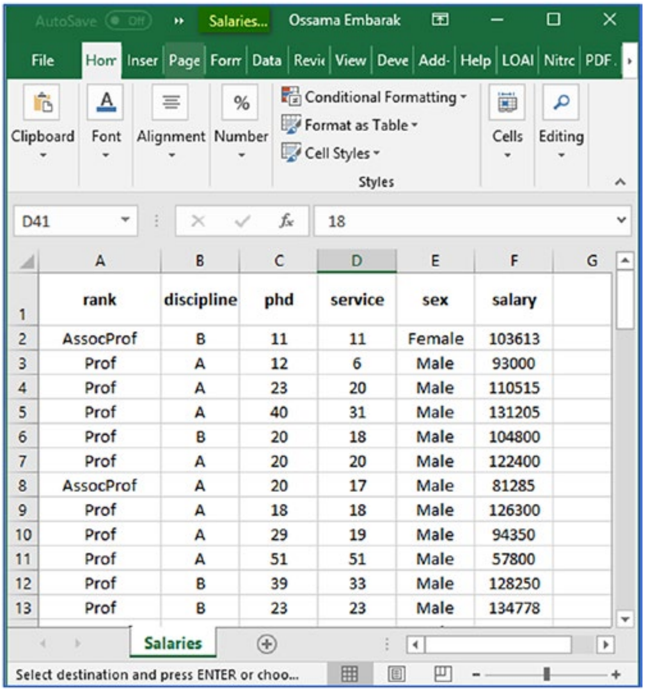
Data Visualization

Python provides numerous methods for data visualization. Various Python libraries can be used for data visualization, such as Pandas, Seaborn, Bokeh, Pygal, and Ploty. Python Pandas is the simplest method for basic plotting. Python Seaborn is great for creating visually appealing statistical charts that include color. Python Bokeh works great for more complicated visualizations, especially for web-based interactive presentations. Python Pygal works well for generating vector and interactive files. However, it does not have the flexibility that other methods do. Python Plotly is the most useful and easiest option for creating highly interactive web-based visualizations.

Bar charts are an essential visualization tool used to compare values in a variety of categories. A bar chart can be vertically or horizontally oriented by adjusting the x- and y-axes, depending on what kind of information or categories the chart needs to present. This chapter demonstrates the use and implementation of various visualization tools; the chapter will use the `salaries.csv` file shown in Figure 7-1 as the data set for plotting purposes.



	A	B	C	D	E	F	G
1	rank	discipline	phd	service	sex	salary	
2	AssocProf	B	11	11	Female	103613	
3	Prof	A	12	6	Male	93000	
4	Prof	A	23	20	Male	110515	
5	Prof	A	40	31	Male	131205	
6	Prof	B	20	18	Male	104800	
7	Prof	A	20	20	Male	122400	
8	AssocProf	A	20	17	Male	81285	
9	Prof	A	18	18	Male	126300	
10	Prof	A	29	19	Male	94350	
11	Prof	A	51	51	Male	57800	
12	Prof	B	39	33	Male	128250	
13	Prof	B	23	23	Male	134778	

Select destination and press ENTER or choo...

Figure 7-1. *Salaries data set*

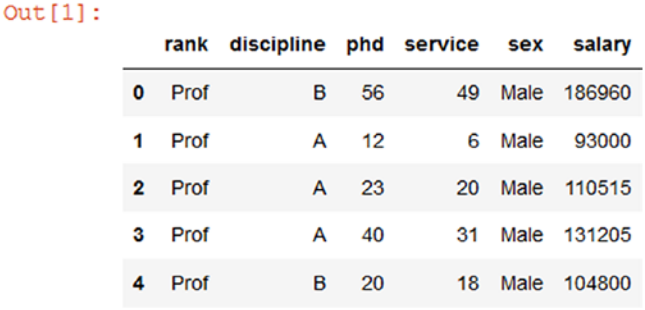
Direct Plotting

Pandas is a Python library with data frame features that supplies built-in options for plotting visualizations in a two-dimensional tabular style. In Listing 7-1, you read the Salaries data set and create some vectors of variables, which are `rank`, `discipline`, `phd`, `service`, `sex`, and `salary`.

Listing 7-1. Reading the Data Set

```
In [3]: import pandas as pd
        dataset = pd.read_csv("./Data/Salaries.csv")
        rank = dataset['rank']
```

```
discipline = dataset['discipline']
phd = dataset['phd']
service = dataset['service']
sex = dataset['sex']
salary = dataset['salary']

dataset.head()
```



Out[1]:

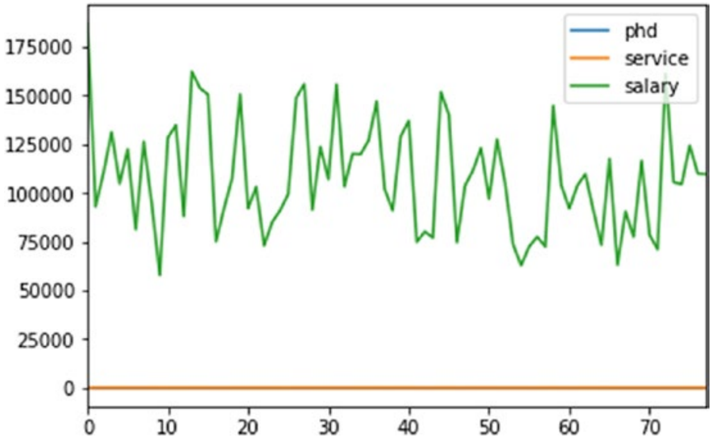
	rank	discipline	phd	service	sex	salary
0	Prof	B	56	49	Male	186960
1	Prof	A	12	6	Male	93000
2	Prof	A	23	20	Male	110515
3	Prof	A	40	31	Male	131205
4	Prof	B	20	18	Male	104800

Line Plot

You can use line plotting as shown in Listing 7-2. It's important to ensure the data units, such as the phd, service, and salary variables, are used for plotting. However, only the salaries are visible, while the phd and service information is not clearly displayed on the plot. This is because the numerical units in the salaries are in the hundreds of thousands, while the phd and services information is in very small units.

Listing 7-2. Visualizing Patterns with High Differences in Numerical Units

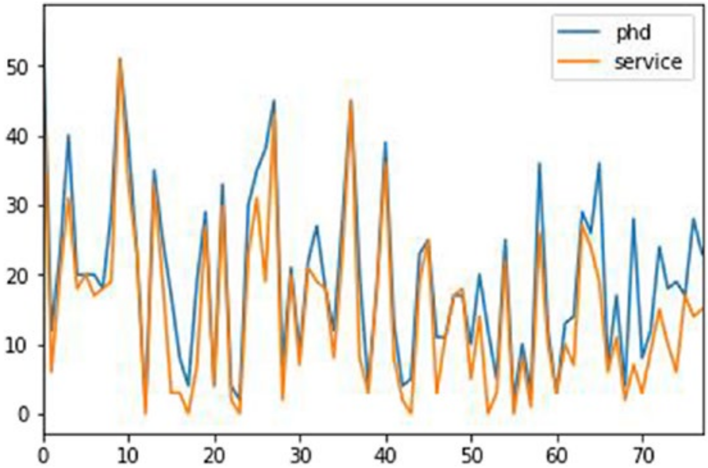
```
In [5]: dataset[["rank", "discipline","phd","service", "sex",
"salary"]].plot()
```



Let's visualize more comparable units such as the `phd` and `services` information, as shown in Listing 7-3. You can observe the correlation between `phd` and `services` over the years, except from age 55 up to 80, where `services` decline, which means that some people left the service at the age of 55 and older.

Listing 7-3. Visualizing Patterns with Close Numerical Units

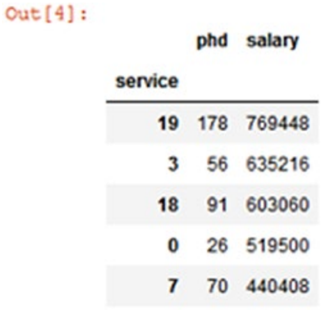
```
 In [6]: dataset[["phd","service"]].plot()
```



In Listing 7-4, you are grouping data by service and summarizing the salaries per service category. Then you sort the derived data set in descending order according to the salaries. Finally, you plot the sorted data set using a bar chart.

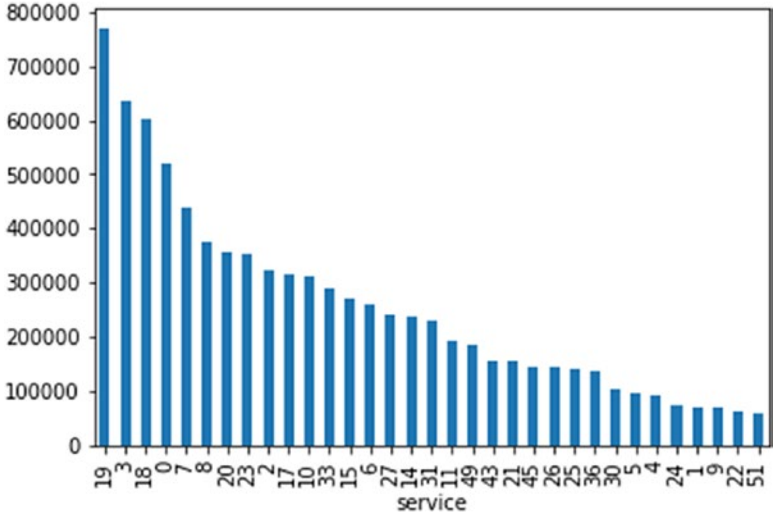
Listing 7-4. Visualizing Salaries per Service Category

```
In [4]: dataset1 = dataset.groupby(['service']).sum()
        dataset1.sort_values("salary", ascending = False,
        inplace=True)
        dataset1.head()
```



```
Out[4]:
                phd  salary
        service
             19  178  769448
              3   56  635216
             18   91  603060
              0   26  519500
              7   70  440408
```

```
In [8]: dataset1["salary"].plot.bar()
```



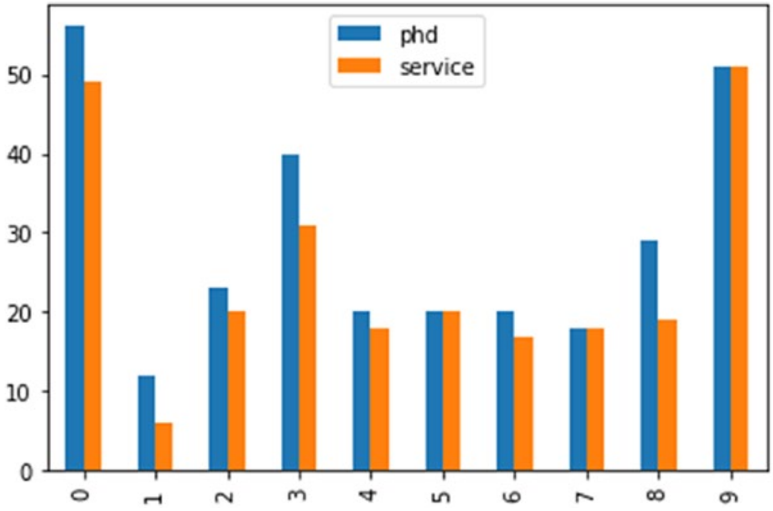
You can see that most people serve approximately 19 years, which is why the highest accumulated salary is from this category.

Bar Plot

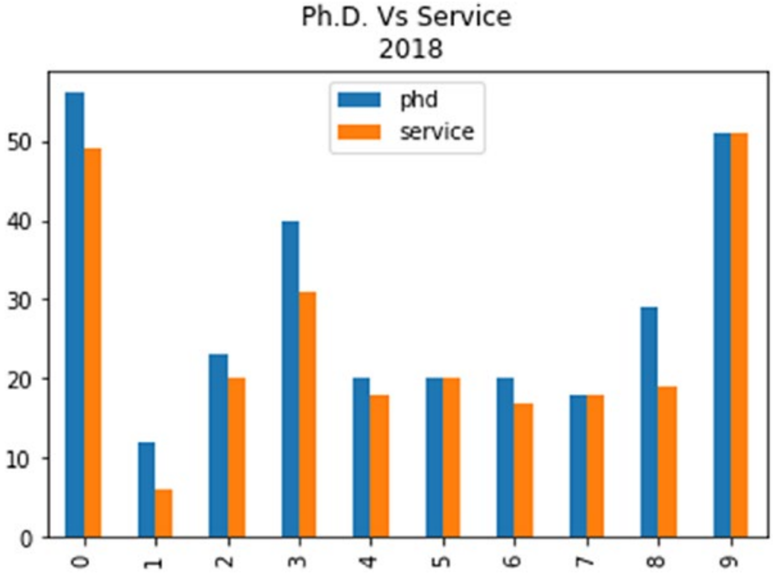
Listing 7-5 shows how to plot the first ten records of phd and services, and you can add a title as well. To add a title to the chart, you need to use `.bar(title="Your title")`.

Listing 7-5. Bar Plotting

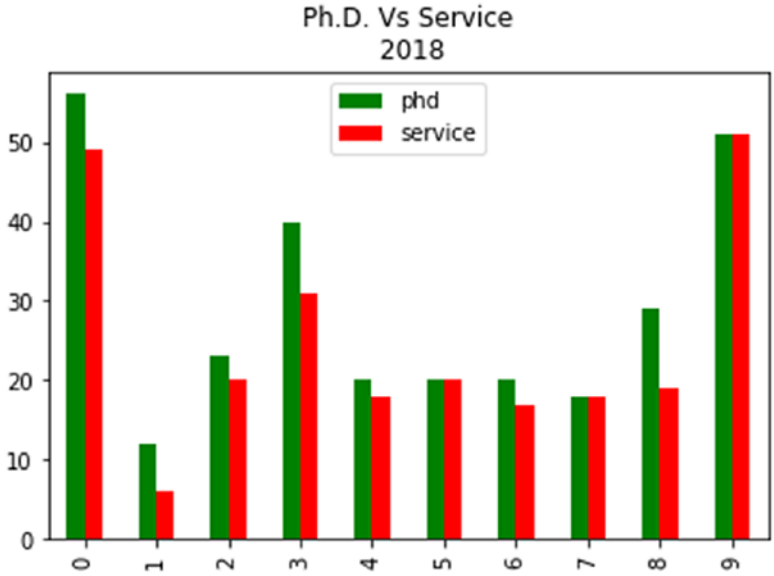
```
In [9]: dataset[[ 'phd', 'service' ]].head(10).plot.bar()
```



```
In [11]: dataset[['phd', 'service']].head(10).plot.bar
(title="Ph.D. Vs Service\n 2018")
```



```
In [12]: dataset[['phd', 'service']].head(10).plot.bar
(title="Ph.D. Vs Service\n 2018" , color=['g','red'])
```

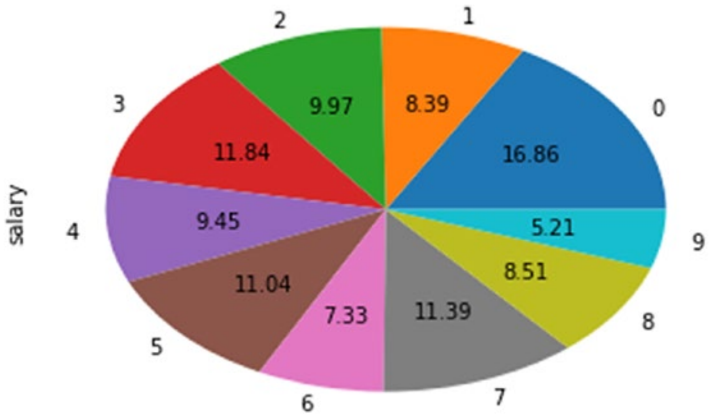


Pie Chart

Pie charts are useful for comparing parts of a whole. They do not show changes over time. Bar graphs are used to compare different groups or to track changes over time. However, when trying to measure change over time, bar graphs are best when the changes are larger. In addition, a pie chart is useful for comparing small variables, but when it comes to a large number of variables, it falls short. Listing 7-6 compares the salary package of ten professionals from the Salaries data set.

Listing 7-6. Pie Chart

```
In [13]: dataset["salary"].head(10).plot.pie(autopct='%.2f')
```

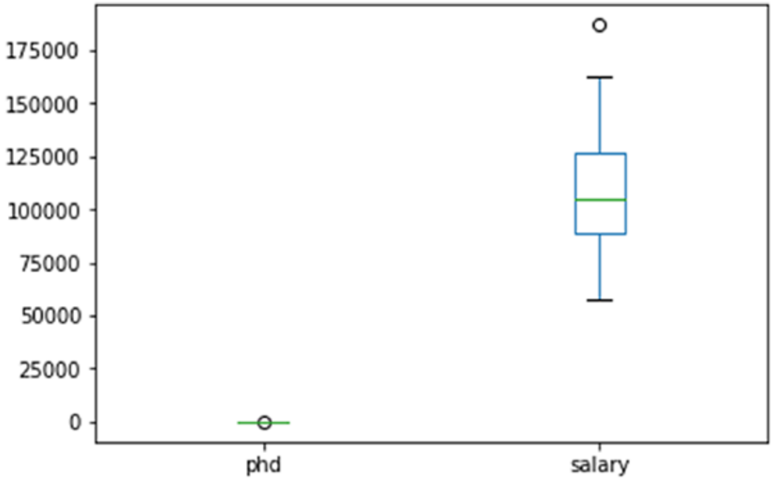


Box Plot

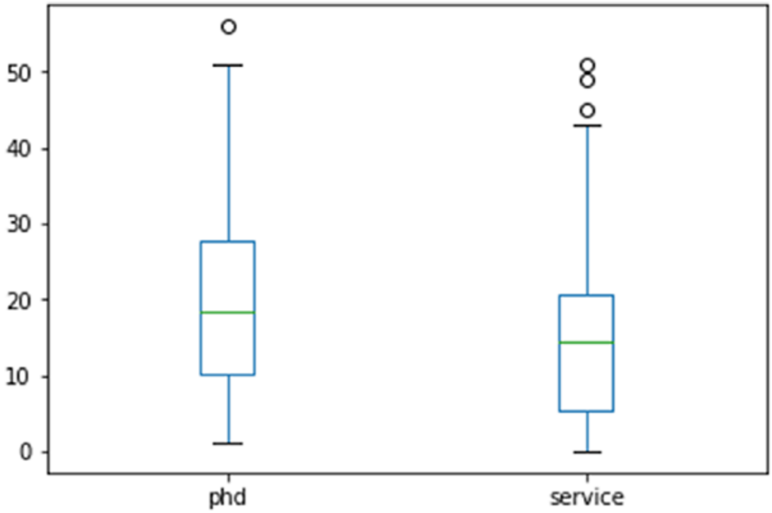
Box plotting is used to compare variables using some statistical values. The comparable variables should be of the same data units; Listing 7-7 shows that when you compare `phd` and `salary`, it produces improper figures and does not provide real comparison information since the `salary` numerical units are much higher than the `phd` numerical values. Plotting `phd` and `services` shows that the median and quantiles of `phd` are higher than the median and quantiles of the `service` information; in addition, the range of `phd` is wider than the range of `service` information.

Listing 7-7. Box Plotting

```
In [14]: dataset[["phd","salary"]].head(100).plot.box()
```



```
In [15]: dataset[["phd","service"]].plot.box()
```

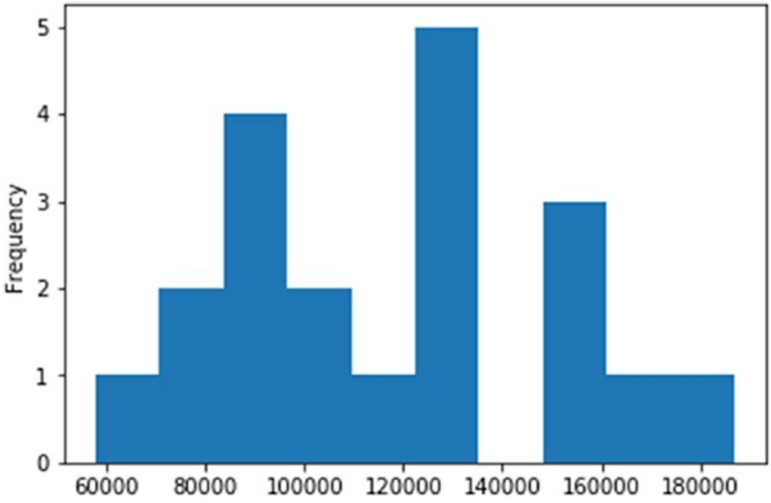


Histogram Plot

A histogram can be used to represent a specific variable or set of variables. Listing 7-8 plots 20 records of the `salaries` variables; it shows that salary packages of about 135,000 are the most frequent in this data set.

Listing 7-8. Histogram Plotting

```
In [16]: dataset["salary"].head(20).plot.hist()
```

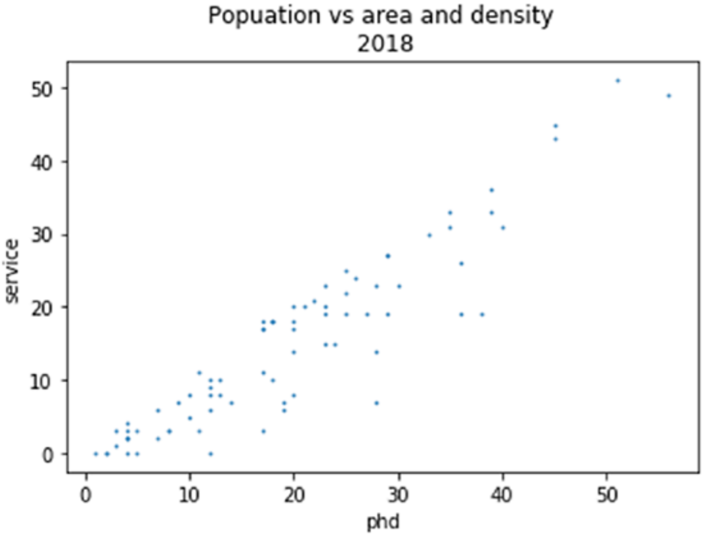


Scatter Plot

A scatter plot shows the relationship between two factors of an experiment (e.g. phd and service). A trend line is used to determine positive, negative, or no correlation. See Listing 7-9.

Listing 7-9. Scatter Plotting

```
In [17]: dataset.plot(kind='scatter', x='phd', y='service',
title='Popuation vs area and density\n 2018', s=0.9)
```



Seaborn Plotting System

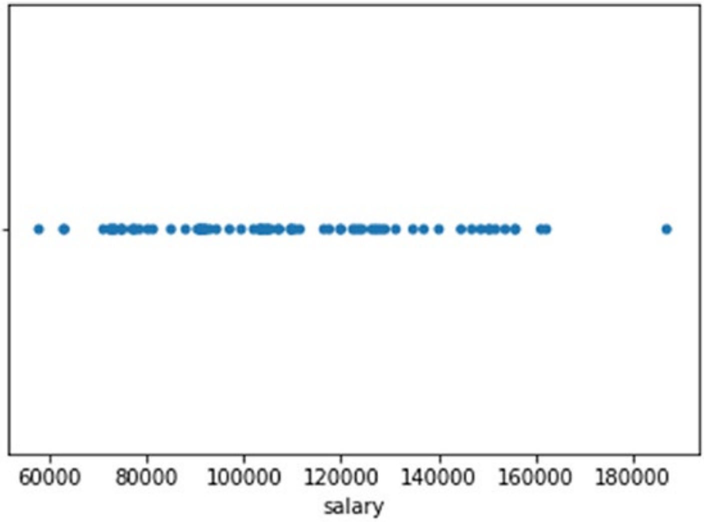
The Python Seaborn library provides various plotting representations for visualizing data. A strip plot is a scatter plot where one of the variables is categorical. Strip plots can be combined with other plots to provide additional information. For example, a box plot with an overlaid strip plot is similar to a violin plot because some additional information about how the underlying data is distributed becomes visible. Seaborn's swarm plot is virtually identical to a strip plot except that it prevents data points from overlapping.

Strip Plot

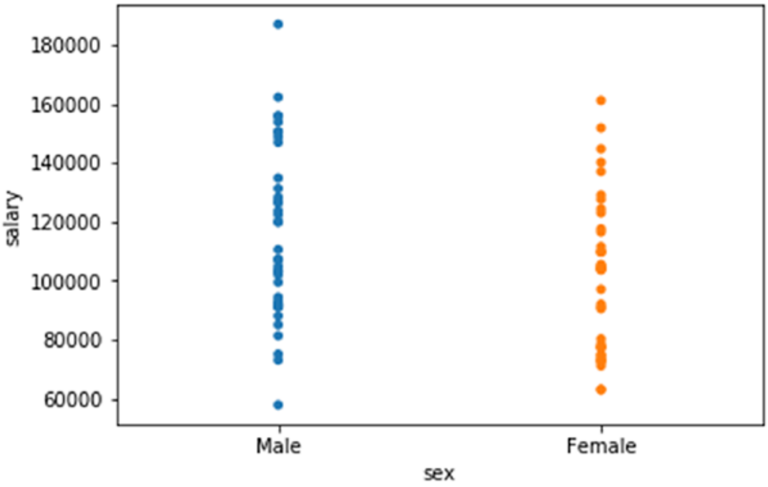
Listing 7-10 uses strip plotting to display data per salary category.

Listing 7-10. Simple Strip Plot

```
In [3]: # Simple stripplot sns.stripplot( x =
dataset['salary'])
```



```
In [4]: # Stripplot over categories
sns.stripplot( x = dataset['sex'], y= dataset['salary'],
data=dataset);
```

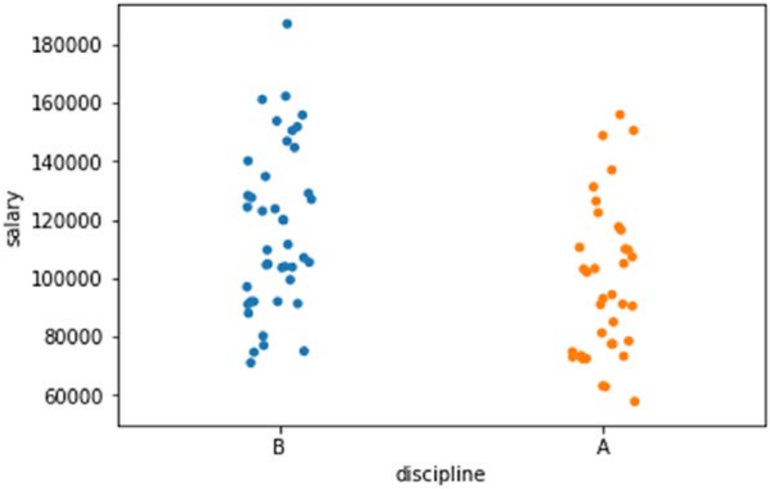


The previous example visualizes the salary variable per gender.

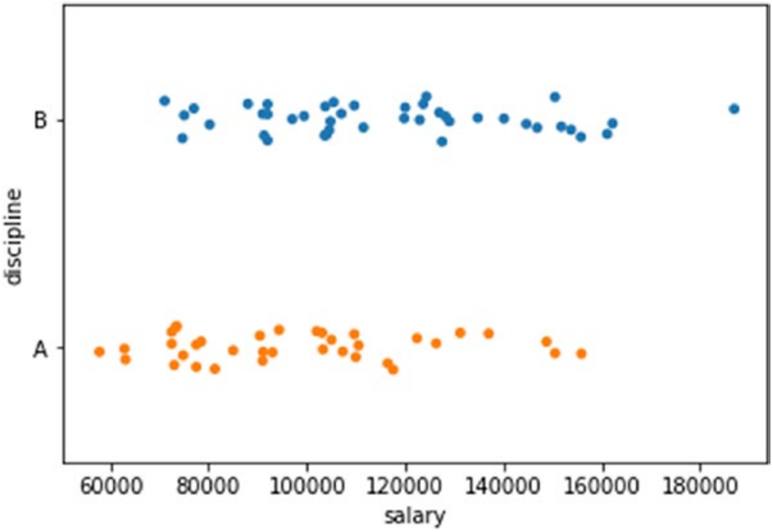
You can visualize the data vertically or horizontally using Listing 7-11, which presents two disciplines, A and B. Discipline B has a bigger range and higher packages compared to discipline A.

Listing 7-11. Strip Plot with Vertical and Horizontal Visualizing

```
In [5]: # Stripplot over categories
sns.stripplot( x = dataset['discipline'], y =
dataset['salary'], data=dataset, jitter=1)
```



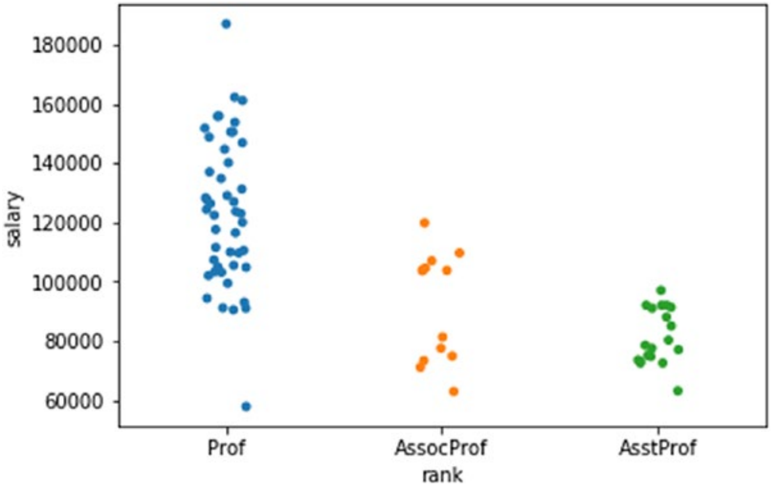
```
In [6]: # Stripplot over categories Horizontal
sns.stripplot( x= dataset['salary'], y = dataset['discipline'],
data=dataset, jitter=True);
```



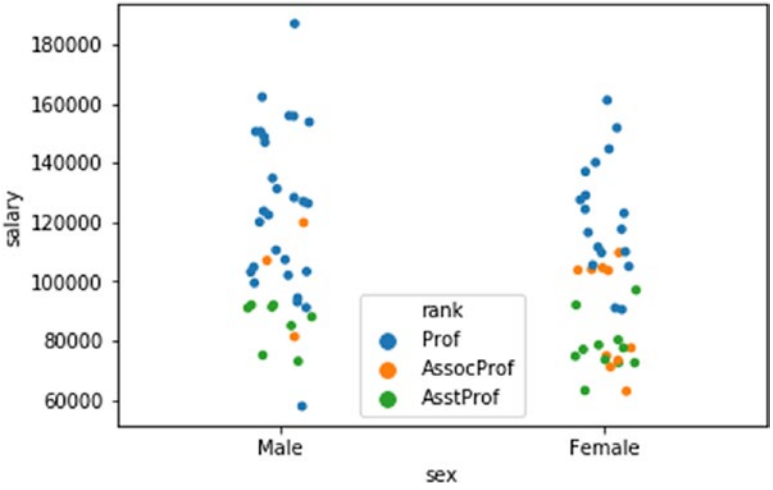
You can visualize data in a strip plot per category; Listing 7-12 uses the assistance prof, associate prof, and full professor categories. The hue attribute is used to determine the legend attribute.

Listing 7-12. Strip Plot per Category

```
In [7]: # Stripplot over categories
sns.stripplot( x = dataset['rank'], y= dataset['salary'],
data=dataset, jitter=True);
```



```
In [8]: # Add hue to the graph
        # Stripplot over categories
          sns.stripplot( x ='sex', y= 'salary', hue='rank',
          data=dataset, jitter=True )
```

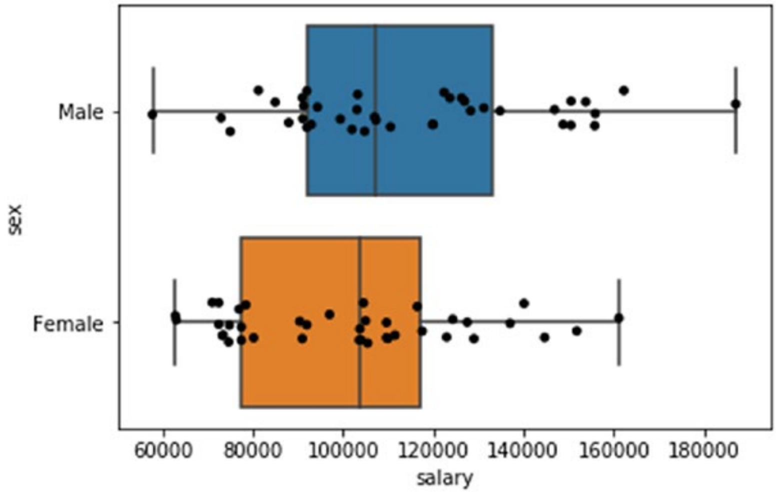


Box Plot

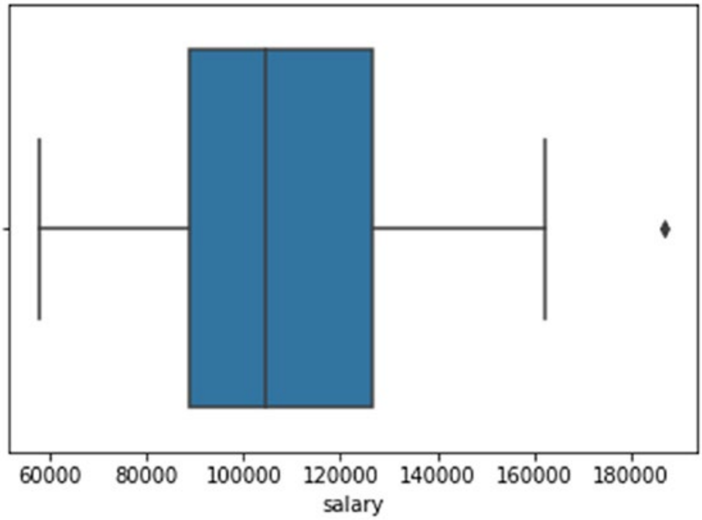
You can combine a box plot and strip plot to give more information on the generated plot (see Listing 7-13). As shown, the Male category has a higher median salary, maximum salary, and range compared to the Female category.

Listing 7-13. Combined Box Plot and Strip Plot Visualization

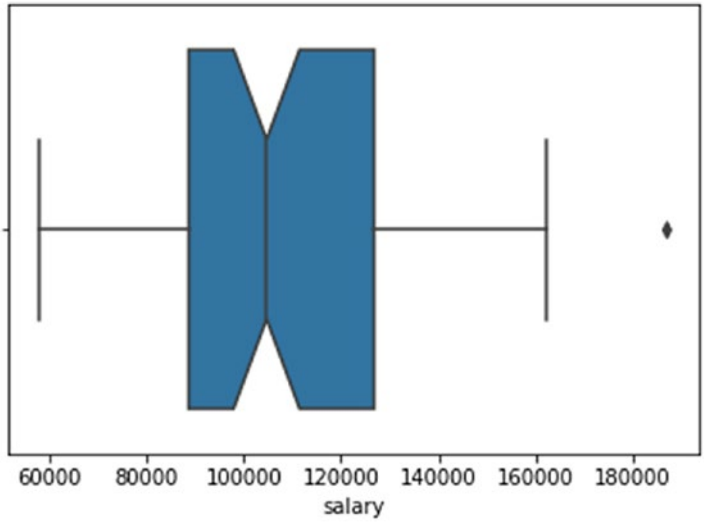
```
In [10]: # Draw data on top of boxplot
         sns.boxplot(x = 'salary', y ='sex', data=dataset,
         whis=np.inf )
         sns.stripplot(x = 'salary', y ='sex', data=dataset,
         jitter=True, color='0.02')
```



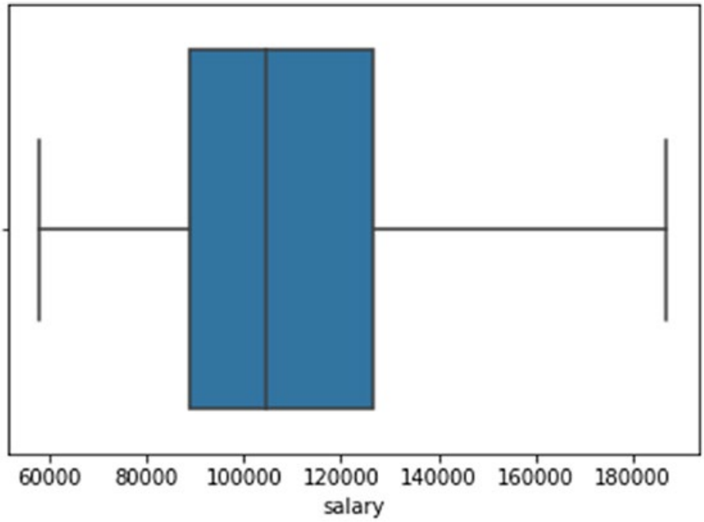
```
In [13]: # box plot salaries
         sns.boxplot(x = dataset['salary'])
```



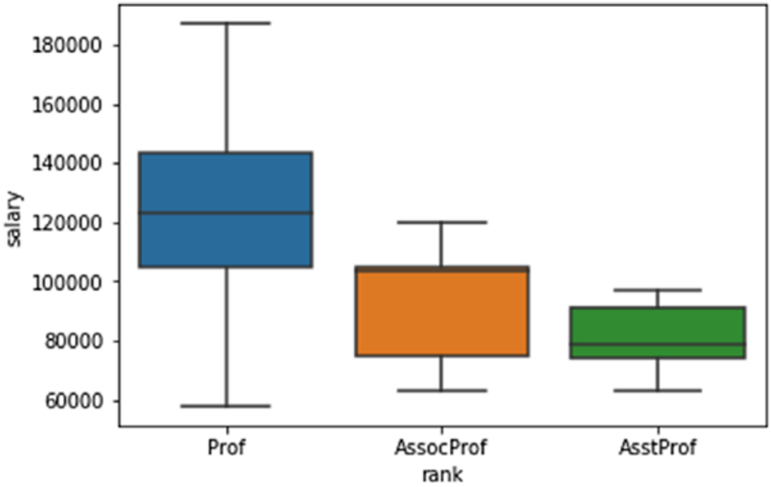
```
In [14]: # box plot salaries
         sns.boxplot(x = dataset['salary'], notch=True)
```



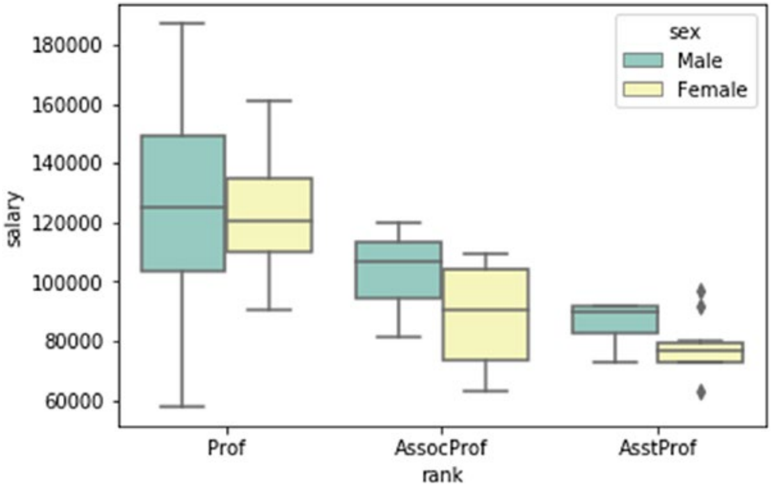
```
In [15]: # box plot salaries
         sns.boxplot(x = dataset['salary'], whis=2)
```



```
In [16]: # box plot per rank
         sns.boxplot(x = 'rank', y = 'salary', data=dataset)
```

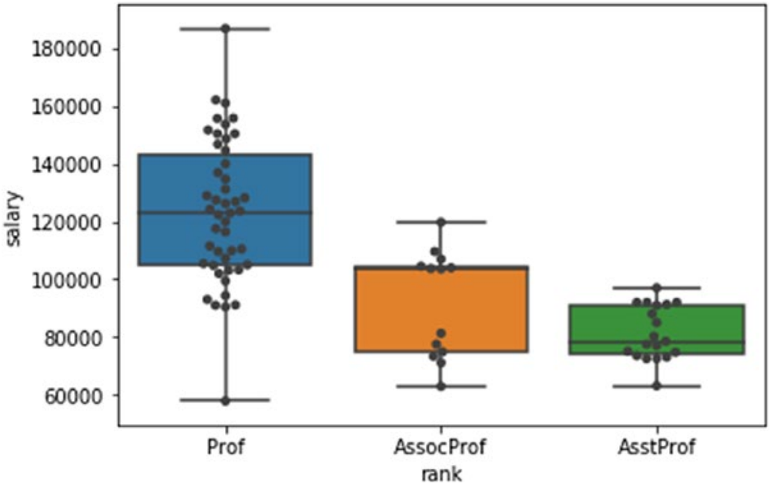


```
In [17]: # box plot per rank
sns.boxplot(x = 'rank', y = 'salary', hue='sex', data=dataset,
palette='Set3')
```



```
In [18]: # box plot per rank
         sns.boxplot(x = 'rank', y = 'salary', data=dataset)
         sns.swarmplot(x = 'rank', y = 'salary', data=dataset,
         color='0.25')
```

Combined Box Plot and Strip Plot Visualization as shown in below figure.

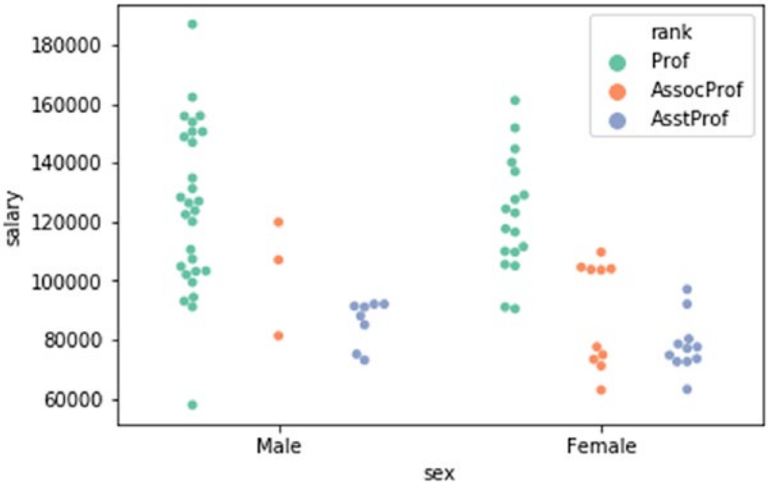


Swarm Plot

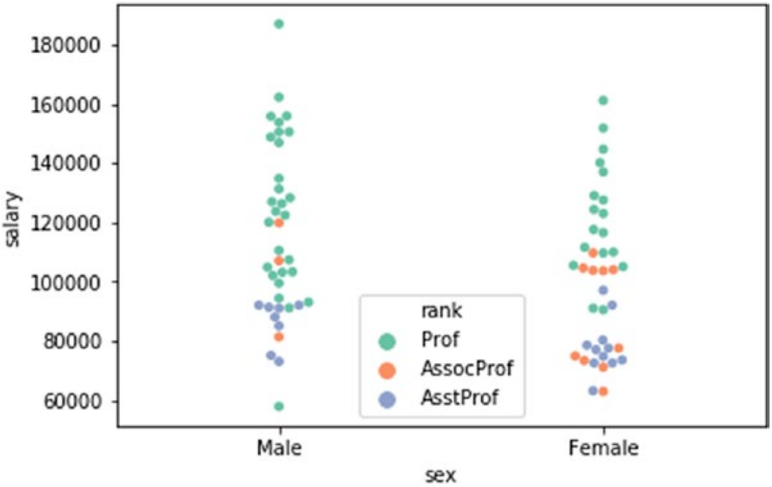
A swarm plot is used to visualize different categories; it gives a clear picture of a variable distribution against other variables. For instance, the salary distribution per gender and per profession indicates that the male professors have the highest salary range. Most of the males are full professors, then associate, and then assistant professors. There are more male professors than female professors, but there are more female associate professors than male associate professors. See Listing 7-14.

Listing 7-14. Swarm ploting of salary against gender

```
In [11]: # swarmplot
sns.swarmplot( x ='sex', y= 'salary', hue='rank', data=dataset,
palette="Set2", dodge=True)
```



```
In [12]: # swarmplot
sns.swarmplot( x ='sex', y= 'salary', hue='rank', data=dataset,
palette="Set2", dodge=False)
```

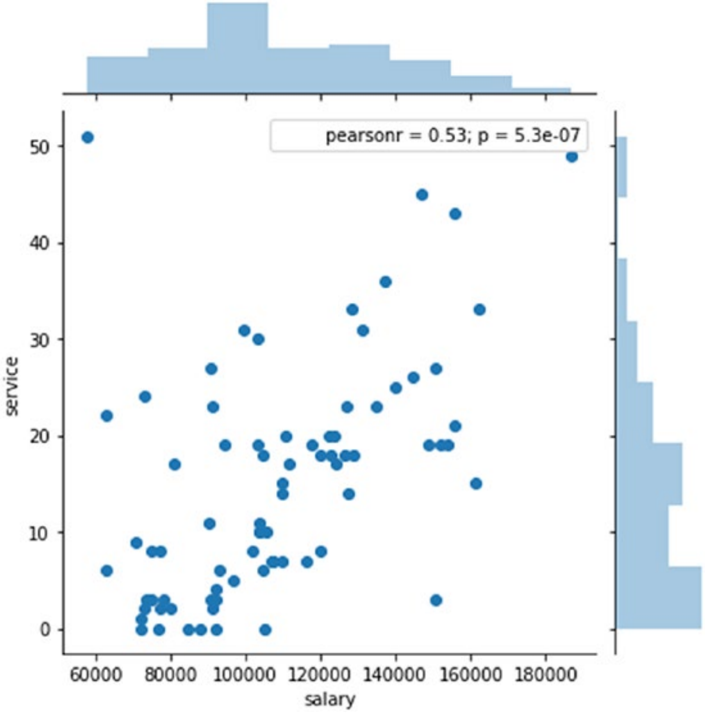


Joint Plot

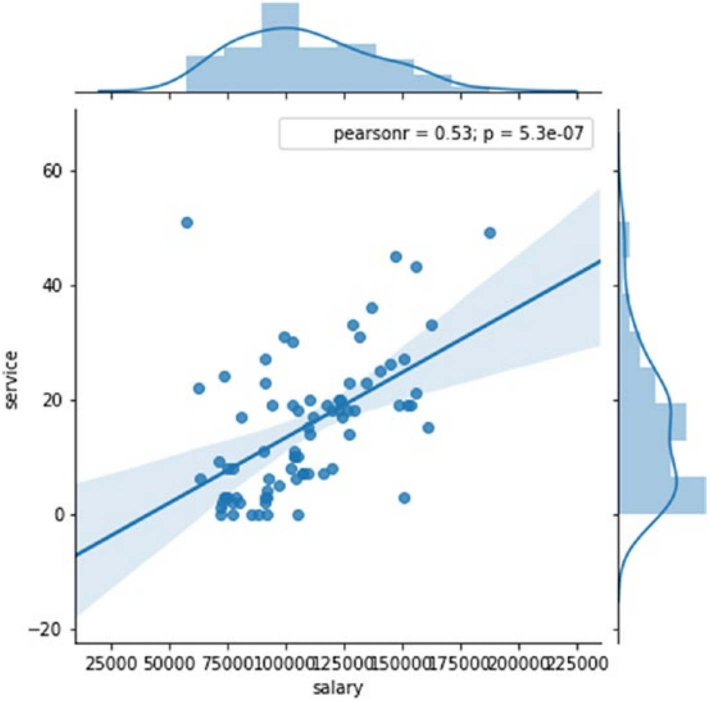
A joint plot combines more than one plot to visualize the selected patterns (see Listing 7-15).

Listing 7-15. Joint Plot Visualization

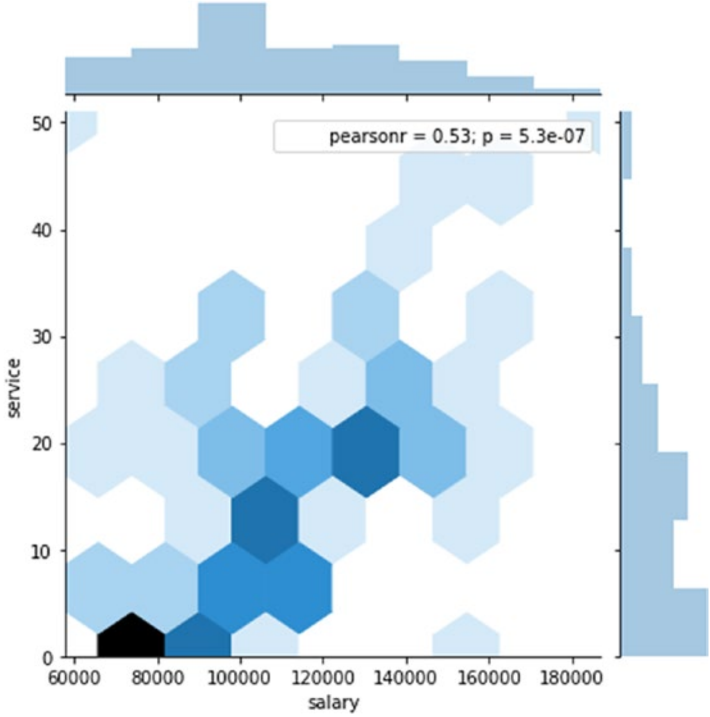
```
In [22]: sns.jointplot(x = 'salary', y = 'service',
data=dataset)
```



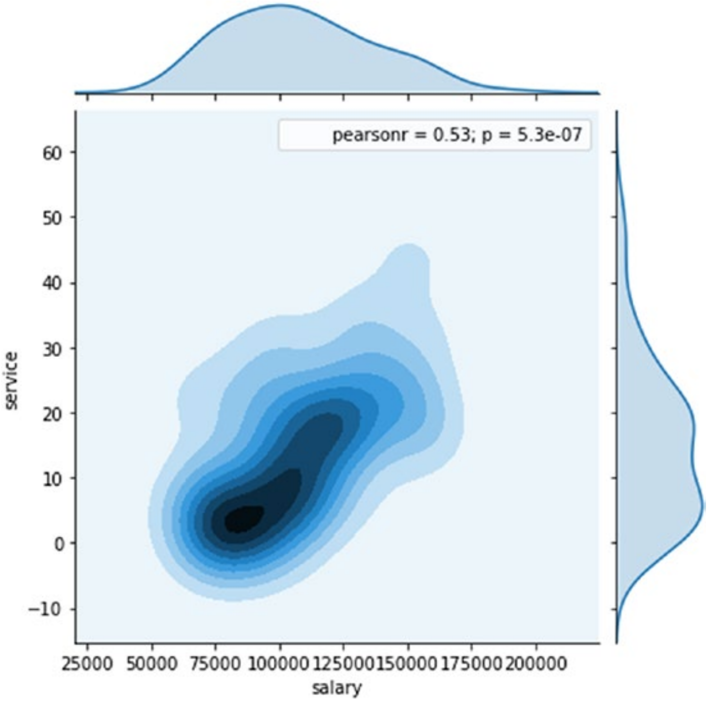
```
In [24]: sns.jointplot('salary', 'service', data=dataset,
kind='reg')
```



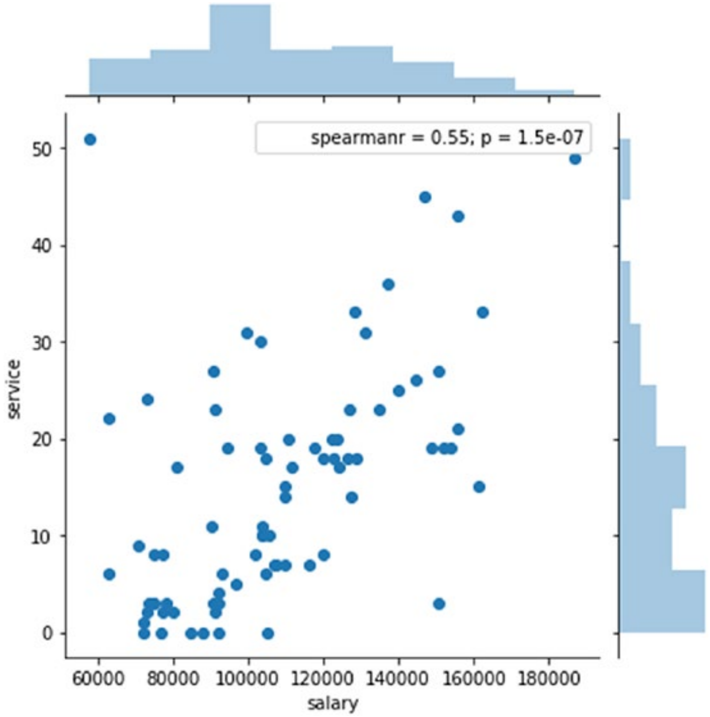
```
In [25]: sns.jointplot('salary', 'service', data=dataset,
kind='hex')
```



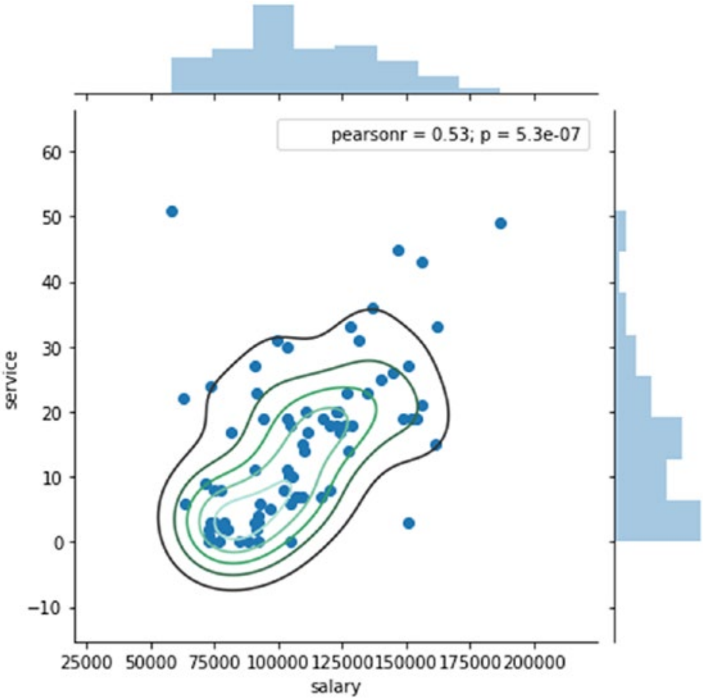
```
In [26]: sns.jointplot('salary', 'service', data=dataset,
kind='kde')
```



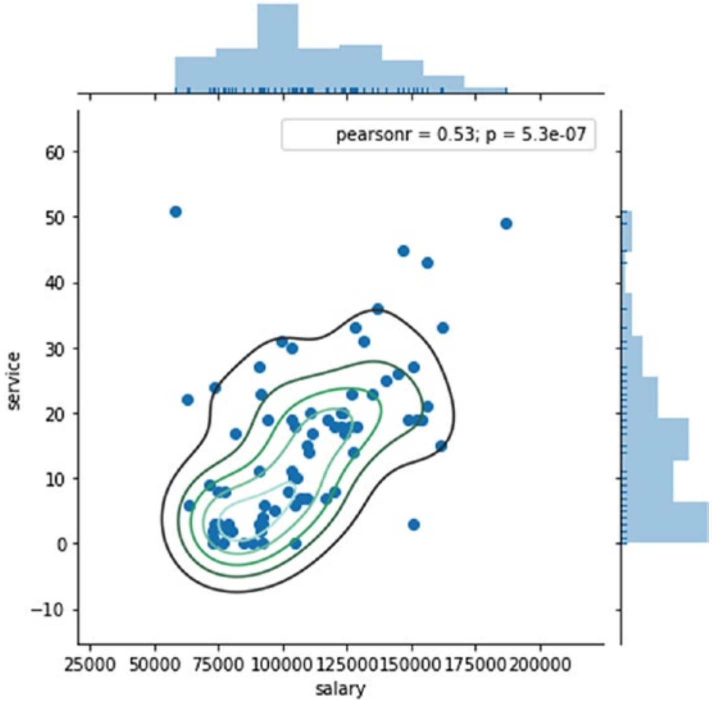
```
In [27]: from scipy.stats import spearmanr sns.
jointplot('salary', 'service', data=dataset, stat_func=
spearmanr )
```



```
In [31]: sns.jointplot('salary', 'service',
         data=dataset).plot_joint(sns.kdeplot, n_levels=6)
```



```
In [32]: sns.jointplot('salary', 'service',
         data=dataset).plot_joint( sns.kdeplot,n_levels=6).
         plot_marginals(sns.rugplot)
```



Matplotlib Plot

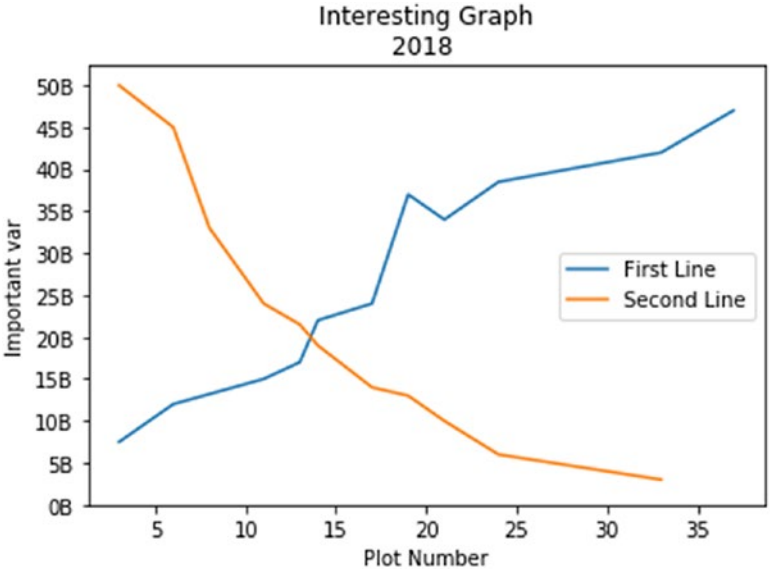
Matplotlib is a Python 2D plotting library that produces high-quality figures in a variety of hard-copy formats and interactive environments across platforms. In Matplotlib, you can add features one by one, such as adding a title, labels, legends, and more.

Line Plot

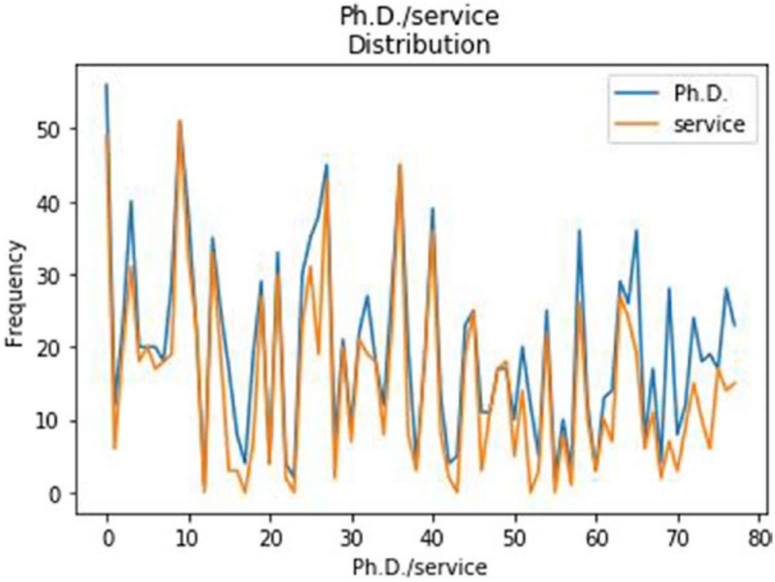
In inline plotting, you should determine the x- and y-axes, and then you can add more features such as a title, a legend, and more (see Listing 7-16).

Listing 7-16. Matplotlib Line Plotting

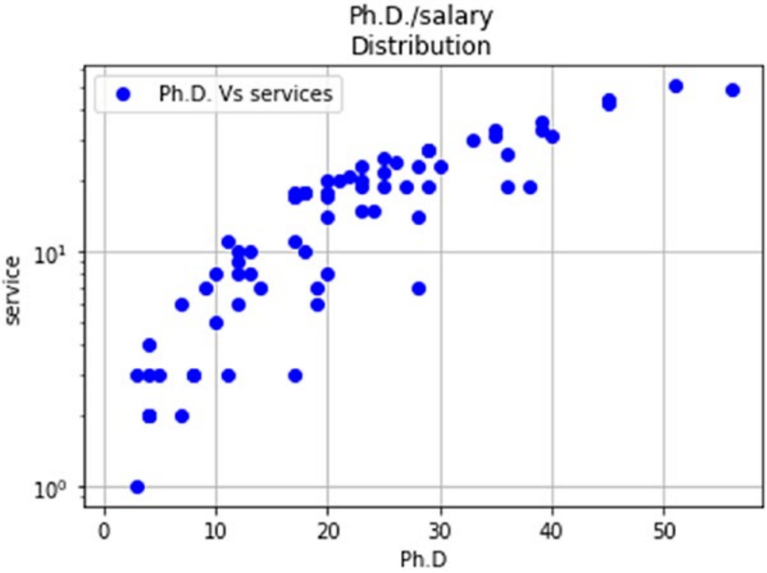
```
In [2]: import matplotlib.pyplot as plt
        x =[3,6,8,11,13,14,17,19,21,24,33,37]
        y = [7.5,12,13.2,15,17,22,24,37,34,38.5,42,47]

        x2 =[3,6,8,11,13,14,17,19,21,24,33]
        y2 = [50,45,33,24,21.5,19,14,13,10,6,3]
        plt.plot(x,y, label='First Line')
        plt.plot(x2, y2, label='Second Line')
        plt.xlabel('Plot Number')
        plt.ylabel('Important var')
        plt.title('Interesting Graph\n2018 ')
        plt.yticks([0,5,10,15,20,25,30,35,40,45,50],
                ['0B','5B','10B','15B','20B','25B','30B','35B',
                '40B','45B','50
        B'])
        plt.legend()
        plt.show()
```



```
In [13]: plt.plot(phd, label='Ph.D.')
         plt.plot(service, label='service')
         plt.xlabel('Ph.D./service')
         plt.ylabel('Frequency')
         plt.title('Ph.D./service\nDistribution')
         plt.legend()
         plt.show()
```



```
In [15]: plt.plot(phd, service, 'bo', label="Ph.D. Vs
services", lw=10)
         plt.grid()
         plt.legend()
         plt.xlabel('Ph.D')
         plt.ylabel('service')
         plt.title('Ph.D./salary\nDistribution')
         plt.yscale('log')
```

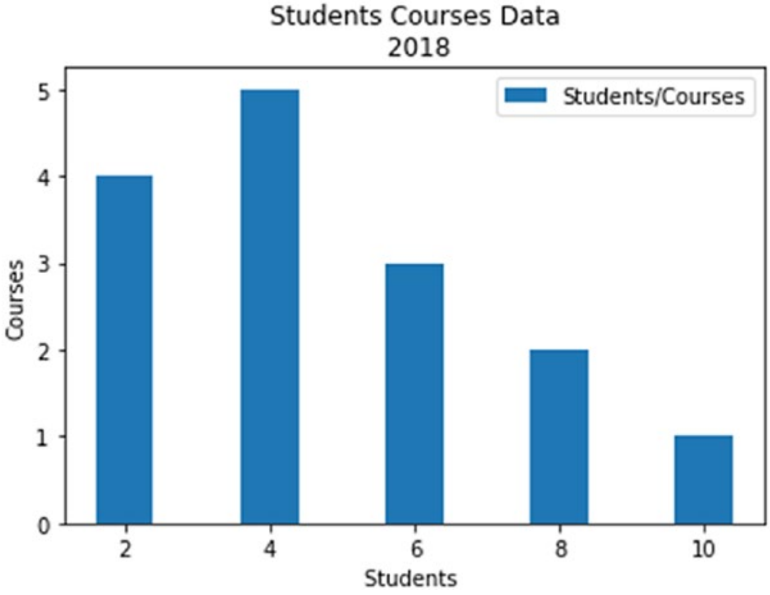


Bar Chart

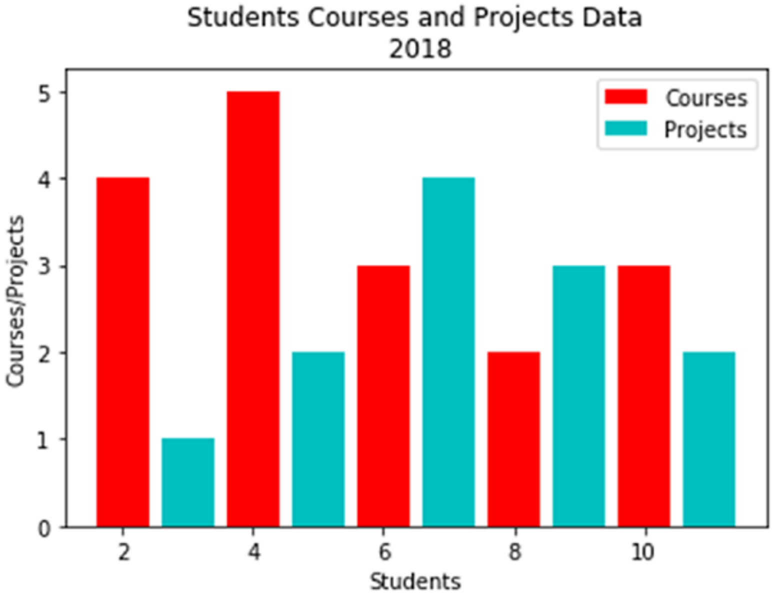
Listing 7-17 shows how to create a bar chart to present students registered for courses; there are two students who are registered for four courses.

Listing 7-17. Matplotlib Bar Chart Plotting

```
In [3]: Students = [2,4,6,8,10]
        Courses = [4,5,3,2,1]
        plt.bar(Students,Courses, label="Students/Courses")
        plt.xlabel('Students ')
        plt.ylabel('Courses')
        plt.title('Students Courses Data\n 2018')
        plt.legend()
        plt.show()
```



```
In [4]: Students = [2,4,6,8,10]
        Courses = [4,5,3,2,3]
        stds = [3,5,7,9,11]
        Projects = [1,2,4,3,2]
        plt.bar(Students, Courses, label="Courses", color='r')
        plt.bar(stds, Projects, label="Projects", color='c')
        plt.xlabel('Students')
        plt.ylabel('Courses/Projects')
        plt.title('Students Courses and Projects Data\n 2018')
        plt.legend()
        plt.show()
```

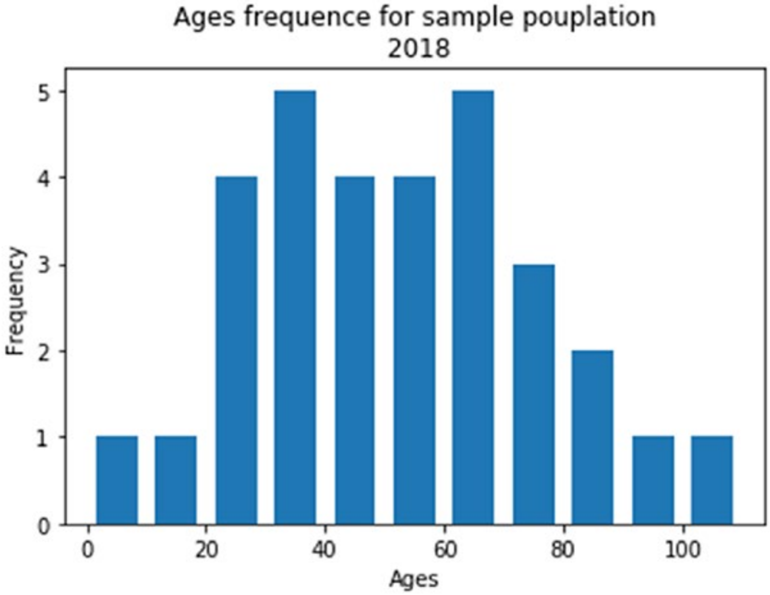


Histogram Plot

Listing 7-18 shows how to create a histogram showing age frequencies; most people in the data set are between 30 and 40. In addition, you can create a histogram of the years of service and the number of PhDs.

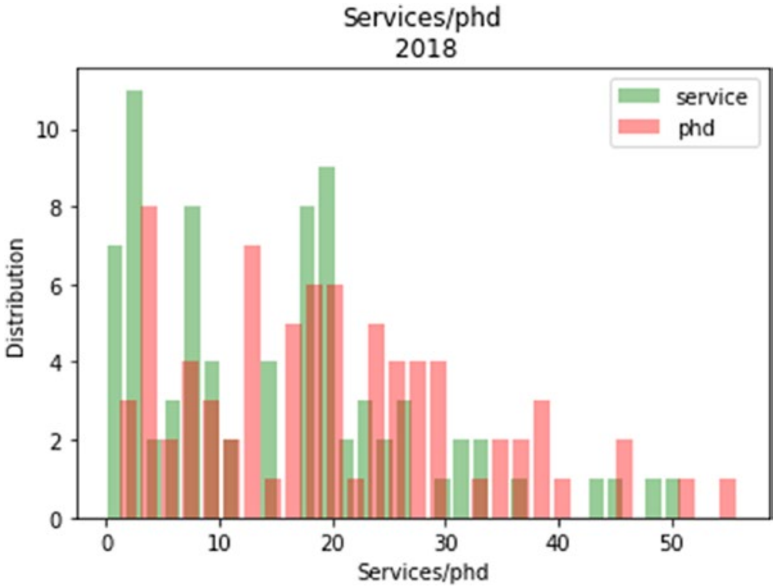
Listing 7-18. Matplotlib Histogram Plotting

```
In [5]: Ages = [22.5, 10, 55, 8, 62, 45, 21, 34, 42, 45, 99,
               75, 82,
                77, 55, 43, 66, 66, 78, 89, 101, 34, 65, 56,
                25, 34,
                52, 25, 63, 37, 32]
        binsx = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110]
        plt.hist(Ages, bins=binsx, histtype='bar', rwidth=0.7)
        plt.xlabel('Ages')
        plt.ylabel('Frequency')
        plt.title('Ages frequency for sample pouplation\n 2018')
        plt.show()
```

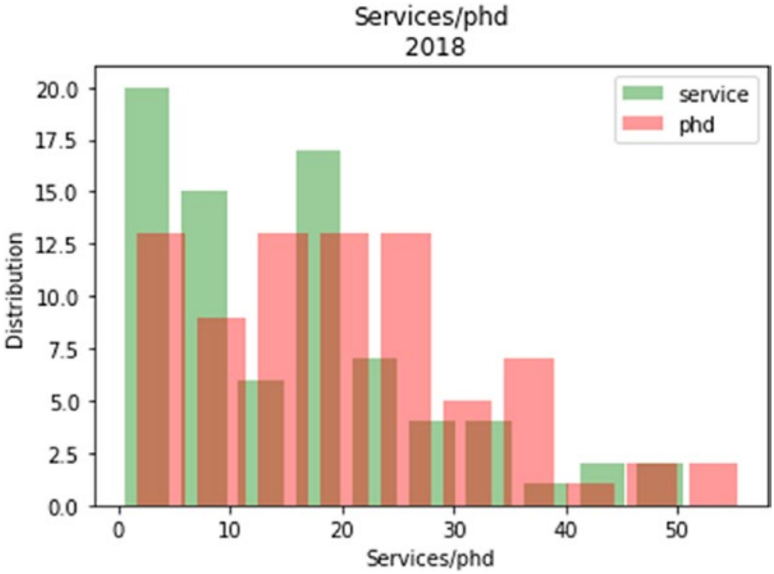


```
In [18]: plt.hist(service, bins=30, alpha=0.4, rwidth=0.8,
         color='green', label='service')
         plt.hist(phd, bins=30, alpha=0.4, rwidth=0.8,
         color='red', label='phd')
         plt.xlabel('Services/phd')
         plt.ylabel('Distribution')
         plt.title('Services/phd\n 2018')
         plt.legend(loc='upper right')
         plt.show()
```

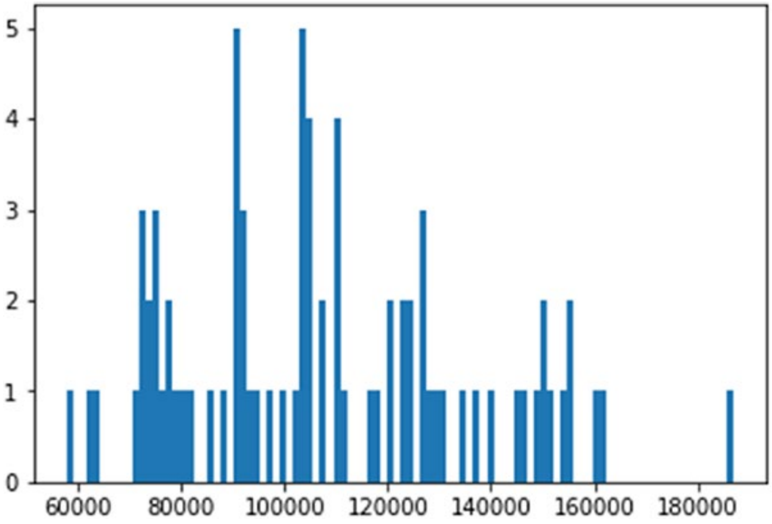
Visualize service years since Ph.D. had attained.



```
In [19]: plt.hist(service, bins=10, alpha=0.4, rwidth=0.8,
         color='green', label='service')
         plt.hist(phd, bins=10, alpha=0.4, rwidth=0.8,
         color='red', label='phd')
         plt.xlabel('Services/phd')
         plt.ylabel('Distribution')
         plt.title('Services/phd\n 2018')
         plt.legend(loc='upper right')
         plt.show()
```



```
In [21]: plt.hist(salary, bins=100)
         plt.show()
```

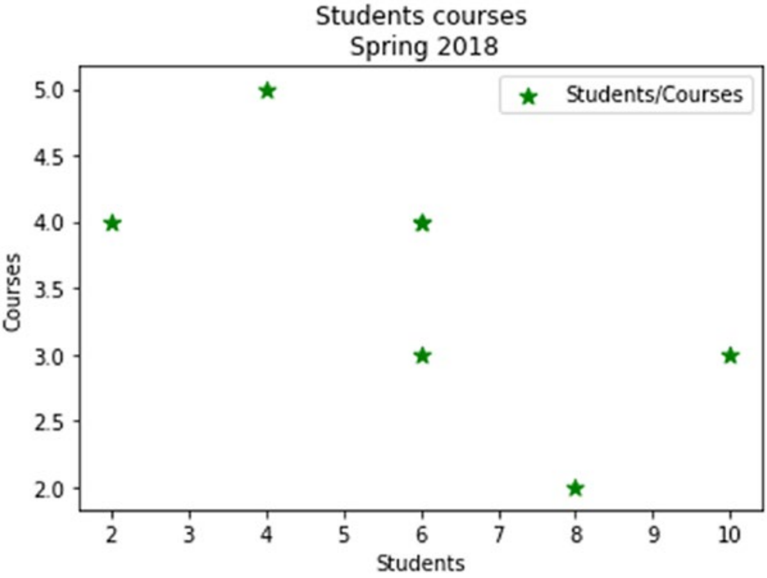


Scatter Plot

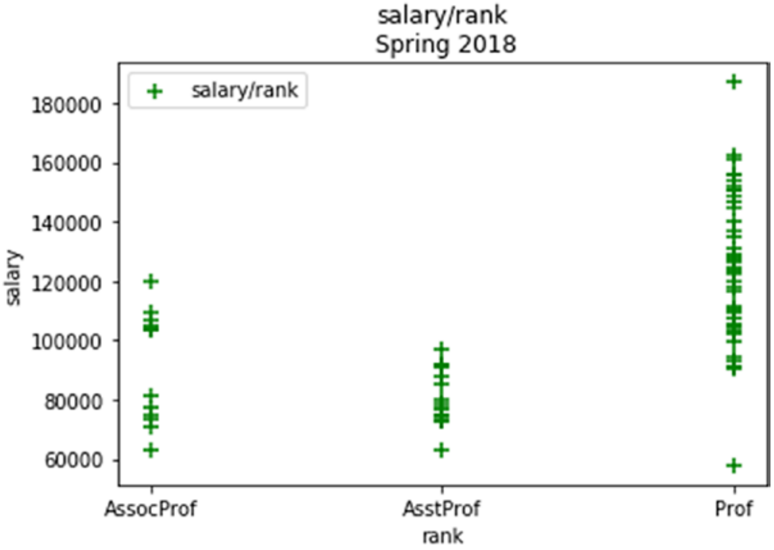
Listing 7-19 shows how to create a scatter plot to present students registered for courses, where four students are registered for five courses.

Listing 7-19. Matplotlib Scatter Plot

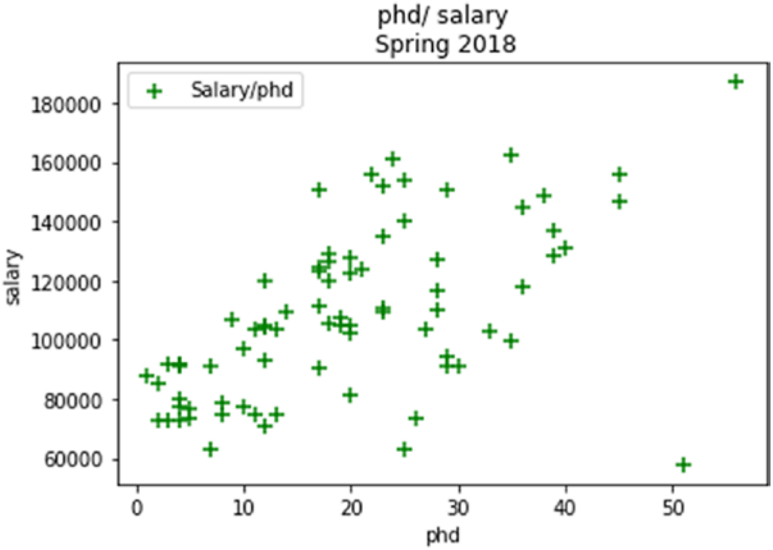
```
In [7]: Students = [2,4,6,8,6,10, 6] Courses = [4,5,3,2,4, 3, 4]
        plt.scatter(Students,Courses, label='Students/Courses',
        color='green', marker='*', s=75 )
        plt.xlabel('Students')
        plt.ylabel('Courses')
        plt.title('Students courses\n Spring 2018')
        plt.legend()
        plt.show()
```



```
In [16]: plt.scatter(rank,salary, label='salary/rank',
         color='g', marker='+', s=50 )
         plt.xlabel('rank') plt.ylabel('salary')
         plt.title('salary/rank\n Spring 2018')
         plt.legend() plt.show()
```



```
In [20]: plt.scatter(phd,salary, label='Salary/phd', color='g',
         marker='+', s=80 )
         plt.xlabel('phd') plt.ylabel('salary')
         plt.title('phd/ salary\n Spring 2018')
         plt.legend() plt.show()
```

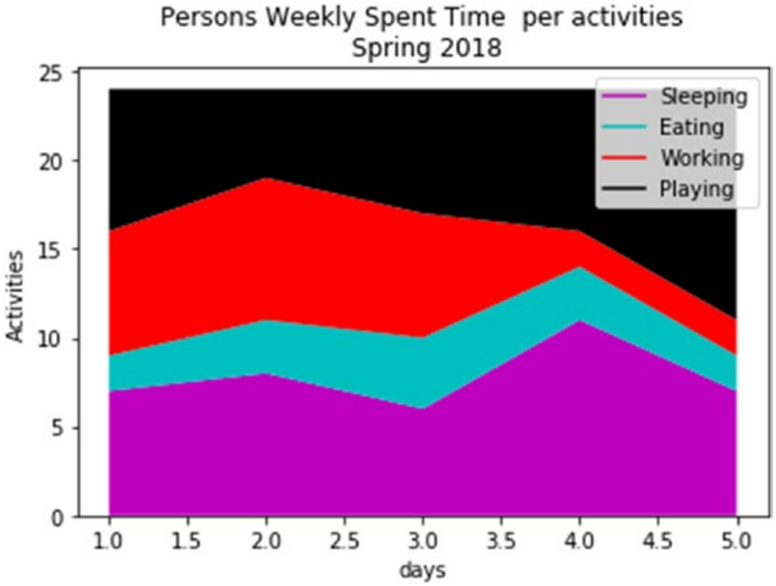


Stack Plot

Stack plots present the frequency of every activity, such as the frequency of sleeping, eating, working, and playing per day (see Listing 7-20). In this data set, on day 2, a person spent eight hours sleeping, three hours in eating, eight hours working, and five hours playing.

Listing 7-20. Persons Weekly Spent Time per activities using Matplotlib Stack Plot

```
In [9]: days = [1,2,3,4,5]
        sleeping = [7,8,6,11,7]
        eating = [2,3,4,3,2]
        working = [7,8,7,2,2]
        playing = [8,5,7,8,13]
        plt.plot([],[], color='m', label='Sleeping')
        plt.plot([],[], color='c', label='Eating')
        plt.plot([],[], color='r', label='Working')
plt.plot([],[], color='k', label='Playing')
plt.stackplot(days, sleeping, eating, working ,
playing, colors=['m','c', 'r', 'k'])
plt.xlabel('days')
plt.ylabel('Activities')
plt.title('Persons Weekly Spent Time per activities\n
Spring 2018')
plt.legend()
plt.show()
```

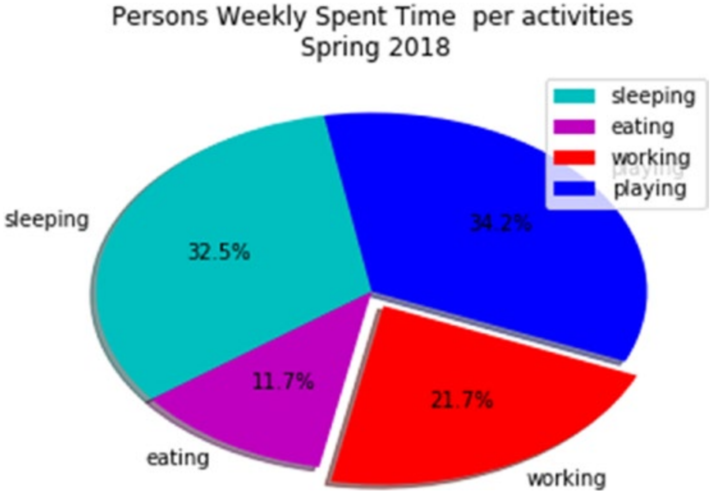


Pie Chart

In Listing 7-21, you are using the explode attribute to slice out a specific activity. After that, you can add the gender and title to the pie chart.

Listing 7-21. Persons Weekly Spent Time per activities using Matplotlib Pie Chart

```
In [10]: days = [1,2,3,4,5]
         sleeping = [7,8,6,11,7]
         eating = [2,3,4,3,2]
         working = [7,8,7,2,2]
         playing = [8,5,7,8,13]
         slices = [39,14,26,41]
         activities = ['sleeping', 'eating', 'working',
         'playing']
         cols = ['c','m','r', 'b','g']

         plt.pie(slices,
             labels= activities,
             colors= cols,
             startangle=100,
                 shadow=True,
         explode = (0.0,0.0,0.09,0),
         autopct = '%1.1f%%')
         plt.title('Persons Weekly Spent Time per activities\n
         Spring 2018')
         plt.legend()
         plt.show()
```



Summary

This chapter covered how to plot data from different collection structures. You learned the following:

- How to directly plot data from a series, data frame, or panel using Python plotting tools such as line plots, bar plots, pie charts, box plots, histogram plots, and scatter plots
- How to implement the Seaborn plotting system using strip plotting, box plotting, swarm plotting, and joint plotting
- How to implement Matplotlib plotting using line plots, bar charts, histogram plots, scatter plots, stack plots, and pie charts

The next chapter will cover the techniques you've studied in this book via two different case studies; it will make recommendations, and much more.

Exercises and Answers

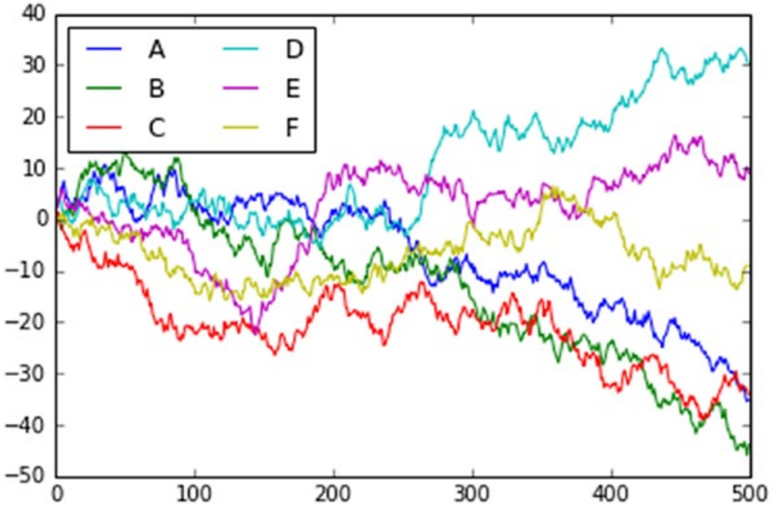
1. Create 500 random temperature readings for six cities over a season and then plot the generated data using Matplotlib.

Answer:

See Listing 7-22.

Listing 7-22. Plotting the Temperature Data of Six Cities

```
In [4]: import matplotlib.pyplot as plt
        plt.style.use('classic')
        %matplotlib inline
        import numpy as np
        import pandas as pd

In [30]: # Create temperature data
        rng = np.random.RandomState(0)
        season1 = np.cumsum(rng.randn(500, 6), 0)

In [32]: # Plot the data with Matplotlib defaults
        plt.plot(season1)
        plt.legend('ABCDEF', ncol=2, loc='upper left');
```



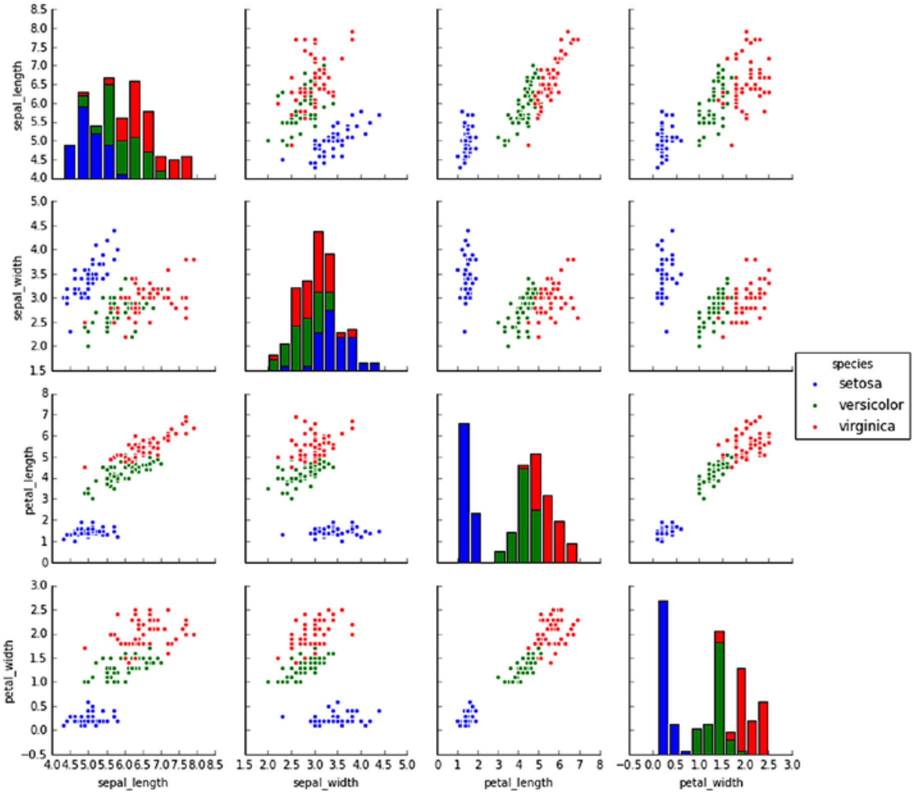
2. Load the well-known Iris data set, which lists measurements of petals and sepals of three iris species. Then plot the correlations between each pair using the `.pairplot()` method.

Answer:

See Listing 7-23.

Listing 7-23. Pair Correlations

```
In [33]: import seaborn as sns
         iris = sns.load_dataset("iris")
         iris.head()
         sns.pairplot(iris, hue='species', size=2.5);
```



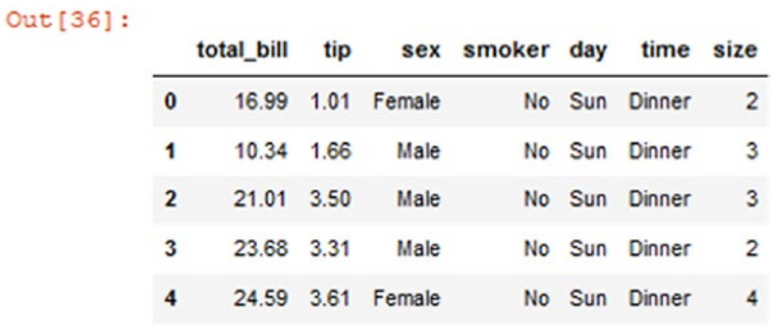
3. Load the well-known Tips data set, which shows the number of tips received by restaurant staff based on various indicator data; then plot the percentage of tips per bill according to staff gender.

Answer:

See Listing 7-24.

Listing 7-24. First five records in the Tips dataset

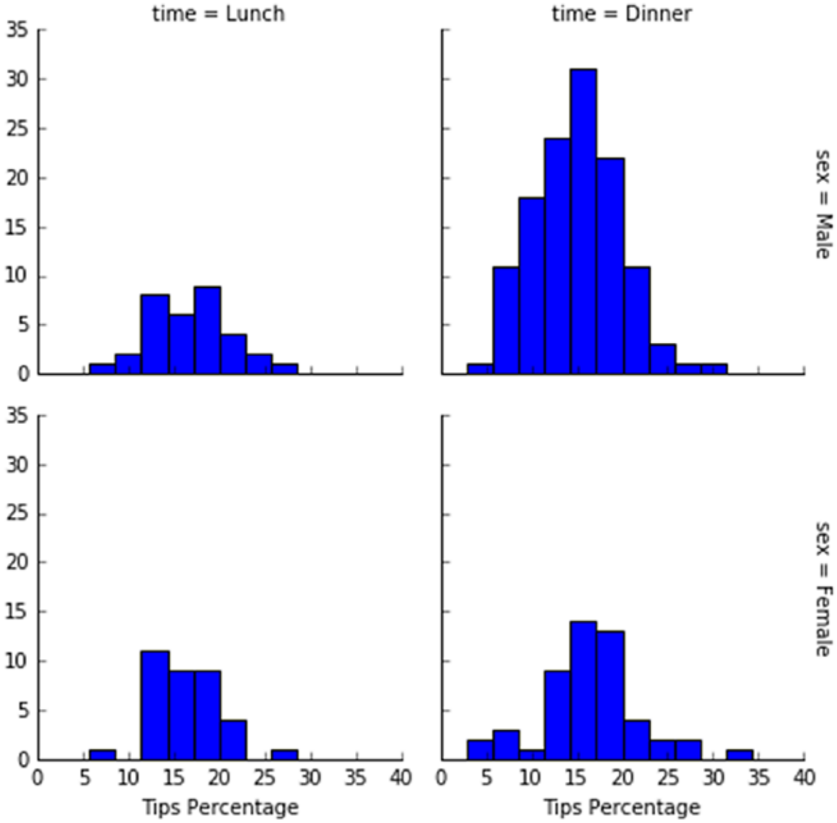
```
In [36]: import seaborn as sns
         tips = sns.load_dataset('tips')
         tips.head()
```



Out[36]:

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

```
In [37]: tips['Tips Percentage'] = 100 * tips['tip'] /
tips['total_bill']
         grid = sns.FacetGrid(tips, row="sex", col="time",
         margin_titles=True)
         grid.map(plt.hist, "Tips Percentage", bins=np.
         linspace(0, 40, 15));
```



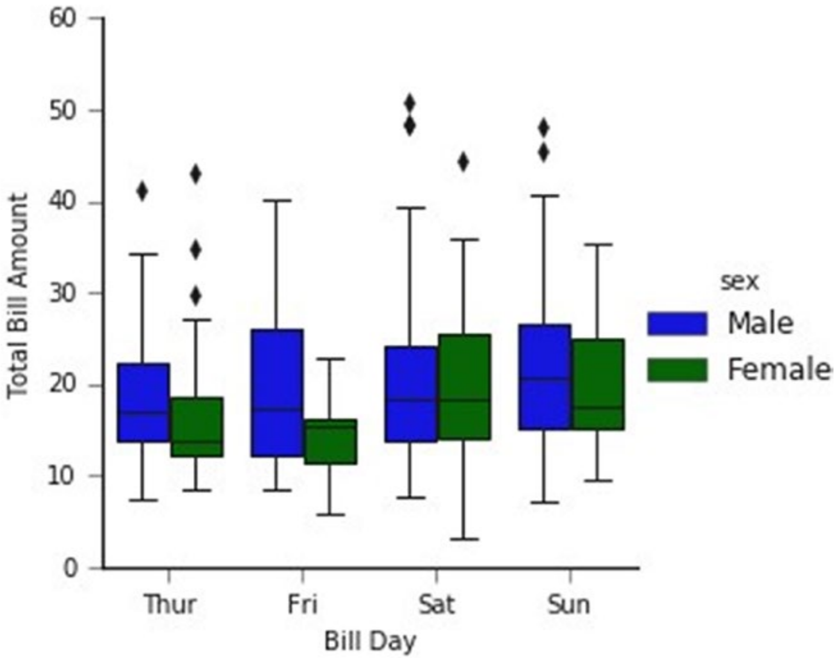
4. Load the well-known Tips data set, which shows the number of tips received by restaurant staff based on various indicator data; then implement the factor plots to visualize the total bill per day according to staff gender.

Answer:

See Listing 7-25.

Listing 7-25. Implementing Factor Plotting

```
In [39]: import seaborn as sns
         tips = sns.load_dataset('tips')
         with sns.axes_style(style='ticks'):
         g = sns.factorplot("day", "total_bill",
         "sex", data=tips, kind="box")
         g.set_axis_labels("Bill Day", "Total Bill Amount")
```



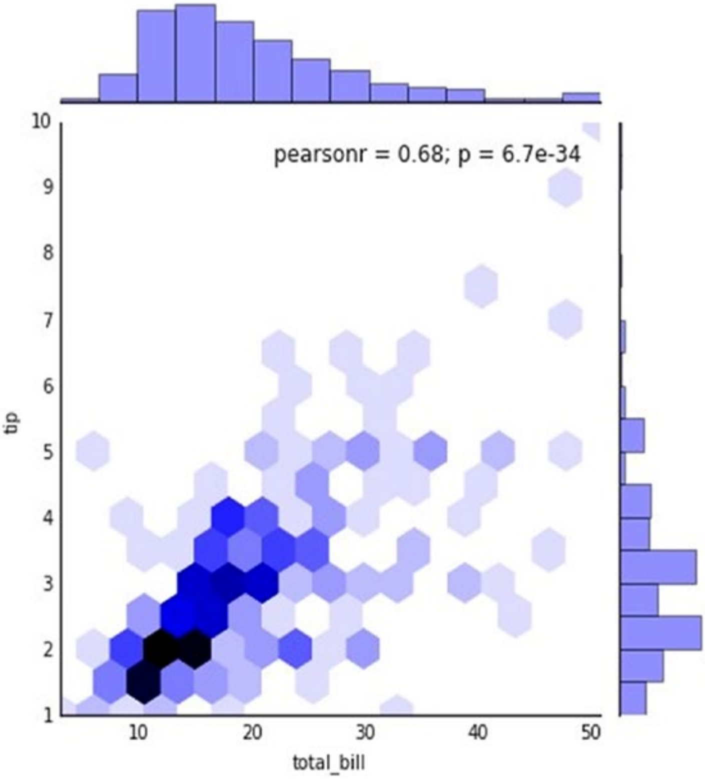
5. Reimplement the previous exercise using the Seaborn joint plot distributions.

Answer:

See Listing 7-26.

Listing 7-26. Implementing Joint Plot Distributions

```
In [43]: import seaborn as sns
         tips = sns.load_dataset('tips')
         with sns.axes_style('white'):
         sns.jointplot( "total_bill", "tip",
         data=tips, kind='hex')
```


pearsonr = 0.68; p = 6.7e-34
tip
total_bill