Pivot Tables

We have seen how the `groupby` abstraction lets us explore relationships within a dataset. A *pivot table* is a similar operation that is commonly seen in spreadsheets and other programs that operate on tabular data. The pivot table takes simple column-wise data as input, and groups the entries into a two-dimensional table that provides a multidimensional summarization of the data. The difference between pivot tables and `groupby` can sometimes cause confusion; it helps me to think of pivot tables as essentially a *multidimensional* version of `groupby` aggregation. That is, you split-apply-combine, but both the split and the combine happen across not a one-dimensional index, but across a two-dimensional grid.

Motivating Pivot Tables ¶

For the examples in this section, we'll use the database of passengers on the *Titanic*, available through the Seaborn library (see Visualization With Seaborn (04.14-Visualization-With-Seaborn.ipynb)):

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
titanic = sns.load_dataset('titanic')
```

In [2]:
```
titanic.head()
```

Out[2]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True

As the output shows, this contains a number of data points on each passenger on that ill-fated voyage, including sex, age, class, fare paid, and much more.

Pivot Tables by Hand

To start learning more about this data, we might begin by grouping according to sex, survival status, or some combination thereof. If you read the previous chapter, you might be tempted to apply a `groupby` operation—for example, let's look at survival rate by sex:

In [3]:
```
titanic.groupby('sex')[['survived']].mean()
```

Out[3]:

	survived
sex	
female	0.742038
male	0.188908

This gives us some initial insight: overall, three of every four females on board survived, while only one in five males survived!

This is useful, but we might like to go one step deeper and look at survival rates by both sex and, say, class. Using the vocabulary of `groupby`, we might proceed using a process like this: we first *group by* class and sex, then *select* survival, *apply* a mean aggregate, *combine* the resulting groups, and finally *unstack* the hierarchical index to reveal the hidden multidimensionality. In code:

In [4]:
```
titanic.groupby(['sex', 'class'])['survived'].aggregate('mean').unstack()
```

Out[4]:

class	First	Second	Third
sex			
female	0.968085	0.921053	0.500000
male	0.368852	0.157407	0.135447

This gives us a better idea of how both sex and class affected survival, but the code is starting to look a bit garbled. While each step of this pipeline makes sense in light of the tools we've previously discussed, the long string of code is not particularly easy to read or use. This two-dimensional `groupby` is common enough that Pandas includes a convenience routine, `pivot_table`, which succinctly handles this type of multidimensional aggregation.

Pivot Table Syntax

Here is the equivalent to the preceding operation using the `DataFrame.pivot_table` method:

In [5]:
```
titanic.pivot_table('survived', index='sex', columns='class', aggfunc='mean')
```

Out[5]:

class	First	Second	Third
sex			
female	0.968085	0.921053	0.500000
male	0.368852	0.157407	0.135447

This is eminently more readable than the manual `groupby` approach, and produces the same result. As you might expect of an early 20th-century transatlantic cruise, the survival gradient favors both higher classes and people recorded as females in the data. First-class females survived with near certainty (hi, Rose!), while only one in eight or so third-class males survived (sorry, Jack!).

Multilevel Pivot Tables

Just as in a `groupby`, the grouping in pivot tables can be specified with multiple levels and via a number of options. For example, we might be interested in looking at age as a third dimension. We'll bin the age using the `pd.cut` function:

In [6]:
```
age = pd.cut(titanic['age'], [0, 18, 80])
titanic.pivot_table('survived', ['sex', age], 'class')
```

Out[6]:

	class	**First**	**Second**	**Third**
sex	**age**			
female	**(0, 18]**	0.909091	1.000000	0.511628
	(18, 80]	0.972973	0.900000	0.423729
male	**(0, 18]**	0.800000	0.600000	0.215686
	(18, 80]	0.375000	0.071429	0.133663

We can apply the same strategy when working with the columns as well; let's add info on the fare paid, using `pd.qcut` to automatically compute quantiles:

In [7]:
```
fare = pd.qcut(titanic['fare'], 2)
titanic.pivot_table('survived', ['sex', age], [fare, 'class'])
```

Out[7]:

	fare	**(-0.001, 14.454]**			**(14.454, 512.329]**		
	class	**First**	**Second**	**Third**	**First**	**Second**	**Third**
sex	**age**						
female	**(0, 18]**	NaN	1.000000	0.714286	0.909091	1.000000	0.318182
	(18, 80]	NaN	0.880000	0.444444	0.972973	0.914286	0.391304
male	**(0, 18]**	NaN	0.000000	0.260870	0.800000	0.818182	0.178571
	(18, 80]	0.0	0.098039	0.125000	0.391304	0.030303	0.192308

The result is a four-dimensional aggregation with hierarchical indices (see Hierarchical Indexing (03.05-Hierarchical-Indexing.ipynb)), shown in a grid demonstrating the relationship between the values.

Additional Pivot Table Options

The full call signature of the `DataFrame.pivot_table` method is as follows:

```
# call signature as of Pandas 1.3.5
DataFrame.pivot_table(data, values=None, index=None, columns=None,
                      aggfunc='mean', fill_value=None, margins=False,
                      dropna=True, margins_name='All', observed=Fals
e,
                      sort=True)
```

We've already seen examples of the first three arguments; here we'll take a quick look at some of the remaining ones. Two of the options, `fill_value` and `dropna`, have to do with missing data and are fairly straightforward; I will not show examples of them here.

The `aggfunc` keyword controls what type of aggregation is applied, which is a mean by default. As with `groupby`, the aggregation specification can be a string representing one of

In [8]:
```
titanic.pivot_table(index='sex', columns='class',
                    aggfunc={'survived':sum, 'fare':'mean'})
```

Out[8]:

	fare			survived		
class	**First**	**Second**	**Third**	**First**	**Second**	**Third**
sex						
female	106.125798	21.970121	16.118810	91	70	72
male	67.226127	19.741782	12.661633	45	17	47

Notice also here that we've omitted the `values` keyword; when specifying a mapping for `aggfunc`, this is determined automatically.

At times it's useful to compute totals along each grouping. This can be done via the `margins` keyword:

In [9]:
```
titanic.pivot_table('survived', index='sex', columns='class', margins=True)
```

Out[9]:

class	**First**	**Second**	**Third**	**All**
sex				
female	0.968085	0.921053	0.500000	0.742038
male	0.368852	0.157407	0.135447	0.188908
All	0.629630	0.472826	0.242363	0.383838

Here, this automatically gives us information about the class-agnostic survival rate by sex, the sex-agnostic survival rate by class, and the overall survival rate of 38%. The margin label can be specified with the `margins_name` keyword; it defaults to `"All"`.

Example: Birthrate Data

As another example, let's take a look at the freely available data on births in the United States, provided by the Centers for Disease Control (CDC). This data can be found at https://raw.githubusercontent.com/jakevdp/data-CDCbirths/master/births.csv (https://raw.githubusercontent.com/jakevdp/data-CDCbirths/master/births.csv) (this dataset has been analyzed rather extensively by Andrew Gelman and his group; see, for example, the blog post on signal processing using Gaussian processes (http://andrewgelman.com/2012/06/14/cool-ass-signal-processing-using-gaussian-processes/)):

[^1]: The CDC dataset used in this section uses the sex assigned at birth, which it calls "gender," and limits the data to male and female. While gender is a spectrum independent of biology, I will be using the same terminology while discussing this dataset for consistency and clarity.

In [10]:
```
# shell command to download the data:
# !cd data && curl -O \
# https://raw.githubusercontent.com/jakevdp/data-CDCbirths/master/births.csv
```

In [11]:
```
births = pd.read_csv('data/births.csv')
```

Taking a look at the data, we see that it's relatively simple—it contains the number of births grouped by date and gender:

In [12]:
```
births.head()
```

Out[12]:

	year	month	day	gender	births
0	1969	1	1.0	F	4046
1	1969	1	1.0	M	4440
2	1969	1	2.0	F	4454
3	1969	1	2.0	M	4548
4	1969	1	3.0	F	4548

We can start to understand this data a bit more by using a pivot table. Let's add a `decade` column, and take a look at male and female births as a function of decade:

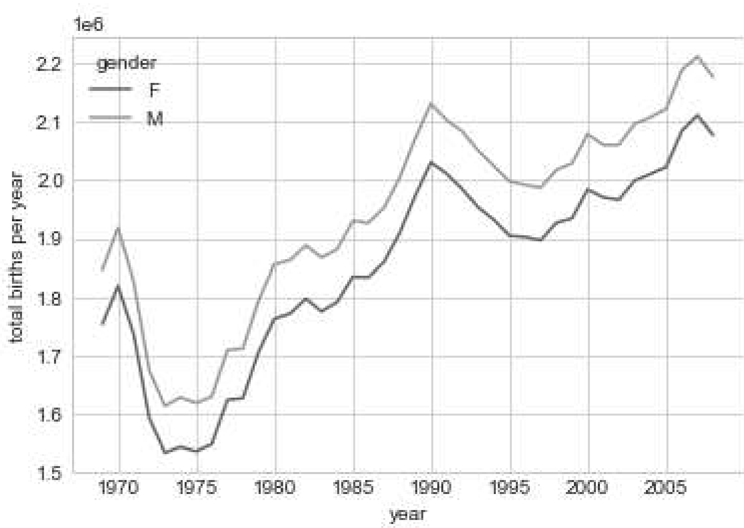
In [13]:
```
births['decade'] = 10 * (births['year'] // 10)
births.pivot_table('births', index='decade', columns='gender', aggfunc='sum')
```

Out[13]:

gender	F	M
decade		
1960	1753634	1846572
1970	16263075	17121550
1980	18310351	19243452
1990	19479454	20420553
2000	18229309	19106428

We see that male births outnumber female births in every decade. To see this trend a bit more clearly, we can use the built-in plotting tools in Pandas to visualize the total number of births by year, as shown in the following figure (see [Introduction to Matplotlib (04.00-Introduction-To-Matplotlib.ipynb)](04.00-Introduction-To-Matplotlib.ipynb) for a discussion of plotting with Matplotlib):

In [14]:
```
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('seaborn-whitegrid')
births.pivot_table(
    'births', index='year', columns='gender', aggfunc='sum').plot()
plt.ylabel('total births per year');
```



With a simple pivot table and the `plot` method, we can immediately see the annual trend in births by gender. By eye, it appears that over the past 50 years male births have outnumbered female births by around 5%.

Though this doesn't necessarily relate to the pivot table, there are a few more interesting features we can pull out of this dataset using the Pandas tools covered up to this point. We must start by cleaning the data a bit, removing outliers caused by mistyped dates (e.g., June 31st) or missing values (e.g., June 99th). One easy way to remove these all at once is to cut

In [15]:
```
quartiles = np.percentile(births['births'], [25, 50, 75])
mu = quartiles[1]
sig = 0.74 * (quartiles[2] - quartiles[0])
```

This final line is a robust estimate of the sample standard deviation, where the 0.74 comes from the interquartile range of a Gaussian distribution (you can learn more about sigma-clipping operations in a book I coauthored with Željko Ivezić, Andrew J. Connolly, and Alexander Gray: *Statistics, Data Mining, and Machine Learning in Astronomy* (https://press.princeton.edu/books/hardcover/9780691198309/statistics-data-mining-and-machine-learning-in-astronomy) (Princeton University Press)).

With this, we can use the `query` method (discussed further in High-Performance Pandas: `eval()` and `query()` (03.12-Performance-Eval-and-Query.ipynb)) to filter out rows with births outside these values:

In [16]:
```
births = births.query('(births > @mu - 5 * @sig) & (births < @mu + 5 * @sig)')
```

Next we set the `day` column to integers; previously it had been a string column because some columns in the dataset contained the value `'null'`:

In [17]:
```
# set 'day' column to integer; it originally was a string due to nulls
births['day'] = births['day'].astype(int)
```

Finally, we can combine the day, month, and year to create a date index (see Working with Time Series (03.11-Working-with-Time-Series.ipynb)). This allows us to quickly compute the weekday corresponding to each row:

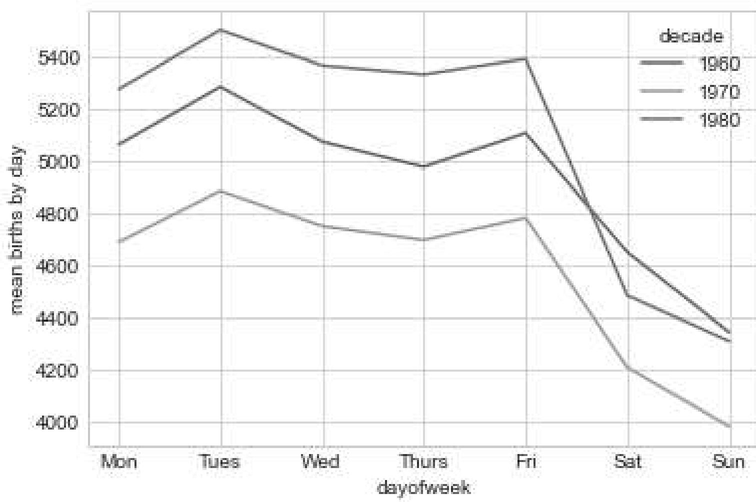
In [18]:
```
# create a datetime index from the year, month, day
births.index = pd.to_datetime(10000 * births.year +
                              100 * births.month +
                              births.day, format='%Y%m%d')

births['dayofweek'] = births.index.dayofweek
```

Using this, we can plot births by weekday for several decades (see the following figure):

In [19]:
```
import matplotlib.pyplot as plt
import matplotlib as mpl

births.pivot_table('births', index='dayofweek',
                   columns='decade', aggfunc='mean').plot()
plt.gca().set(xticks=range(7),
              xticklabels=['Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat', 'Sun']
plt.ylabel('mean births by day');
```



Apparently births are slightly less common on weekends than on weekdays! Note that the 1990s and 2000s are missing because starting in 1989, the CDC data contains only the month of birth.

Another interesting view is to plot the mean number of births by the day of the year. Let's first group the data by month and day separately:

In [20]:
```
births_by_date = births.pivot_table('births',
                                    [births.index.month, births.index.day])
births_by_date.head()
```

Out[20]:

		births
	1	4009.225
	2	4247.400
1	3	4500.900
	4	4571.350
	5	4603.625

The result is a multi-index over months and days. To make this visualizable, let's turn these months and days into dates by associating them with a dummy year variable (making sure to choose a leap year so February 29th is correctly handled!):

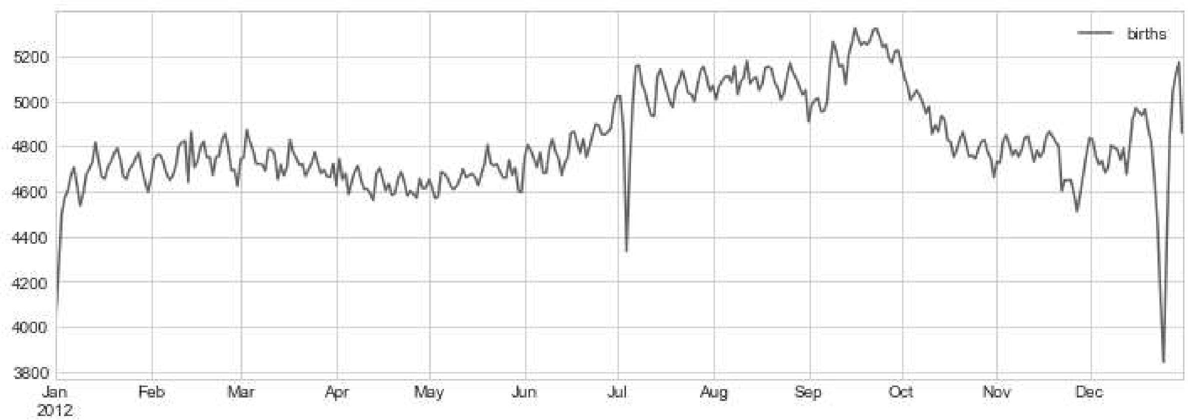
In [21]:
```
from datetime import datetime
births_by_date.index = [datetime(2012, month, day)
                        for (month, day) in births_by_date.index]
births_by_date.head()
```

Out[21]:

	births
2012-01-01	4009.225
2012-01-02	4247.400
2012-01-03	4500.900
2012-01-04	4571.350
2012-01-05	4603.625

Focusing on the month and day only, we now have a time series reflecting the average number of births by date of the year. From this, we can use the `plot` method to plot the data. It reveals some interesting trends, as you can see in the following figure:

In [22]:
```
# Plot the results
fig, ax = plt.subplots(figsize=(12, 4))
births_by_date.plot(ax=ax);
```



In particular, the striking feature of this graph is the dip in birthrate on US holidays (e.g., Independence Day, Labor Day, Thanksgiving, Christmas, New Year's Day), although this likely reflects trends in scheduled/induced births rather than some deep psychosomatic effect on natural births. For more discussion of this trend, see the analysis and links in Andrew Gelman's blog post (http://andrewgelman.com/2012/06/14/cool-ass-signal-processing-using-gaussian-processes/) on the subject. We'll return to this figure in Example:-Effect-of-Holidays-on-US-Births (04.09-Text-and-Annotation.ipynb), where we will use Matplotlib's tools to annotate this plot.

Looking at this short example, you can see that many of the Python and Pandas tools we've seen to this point can be combined and used to gain insight from a variety of datasets. We will see some more sophisticated applications of these data manipulations in future chapters!