Module 3 - Statistics Essentials and Data Pre-processing with Python

Data Visualization with Matplotlib

We'll now take a high level look at the Matplotlib package for visualization in Python. This notebook discusses the basic data visualization topics and doesn't delve much into the details as the previous two notebooks.

Matplotlib is a multi-platform data visualization library built on NumPy arrays, and designed to work with the broader SciPy stack. One of Matplotlib's most important features is its ability to play well with many operating systems and graphics backends. Matplotlib supports dozens of backends and output types, which means you can count on it to work regardless of which operating system you are using or which output format you wish. It has led to a large user base, which in turn has led to an active developer base and Matplotlib's powerful tools and ubiquity within the scientific Python world.

Recent Matplotlib versions make it relatively easy to set new global plotting styles, and people have been developing new packages that build on its powerful internals to drive Matplotlib via cleaner, more modern APIs—for example, Seaborn, ggpy, HoloViews, Altair, and even Pandas itself can be used as wrappers around Matplotlib's API.

General Matplotlib Tips

Before we dive into the details of creating visualizations with Matplotlib, there are a few useful things you should know about using the package.

Importing Matplotlib

Just as we use the `np` shorthand for NumPy and the `pd` shorthand for Pandas, we will use some standard shorthands for Matplotlib imports:

In [1]:
```
import matplotlib as mpl
import matplotlib.pyplot as plt
```

The `plt` interface is what we will use most often, as we shall see throughout this chapter.

Setting Styles

We will use the `plt.style` directive to choose appropriate aesthetic styles for our figures. Here we will set the `classic` style, which ensures that the plots we create use the classic Matplotlib style:

In [2]:
```
plt.style.use('classic')
```

Throughout this section, we will adjust this style as needed. Note that the stylesheets used here are supported as of Matplotlib version 1.5; if you are using an earlier version of Matplotlib, only the default style is available.

Plotting from an IPython/Jupyter notebook

Plotting interactively within an IPython/Jupyter notebook can be done with the `%matplotlib` command, and works in a similar way to the IPython shell. In the IPython notebook, you also have the option of embedding graphics directly in the notebook, with two possible options:

- `%matplotlib notebook` will lead to *interactive* plots embedded within the notebook
- `%matplotlib inline` will lead to *static* images of your plot embedded in the notebook

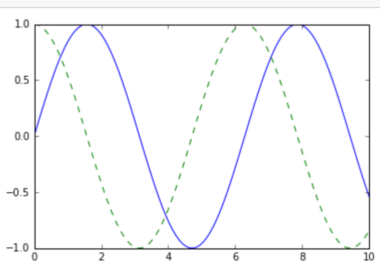
For this book, we will generally opt for `%matplotlib inline`:

In [3]:
```
%matplotlib inline
```

After running this command (it needs to be done only once per kernel/session), any cell within the notebook that creates a plot will embed a PNG image of the resulting graphic:

In [4]:
```
import numpy as np
x = np.linspace(0, 10, 100)

fig = plt.figure()
plt.plot(x, np.sin(x), '-')
plt.plot(x, np.cos(x), '--');
```



Two Interfaces for the Price of One

A potentially confusing feature of Matplotlib is its dual interfaces: a convenient MATLAB-style state-based interface, and a more powerful object-oriented interface. We'll quickly highlight the differences between the two here.

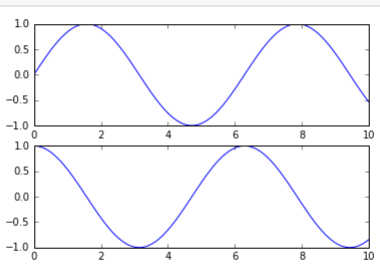
MATLAB-style Interface

Matplotlib was originally written as a Python alternative for MATLAB users, and much of its syntax reflects that fact. The MATLAB-style tools are contained in the pyplot (`plt`) interface. For example, the following code will probably look quite familiar to MATLAB users:

In [5]:
```
plt.figure()  # create a plot figure

# create the first of two panels and set current axis
plt.subplot(2, 1, 1) # (rows, columns, panel number)
plt.plot(x, np.sin(x))

# create the second panel and set current axis
plt.subplot(2, 1, 2)
plt.plot(x, np.cos(x));
```



It is important to note that this interface is *stateful*: it keeps track of the "current" figure and axes, which are where all `plt` commands are applied. You can get a reference to these using the `plt.gcf()` (get current figure) and `plt.gca()` (get current axes) routines.

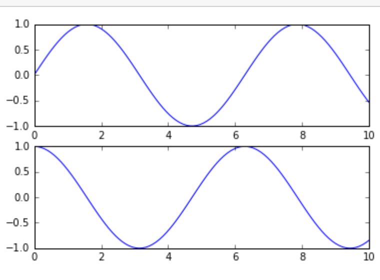
While this stateful interface is fast and convenient for simple plots, it is easy to run into problems. For example, once the second panel is created, how can we go back and add something to the first? This is possible within the MATLAB-style interface, but a bit clunky. Fortunately, there is a better way.

Object-oriented interface

The object-oriented interface is available for these more complicated situations, and for when you want more control over your figure. Rather than depending on some notion of an "active" figure or axes, in the object-oriented interface the plotting functions are *methods* of explicit `Figure` and `Axes` objects. To re-create the previous plot using this style of plotting, you might do the following:

In [6]:
```
# First create a grid of plots
# ax will be an array of two Axes objects
fig, ax = plt.subplots(2)

# Call plot() method on the appropriate object
ax[0].plot(x, np.sin(x))
ax[1].plot(x, np.cos(x));
```



For more simple plots, the choice of which style to use is largely a matter of preference, but the object-oriented approach can become a necessity as plots become more complicated. Throughout this notebook, we will switch between the MATLAB-style and object-oriented interfaces, depending on what is most convenient. In most cases, the difference is as small as switching `plt.plot()` to `ax.plot()`, but there are a few gotchas that we will highlight as they come up in the following sections.

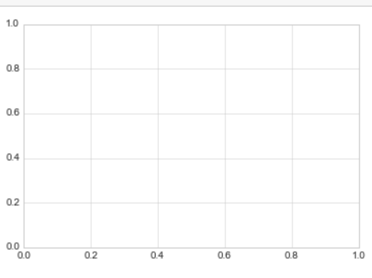
Simple Line Plots

Perhaps the simplest of all plots is the visualization of a single function $y = f(x)$. Here we will take a first look at creating a simple plot of this type.

In [7]:
```
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('seaborn-whitegrid')
import numpy as np
```

For all Matplotlib plots, we start by creating a figure and an axes. In their simplest form, a figure and axes can be created as follows:

In [8]:
```
fig = plt.figure()
ax = plt.axes()
```

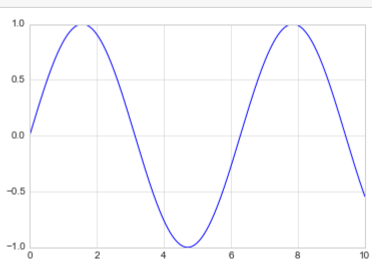


In Matplotlib, the *figure* (an instance of the class `plt.Figure`) can be thought of as a single container that contains all the objects representing axes, graphics, text, and labels. The *axes* (an instance of the class `plt.Axes`) is what we see above: a bounding box with ticks and labels, which will eventually contain the plot elements that make up our visualization. We'll commonly use the variable name `fig` to refer to a figure instance, and `ax` to refer to an axes instance or group of axes instances.

Once we have created an axes, we can use the `ax.plot` function to plot some data. Let's start with a simple sinusoid:

In [9]:
```
fig = plt.figure()
ax = plt.axes()

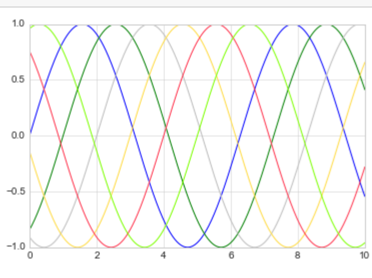
x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x));
```



Adjusting the Plot: Line Colors and Styles

The first adjustment you might wish to make to a plot is to control the line colors and styles. The `plt.plot()` function takes additional arguments that can be used to specify these. To adjust the color, you can use the `color` keyword, which accepts a string argument representing virtually any imaginable color. The color can be specified in a variety of ways:

In [10]:
```
plt.plot(x, np.sin(x - 0), color='blue')        # specify color by name
plt.plot(x, np.sin(x - 1), color='g')           # short color code (rgbcmyk)
plt.plot(x, np.sin(x - 2), color='0.75')        # Grayscale between 0 and 1
plt.plot(x, np.sin(x - 3), color='#FFDD44')     # Hex code (RRGGBB from 00 to FF)
plt.plot(x, np.sin(x - 4), color=(1.0,0.2,0.3)) # RGB tuple, values 0 to 1
plt.plot(x, np.sin(x - 5), color='chartreuse'); # all HTML color names supported
```



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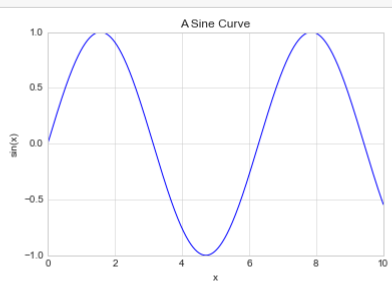
plt.plot(x, np.sin(x - 5), color='chartreuse'); # all HTML color names supported
```

Labeling Plots

As the last piece of this section, we'll briefly look at the labeling of plots: titles, axis labels, and simple legends.

Titles and axis labels are the simplest such labels—there are methods that can be used to quickly set them:

In [12]:
```
plt.plot(x, np.sin(x))
plt.title("A Sine Curve")
plt.xlabel("x")
plt.ylabel("sin(x)");
```



The position, size, and style of these labels can be adjusted using optional arguments to the function. For more information, see the Matplotlib documentation and the docstrings of each of these functions.

Simple Scatter Plots

Another commonly used plot type is the simple scatter plot, a close cousin of the line plot. Instead of points being joined by line segments, here the points are represented individually with a dot, circle, or other shape. We'll start by setting up the notebook for plotting and importing the functions we will use:

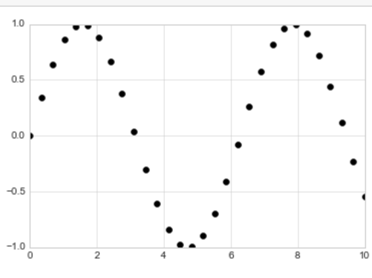
In [13]:
```
%matplotlib inline
plt.style.use('seaborn-whitegrid')
```

Scatter Plots with `plt.plot`

In the previous section we looked at `plt.plot` / `ax.plot` to produce line plots. It turns out that this same function can produce scatter plots as well:

In [14]:
```
x = np.linspace(0, 10, 30)
y = np.sin(x)

plt.plot(x, y, 'o', color='black');
```

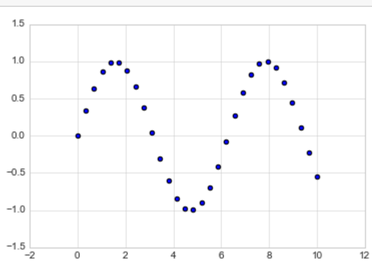


The third argument in the function call is a character that represents the type of symbol used for the plotting. Just as you can specify options such as `'-'`, `'--'` to control the line style, the marker style has its own set of short string codes. The full list of available symbols can be seen in the documentation of `plt.plot`, or in Matplotlib's online documentation.

Scatter Plots with `plt.scatter`

A second, more powerful method of creating scatter plots is the `plt.scatter` function, which can be used very similarly to the `plt.plot` function:

In [15]:
```
plt.scatter(x, y, marker='o');
```

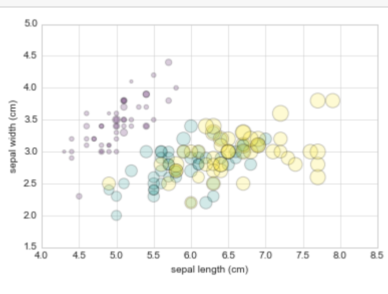


The primary difference of `plt.scatter` from `plt.plot` is that it can be used to create scatter plots where the properties of each individual point (size, face color, edge color, etc.) can be individually controlled or mapped to data.

Let's show this by creating a random scatter plot with points of many colors and sizes. For example, we might use the Iris data from Scikit-Learn, where each sample is one of three types of flowers that has had the size of its petals and sepals carefully measured:

In [16]:
```
from sklearn.datasets import load_iris
iris = load_iris()
features = iris.data.T

plt.scatter(features[0], features[1], alpha=0.2,
            s=100*features[3], c=iris.target, cmap='viridis')
plt.xlabel(iris.feature_names[0])
plt.ylabel(iris.feature_names[1]);
```



We can see that this scatter plot has given us the ability to simultaneously explore four different dimensions of the data: the (x, y) location of each point corresponds to the sepal length and width, the size of the point is related to the petal width, and the color is related to the particular species of flower. Multicolor and multifeature scatter plots like this can be useful for both exploration and presentation of data.

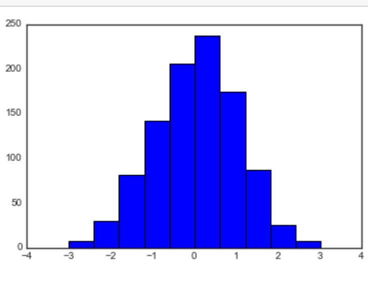
Histograms, Binnings, and Density

A simple histogram can be a great first step in understanding a dataset.

In [17]:
```
%matplotlib inline
plt.style.use('seaborn-white')

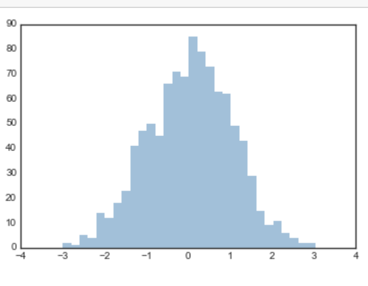
data = np.random.randn(1000)
```

In [18]:
```
plt.hist(data);
```



The `hist()` function has many options to tune both the calculation and the display; here's an example of a more customized histogram:

In [22]:
```
plt.hist(data, bins=30, alpha=0.5,
         histtype='stepfilled', color='steelblue',
         edgecolor='none');
```

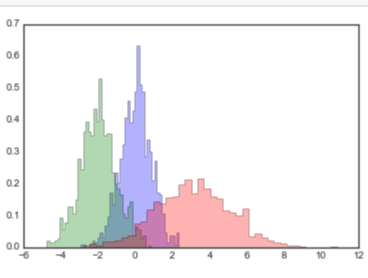


The `plt.hist` docstring has more information on other customization options available. I find this combination of `histtype='stepfilled'` along with some transparency `alpha` to be very useful when comparing histograms of several distributions:

In [24]:
```
x1 = np.random.normal(0, 0.8, 1000)
x2 = np.random.normal(-2, 1, 1000)
x3 = np.random.normal(3, 2, 1000)

kwargs = dict(histtype='stepfilled', alpha=0.3, density=True, bins=40)

plt.hist(x1, **kwargs)
plt.hist(x2, **kwargs)
plt.hist(x3, **kwargs);
```



If you would like to simply compute the histogram (that is, count the number of points in a given bin) and not display it, the `np.histogram()` function is available:

In [25]:
```
counts, bin_edges = np.histogram(data, bins=5)
print(counts)
```

```
[ 38 224 443 261  34]
```
