NumPy has fast built-in aggregation functions for working on arrays; we'll discuss and demonstrate some of them here.

Summing the Values in an Array

As a quick example, consider computing the sum of all values in an array. Python itself can do this using the built-in `sum` function:

```
In[1]: import numpy as np
```

```
In[2]: L = np.random.random(100)
       sum(L)
```

```
Out[2]: 55.61209116604941
```

The syntax is quite similar to that of NumPy's `sum` function, and the result is the same in the simplest case:

```
In[3]: np.sum(L)
```

```
Out[3]: 55.612091166049424
```

However, because it executes the operation in compiled code, NumPy's version of the operation is computed much more quickly:

```
In[4]: big_array = np.random.rand(1000000)
       %timeit sum(big_array)
       %timeit np.sum(big_array)
```

```
10 loops, best of 3: 104 ms per loop
1000 loops, best of 3: 442 µs per loop
```

Be careful, though: the `sum` function and the `np.sum` function are not identical, which can sometimes lead to confusion! In particular, their optional arguments have different meanings, and `np.sum` is aware of multiple array dimensions, as we will see in the following section.

Minimum and Maximum

Similarly, Python has built-in `min` and `max` functions, used to find the minimum value and maximum value of any given array:

```
In[5]: min(big_array), max(big_array)
```

```
Out[5]: (1.1717128136634614e-06, 0.9999976784968716)
```

NumPy's corresponding functions have similar syntax, and again operate much more quickly:

```
In[6]: np.min(big_array), np.max(big_array)
```

```
Out[6]: (1.1717128136634614e-06, 0.9999976784968716)
```

```
In[7]: %timeit min(big_array)
       %timeit np.min(big_array)

10 loops, best of 3: 82.3 ms per loop
1000 loops, best of 3: 497 µs per loop
```

For `min`, `max`, `sum`, and several other NumPy aggregates, a shorter syntax is to use methods of the array object itself:

```
In[8]: print(big_array.min(), big_array.max(), big_array.sum())

1.17171281366e-06 0.999997678497 499911.628197
```

Whenever possible, make sure that you are using the NumPy version of these aggregates when operating on NumPy arrays!

Multidimensional aggregates

One common type of aggregation operation is an aggregate along a row or column. Say you have some data stored in a two-dimensional array:

```
In[9]: M = np.random.random((3, 4))
       print(M)

[[ 0.8967576   0.03783739  0.75952519  0.06682827]
 [ 0.8354065   0.99196818  0.19544769  0.43447084]
 [ 0.66859307  0.15038721  0.37911423  0.6687194 ]]
```

By default, each NumPy aggregation function will return the aggregate over the entire array:

```
In[10]: M.sum()

Out[10]: 6.0850555667307118
```

Aggregation functions take an additional argument specifying the *axis* along which the aggregate is computed. For example, we can find the minimum value within each column by specifying `axis=0`:

```
In[11]: M.min(axis=0)

Out[11]: array([ 0.66859307,  0.03783739,  0.19544769,  0.06682827])
```

The function returns four values, corresponding to the four columns of numbers.

Similarly, we can find the maximum value within each row:

```
In[12]: M.max(axis=1)

Out[12]: array([ 0.8967576 ,  0.99196818,  0.6687194 ])
```

The way the axis is specified here can be confusing to users coming from other languages. The `axis` keyword specifies the *dimension of the array that will be collapsed*, rather than the dimension that will be returned. So specifying `axis=0` means that the first axis will be collapsed: for two-dimensional arrays, this means that values within each column will be aggregated.

Other aggregation functions

NumPy provides many other aggregation functions, but we won't discuss them in detail here. Additionally, most aggregates have a `NaN`-safe counterpart that computes the result while ignoring missing values, which are marked by the special IEEE floating-point `NaN` value (for a fuller discussion of missing data, see "Handling Missing Data" on page 119). Some of these `NaN`-safe functions were not added until NumPy 1.8, so they will not be available in older NumPy versions.

Table 2-3 provides a list of useful aggregation functions available in NumPy.

Table 2-3. Aggregation functions available in NumPy

Function Name	NaN-safe Version	Description
`np.sum`	`np.nansum`	Compute sum of elements
`np.prod`	`np.nanprod`	Compute product of elements
`np.mean`	`np.nanmean`	Compute median of elements
`np.std`	`np.nanstd`	Compute standard deviation
`np.var`	`np.nanvar`	Compute variance
`np.min`	`np.nanmin`	Find minimum value
`np.max`	`np.nanmax`	Find maximum value
`np.argmin`	`np.nanargmin`	Find index of minimum value
`np.argmax`	`np.nanargmax`	Find index of maximum value
`np.median`	`np.nanmedian`	Compute median of elements
`np.percentile`	`np.nanpercentile`	Compute rank-based statistics of elements
`np.any`	N/A	Evaluate whether any elements are true
`np.all`	N/A	Evaluate whether all elements are true

We will see these aggregates often throughout the rest of the book.

Example: What Is the Average Height of US Presidents?

Aggregates available in NumPy can be extremely useful for summarizing a set of values. As a simple example, let's consider the heights of all US presidents. This data is available in the file *president_heights.csv*, which is a simple comma-separated list of labels and values:

```
In[13]: !head -4 data/president_heights.csv

order,name,height(cm)
1,George Washington,189
```

CHAPTER 3

Data Manipulation with Pandas

In the previous chapter, we dove into detail on NumPy and its `ndarray` object, which provides efficient storage and manipulation of dense typed arrays in Python. Here we'll build on this knowledge by looking in detail at the data structures provided by the Pandas library. Pandas is a newer package built on top of NumPy, and provides an efficient implementation of a `DataFrame`. `DataFrame`s are essentially multidimensional arrays with attached row and column labels, and often with heterogeneous types and/or missing data. As well as offering a convenient storage interface for labeled data, Pandas implements a number of powerful data operations familiar to users of both database frameworks and spreadsheet programs.

As we saw, NumPy's `ndarray` data structure provides essential features for the type of clean, well-organized data typically seen in numerical computing tasks. While it serves this purpose very well, its limitations become clear when we need more flexibility (attaching labels to data, working with missing data, etc.) and when attempting operations that do not map well to element-wise broadcasting (groupings, pivots, etc.), each of which is an important piece of analyzing the less structured data available in many forms in the world around us. Pandas, and in particular its `Series` and `DataFrame` objects, builds on the NumPy array structure and provides efficient access to these sorts of "data munging" tasks that occupy much of a data scientist's time.

In this chapter, we will focus on the mechanics of using `Series`, `DataFrame`, and related structures effectively. We will use examples drawn from real datasets where appropriate, but these examples are not necessarily the focus.

Installing and Using Pandas

Installing Pandas on your system requires NumPy to be installed, and if you're building the library from source, requires the appropriate tools to compile the C and

Cython sources on which Pandas is built. Details on this installation can be found in the Pandas documentation. If you followed the advice outlined in the preface and used the Anaconda stack, you already have Pandas installed.

Once Pandas is installed, you can import it and check the version:

```
In[1]: import pandas
       pandas.__version__
```

```
Out[1]: '0.18.1'
```

Just as we generally import NumPy under the alias `np`, we will import Pandas under the alias `pd`:

```
In[2]: import pandas as pd
```

This import convention will be used throughout the remainder of this book.

Reminder About Built-In Documentation

As you read through this chapter, don't forget that IPython gives you the ability to quickly explore the contents of a package (by using the tab-completion feature) as well as the documentation of various functions (using the `?` character). (Refer back to "Help and Documentation in IPython" on page 3 if you need a refresher on this.)

For example, to display all the contents of the `pandas` namespace, you can type this:

```
In [3]: pd.<TAB>
```

And to display the built-in Pandas documentation, you can use this:

```
In [4]: pd?
```

More detailed documentation, along with tutorials and other resources, can be found at *http://pandas.pydata.org/*.

Introducing Pandas Objects

At the very basic level, Pandas objects can be thought of as enhanced versions of NumPy structured arrays in which the rows and columns are identified with labels rather than simple integer indices. As we will see during the course of this chapter, Pandas provides a host of useful tools, methods, and functionality on top of the basic data structures, but nearly everything that follows will require an understanding of what these structures are. Thus, before we go any further, let's introduce these three fundamental Pandas data structures: the `Series`, `DataFrame`, and `Index`.

We will start our code sessions with the standard NumPy and Pandas imports:

```
In[1]: import numpy as np
       import pandas as pd
```

The Pandas Series Object

A Pandas `Series` is a one-dimensional array of indexed data. It can be created from a list or array as follows:

```
In[2]: data = pd.Series([0.25, 0.5, 0.75, 1.0])
       data

Out[2]: 0    0.25
        1    0.50
        2    0.75
        3    1.00
        dtype: float64
```

As we see in the preceding output, the `Series` wraps both a sequence of values and a sequence of indices, which we can access with the `values` and `index` attributes. The `values` are simply a familiar NumPy array:

```
In[3]: data.values

Out[3]: array([ 0.25,  0.5 ,  0.75,  1.  ])
```

The `index` is an array-like object of type `pd.Index`, which we'll discuss in more detail momentarily:

```
In[4]: data.index

Out[4]: RangeIndex(start=0, stop=4, step=1)
```

Like with a NumPy array, data can be accessed by the associated index via the familiar Python square-bracket notation:

```
In[5]: data[1]

Out[5]: 0.5

In[6]: data[1:3]

Out[6]: 1    0.50
        2    0.75
        dtype: float64
```

As we will see, though, the Pandas `Series` is much more general and flexible than the one-dimensional NumPy array that it emulates.

Series as generalized NumPy array

From what we've seen so far, it may look like the `Series` object is basically interchangeable with a one-dimensional NumPy array. The essential difference is the presence of the index: while the NumPy array has an *implicitly defined* integer index used to access the values, the Pandas `Series` has an *explicitly defined* index associated with the values.

This explicit index definition gives the `Series` object additional capabilities. For example, the index need not be an integer, but can consist of values of any desired type. For example, if we wish, we can use strings as an index:

```
In[7]: data = pd.Series([0.25, 0.5, 0.75, 1.0],
                        index=['a', 'b', 'c', 'd'])
       data

Out[7]: a    0.25
        b    0.50
        c    0.75
        d    1.00
        dtype: float64
```

And the item access works as expected:

```
In[8]: data['b']

Out[8]: 0.5
```

We can even use noncontiguous or nonsequential indices:

```
In[9]: data = pd.Series([0.25, 0.5, 0.75, 1.0],
                        index=[2, 5, 3, 7])
       data

Out[9]: 2    0.25
        5    0.50
        3    0.75
        7    1.00
        dtype: float64

In[10]: data[5]

Out[10]: 0.5
```

Series as specialized dictionary

In this way, you can think of a Pandas `Series` a bit like a specialization of a Python dictionary. A dictionary is a structure that maps arbitrary keys to a set of arbitrary values, and a `Series` is a structure that maps typed keys to a set of typed values. This typing is important: just as the type-specific compiled code behind a NumPy array makes it more efficient than a Python list for certain operations, the type information of a Pandas `Series` makes it much more efficient than Python dictionaries for certain operations.

We can make the `Series`-as-dictionary analogy even more clear by constructing a `Series` object directly from a Python dictionary:

```
In[11]: population_dict = {'California': 38332521,
                           'Texas': 26448193,
                           'New York': 19651127,
                           'Florida': 19552860,
                           'Illinois': 12882135}
        population = pd.Series(population_dict)
        population
```

```
Out[11]: California    38332521
         Florida       19552860
         Illinois      12882135
         New York      19651127
         Texas         26448193
         dtype: int64
```

By default, a `Series` will be created where the index is drawn from the sorted keys. From here, typical dictionary-style item access can be performed:

```
In[12]: population['California']
```

```
Out[12]: 38332521
```

Unlike a dictionary, though, the `Series` also supports array-style operations such as slicing:

```
In[13]: population['California':'Illinois']
```

```
Out[13]: California    38332521
         Florida       19552860
         Illinois      12882135
         dtype: int64
```

We'll discuss some of the quirks of Pandas indexing and slicing in "Data Indexing and Selection" on page 107.

Constructing Series objects

We've already seen a few ways of constructing a Pandas `Series` from scratch; all of them are some version of the following:

```
>>> pd.Series(data, index=index)
```

where `index` is an optional argument, and `data` can be one of many entities.

For example, `data` can be a list or NumPy array, in which case `index` defaults to an integer sequence:

```
In[14]: pd.Series([2, 4, 6])
```

```
Out[14]: 0    2
         1    4
         2    6
         dtype: int64
```

`data` can be a scalar, which is repeated to fill the specified index:

```
In[15]: pd.Series(5, index=[100, 200, 300])

Out[15]: 100    5
         200    5
         300    5
         dtype: int64
```

`data` can be a dictionary, in which `index` defaults to the sorted dictionary keys:

```
In[16]: pd.Series({2:'a', 1:'b', 3:'c'})

Out[16]: 1    b
         2    a
         3    c
         dtype: object
```

In each case, the index can be explicitly set if a different result is preferred:

```
In[17]: pd.Series({2:'a', 1:'b', 3:'c'}, index=[3, 2])

Out[17]: 3    c
         2    a
         dtype: object
```

Notice that in this case, the `Series` is populated only with the explicitly identified keys.

The Pandas DataFrame Object

The next fundamental structure in Pandas is the `DataFrame`. Like the `Series` object discussed in the previous section, the `DataFrame` can be thought of either as a generalization of a NumPy array, or as a specialization of a Python dictionary. We'll now take a look at each of these perspectives.

DataFrame as a generalized NumPy array

If a `Series` is an analog of a one-dimensional array with flexible indices, a `DataFrame` is an analog of a two-dimensional array with both flexible row indices and flexible column names. Just as you might think of a two-dimensional array as an ordered sequence of aligned one-dimensional columns, you can think of a `DataFrame` as a sequence of aligned `Series` objects. Here, by "aligned" we mean that they share the same index.

To demonstrate this, let's first construct a new `Series` listing the area of each of the five states discussed in the previous section:

```
In[18]:
area_dict = {'California': 423967, 'Texas': 695662, 'New York': 141297,
             'Florida': 170312, 'Illinois': 149995}
```

```
area = pd.Series(area_dict)
area
```

```
Out[18]: California    423967
         Florida       170312
         Illinois      149995
         New York      141297
         Texas         695662
         dtype: int64
```

Now that we have this along with the `population` `Series` from before, we can use a dictionary to construct a single two-dimensional object containing this information:

```
In[19]: states = pd.DataFrame({'population': population,
                               'area': area})
        states
```

```
Out[19]:             area      population
         California  423967    38332521
         Florida     170312    19552860
         Illinois    149995    12882135
         New York    141297    19651127
         Texas       695662    26448193
```

Like the `Series` object, the `DataFrame` has an `index` attribute that gives access to the index labels:

```
In[20]: states.index
```

```
Out[20]:
Index(['California', 'Florida', 'Illinois', 'New York', 'Texas'], dtype='object')
```

Additionally, the `DataFrame` has a `columns` attribute, which is an `Index` object holding the column labels:

```
In[21]: states.columns
```

```
Out[21]: Index(['area', 'population'], dtype='object')
```

Thus the `DataFrame` can be thought of as a generalization of a two-dimensional NumPy array, where both the rows and columns have a generalized index for accessing the data.

DataFrame as specialized dictionary

Similarly, we can also think of a `DataFrame` as a specialization of a dictionary. Where a dictionary maps a key to a value, a `DataFrame` maps a column name to a `Series` of column data. For example, asking for the `'area'` attribute returns the `Series` object containing the areas we saw earlier:

```
In[22]: states['area']
```

```
Out[22]: California    423967
         Florida       170312
```