This notebook was adapted from the [Python Data Science Handbook (http://shop.oreilly.com/product/0636920034919.do)](http://shop.oreilly.com/product/0636920034919.do) by Jake VanderPlas; the content is available [on GitHub (https://github.com/jakevdp/PythonDataScienceHandbook)](https://github.com/jakevdp/PythonDataScienceHandbook).

Visualization with Matplotlib

Matplotlib is a multi-platform data visualization library built on NumPy arrays.

General Matplotlib Tips

Importing Matplotlib

Just as we use the `np` shorthand for NumPy, 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.

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')
```

`show()` or No `show()`? How to Display Your Plots

The best use of Matplotlib differs depending on how you are using it; roughly, the three applicable contexts are using Matplotlib in a script, in an IPython terminal, or in an IPython notebook.

Plotting from a script

If you are using Matplotlib from within a script, the function `plt.show()` is your friend. `plt.show()` starts an event loop, looks for all currently active figure objects, and opens one or more interactive windows that display your figure or figures.

So, for example, you may have a file called *myplot.py* containing the following:

```python
# ------- file: myplot.py ------
import matplotlib.pyplot as plt
import numpy as np

x = np.linspace(0, 10, 100)

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

plt.show()
```

You can then run this script from the command-line prompt, which will result in a window opening with your figure displayed:

```
$ python myplot.py
```

The `plt.show()` command does a lot under the hood, as it must interact with your system's interactive graphical backend. The details of this operation can vary greatly from system to system and even installation to installation, but matplotlib does its best to hide all these details from you.

One thing to be aware of: the `plt.show()` command should be used *only once* per Python session, and is most often seen at the very end of the script. Multiple `show()` commands can lead to unpredictable backend-dependent behavior, and should mostly be avoided.

Plotting from an IPython shell

It can be very convenient to use Matplotlib interactively within an IPython shell. IPython is built to work well with Matplotlib if you specify Matplotlib mode. To enable this mode, you can use the `%matplotlib` magic command after starting `ipython` :

```
In [1]: %matplotlib
Using matplotlib backend: TkAgg

In [2]: import matplotlib.pyplot as plt
```

At this point, any `plt` plot command will cause a figure window to open, and further commands can be run to update the plot. Some changes (such as modifying properties of lines that are already drawn) will not draw automatically: to force an update, use `plt.draw()` . Using `plt.show()` in Matplotlib mode is not required.

Plotting from an IPython notebook

The IPython notebook is a browser-based interactive data analysis tool that can combine narrative, code, graphics, HTML elements, and much more into a single executable document.

Plotting interactively within an IPython 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

We will generally opt for `%matplotlib inline` :

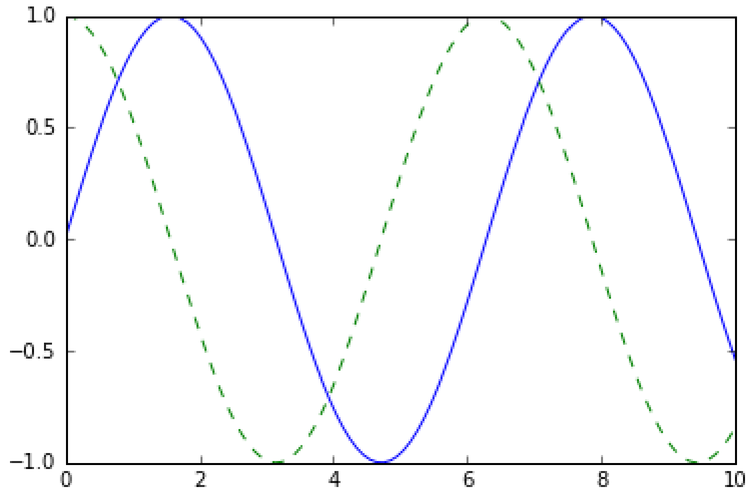
In [3]:

```
%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), '--');
```



Saving Figures to File

One nice feature of Matplotlib is the ability to save figures in a wide variety of formats. Saving a figure can be done using the `savefig()` command. For example, to save the previous figure as a PNG file, you can run this:

In [5]:

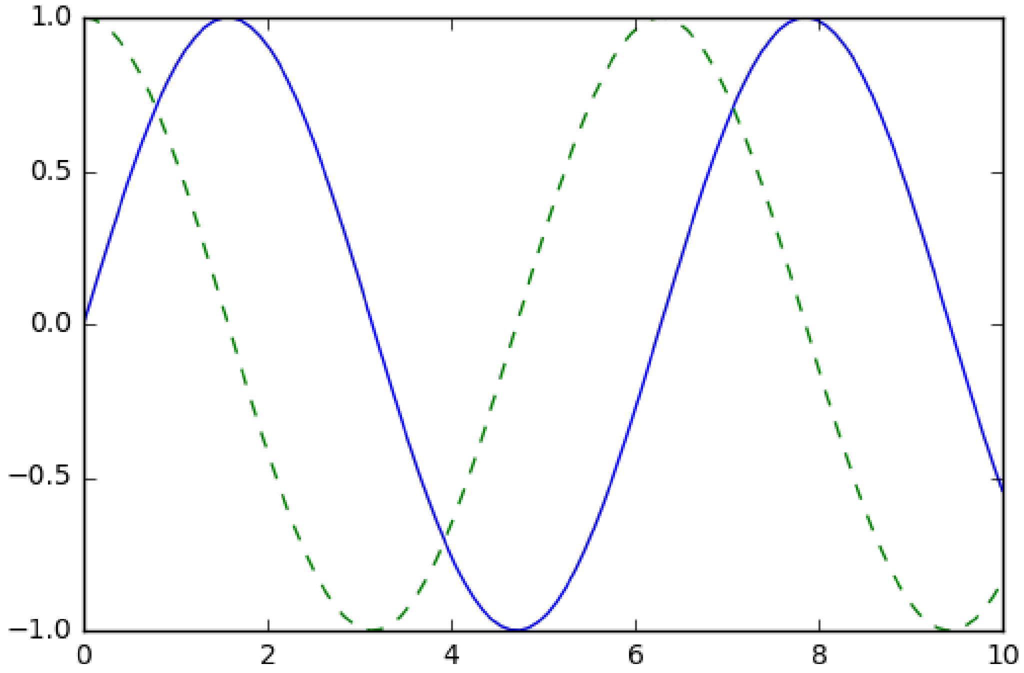
```
fig.savefig('my_figure.png')
```

We now have a file called `my_figure.png` in the current working directory. To confirm that it contains what we think it contains, let's use the IPython `Image` object to display the contents of this file:

In [6]:

```
from IPython.display import Image
Image('my_figure.png')
```

Out[6]:



In `savefig()` , the file format is inferred from the extension of the given filename. Depending on what backends you have installed, many different file formats are available. The list of supported file types can be found for your system by using the following method of the figure canvas object:

In [7]:

```
fig.canvas.get_supported_filetypes()
```

Out[7]:

```
{'eps': 'Encapsulated Postscript',
 'jpeg': 'Joint Photographic Experts Group',
 'jpg': 'Joint Photographic Experts Group',
 'pdf': 'Portable Document Format',
 'pgf': 'PGF code for LaTeX',
 'png': 'Portable Network Graphics',
 'ps': 'Postscript',
 'raw': 'Raw RGBA bitmap',
 'rgba': 'Raw RGBA bitmap',
 'svg': 'Scalable Vector Graphics',
 'svgz': 'Scalable Vector Graphics',
 'tif': 'Tagged Image File Format',
 'tiff': 'Tagged Image File Format'}
```

Note that when saving your figure, it's not necessary to use `plt.show()` or related commands discussed earlier.

Two Interfaces

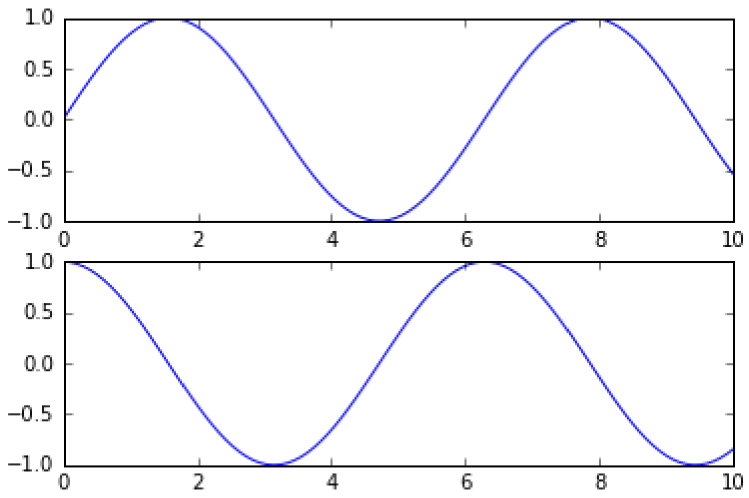
A potentially confusing feature of Matplotlib is its dual interfaces: a convenient MATLAB-style state-based interface, and a more powerful object-oriented interface. We'll quickly highlight the differences between the two here.

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 [8]:

```
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.

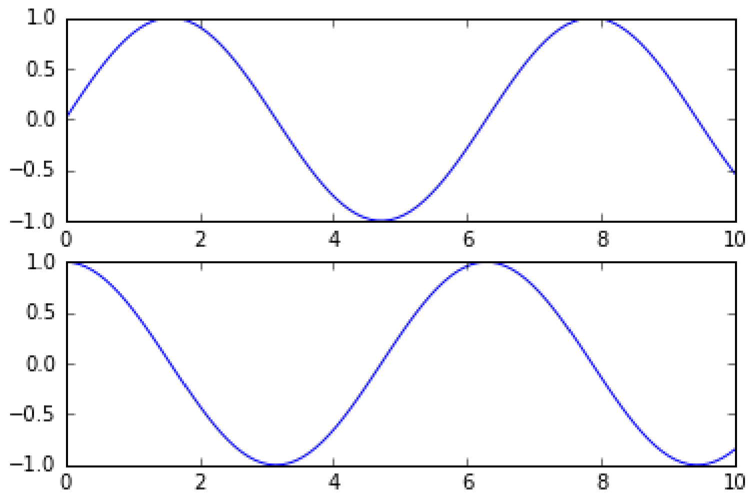
While this stateful interface is fast and convenient for simple plots, it is easy to run into problems. For example, once the second panel is created, how can we go back and add something to the first? This is possible within the MATLAB-style interface, but a bit clunky. Fortunately, there is a better 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 [9]:

```
# 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.

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. As with all the following sections, we'll start by setting up the notebook for plotting and importing the packages we will use:

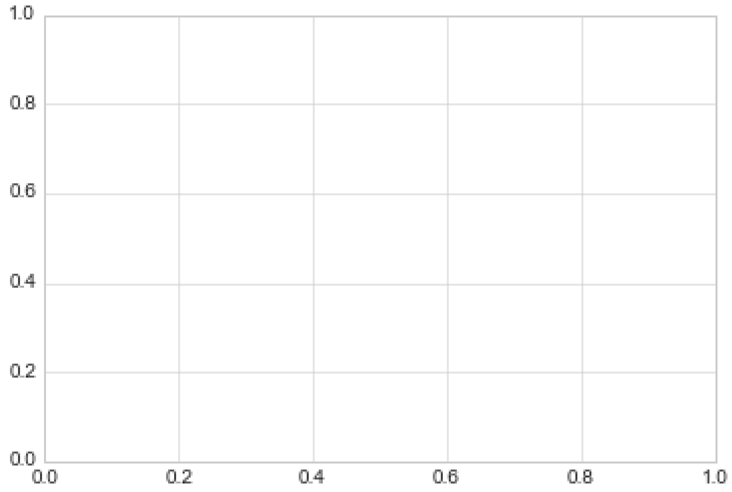
In [10]:

```
%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 [11]:

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

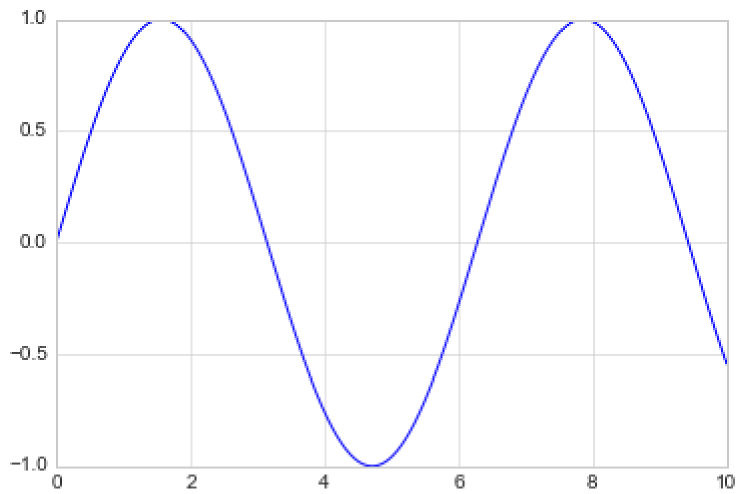


In Matplotlib, the *figure* (an instance of the class `plt.Figure`) can be thought of as a single container that contains all the objects representing axes, graphics, text, and labels. The *axes* (an instance of the class `plt.Axes`) is what we see above: a bounding box with ticks and labels, which will 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 [12]:

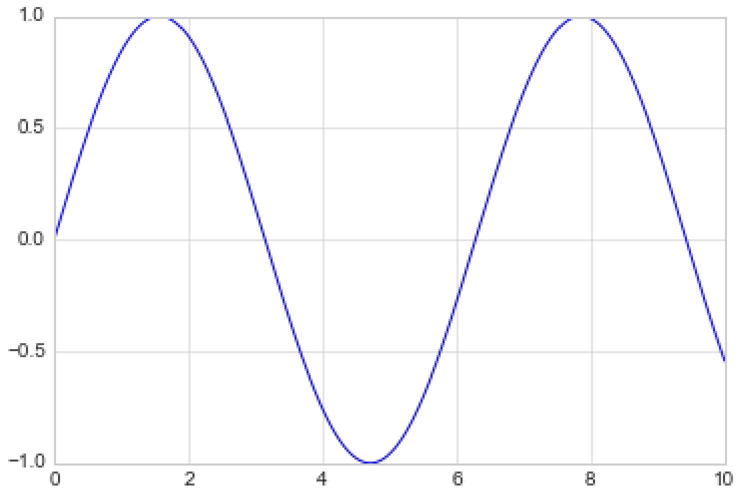
```
fig = plt.figure()
ax = plt.axes()

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:

In [13]:

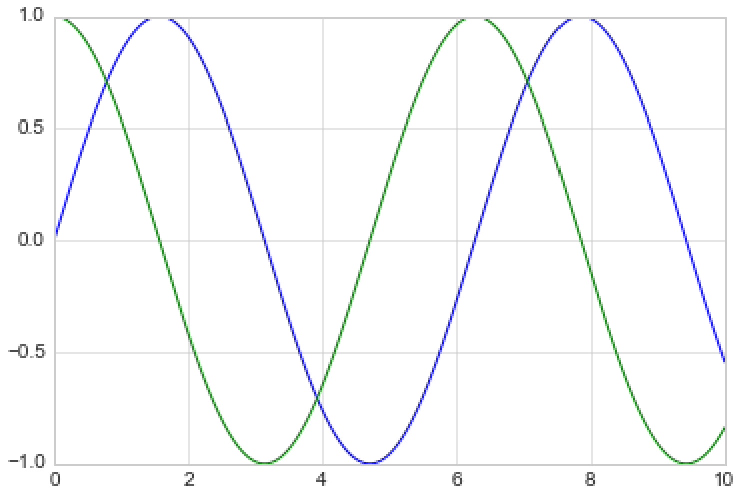
```
plt.plot(x, np.sin(x));
```



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

In [14]:

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



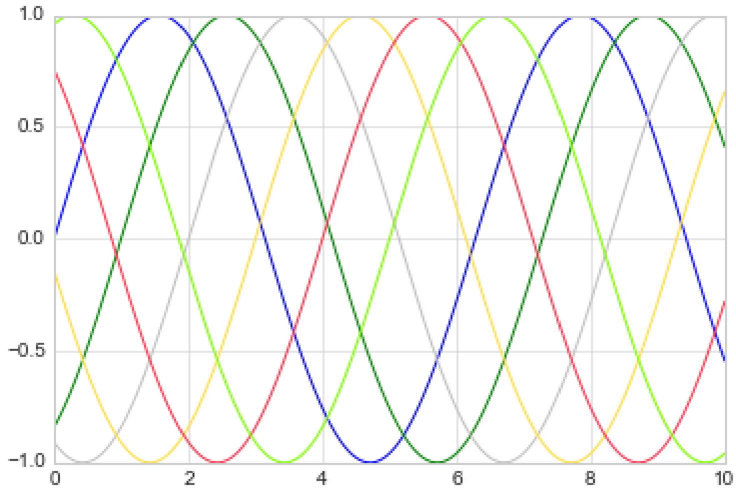
We'll now dive into some more details about how to control the appearance of the axes and lines.

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:

In [15]:

```
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
```

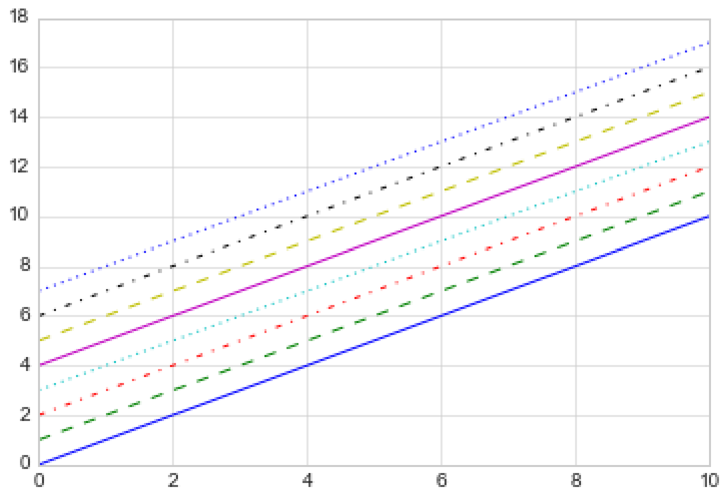


If no color is specified, Matplotlib will automatically cycle through a set of default colors for multiple lines.

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

In [16]:

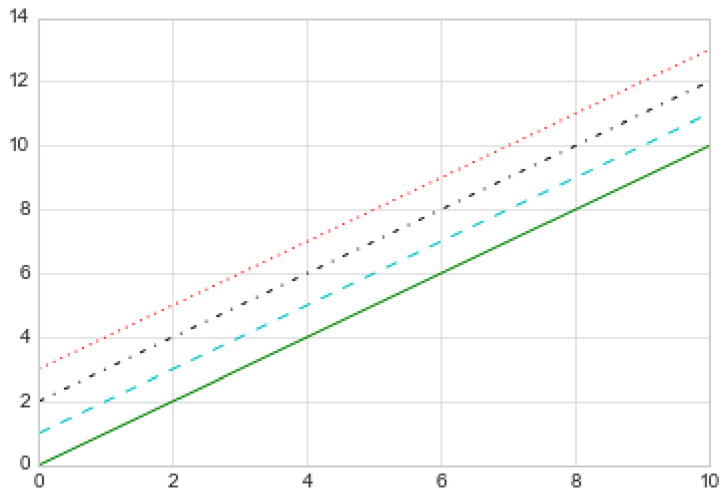
```
plt.plot(x, x + 0, linestyle='solid')
plt.plot(x, x + 1, linestyle='dashed')
plt.plot(x, x + 2, linestyle='dashdot')
plt.plot(x, x + 3, linestyle='dotted');

# 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
```



These `linestyle` and `color` codes can be combined into a single non-keyword argument to the `plt.plot()` function:

In [17]:

```
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
```

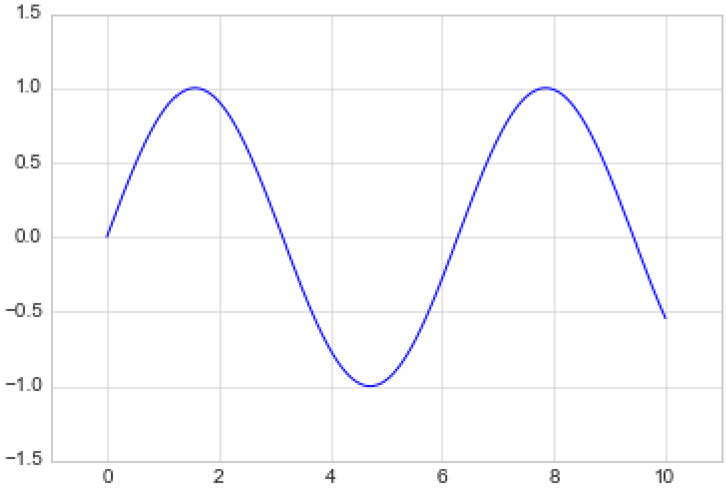


Adjusting the Plot: Axes Limits

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:

In [18]:

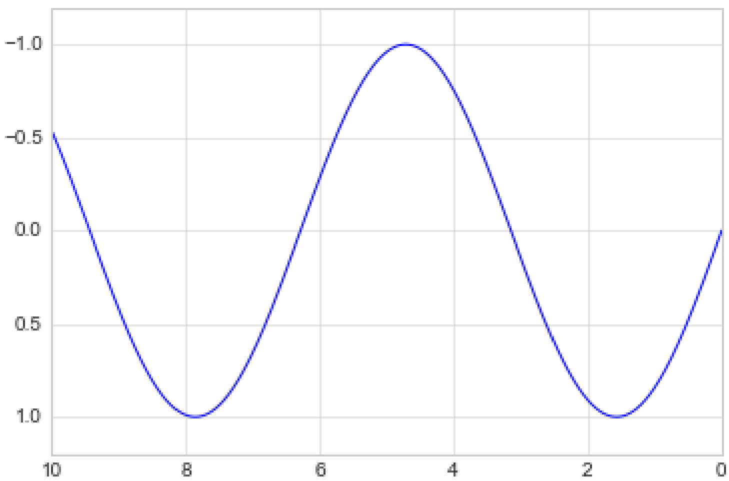
```
plt.plot(x, np.sin(x))

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:

In [19]:

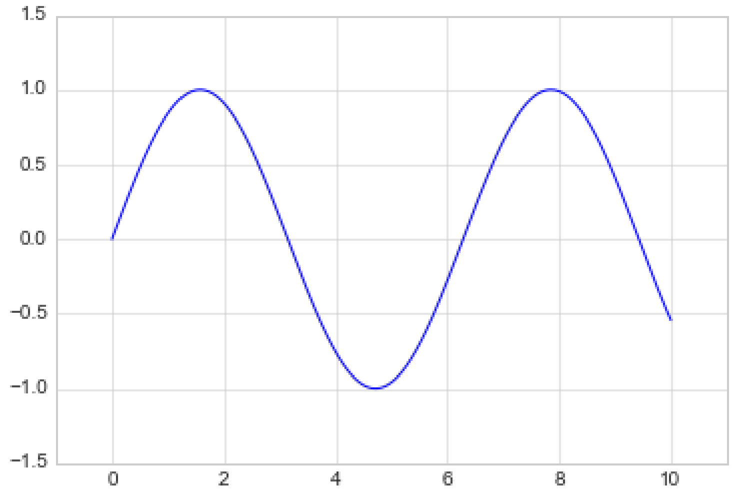
```
plt.plot(x, np.sin(x))

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]` :

In [20]:

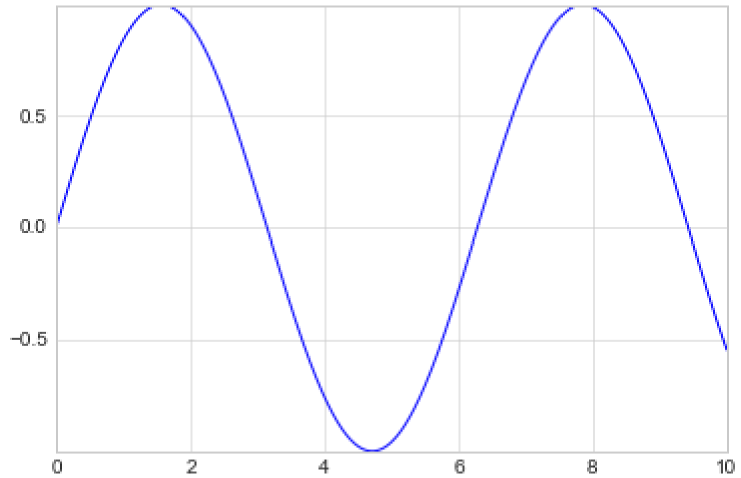
```
plt.plot(x, np.sin(x))
plt.axis([-1, 11, -1.5, 1.5]);
```



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

In [21]:

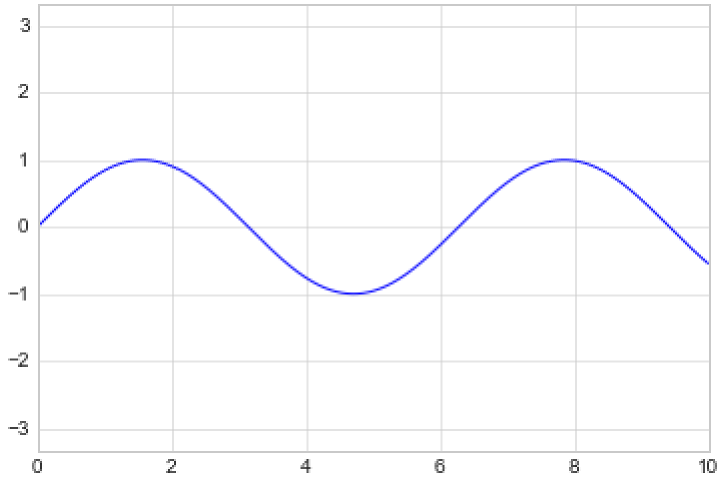
```
plt.plot(x, np.sin(x))
plt.axis('tight');
```



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`:

In [22]:

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



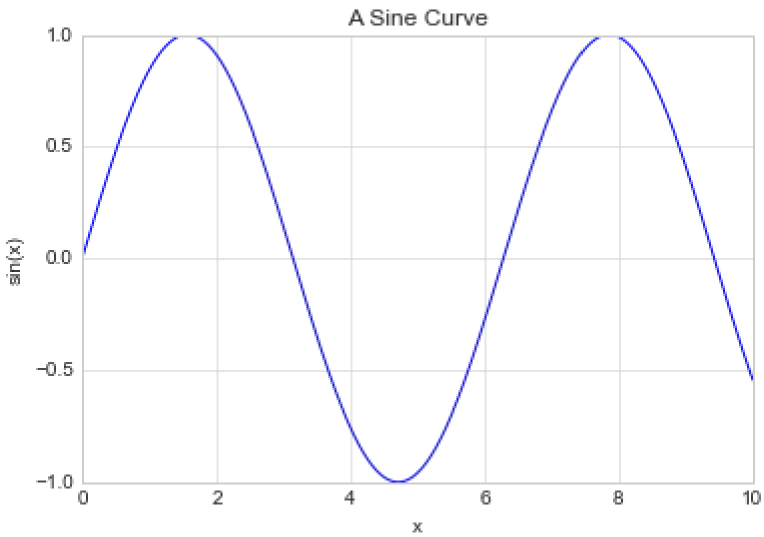
Labeling Plots

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 [23]:

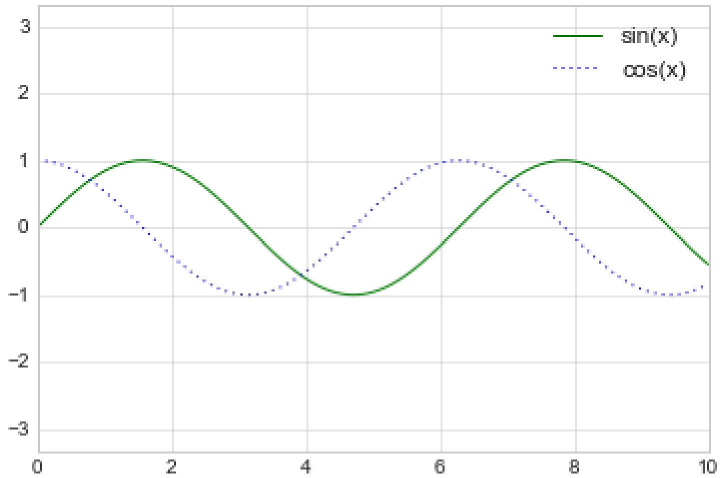
```
plt.plot(x, np.sin(x))
plt.title("A Sine Curve")
plt.xlabel("x")
plt.ylabel("sin(x)");
```



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.

In [24]:

```
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();
```



The object-oriented interface

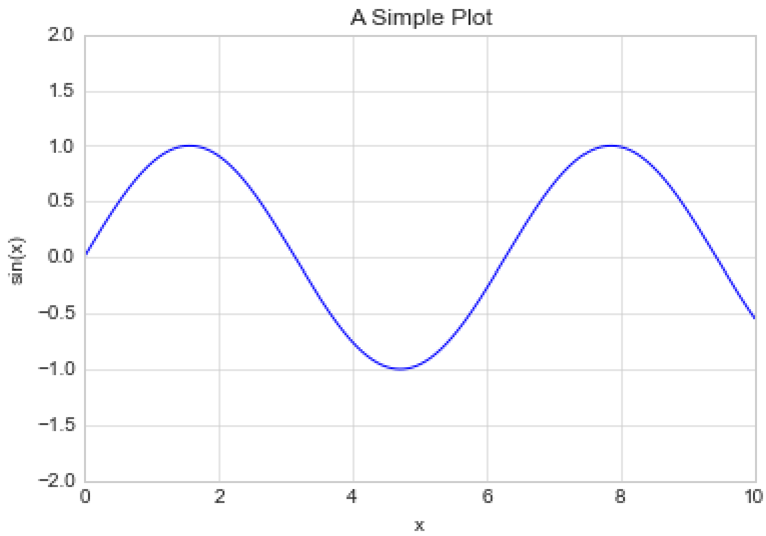
While most `plt` functions translate directly to `ax` methods (such as `plt.plot()` → `ax.plot()` , `plt.legend()` → `ax.legend()` , etc.), this is not the case for all commands. In particular, functions to set limits, labels, and titles are slightly modified. For transitioning between MATLAB-style functions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

In [25]:

```
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

Another commonly used plot type is the simple scatter plot. 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 [26]:

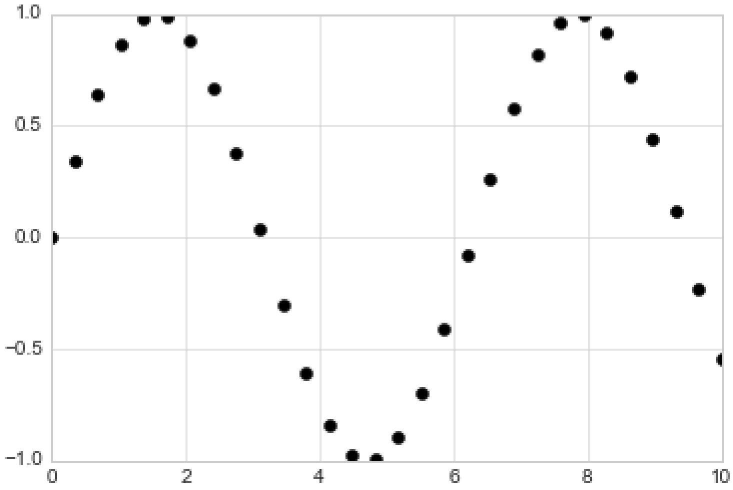
```
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('seaborn-whitegrid')
import numpy as np
```

Scatter Plots with `plt.plot`

We have looked at `plt.plot` / `ax.plot` to produce line plots. It turns out that this same function can produce scatter plots as well:

In [27]:

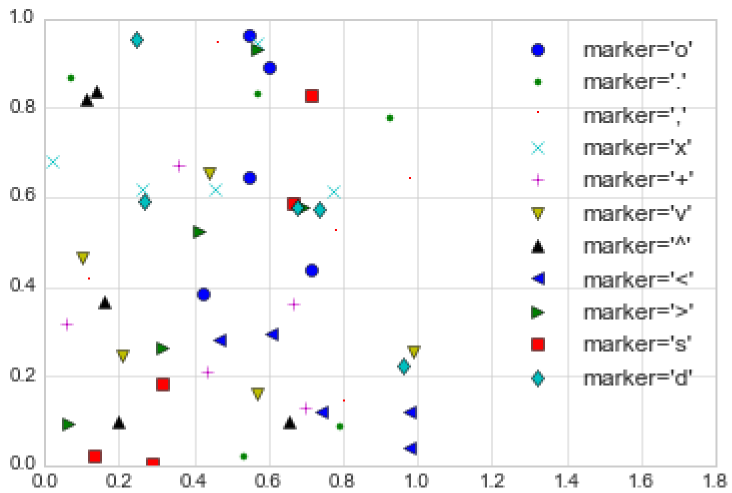
```
x = np.linspace(0, 10, 30)
y = np.sin(x)

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. We'll show a number of the more common ones here:

In [28]:

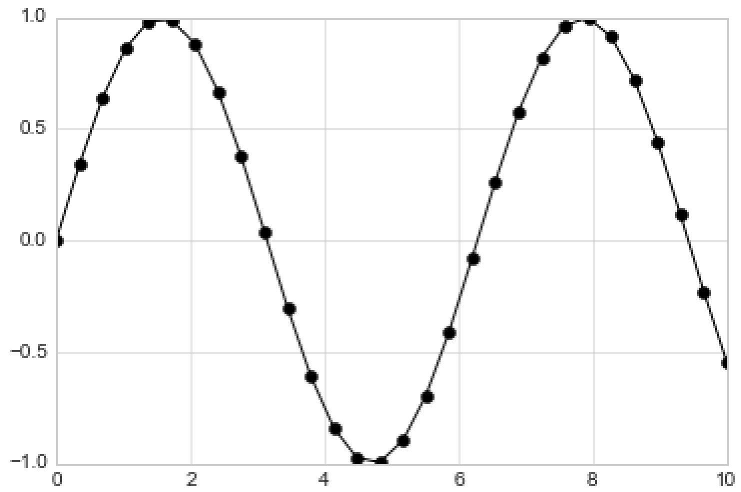
```
rng = np.random.RandomState(0)
for marker in ['o', '.', ',', 'x', '+', 'v', '^', '<', '>', 's', 'd']:
    plt.plot(rng.rand(5), rng.rand(5), marker,
             label="marker='{0}'".format(marker))
plt.legend(numpoints=1)
plt.xlim(0, 1.8);
```



These character codes can be used together with line and color codes to plot points along with a line connecting them:

In [29]:

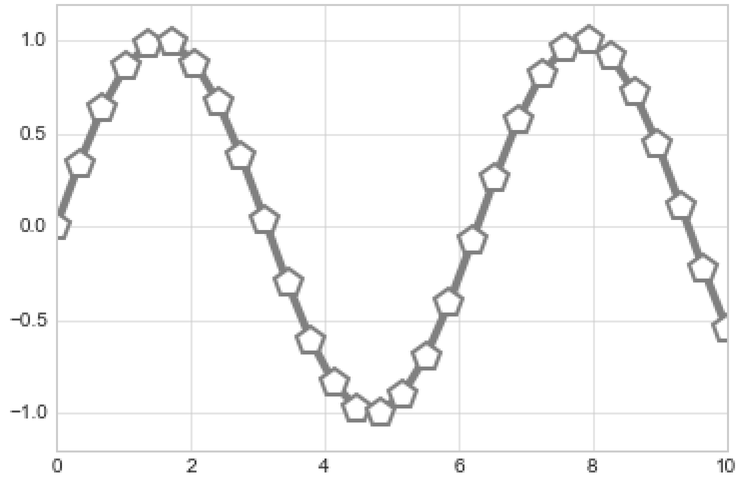
```
plt.plot(x, y, '-ok');
```



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

In [30]:

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

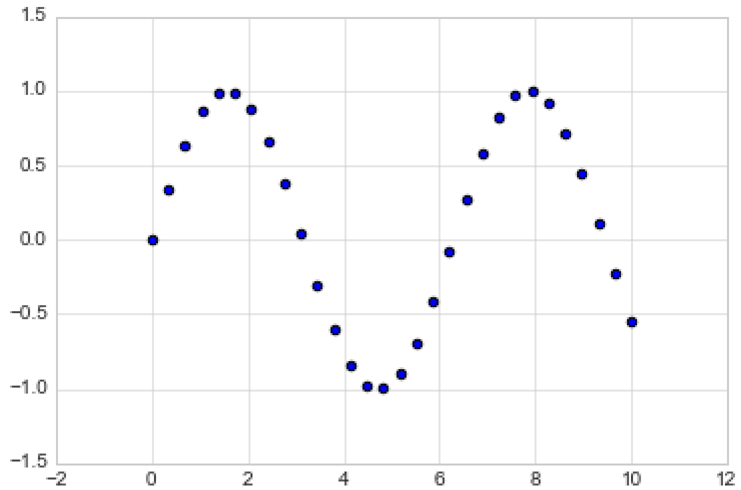


Scatter Plots with `plt.scatter`

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 [31]:

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

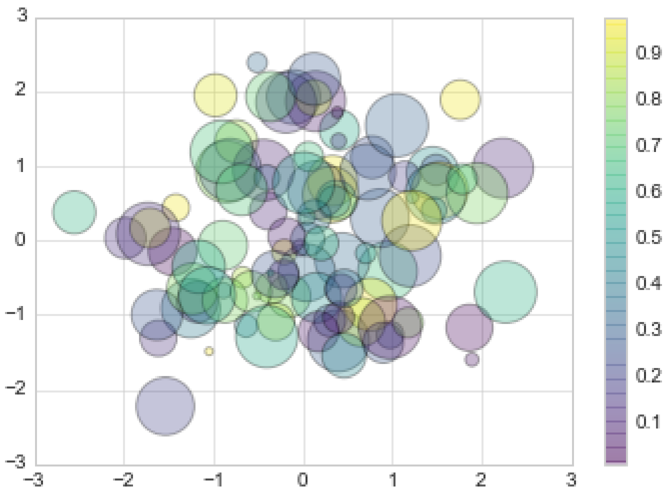


The primary difference of `plt.scatter` from `plt.plot` is that it can be used to create scatter plots where the properties of each individual point (size, face color, edge color, etc.) can be individually controlled or mapped to data.

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:

In [32]:

```
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
```



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

Aside from the different features available in `plt.plot` and `plt.scatter`, why might you choose to use one over the other? While it doesn't matter as much for small amounts of data, as datasets get larger than a few thousand points, `plt.plot` can be noticeably more efficient than `plt.scatter`. The reason is that `plt.scatter` has the capability to render a different size and/or color for each point, so the renderer must do the extra work of constructing each point individually. In `plt.plot`, on the other hand, the points are always essentially clones of each other, so the work of determining the appearance of the points is done only once for the entire set of data. For large datasets, the difference between these two can lead to vastly different performance, and for this reason, `plt.plot` should be preferred over `plt.scatter` for large datasets.

Visualizing Errors

Basic Errorbars

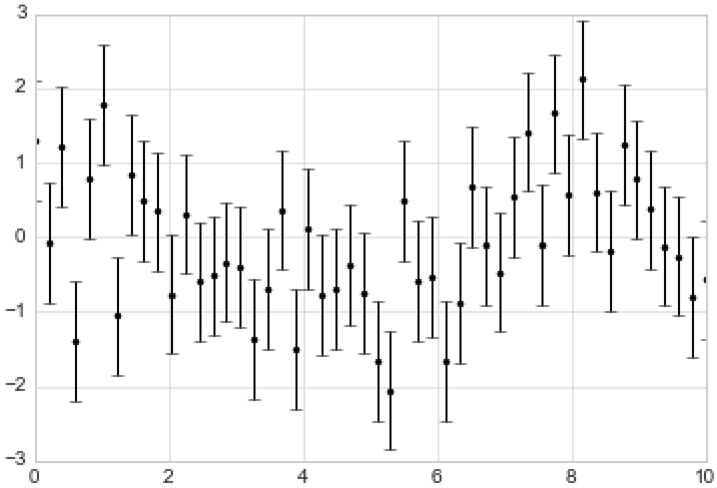
A basic errorbar can be created with a single Matplotlib function call:

In [33]:

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

In [34]:

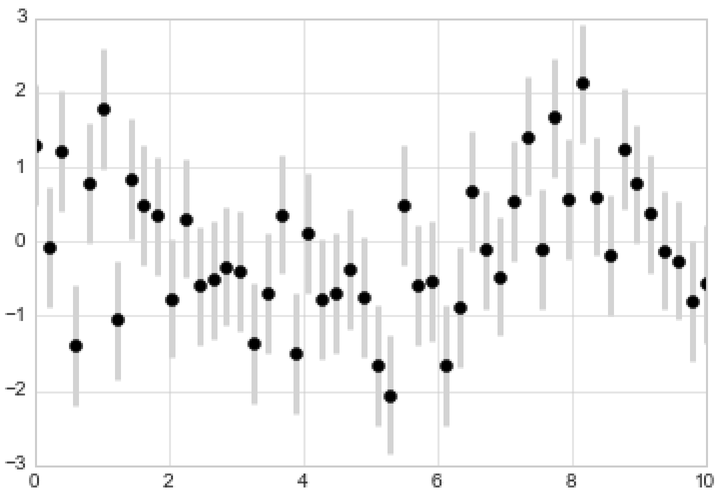
```
x = np.linspace(0, 10, 50)
dy = 0.8
y = np.sin(x) + dy * np.random.randn(50)

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`. In addition to these basic options, the `errorbar` function has many options to fine-tune the outputs.

In [35]:

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



Density and Contour Plots

Sometimes it is useful to display three-dimensional data in two dimensions using contours or color-coded regions. There are three Matplotlib functions that can be helpful for this task: `plt.contour` for contour plots, `plt.contourf` for filled contour plots, and `plt.imshow` for showing images. This section looks at several examples of using these. We'll start by setting up the notebook for plotting and importing the functions we will use:

In [36]:

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

We'll start by demonstrating a contour plot using a function $z = f(x, y)$.

In [37]:

```
def f(x, y):
    return np.sin(x) ** 10 + np.cos(10 + y * x) * np.cos(x)
```

A contour plot can be created with the `plt.contour` function. It takes three arguments: a grid of *x* values, a grid of *y* values, and a grid of *z* values. The *x* and *y* values represent positions on the plot, and the *z* values will be represented by the contour levels. Perhaps the most straightforward way to prepare such data is to use the `np.meshgrid` function, which builds two-dimensional grids from one-dimensional arrays:

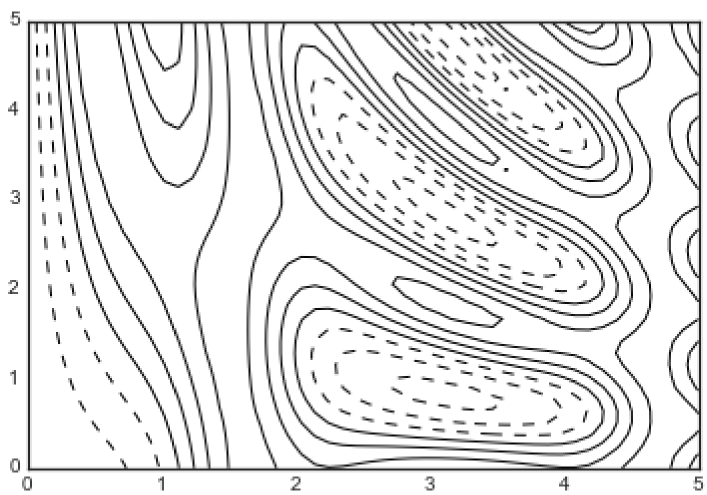
In [38]:

```
x = np.linspace(0, 5, 50)
y = np.linspace(0, 5, 40)

X, Y = np.meshgrid(x, y)
Z = f(X, Y)
```

Now let's look at this with a standard line-only contour plot:

In [39]:

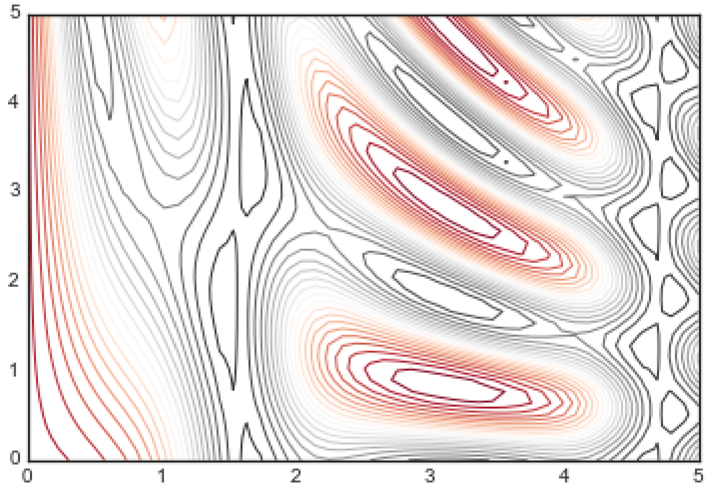
```
plt.contour(X, Y, Z, colors='black');
```



Notice that by default when a single color is used, negative values are represented by dashed lines, and positive values by solid lines. Alternatively, the lines can be color-coded by specifying a colormap with the `cmap` argument. Here, we'll also specify that we want more lines to be drawn—20 equally spaced intervals within the data range:

In [40]:

```
plt.contour(X, Y, Z, 20, cmap='RdGy');
```



Here we chose the `RdGy` (short for *Red-Gray*) colormap, which is a good choice for centered data. Matplotlib has a wide range of colormaps available, which you can easily browse in IPython by doing a tab completion on the `plt.cm` module:

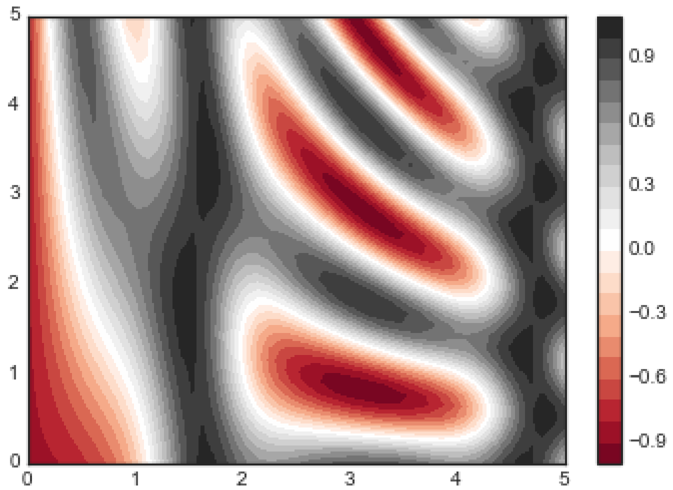
```
plt.cm.<TAB>
```

Our plot is looking nicer, but the spaces between the lines may be a bit distracting. We can change this by switching to a filled contour plot using the `plt.contourf()` function (notice the `f` at the end), which uses largely the same syntax as `plt.contour()`.

Additionally, we'll add a `plt.colorbar()` command, which automatically creates an additional axis with labeled color information for the plot:

In [41]:

```
plt.contourf(X, Y, Z, 20, cmap='RdGy')
plt.colorbar();
```



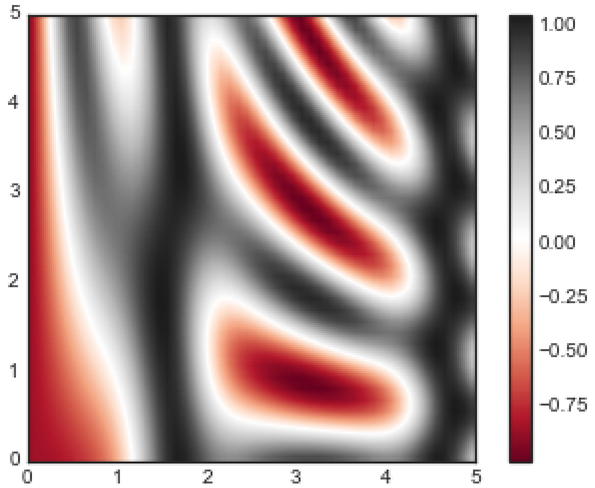
The colorbar makes it clear that the black regions are "peaks," while the red regions are "valleys."

One potential issue with this plot is that it is a bit "splotchy." That is, the color steps are discrete rather than continuous, which is not always what is desired. This could be remedied by setting the number of contours to a very high number, but this results in a rather inefficient plot: Matplotlib must render a new polygon for each step in the level. A better way to handle this is to use the `plt.imshow()` function, which interprets a two-dimensional grid of data as an image.

The following code shows this:

In [42]:

```
plt.imshow(Z, extent=[0, 5, 0, 5], origin='lower', cmap='RdGy')
plt.colorbar()
plt.axis(aspect='image');
```



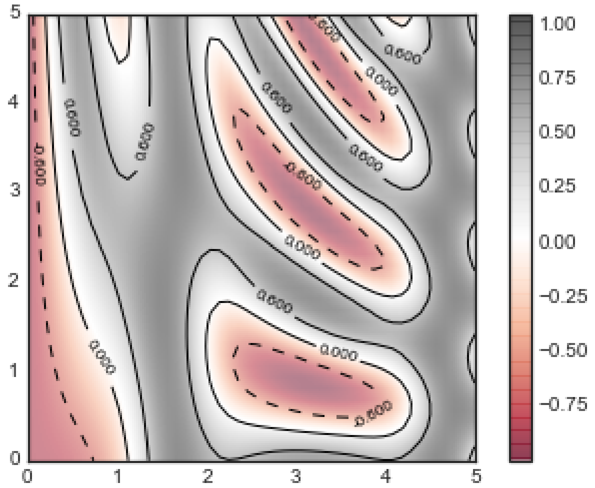
Notes:

- `plt.imshow()` doesn't accept an *x* and *y* grid, so you must manually specify the *extent* [*xmin*, *xmax*, *ymin*, *ymax*] of the image on the plot.
- `plt.imshow()` by default follows the standard image array definition where the origin is in the upper left, not in the lower left as in most contour plots. This must be changed when showing gridded data.
- `plt.imshow()` will automatically adjust the axis aspect ratio to match the input data; this can be changed by setting, for example, `plt.axis(aspect='image')` to make *x* and *y* units match.

Finally, it can sometimes be useful to combine contour plots and image plots. For example, here we'll use a partially transparent background image (with transparency set via the `alpha` parameter) and overplot contours with labels on the contours themselves (using the `plt.clabel()` function):

In [43]:

```
contours = plt.contour(X, Y, Z, 3, colors='black')
plt.clabel(contours, inline=True, fontsize=8)

plt.imshow(Z, extent=[0, 5, 0, 5], origin='lower', cmap='RdGy', alpha=0.5)
plt.colorbar();
```



The combination of these three functions— `plt.contour` , `plt.contourf` , and `plt.imshow` —gives nearly limitless possibilities for displaying this sort of three-dimensional data within a two-dimensional plot.

Histograms and Binnings

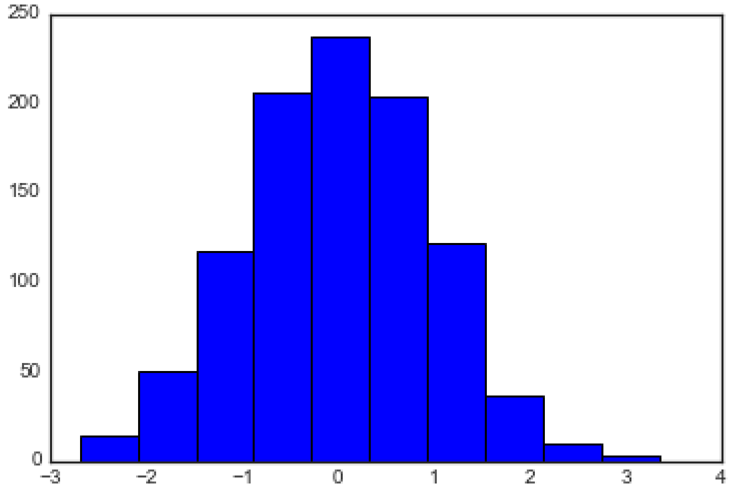
A simple histogram can be a great first step in understanding a dataset.

In [44]:

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

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

In [45]:

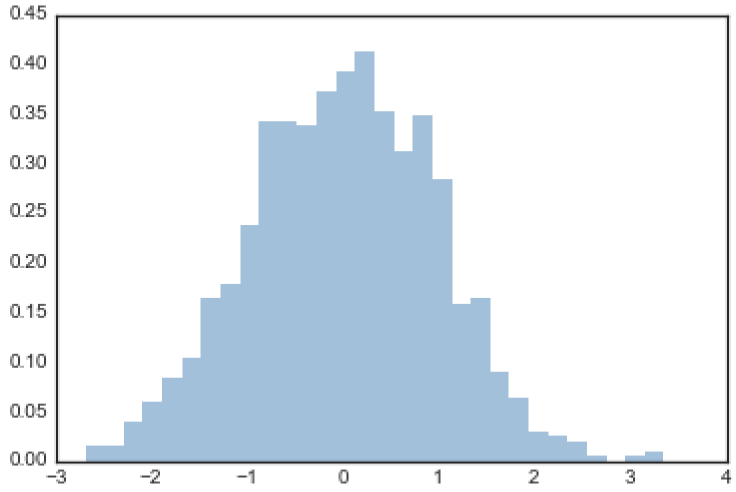
```
plt.hist(data);
```



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

In [46]:

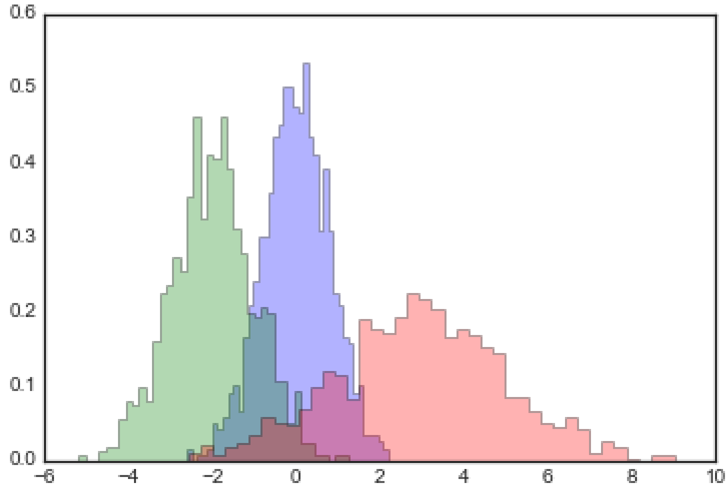
```
plt.hist(data, bins=30, density=True, alpha=0.5,
         histtype='stepfilled', color='steelblue',
         edgecolor='none');
```



A combination of `histtype='stepfilled'` along with some transparency `alpha` to be very useful when comparing histograms of several distributions:

In [47]:

```
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 [48]:

```
counts, bin_edges = np.histogram(data, bins=5)
print(counts)
```

```
[ 64 323 441 159  13]
```

Two-Dimensional Histograms and Binnings

Just as we create histograms in one dimension by dividing the number-line into bins, we can also create histograms in two-dimensions by dividing points among two-dimensional bins. We'll take a brief look at several ways to do this here. We'll start by defining some data—an `x` and `y` array drawn from a multivariate Gaussian distribution:

In [49]:

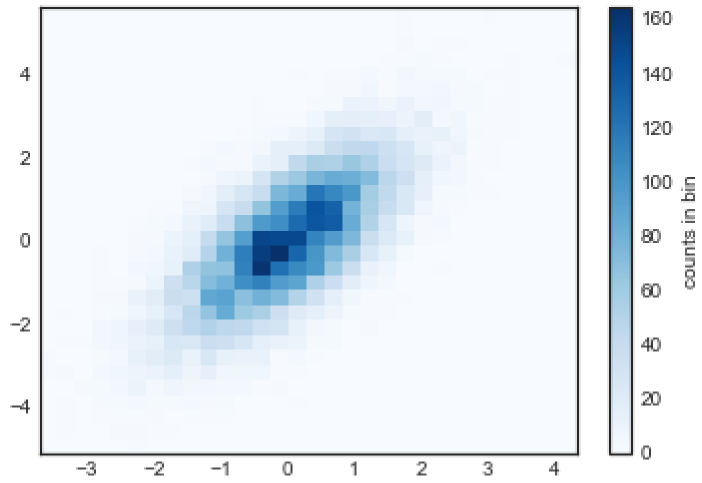
```
mean = [0, 0]
cov = [[1, 1], [1, 2]]
x, y = np.random.multivariate_normal(mean, cov, 10000).T
```

`plt.hist2d` : Two-dimensional histogram

One straightforward way to plot a two-dimensional histogram is to use Matplotlib's `plt.hist2d` function:

In [50]:

```
plt.hist2d(x, y, bins=30, cmap='Blues')
cb = plt.colorbar()
cb.set_label('counts in bin')
```



Just as with `plt.hist` , `plt.hist2d` has a number of extra options to fine-tune the plot and the binning, which are nicely outlined in the function docstring. Further, just as `plt.hist` has a counterpart in `np.histogram` , `plt.hist2d` has a counterpart in `np.histogram2d` , which can be used as follows:

In [51]:

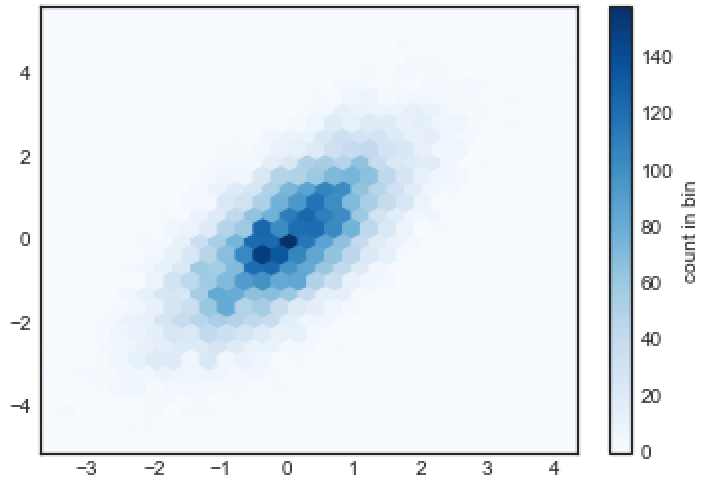
```
counts, xedges, yedges = np.histogram2d(x, y, bins=30)
```

`plt.hexbin` : Hexagonal binnings

The two-dimensional histogram creates a tesselation of squares across the axes. Another natural shape for such a tesselation is the regular hexagon. For this purpose, Matplotlib provides the `plt.hexbin` routine, which will represents a two-dimensional dataset binned within a grid of hexagons:

In [52]:

```
plt.hexbin(x, y, gridsize=30, cmap='Blues')
cb = plt.colorbar(label='count in bin')
```



`plt.hexbin` has a number of interesting options, including the ability to specify weights for each point, and to change the output in each bin to any NumPy aggregate (mean of weights, standard deviation of weights, etc.).

Multiple Subplots

Sometimes it is helpful to compare different views of data side by side. To this end, Matplotlib has the concept of *subplots*: groups of smaller axes that can exist together within a single figure. These subplots might be insets, grids of plots, or other more complicated layouts.

In [53]:

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

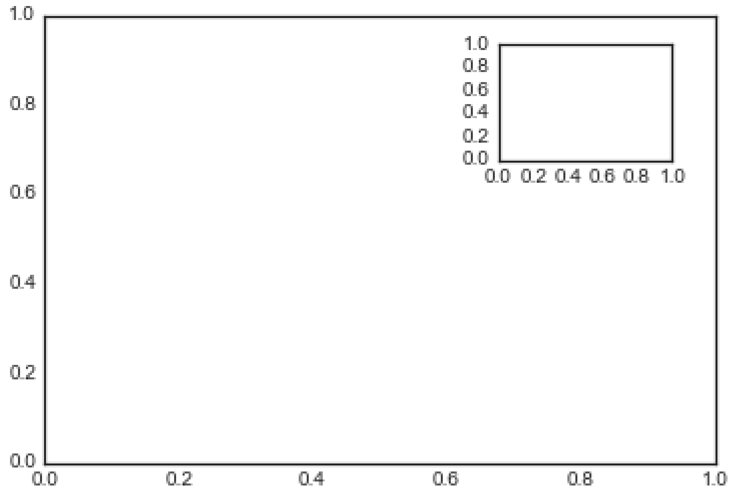
`plt.axes`: Subplots by Hand

The most basic method of creating an axes is to use the `plt.axes` function. As we've seen previously, by default this creates a standard axes object that fills the entire figure. `plt.axes` also takes an optional argument that is a list of four numbers in the figure coordinate system. These numbers represent `[left, bottom, width, height]` in the figure coordinate system, which ranges from 0 at the bottom left of the figure to 1 at the top right of the figure.

For example, we might create an inset axes at the top-right corner of another axes by setting the *x* and *y* position to 0.65 (that is, starting at 65% of the width and 65% of the height of the figure) and the *x* and *y* extents to 0.2 (that is, the size of the axes is 20% of the width and 20% of the height of the figure):

In [54]:

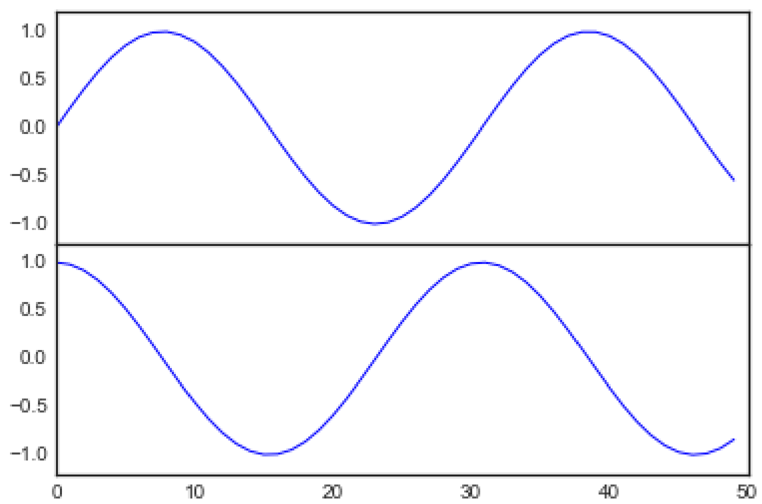
```
ax1 = plt.axes()  # standard axes
ax2 = plt.axes([0.65, 0.65, 0.2, 0.2])
```



The equivalent of this command within the object-oriented interface is `fig.add_axes()` . Let's use this to create two vertically stacked axes:

In [55]:

```
fig = plt.figure()
ax1 = fig.add_axes([0.1, 0.5, 0.8, 0.4], xticklabels=[], ylim=(-1.2, 1.2))
ax2 = fig.add_axes([0.1, 0.1, 0.8, 0.4], ylim=(-1.2, 1.2))

x = np.linspace(0, 10)
ax1.plot(np.sin(x))
ax2.plot(np.cos(x));
```



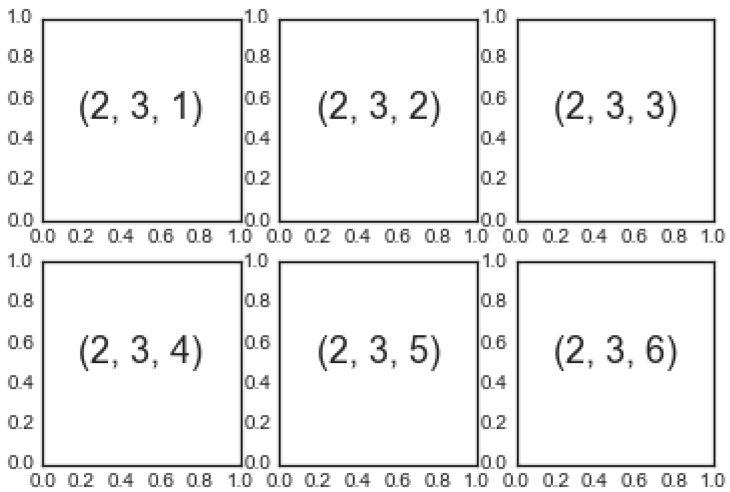
We now have two axes (the top with no tick labels) that are just touching: the bottom of the upper panel (at position 0.5) matches the top of the lower panel (at position 0.1 + 0.4).

plt.subplot : Simple Grids of Subplots

Aligned columns or rows of subplots are a common-enough need that Matplotlib has several convenience routines that make them easy to create. The lowest level of these is `plt.subplot()` , which creates a single subplot within a grid. As you can see, this command takes three integer arguments—the number of rows, the number of columns, and the index of the plot to be created in this scheme, which runs from the upper left to the bottom right:

In [56]:

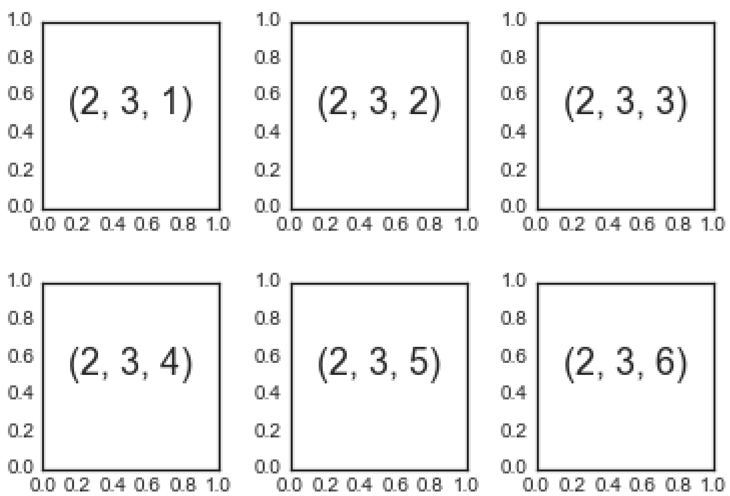
```
for i in range(1, 7):
    plt.subplot(2, 3, i)
    plt.text(0.5, 0.5, str((2, 3, i)), fontsize=18, ha='center')
```



The command `plt.subplots_adjust` can be used to adjust the spacing between these plots. The following code uses the equivalent object-oriented command, `fig.add_subplot()` :

In [57]:

```
fig = plt.figure()
fig.subplots_adjust(hspace=0.4, wspace=0.4)
for i in range(1, 7):
    ax = fig.add_subplot(2, 3, i)
    ax.text(0.5, 0.5, str((2, 3, i)), fontsize=18, ha='center')
```



We've used the `hspace` and `wspace` arguments of `plt.subplots_adjust` , which specify the spacing along the height and width of the figure, in units of the subplot size (in this case, the space is 40% of the subplot width and height).

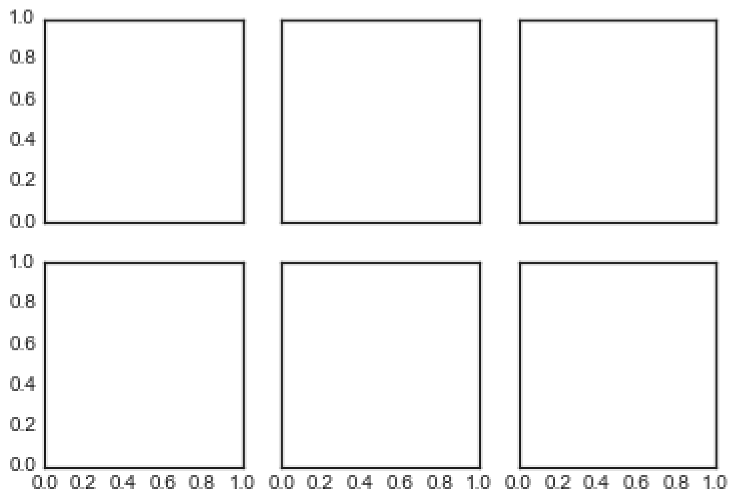
`plt.subplots`: The Whole Grid in One Go

The approach just described can become quite tedious when creating a large grid of subplots, especially if you'd like to hide the x- and y-axis labels on the inner plots. For this purpose, `plt.subplots()` is the easier tool to use (note the `s` at the end of `subplots`). Rather than creating a single subplot, this function creates a full grid of subplots in a single line, returning them in a NumPy array. The arguments are the number of rows and number of columns, along with optional keywords `sharex` and `sharey`, which allow you to specify the relationships between different axes.

Here we'll create a 2×3 grid of subplots, where all axes in the same row share their y-axis scale, and all axes in the same column share their x-axis scale:

In [58]:

```
fig, ax = plt.subplots(2, 3, sharex='col', sharey='row')
```

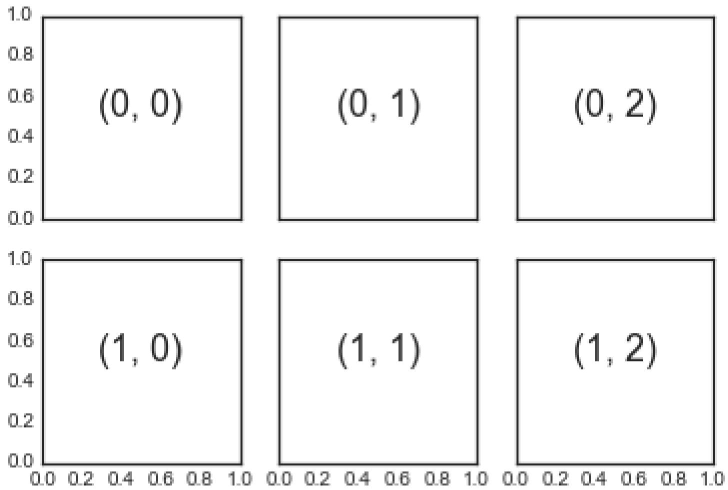


Note that by specifying `sharex` and `sharey`, we've automatically removed inner labels on the grid to make the plot cleaner. The resulting grid of axes instances is returned within a NumPy array, allowing for convenient specification of the desired axes using standard array indexing notation:

In [59]:

```
# axes are in a two-dimensional array, indexed by [row, col]
for i in range(2):
    for j in range(3):
        ax[i, j].text(0.5, 0.5, str((i, j)), fontsize=18, ha='center')
fig
```

Out[59]:



In comparison to `plt.subplot()` , `plt.subplots()` is more consistent with Python's conventional 0-based indexing.

`plt.GridSpec` : More Complicated Arrangements

To go beyond a regular grid to subplots that span multiple rows and columns, `plt.GridSpec()` is the best tool. The `plt.GridSpec()` object does not create a plot by itself; it is simply a convenient interface that is recognized by the `plt.subplot()` command. For example, a gridspec for a grid of two rows and three columns with some specified width and height space looks like this:

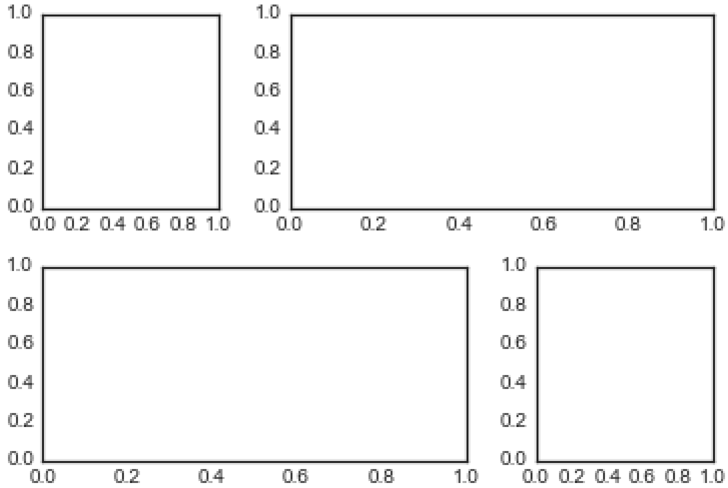
In [60]:

```
grid = plt.GridSpec(2, 3, wspace=0.4, hspace=0.3)
```

From this we can specify subplot locations and extents using the familiary Python slicing syntax:

In [61]:

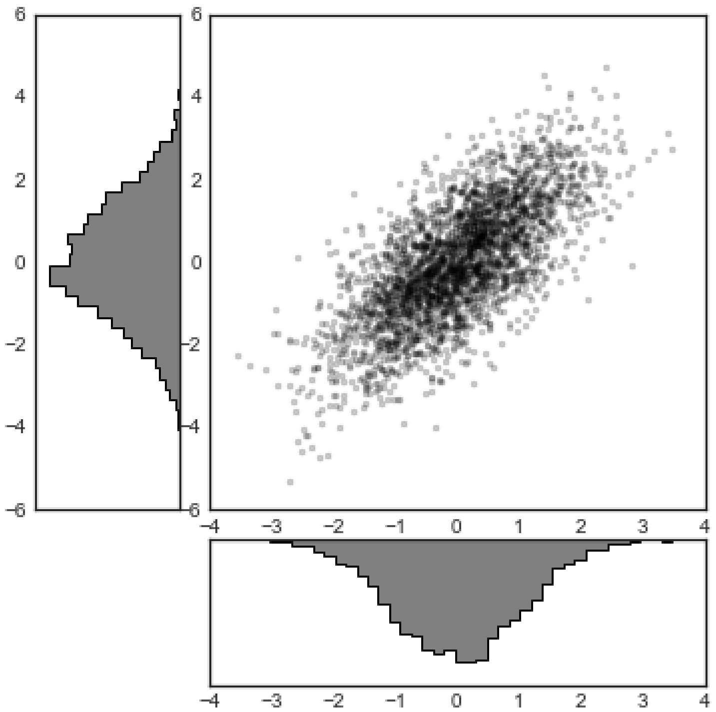
```
plt.subplot(grid[0, 0])
plt.subplot(grid[0, 1:])
plt.subplot(grid[1, :2])
plt.subplot(grid[1, 2]);
```



This type of flexible grid alignment has a wide range of uses. For example, creating multi-axes histogram plots like the ones shown here:

In [62]:

```
# Create some normally distributed data
mean = [0, 0]
cov = [[1, 1], [1, 2]]
x, y = np.random.multivariate_normal(mean, cov, 3000).T

# Set up the axes with gridspec
fig = plt.figure(figsize=(6, 6))
grid = plt.GridSpec(4, 4, hspace=0.2, wspace=0.2)
main_ax = fig.add_subplot(grid[:-1, 1:])
y_hist = fig.add_subplot(grid[:-1, 0], xticklabels=[], sharey=main_ax)
x_hist = fig.add_subplot(grid[-1, 1:], yticklabels=[], sharex=main_ax)

# scatter points on the main axes
main_ax.plot(x, y, 'ok', markersize=3, alpha=0.2)

# histogram on the attached axes
x_hist.hist(x, 40, histtype='stepfilled', orientation='vertical', color='gray')
x_hist.invert_yaxis()

y_hist.hist(y, 40, histtype='stepfilled', orientation='horizontal', color='gray')
y_hist.invert_xaxis()
```



In [ ]: