```
101           AZ  total  2010   6408790.0     Arizona       114006.0
189           AR  total  2010   2922280.0    Arkansas        53182.0
197           CA  total  2010  37333601.0  California       163707.0
```

Now let's compute the population density and display it in order. We'll start by reindexing our data on the state, and then compute the result:

```
In[31]: data2010.set_index('state', inplace=True)
        density = data2010['population'] / data2010['area (sq. mi)']
```

```
In[32]: density.sort_values(ascending=False, inplace=True)
        density.head()
```

```
Out[32]: state
         District of Columbia    8898.897059
         Puerto Rico             1058.665149
         New Jersey              1009.253268
         Rhode Island             681.339159
         Connecticut              645.600649
         dtype: float64
```

The result is a ranking of US states plus Washington, DC, and Puerto Rico in order of their 2010 population density, in residents per square mile. We can see that by far the densest region in this dataset is Washington, DC (i.e., the District of Columbia); among states, the densest is New Jersey.

We can also check the end of the list:

```
In[33]: density.tail()
```

```
Out[33]: state
         South Dakota    10.583512
         North Dakota     9.537565
         Montana          6.736171
         Wyoming          5.768079
         Alaska           1.087509
         dtype: float64
```

We see that the least dense state, by far, is Alaska, averaging slightly over one resident per square mile.

This type of messy data merging is a common task when one is trying to answer questions using real-world data sources. I hope that this example has given you an idea of the ways you can combine tools we've covered in order to gain insight from your data!

Aggregation and Grouping

An essential piece of analysis of large data is efficient summarization: computing aggregations like `sum()`, `mean()`, `median()`, `min()`, and `max()`, in which a single number gives insight into the nature of a potentially large dataset. In this section, we'll explore aggregations in Pandas, from simple operations akin to what we've seen on NumPy arrays, to more sophisticated operations based on the concept of a `groupby`.

Planets Data

Here we will use the Planets dataset, available via the Seaborn package (see "Visualization with Seaborn" on page 311). It gives information on planets that astronomers have discovered around other stars (known as *extrasolar planets* or *exoplanets* for short). It can be downloaded with a simple Seaborn command:

```
In[2]: import seaborn as sns
       planets = sns.load_dataset('planets')
       planets.shape

Out[2]: (1035, 6)

In[3]: planets.head()

Out[3]:    method           number  orbital_period  mass   distance  year
        0  Radial Velocity  1       269.300         7.10   77.40     2006
        1  Radial Velocity  1       874.774         2.21   56.95     2008
        2  Radial Velocity  1       763.000         2.60   19.84     2011
        3  Radial Velocity  1       326.030         19.40  110.62    2007
        4  Radial Velocity  1       516.220         10.50  119.47    2009
```

This has some details on the 1,000+ exoplanets discovered up to 2014.

Simple Aggregation in Pandas

Earlier we explored some of the data aggregations available for NumPy arrays ("Aggregations: Min, Max, and Everything in Between" on page 58). As with a one-dimensional NumPy array, for a Pandas `Series` the aggregates return a single value:

```
In[4]: rng = np.random.RandomState(42)
       ser = pd.Series(rng.rand(5))
       ser

Out[4]: 0    0.374540
        1    0.950714
        2    0.731994
        3    0.598658
        4    0.156019
        dtype: float64

In[5]: ser.sum()

Out[5]: 2.8119254917081569

In[6]: ser.mean()

Out[6]: 0.56238509834163142
```

For a `DataFrame`, by default the aggregates return results within each column: