:30:00'],
               dtype='datetime64[ns]', freq='150T')
```

Problem 2. The file `paychecks.csv` contains values of an hourly employee's last 93 paychecks. He started working March 13, 2008. This company hands out paychecks on the first and third Fridays of the month.

Read in the data, using `pd.date_range()` to generate the `DatetimeIndex`. Plot the data. (Hint: use the `union()` method of `DatetimeIndex` class.)

Periods

The pandas `Timestamp` object represents a precise moment in time on a given day. Some data, however, is recorded over a time interval, and it wouldn't make sense to place an exact timestamp on any of the measurements. For example, a record of the number of steps walked in a day, box office earnings per week, quarterly earnings, and so on. This kind of data is better represented with the pandas `Period` object and the corresponding `PeriodIndex`.

The constructor of the `Period` accepts a `value` and a `freq`. The `value` parameter indicates the label for a given `Period`. This label is tied to the **end** of the defined `Period`. The `freq` indicates the length of the `Period` and also (in some cases) indicates the offset of the `Period`. The `freq` parameter accepts the majority, but not all, of frequencies listed in Table 10.3.

```
# The default value for 'freq' is "M" for months.
>>> p1 = pd.Period("2016-10")
>>> p1.start_time                    # The start and end times of the period
Timestamp('2016-10-01 00:00:00')     # are recorded as Timestamps.
```

```
>>> p1.end_time
Timestamp('2016-10-31 23:59:59.999999999')

# Represent the annual period ending in December that includes 10/03/2016.
>>> p2 = pd.Period("2016-10-03", freq="A-DEC")
>>> p2.start_time
Timestamp('2007-01-01 00:00:00')
>>> p2.end_time
Timestamp('2007-12-31 23:59:59.999999999')

# Get the weekly period ending on a Saturday that includes 10/03/2016.
>>> print(pd.Period("2016-10-03", freq="W-SAT"))
2016-10-02/2016-10-08
```

Like the `pd.date_range()` method, the `pd.period_range()` method is useful for generating a `PeriodIndex` for unindexed data. The syntax is essentially identical to that of `pd.date_range()`. When using `pd.period_range()`, remember that the `freq` parameter marks the end of the period.

```
# Represent quarters from 2008 to 2010, with Q4 ending in December.
>>> pd.period_range(start="2008", end="2010-12", freq="Q-DEC")
PeriodIndex(['2008Q1', '2008Q2', '2008Q3', '2008Q4', '2009Q1', '2009Q2',
             '2009Q3', '2009Q4', '2010Q1', '2010Q2', '2010Q3', '2010Q4'],
            dtype='period[Q-DEC]', freq='Q-DEC')
```

After creating a `PeriodIndex`, the `freq` parameter can be changed via the `asfreq()` method.

```
# Get every three months form March 2010 to the start of 2011.
>>> p = pd.period_range("2010-03", "2011", freq="3M")
>>> p
PeriodIndex(['2010-03', '2010-06', '2010-09', '2010-12'],
            dtype='period[3M]', freq='3M')

# Change frequency to be quarterly.
>>> p.asfreq("Q-DEC")
PeriodIndex(['2010Q2', '2010Q3', '2010Q4', '2011Q1'],
            dtype='period[Q-DEC]', freq='Q-DEC')
```

Say you have created a `PeriodIndex`, but the bounds are not exactly where you expected they would be. You can actually shift `PeriodIndex` obejcts by adding or subtracting an integer, n. The resulting `PeriodIndex` will be shifted by $n \times$ `freq`.

```
# Shift index by 1
>>> p -= 1
>>> p
PeriodIndex(['2010Q1', '2010Q2', '2010Q3', '2010Q4'],
            dtype='int64', freq='Q-DEC')
```

If for any reason you need to switch from periods to timestamps, pandas provides a very simple method to do so.

```
# Convert to timestamp (last day of each quarter)
>>> p = p.to_timestamp(how='end')
>>> p
DatetimeIndex(['2010-03-31', '2010-06-30', '2010-09-30', '2010-12-31'],
              dtype='datetime64[ns]', freq='Q-DEC')
```

Similarly, you can switch from timestamps to periods.

```
>>> p.to_period("Q-DEC")
PeriodIndex(['2010Q1', '2010Q2', '2010Q3', '2010Q4'],
            dtype='int64', freq='Q-DEC')
```

Problem 3. The file `finances.csv` contains a list of simulated quarterly earnings and expense totals from a fictional company. Load the data into a `Series` or `DataFrame` with a `PeriodIndex` with a quarterly frequency. Assume the fiscal year starts at the beginning of September and that the data begins in September 1978. Plot the data.

Operations on Time Series

There are certain operations only available to Series and DataFrames that have a `DatetimeIndex`. A sampling of this functionality is described throughout the remainder of this lab.

Slicing

Slicing is much more flexible in pandas for time series. We can slice by year, by month, or even use traditional slicing syntax to select a range of dates.

```
# Select all rows in a given year
>>> df["2010"]
                   0         1
2010-01-01  0.566694  1.093125
2010-02-01 -0.219856  0.852917
2010-03-01  1.511347 -1.324036

# Select all rows in a given month of a given year
>>> df["2012-01"]
                   0         1
2012-01-01  0.212141  0.859555
2012-01-02  1.483123 -0.520873
2012-01-03  1.436843  0.596143

# Select a range of dates using traditional slicing syntax
>>> df["2010-1-2":"2011-12-31"]
                   0         1
2010-02-01 -0.219856  0.852917
```

```
2010-03-01  1.511347 -1.324036
2011-01-01  0.300766  0.934895
```

Resampling

Imagine you have a dataset that does not have datapoints at a fixed frequency. For example, a dataset of website traffic would take on this form. Because the datapoints occur at irregular intervals, it may be more difficult to procure any meaningful insight. In situations like these, *resampling* your data is worth considering.

The two main forms of resampling are *downsampling* (aggregating data into fewer intervals) and *upsampling* (adding more intervals).

To downsample, use the `resample()` method of the `Series` or `DataFrame`. This method is similar to `groupby()` in that it groups different entries o together, and requires some kind of aggregation to produce a new data set. The first parameter to `resample()` is an offset string from Table 10.3: `"D"` for daily, `"H"` for hourly, and so on.

```
>>> import numpy as np

# Get random data for every day from 2000 to 2010.
>>> dates = pd.date_range(start="2000-1-1", end='2009-12-31', freq='D')
>>> df = pd.Series(np.random.random(len(days)), index=dates)
>>> df
2000-01-01    0.559
2000-01-02    0.874
2000-01-03    0.774
                ...
2009-12-29    0.837
2009-12-30    0.472
2009-12-31    0.211
Freq: D, Length: 3653, dtype: float64

# Group the data by year.
>>> years = df.resample("A")        # 'A' for 'annual'.
>>> years.agg(len)                  # Number of entries per year.
2000-12-31    366.0
2001-12-31    365.0
2002-12-31    365.0
                ...
2007-12-31    365.0
2008-12-31    366.0
2009-12-31    365.0
Freq: A-DEC, dtype: float64

>>> years.mean()                    # Average entry by year.
2000-12-31    0.491
2001-12-31    0.514
2002-12-31    0.484
                ...
```

```
2007-12-31    0.508
2008-12-31    0.521
2009-12-31    0.523
Freq: A-DEC, dtype: float64

# Group the data by month.
>>> months = df.resample("M")
>>> len(months.mean())              # 12 months x 10 years = 120 months.
120
```

Problem 4. The file `website_traffic.csv` contains records for different visits to a fictitious website. Read in the data, calculate the duration of each visit (in seconds), and convert the index to a `DatetimeIndex`. Use downsampling to calculate the average visit duration by minute, and the average visit duration by hour. Plot both results on the same graph.

Elementary Time Series Analysis

Shifting

`DataFrame` and `Series` objects have a `shift()` method that allows you to move data up or down relative to the index. When dealing with time series data, we can also shift the `DatetimeIndex` relative to a time offset.

```
>>> df = pd.DataFrame(dict(VALUE=np.random.rand(5)),
                      index=pd.date_range("2016-10-7", periods=5, freq='D'))
>>> df
               VALUE
2016-10-07  0.127895
2016-10-08  0.811226
2016-10-09  0.656711
2016-10-10  0.351431
2016-10-11  0.608767

>>> df.shift(1)
               VALUE
2016-10-07       NaN
2016-10-08  0.127895
2016-10-09  0.811226
2016-10-10  0.656711
2016-10-11  0.351431

>>> df.shift(-2)
               VALUE
2016-10-07  0.656711
2016-10-08  0.351431
2016-10-09  0.608767
```

```
2016-10-10       NaN
2016-10-11       NaN

>>> df.shift(14, freq="D")
               VALUE
2016-10-21  0.127895
2016-10-22  0.811226
2016-10-23  0.656711
2016-10-24  0.351431
2016-10-25  0.608767
```

Shifting data makes it easy to gather statistics about changes from one timestamp or period to the next.

```
# Find the changes from one period/timestamp to the next
>>> df - df.shift(1)            # Equivalent to df.diff().
               VALUE
2016-10-07       NaN
2016-10-08  0.683331
2016-10-09 -0.154516
2016-10-10 -0.305279
2016-10-11  0.257336
```

Problem 5. Compute the following information about the DJIA dataset from Problem 1.

- The single day with the largest gain.
- The single day with the largest loss.
- The month with the largest gain.
- The month with the largest loss.

For the monthly statistics, define the gain (or loss) to be the difference between the DJIA on the last and first days of the month.

Rolling Functions and Exponentially-Weighted Moving Functions

Many time series are inherently noisy. To analyze general trends in data, we use *rolling functions* and *exponentially-weighted moving (EWM)* functions.

Rolling functions, or *moving window functions*, perform some kind of calculation on just a window of data. There are a few rolling functions that come standard with pandas.

Rolling Functions (Moving Window Functions)

One of the most commonly used rolling functions is the *rolling average*, which takes the average value over a window of data.

```
# Generate a time series using random walk from a uniform distribution.
N = 10000
bias = 0.01
s = np.zeros(N)
s[1:] = np.random.uniform(low=-1, high=1, size=N-1) + bias
s = pd.Series(s.cumsum(),
              index=pd.date_range("2015-10-20", freq='H', periods=N))

# Plot the original data together with a rolling average.
ax1 = plt.subplot(121)
s.plot(color="gray", lw=.3, ax=ax1)
s.rolling(window=200).mean().plot(color='r', lw=1, ax=ax1)
ax1.legend(["Actual", "Rolling"], loc="lower right")
ax1.set_title("Rolling Average")
```

The function call `s.rolling(window=200)` creates a `pd.core.rolling.Window` object that can be aggregated with a function like `mean()`, `std()`, `var()`, `min()`, `max()`, and so on.

Exponentially-Weighted Moving (EWM) Functions

Whereas a moving window function gives equal weight to the whole window, an *exponentially-weighted moving* function gives more weight to the most recent data points.

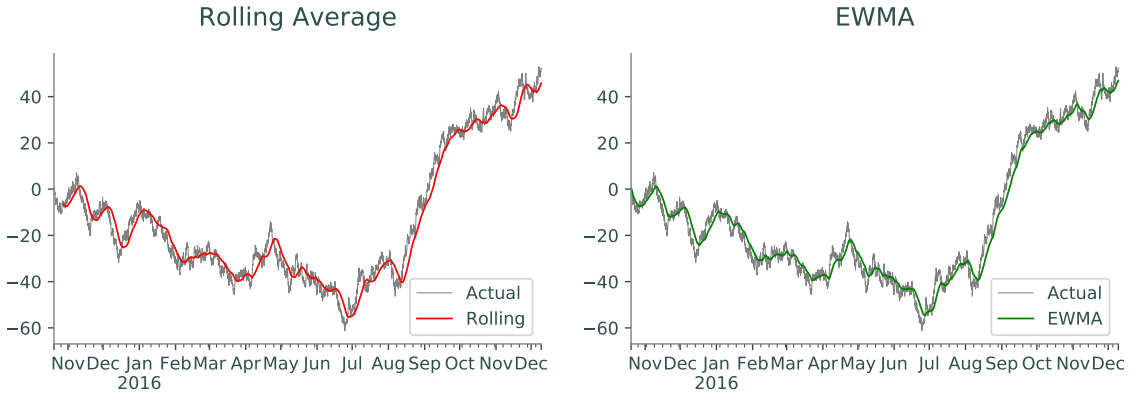
In the case of a *exponentially-weighted moving average* (EWMA), each data point is calculated as follows.

$$z_i = \alpha \bar{x}_i + (1 - \alpha) z_{i-1},$$

where z_i is the value of the EWMA at time i, $\bar{x}_i$ is the average for the i-th window, and α is the decay factor that controls the importance of previous data points. Notice that $\alpha = 1$ reduces to the rolling average.

More commonly, the decay is expressed as a function of the window size. In fact, the `span` for an EWMA is nearly analogous to `window` size for a rolling average.

Notice the syntax for EWM functions is very similar to that of rolling functions.



(a) (b)

Figure 10.1: Rolling average and EWMA.

```
ax2 = plt.subplot(121)
s.plot(color="gray", lw=.3, ax=ax2)
s.ewm(span=200).mean().plot(color='g', lw=1, ax=ax2)
ax2.legend(["Actual", "EWMA"], loc="lower right")
ax2.set_title("EWMA")
```

Problem 6. Plot the following from the DJIA dataset with a window or span of 30, 120, and 365.

- The original data points.
- Rolling average.
- Exponential average.
- Minimum rolling values.
- Maximum rolling values.

Describe how varying the length of the window changes the approximation to the data.