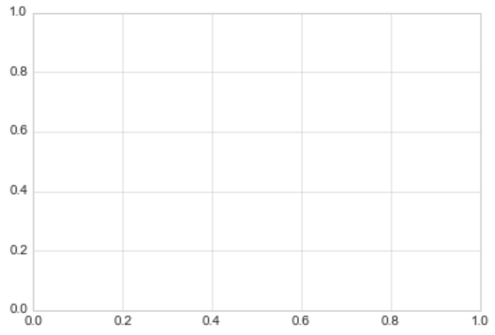
Simple Line Plots

The simplest plot is the one that only shows one function, y=f (x). First, we'll examine the basics of making a plot like this. We'll begin, as we do in each succeeding section, by importing the necessary packages and preparing the notebook for plotting.

```
%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:

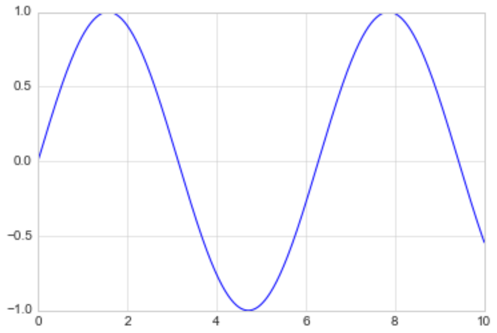
```
fig = plt.figure()
ax = plt.axes()
```



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. Throughout this book, 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.

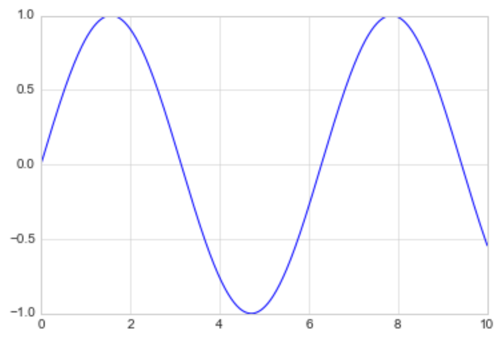
Once we have created an axes, we can use the `ax.plot` function to plot some data. Let's start with a simple sinusoid:

```
fig = plt.figure()
ax = plt.axes()

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



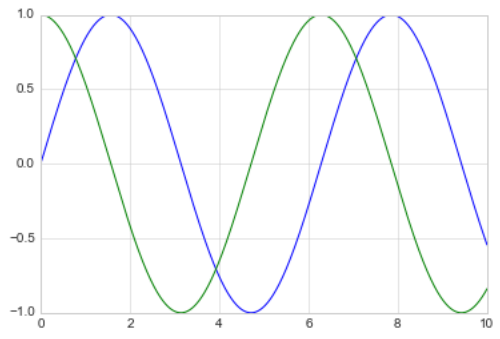
Alternatively, we can use the pylab interface and let the figure and axes be created for us in the background

```
plt.plot(x, np.sin(x));
```



If we want to create a single figure with multiple lines, we can simply call the `plot` function multiple times:

```
plt.plot(x, np.sin(x))
plt.plot(x, np.cos(x));
```

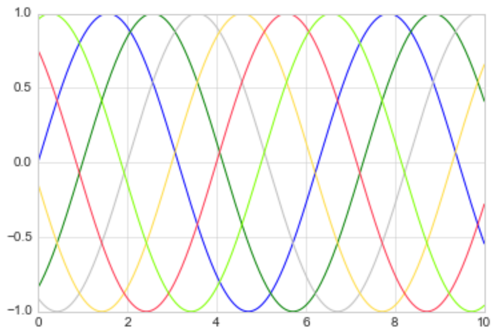


That's all there is to plotting simple functions in Matplotlib! We'll now dive into some more details about how to control the appearance of the axes and lines.

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:

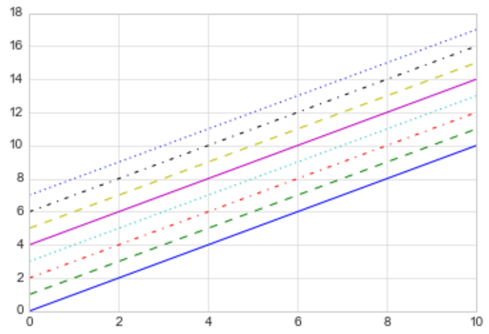
```
plt.plot(x, np.sin(x - 0), color='blue')        # specify color by name
plt.plot(x, np.sin(x - 1), color='g')           # short color code
(rgbcmyk)
plt.plot(x, np.sin(x - 2), color='0.75')        # Grayscale between 0 and 1
plt.plot(x, np.sin(x - 3), color='#FFDD44')     # Hex code (RRGGBB from 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
```



If no color is specified, Matplotlib will automatically cycle through a set of default colors for multiple lines.

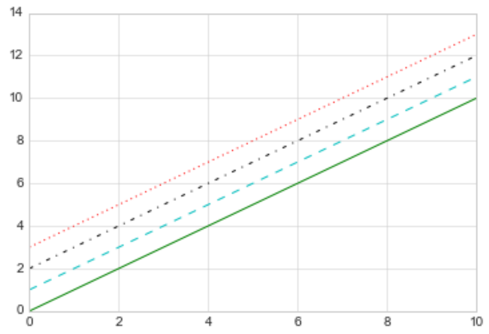
Similarly, the line style can be adjusted using the `linestyle` keyword:

```
plt.plot(x, x + 0, linestyle='solid')
plt.plot(x, x + 1, linestyle='dashed')
plt.plot(x, x + 2, linestyle='dashdot')
plt.plot(x, x + 3, linestyle='dotted');

# For short, you can use the following codes:
plt.plot(x, x + 4, linestyle='-')  # solid
plt.plot(x, x + 5, linestyle='--') # dashed
plt.plot(x, x + 6, linestyle='-.') # dashdot
plt.plot(x, x + 7, linestyle=':');  # dotted
```



If you would like to be extremely terse, these `linestyle` and `color` codes can be combined into a single non-keyword argument to the `plt.plot()` function:

```
plt.plot(x, x + 0, '-g')  # solid green
plt.plot(x, x + 1, '--c') # dashed cyan
plt.plot(x, x + 2, '-.k') # dashdot black
plt.plot(x, x + 3, ':r');  # dotted red
```



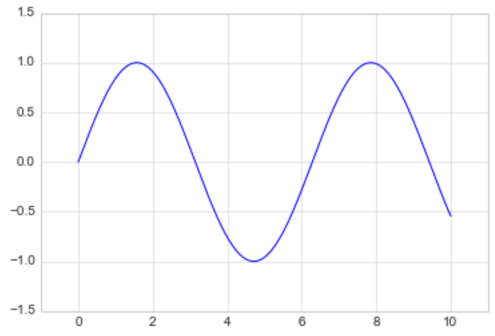
These single-character color codes reflect the standard abbreviations in the RGB (Red/Green/Blue) and CMYK (Cyan/Magenta/Yellow/blacK) color systems, commonly used for digital color graphics.

There are many other keyword arguments that can be used to fine-tune the appearance of the plot; for more details, I'd suggest viewing the docstring of the `plt.plot()` function using IPython's help tools

Adjusting the Plot: Axes Limits

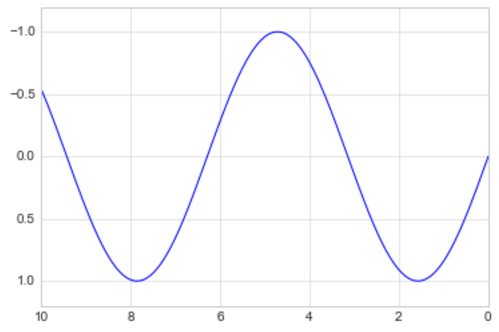
Matplotlib does a decent job of choosing default axes limits for your plot, but sometimes it's nice to have finer control. The most basic way to adjust axis limits is to use the `plt.xlim()` and `plt.ylim()` methods:

```
plt.plot(x, np.sin(x))

plt.xlim(-1, 11)
plt.ylim(-1.5, 1.5);
```



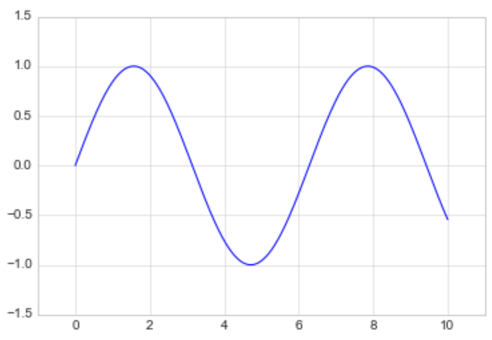
If for some reason you'd like either axis to be displayed in reverse, you can simply reverse the order of the arguments:

```
plt.plot(x, np.sin(x))

plt.xlim(10, 0)
plt.ylim(1.2, -1.2);
```



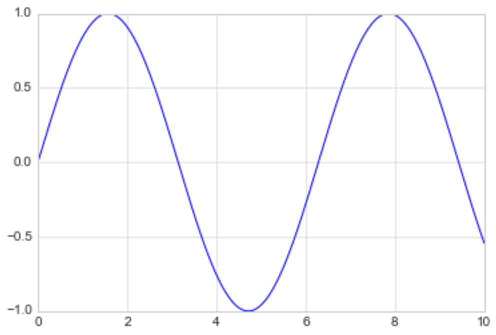
A useful related method is `plt.axis()` (note here the potential confusion between *axes* with an *e*, and *axis* with an *i*). The `plt.axis()` method allows you to set the `x` and `y` limits with a single call, by passing a list which specifies `[xmin, xmax, ymin, ymax]`:

```
plt.plot(x, np.sin(x))
plt.axis([-1, 11, -1.5, 1.5]);
```



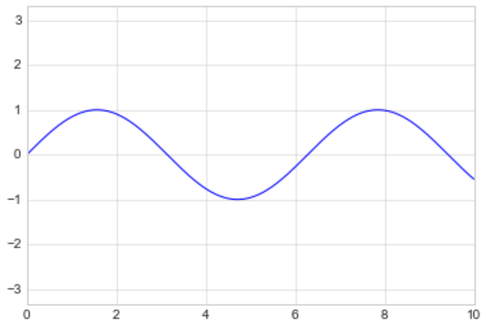
The `plt.axis()` method goes even beyond this, allowing you to do things like automatically tighten the bounds around the current plot:

```
plt.plot(x, np.sin(x))
plt.axis('tight');
```



It allows even higher-level specifications, such as ensuring an equal aspect ratio so that on your screen, one unit in `x` is equal to one unit in `y`:

```
plt.plot(x, np.sin(x))
plt.axis('equal');
```



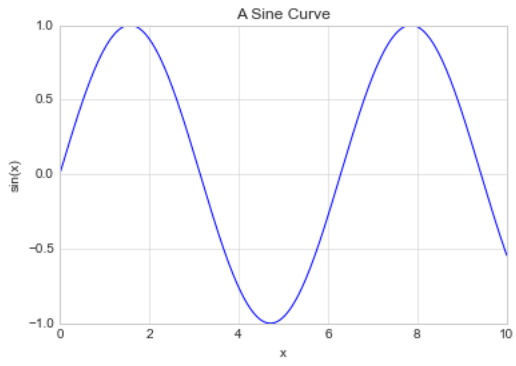
For more information on axis limits and the other capabilities of the `plt.axis` method, refer to the `plt.axis` docstring.

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:

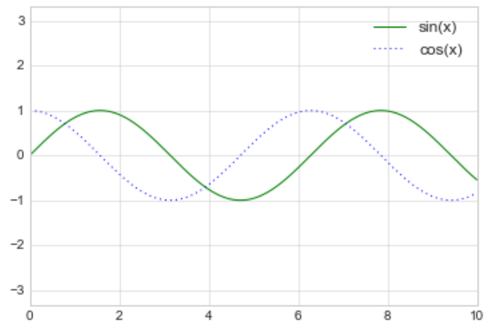
```
plt.plot(x, np.sin(x))
plt.title("A Sine Curve")
plt.xlabel("x")
plt.ylabel("sin(x)");
```



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.

When multiple lines are being shown within a single axes, it can be useful to create a plot legend that labels each line type. Again, Matplotlib has a built-in way of quickly creating such a legend. It is done via the (you guessed it) `plt.legend()` method. Though there are several valid ways of using this, I find it easiest to specify the label of each line using the `label` keyword of the plot function:

```
plt.plot(x, np.sin(x), '-g', label='sin(x)')
plt.plot(x, np.cos(x), ':b', label='cos(x)')
plt.axis('equal')

plt.legend();
```



As you can see, the `plt.legend()` function keeps track of the line style and color, and matches these with the correct label. More information on specifying and formatting plot legends can be found in the `plt.legend` docstring.

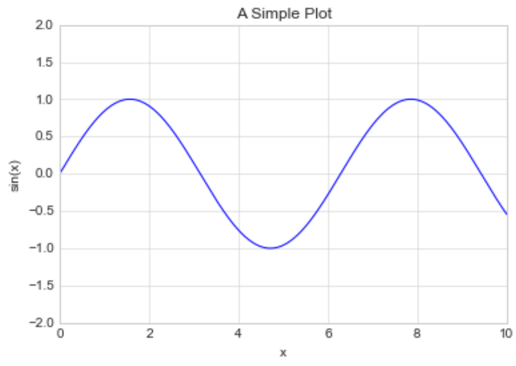
Aside: Matplotlib Gotchas

While most `plt` functions translate directly to `ax` methods (such as `plt.plot()` → `ax.plot()`, `plt.legend()` → `ax.legend()`, etc.), this is not the case for all commands. In particular, functions to set limits, labels, and titles are slightly modified. For transitioning between MATLAB-style functions and object-oriented methods, make the following changes:

- `plt.xlabel()` → `ax.set_xlabel()`
- `plt.ylabel()` → `ax.set_ylabel()`
- `plt.xlim()` → `ax.set_xlim()`
- `plt.ylim()` → `ax.set_ylim()`
- `plt.title()` → `ax.set_title()`

In the object-oriented interface to plotting, rather than calling these functions individually, it is often more convenient to use the `ax.set()` method to set all these properties at once:

```
ax = plt.axes()
ax.plot(x, np.sin(x))
ax.set(xlim=(0, 10), ylim=(-2, 2),
       xlabel='x', ylabel='sin(x)',
       title='A Simple Plot');
```



Simple Scatter Plots

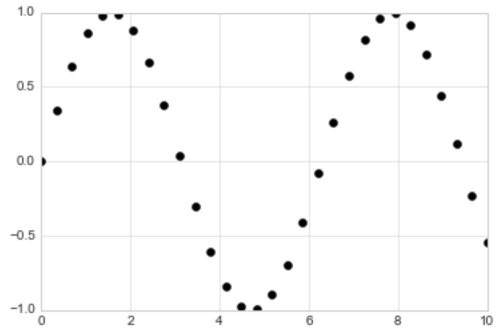
The simple scatter plot is another typical plot style that is related to the line plot. Here, dots, circles, and other non-linear shapes are used to represent points instead of lines. First, we'll import the necessary functions into the notebook and prepare it for plotting:

```
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('seaborn-whitegrid')
import numpy as np
```

Scatter Plots with `plt.plot`

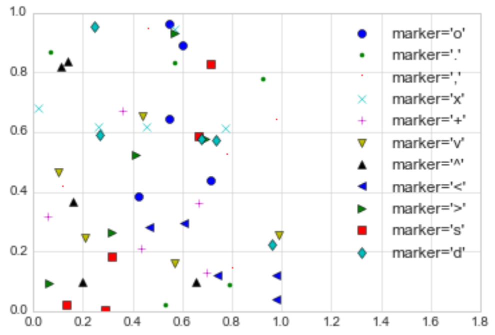
In the previous section we looked at `plt.plot`/`ax.plot` to produce line plots. It turns out that this same function can produce scatter plots as well:

```
x = np.linspace(0, 10, 30)
y = np.sin(x)

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



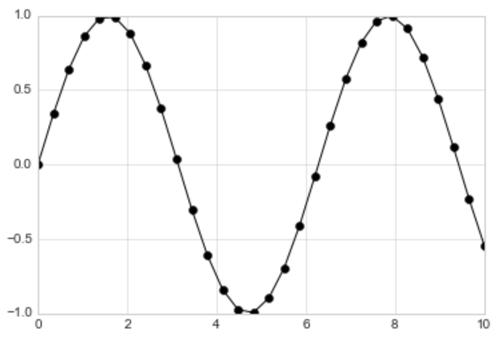
A character representing the kind of symbol used for the charting is given as the third parameter to the function call. The marker style may be changed using a similar set of short string codes as those used to modify the line style ('-', '—'). Plt.plot's manual, or Matplotlib's web docs, will show you the entire set of symbols you may use. Many of the options are obvious; we'll demonstrate some of the most typical:

```
rng = np.random.RandomState(0)
for marker in ['o', '.', ',', 'x', '+', 'v', '^', '<', '>', 's', 'd']:
    plt.plot(rng.rand(5), rng.rand(5), marker,
             label="marker='{0}'".format(marker))
plt.legend(numpoints=1)
plt.xlim(0, 1.8);
```



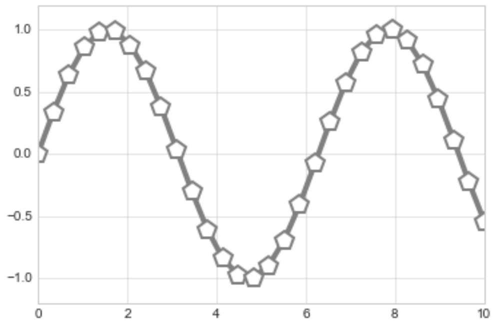
For even more possibilities, these character codes can be used together with line and color codes to plot points along with a line connecting them:

```
plt.plot(x, y, '-ok');
```



Additional keyword arguments to `plt.plot` specify a wide range of properties of the lines and markers:

```
plt.plot(x, y, '-p', color='gray',
         markersize=15, linewidth=4,
         markerfacecolor='white',
         markeredgecolor='gray',
         markeredgewidth=2)
plt.ylim(-1.2, 1.2);
```

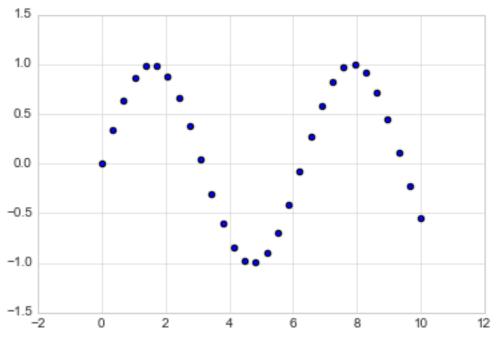


This type of flexibility in the `plt.plot` function allows for a wide variety of possible visualization options. For a full description of the options available, refer to the `plt.plot` documentation.

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:

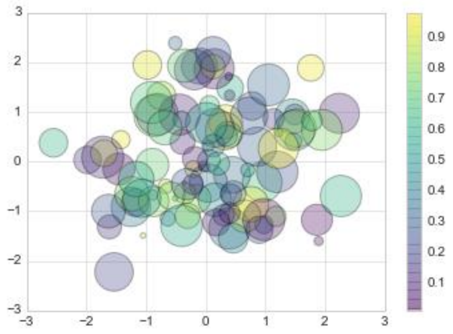
```
plt.scatter(x, y, marker='o');
```



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. In order to better see the overlapping results, we'll also use the `alpha` keyword to adjust the transparency level:

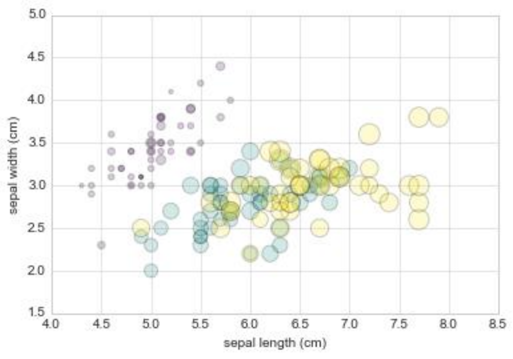
```
rng = np.random.RandomState(0)
x = rng.randn(100)
y = rng.randn(100)
colors = rng.rand(100)
sizes = 1000 * rng.rand(100)

plt.scatter(x, y, c=colors, s=sizes, alpha=0.3,
            cmap='viridis')
plt.colorbar();  # show color scale
```



Notice that the color argument is automatically mapped to a color scale (shown here by the `colorbar()` command), and that the size argument is given in pixels. In this way, the color and size of points can be used to convey information in the visualization, in order to visualize multidimensional data.

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:

```
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]);
```



Because of this scatter plot, we can examine four different dimensions of the data at once: the (x, y) position of each point corresponds to the length and width of the sepals, the size of the point is related to the width of the petals, and the color is related to the specific flower species. This kind of scatter plot, which combines several colors and features, may be used for both data exploration and presentation.

`plot` Versus `scatter`: A Note on Efficiency

Why would you use plt.plot instead of plt.scatter, besides the fact that they offer distinct functionality? Though it may not make a huge difference for smaller datasets, plt.plot can be significantly faster than plt.scatter once you have more than a few thousand points. The renderer must do the extra work of constructing each point individually because plt.scatter can render a different size and/or color for each point. On the other hand, plt.plot's points are virtually identical at all times, meaning that the effort required to determine the points' appearance is performed just once across the board. As the difference between the two can have a significant impact on performance, plt.plot is recommended over plt.scatter for large datasets.

Visualizing Errors

Accurate reporting of the number itself is crucial for any scientific measurement, but accurate accounting for errors is just as important, if not more so. Let's say I'm trying to determine the value of the Hubble Constant, a local indicator of the expansion rate of the Universe, and I plan on using some astrophysical observations to do so. According to my measurements, the value is 74 (km/s)/Mpc, while the current literature suggests a value of around 71 (km/s)/Mpc. Do all of the numbers add up? Given this data, "there is no way to know" is the only reasonable response.

Suppose I augment this information with reported uncertainties: the current literature suggests a value of around 71 ±

2.5 (km/s)/Mpc, and my method has measured a value of 74 ±

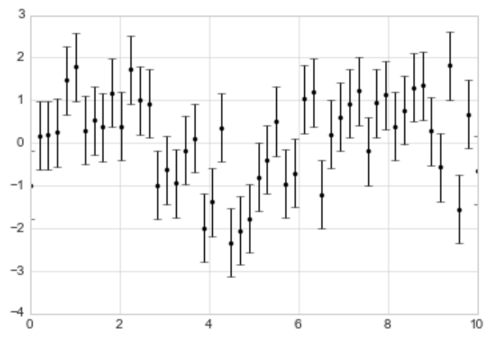
5 (km/s)/Mpc. Now are the values consistent? That is a question that can be quantitatively answered.

In visualization of data and results, showing these errors effectively can make a plot convey much more complete information.

Basic Errorbars

A basic errorbar can be created with a single Matplotlib function call:

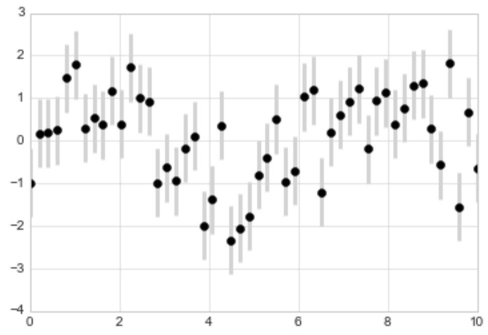
```
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('seaborn-whitegrid')
import numpy as np
x = np.linspace(0, 10, 50)
dy = 0.8
y = np.sin(x) + dy * np.random.randn(50)

plt.errorbar(x, y, yerr=dy, fmt='.k');
```



Here the `fmt` is a format code controlling the appearance of lines and points, and has the same syntax as the shorthand used in `plt.plot`, outlined in Simple Line Plots and Simple Scatter Plots.

In addition to these basic options, the `errorbar` function has many options to fine-tune the outputs. Using these additional options you can easily customize the aesthetics of your errorbar plot. I often find it helpful, especially in crowded plots, to make the errorbars lighter than the points themselves:

```
plt.errorbar(x, y, yerr=dy, fmt='o', color='black',
             ecolor='lightgray', elinewidth=3, capsize=0);
```



In addition to these options, you can also specify horizontal errorbars (`xerr`), one-sided errorbars, and many other variants. For more information on the options available, refer to the docstring of `plt.errorbar`.

Continuous Errors

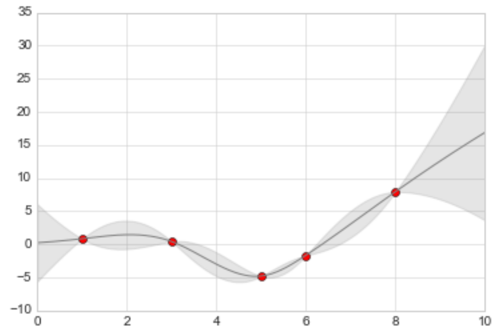
In some situations it is desirable to show errorbars on continuous quantities. Though Matplotlib does not have a built-in convenience routine for this type of application, it's relatively easy to combine primitives like `plt.plot` and `plt.fill_between` for a useful result.

Here we'll perform a simple *Gaussian process regression*, using the Scikit-Learn API This is a method of fitting a very flexible non-parametric function to data with a continuous measure of the uncertainty. We won't delve into the details of Gaussian process regression at this point, but will focus instead on how you might visualize such a continuous error measurement:

```
from sklearn.gaussian_process import GaussianProcess

# define the model and draw some data
model = lambda x: x * np.sin(x)
xdata = np.array([1, 3, 5, 6, 8])
ydata = model(xdata)

# Compute the Gaussian process fit
gp = GaussianProcess(corr='cubic', theta0=1e-2, thetaL=1e-4, thetaU=1E-1,
                     random_start=100)
gp.fit(xdata[:, np.newaxis], ydata)

xfit = np.linspace(0, 10, 1000)
yfit, MSE = gp.predict(xfit[:, np.newaxis], eval_MSE=True)
dyfit = 2 * np.sqrt(MSE)  # 2*sigma ~ 95% confidence region
```

We now have `xfit`, `yfit`, and `dyfit`, which sample the continuous fit to our data. We could pass these to the `plt.errorbar` function as above, but we don't really want to plot 1,000 points with 1,000 errorbars. Instead, we can use the `plt.fill_between` function with a light color to visualize this continuous error:

```
# Visualize the result
plt.plot(xdata, ydata, 'or')
plt.plot(xfit, yfit, '-', color='gray')

plt.fill_between(xfit, yfit - dyfit, yfit + dyfit,
                 color='gray', alpha=0.2)
plt.xlim(0, 10);
```



Note what we've done here with the `fill_between` function: we pass an x value, then the lower y-bound, then the upper y-bound, and the result is that the area between these regions is filled.

The resulting figure gives a very intuitive view into what the Gaussian process regression algorithm is doing: in regions near a measured data point, the model is strongly constrained and this is reflected in the small model errors. In regions far from a measured data point, the model is not strongly constrained, and the model errors increase.

For more information on the options available in `plt.fill_between()` (and the closely related `plt.fill()` function), see the function docstring or the Matplotlib documentation.