Handout Week 4: Matplotlib for Visualization

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based on the notes by Jake VanderPlas

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1 Introduction

We'll now take an in-depth look at the Matplotlib package for visualization in Python. Matplotlib is a multi-platform data visualization library built on NumPy arrays, and designed to work with the broader SciPy stack. It was conceived by John Hunter in 2002, originally as a patch to IPython for enabling interactive MATLAB-style plotting via gnuplot from the IPython command line. IPython's creator, Fernando Perez, was at the time scrambling to finish his PhD, and let John know he wouldn't have time to review the patch for several months. John took this as a cue to set out on his own, and the Matplotlib package was born, with version 0.1 released in 2003. It received an early boost when it was adopted as the plotting package of choice of the Space Telescope Science Institute (the folks behind the Hubble Telescope), which financially supported Matplotlib's development and greatly expanded its capabilities.

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. This cross-platform, everything-to-everyone approach has been one of the great strengths of Matplotlib. 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.

In recent years, however, the interface and style of Matplotlib have begun to show their age. Newer tools like ggplot and ggvis in the R language, along with web visualization toolkits based on D3js and HTML5 canvas, often make Matplotlib feel clunky and old-fashioned. Still, I'm of the opinion that we cannot ignore Matplotlib's strength as a well-tested, cross-platform graphics engine. 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. Even with wrappers like these, it is still often useful to dive into Matplotlib's syntax to adjust the final plot output. For this reason, I believe that Matplotlib itself will remain a vital piece of the data visualization stack, even if new tools mean the community gradually moves away from using the Matplotlib API directly.

1.1 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:

[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 handout.

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

A visualization you can't see won't be of much use, but just how you view your Matplotlib plots depends on the context. 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.

1.2.1 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:

```
# ------- 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.

1.2.2 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:

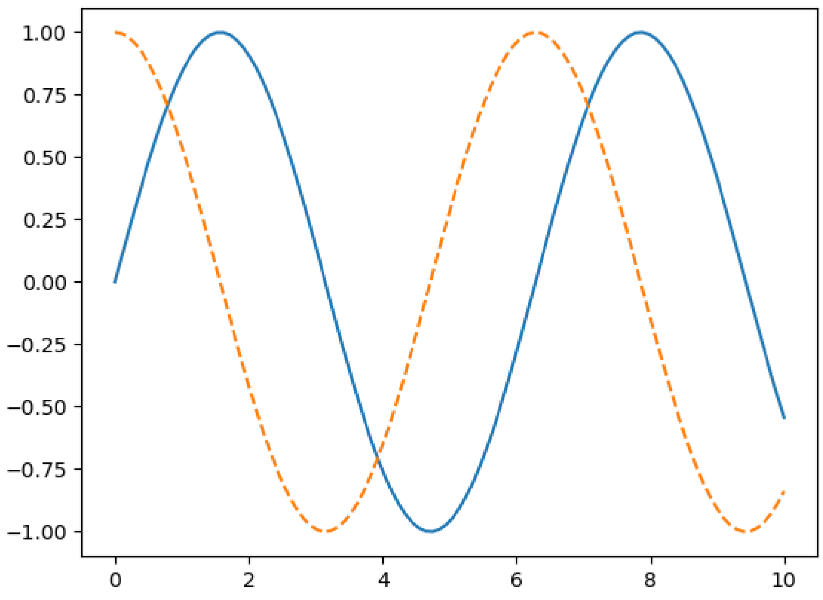
- `%matplotlib notebook` will lead to *interactive* plots embedded within the notebook
- `%matplotlib inline` will lead to *static* images of your plot embedded in the notebook

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

[2]:
```
%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:

[3]:
```
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), '--');
```



1.3 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:

[4]:
```
fig.savefig('my_figure.png')
```

We now have a file called `my_figure.png` in the working directory. Note that when saving your figure, it's not necessary to use `plt.show()` or related commands discussed earlier.

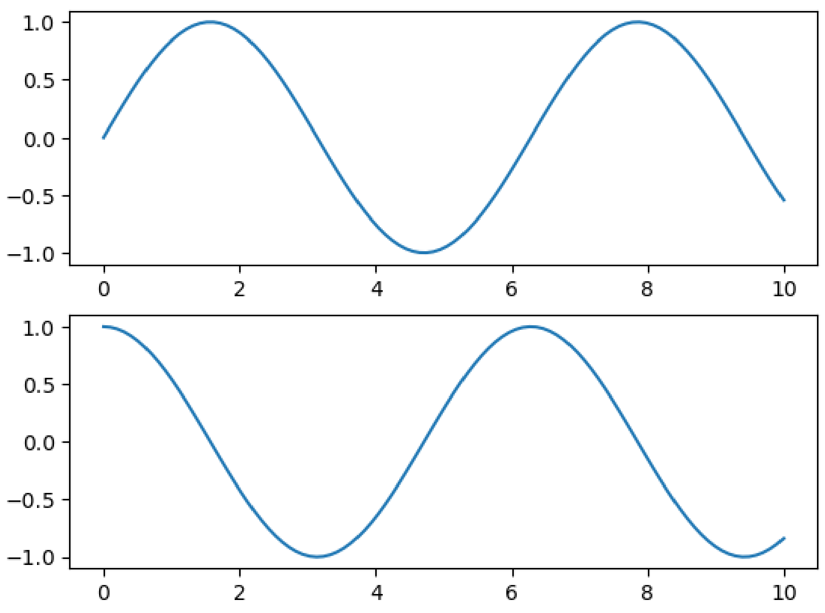
1.4 Two Interfaces for the Price of One

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.

1.4.1 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:

[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));
```



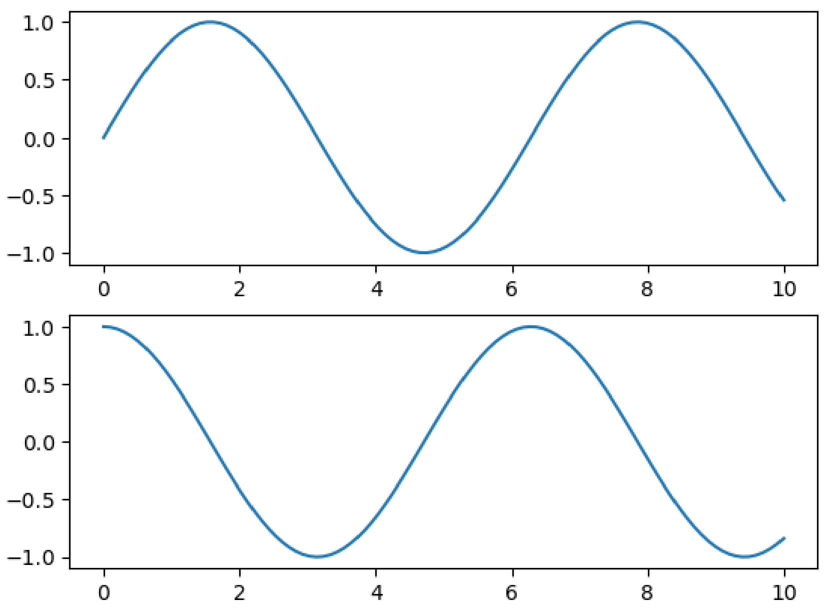
It is important to note that this interface is *stateful*: it keeps track of the "current" figure and axes, which are where all `plt` commands are applied. You can get a reference to these using the `plt.gcf()` (get current figure) and `plt.gca()` (get current axes) routines.

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.

1.4.2 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:

[6]:
```python
# 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 chapter, 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.

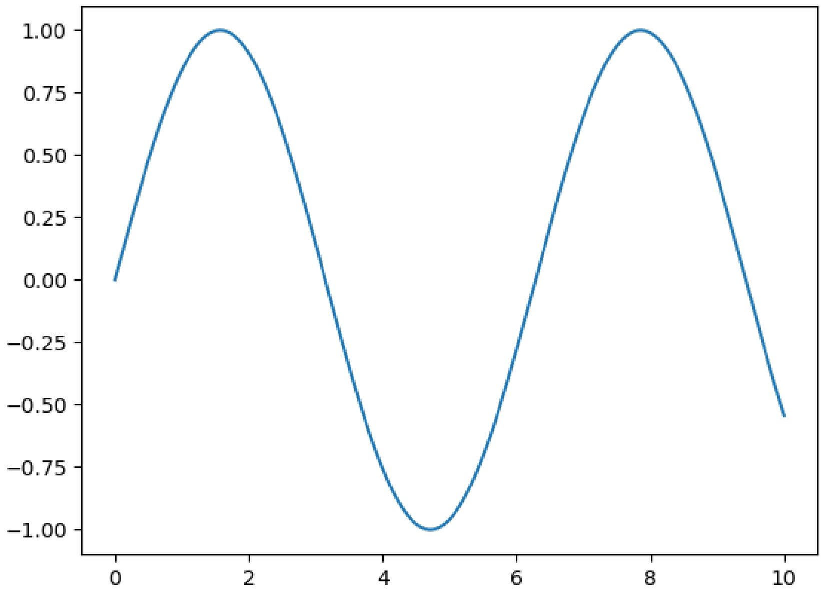
2 Simple Line Plots

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:

[7]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
```

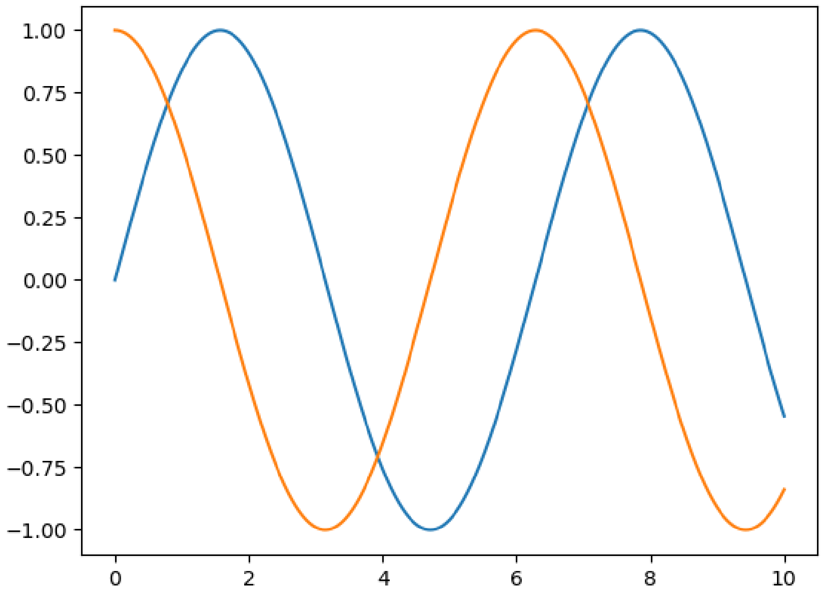
We can let the figure and axes be created as follows:

[8]:
```
x = np.linspace(0, 10, 1000)
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:

[9]:
```python
plt.plot(x, np.sin(x))
plt.plot(x, np.cos(x));
```

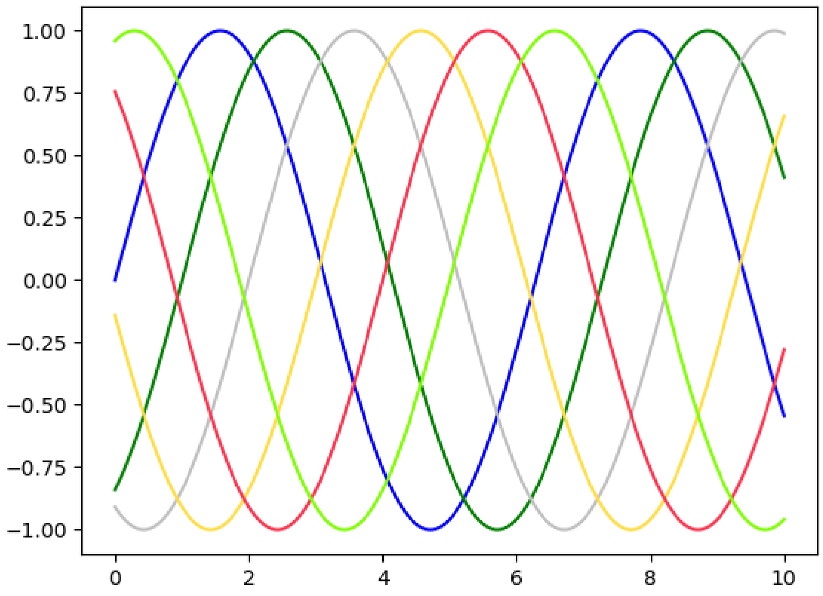


That's all there is to plotting simple functions in Matplotlib! We'll now dive into some more details about how to control the appearance of the axes and lines.

2.1 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:

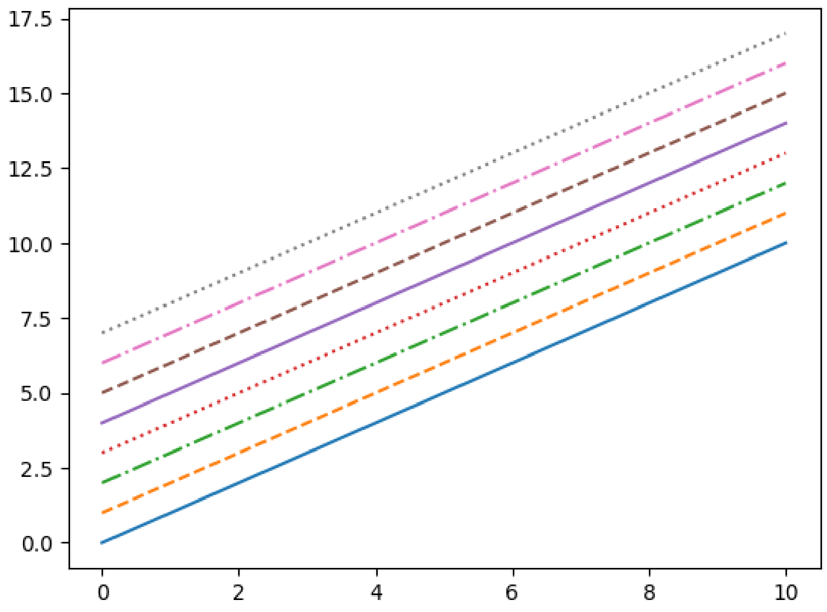
[10]:
```
plt.plot(x, np.sin(x - 0), color='blue')        # specify color by name
plt.plot(x, np.sin(x - 1), color='g')           # short color code (rgbcmyk)
plt.plot(x, np.sin(x - 2), color='0.75')        # Grayscale between 0 and 1
plt.plot(x, np.sin(x - 3), color='#FFDD44')     # Hex code (RRGGBB 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
```



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

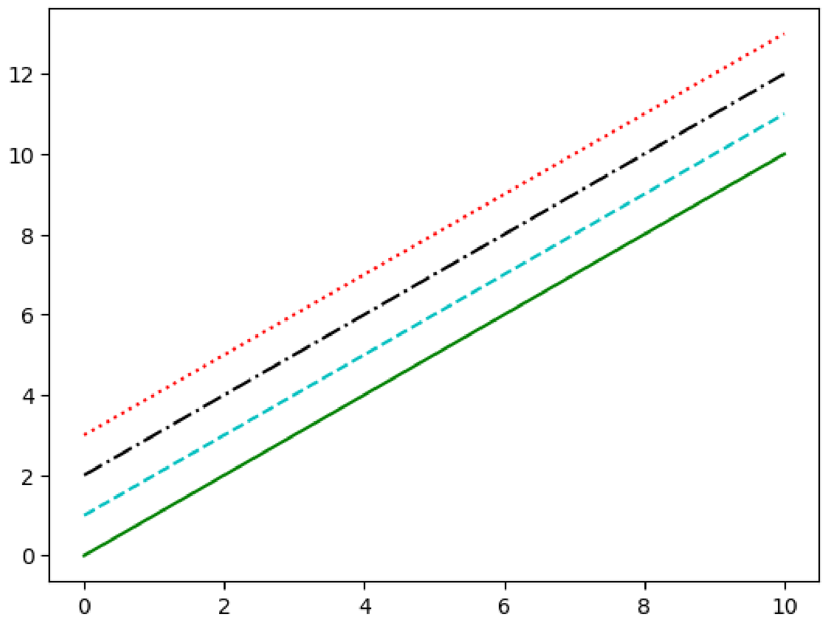
Similarly, the line style can be adjusted using the `linestyle` keyword:

[11]:
```
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:

```
[12]: 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
```



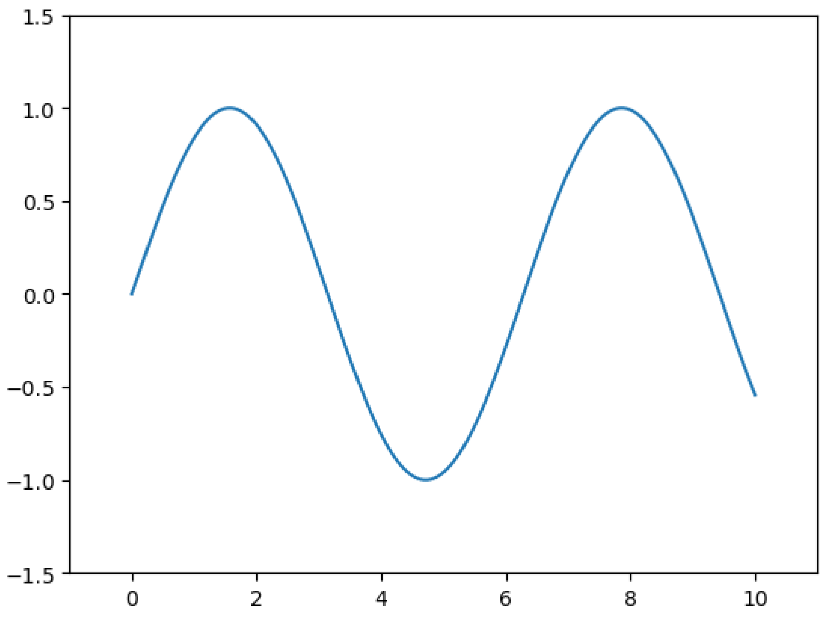
These single-character color codes reflect the standard abbreviations in the RGB (Red/Green/Blue) and CMYK (Cyan/Magenta/Yellow/blacK) color systems, commonly used for digital color graphics.

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.

2.2 Adjusting the Plot: Axes Limits

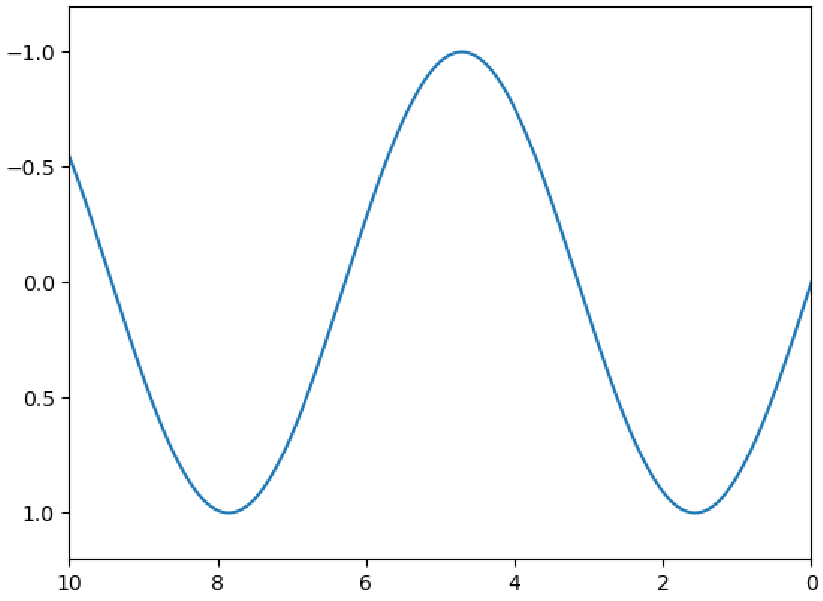
Matplotlib does a decent job of choosing default axes limits for your plot, but sometimes it's nice to have finer control. The most basic way to adjust axis limits is to use the `plt.xlim()` and `plt.ylim()` methods:

[13]:
```
plt.plot(x, np.sin(x))

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



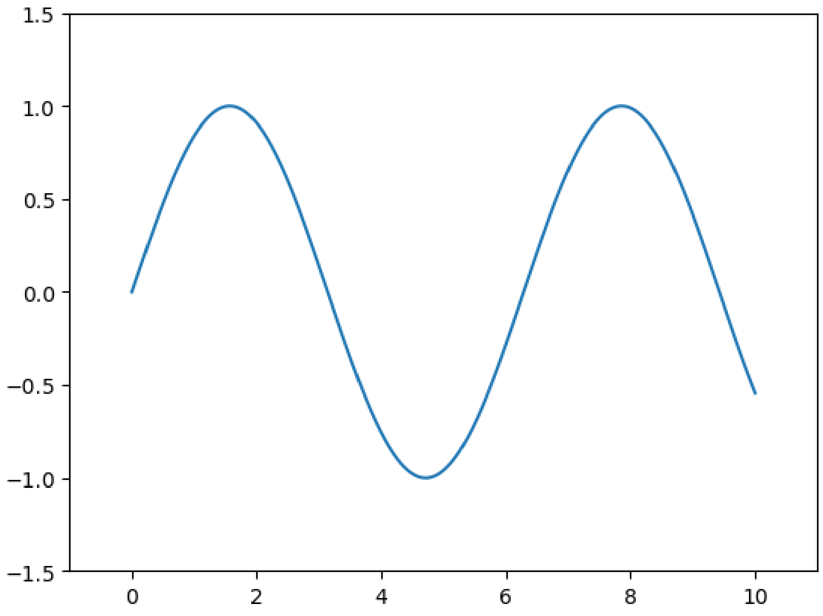
If for some reason you'd like either axis to be displayed in reverse, you can simply reverse the order of the arguments:

[14]:
```
plt.plot(x, np.sin(x))

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



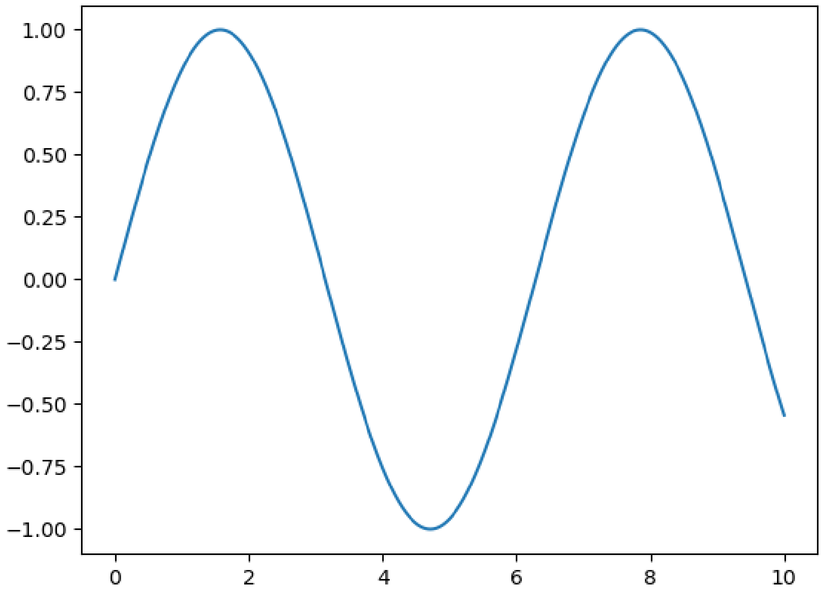
A useful related method is `plt.axis()` (note here the potential confusion between *axes* with an *e*, and *axis* with an *i*). The `plt.axis()` method allows you to set the `x` and `y` limits with a single call, by passing a list which specifies `[xmin, xmax, ymin, ymax]`:

[15]:
```
plt.plot(x, np.sin(x))
plt.axis([-1, 11, -1.5, 1.5]);
```



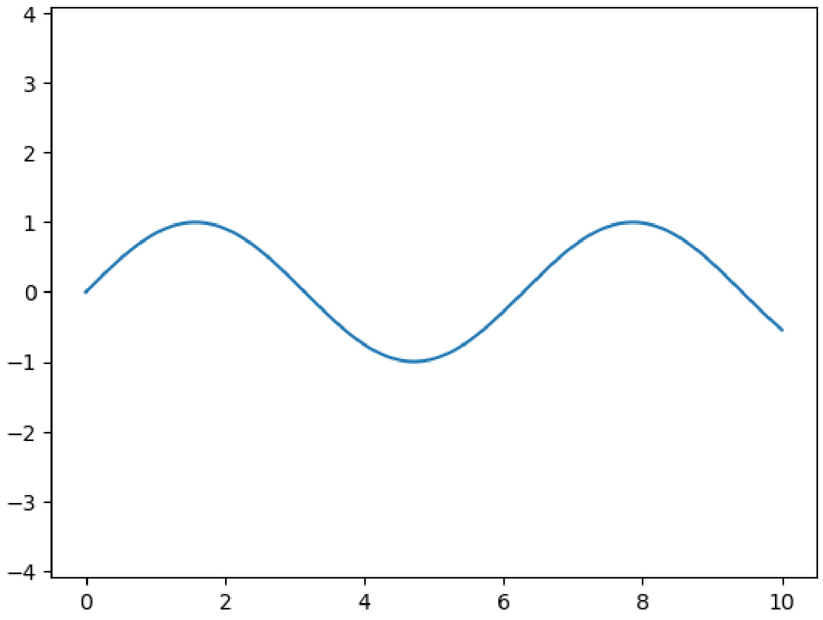
The `plt.axis()` method goes even beyond this, allowing you to do things like automatically tighten the bounds around the current plot:

[16]:
```
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`:

[17]:
```
plt.plot(x, np.sin(x))
plt.axis('equal');
```



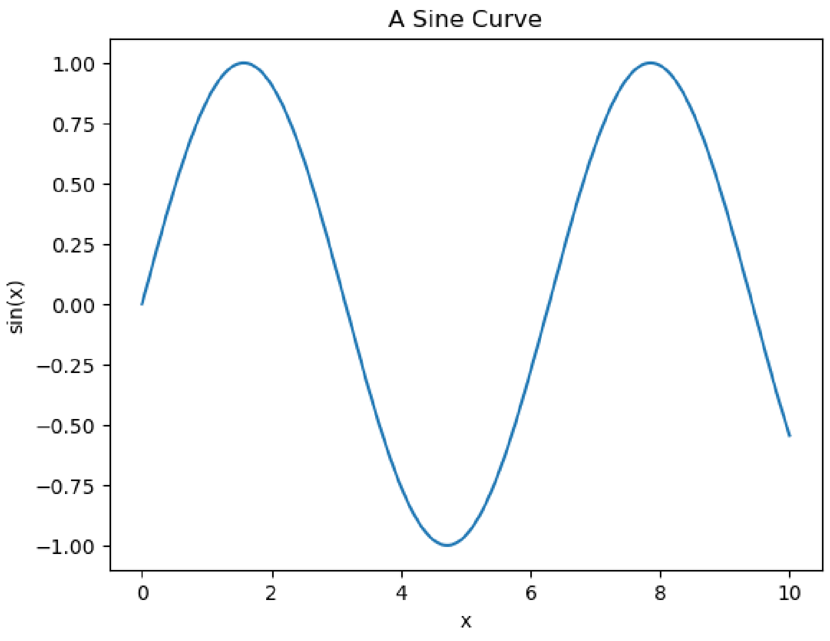
For more information on axis limits and the other capabilities of the `plt.axis` method, refer to the `plt.axis` docstring.

2.3 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:

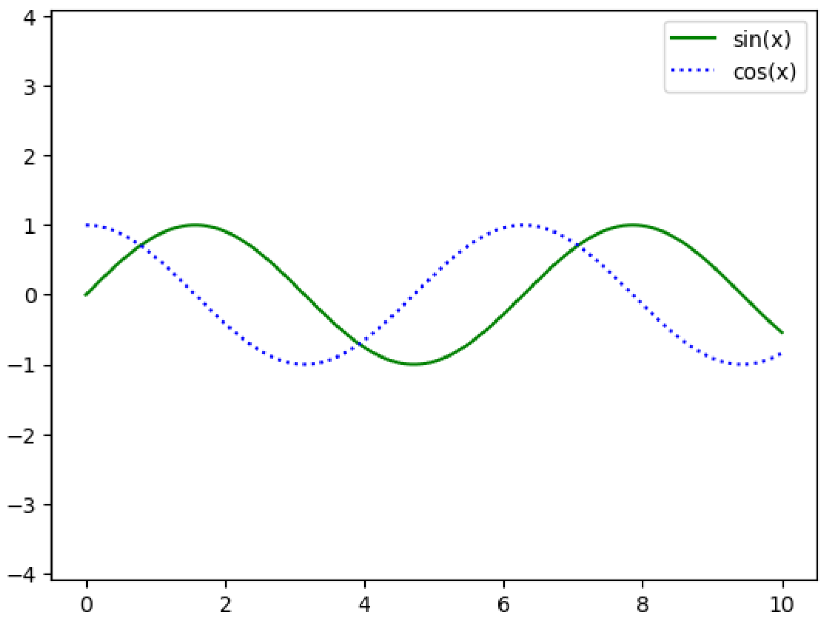
[18]:
```
plt.plot(x, np.sin(x))
plt.title("A Sine Curve")
plt.xlabel("x")
plt.ylabel("sin(x)");
```



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:

[19]:
```
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.

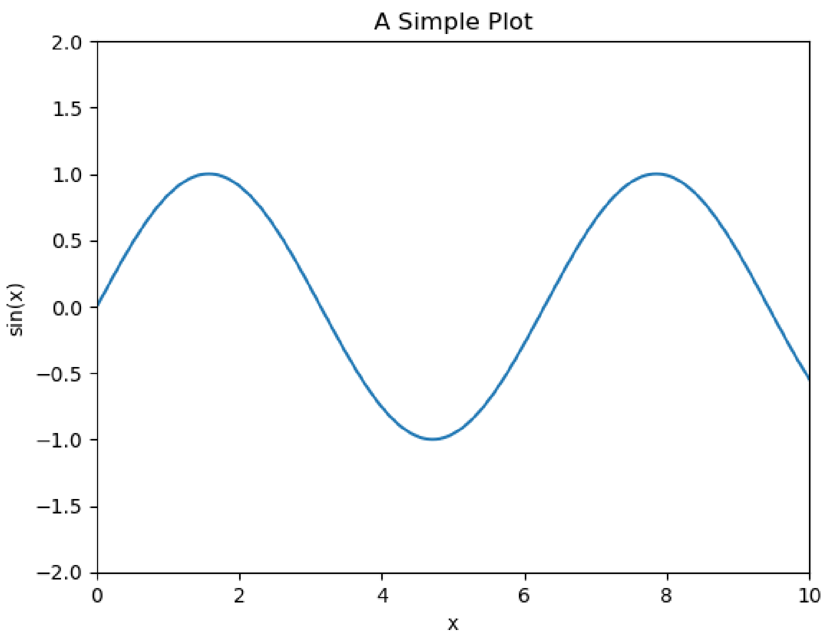
2.4 Aside: Matplotlib Gotchas

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:

[20]:
```
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');
```



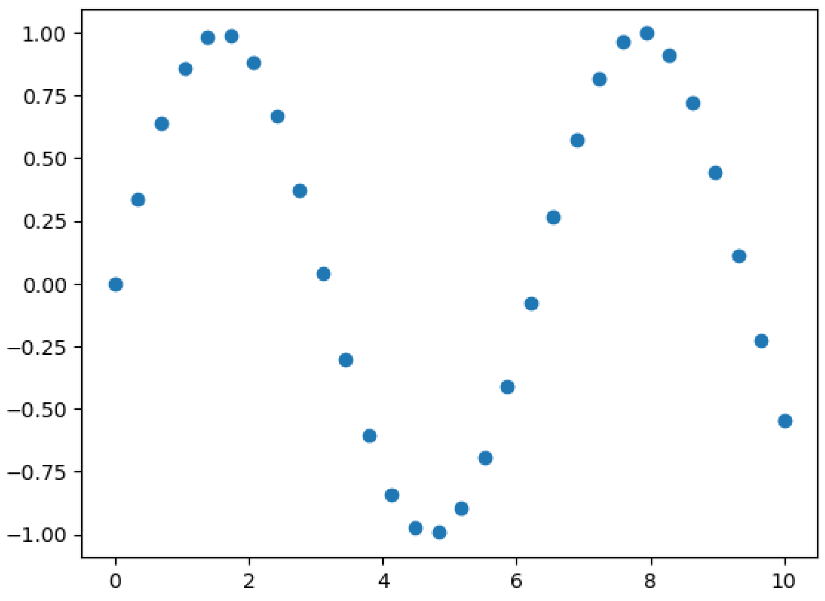
3 Simple Scatter Plots

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:

[21]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
```

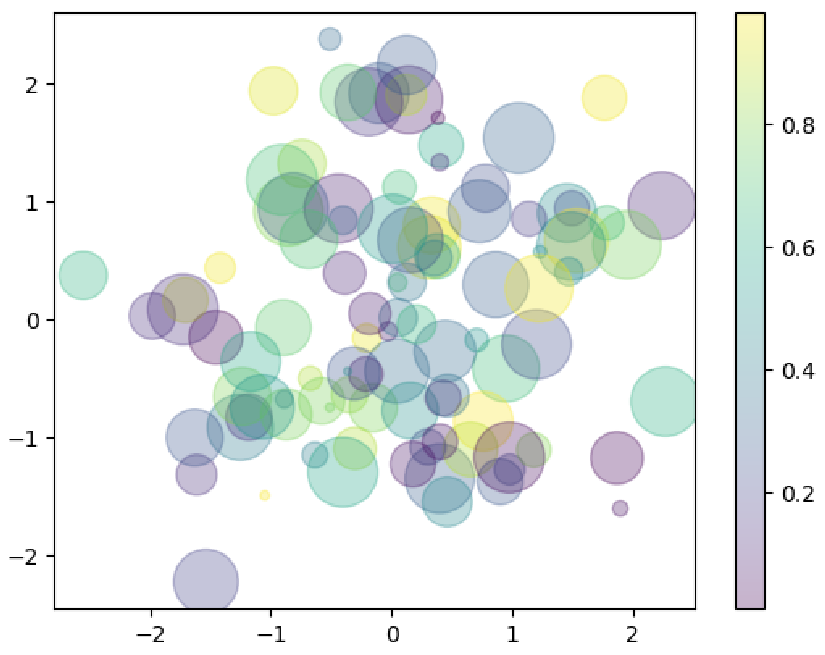
A second, more powerful method of creating scatter plots is the `plt.scatter` function:

[22]:
```
x = np.linspace(0, 10, 30)
y = np.sin(x)

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



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:

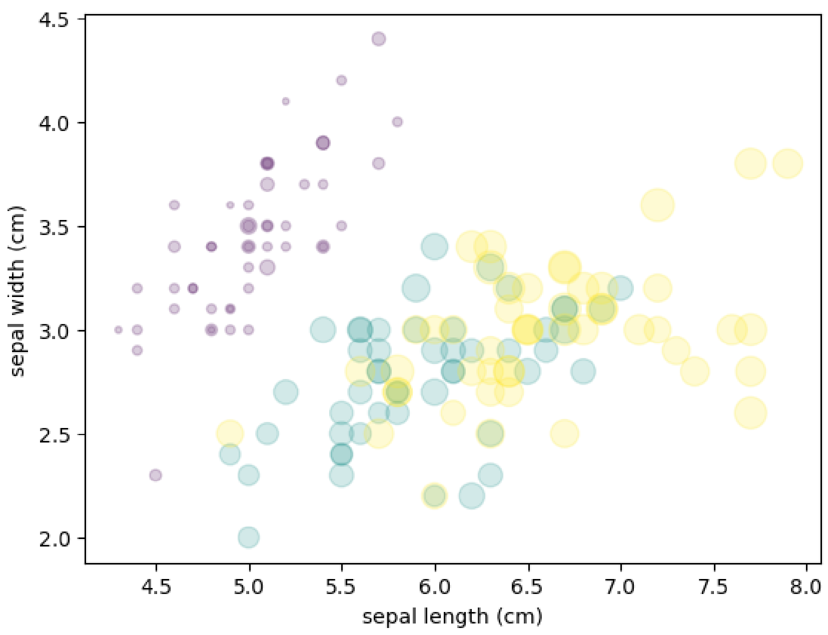
[23]:
```
rng = np.random.RandomState(0)
x = rng.randn(100)
y = rng.randn(100)
colors = rng.rand(100)
sizes = 1000 * rng.rand(100)

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:

[24]:
```
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]);
```



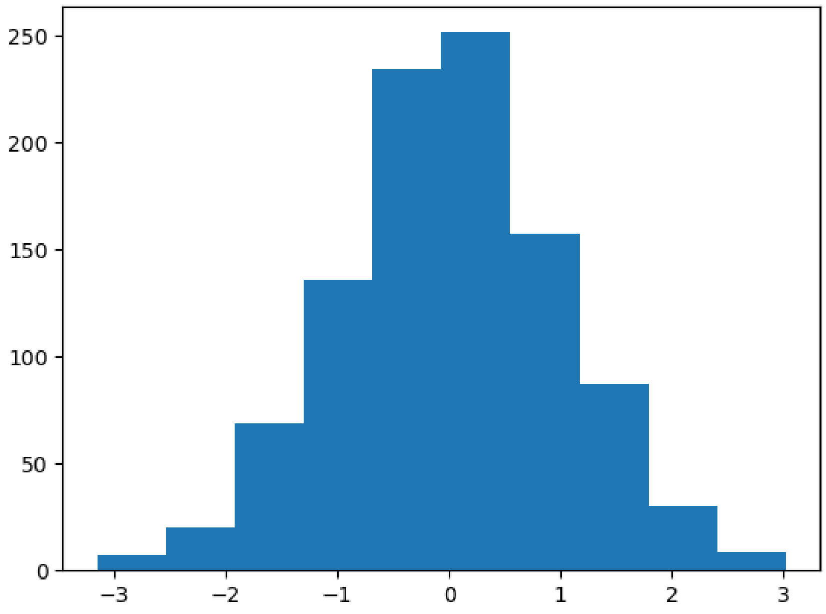
We can see that this scatter plot has given us the ability to simultaneously explore four different dimensions of the data: the (x, y) location of each point corresponds to the sepal length and width, the size of the point is related to the petal width, and the color is related to the particular species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

4 Histograms, Binnings, and Density

A simple histogram can be a great first step in understanding a dataset. Matplotlib's histogram function can create a basic histogram in one line, once the normal boiler-plate imports are done:

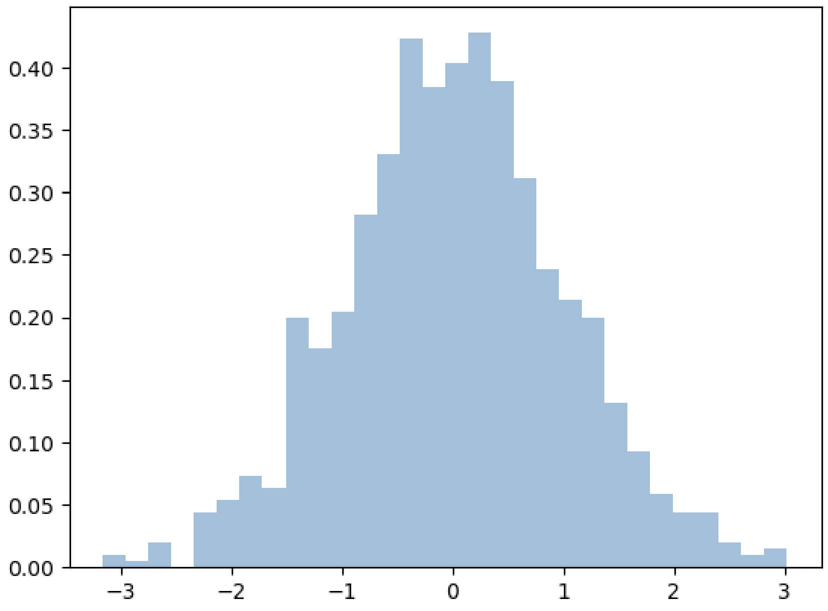
[25]:
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt

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

[26]:
```
plt.hist(data);
```



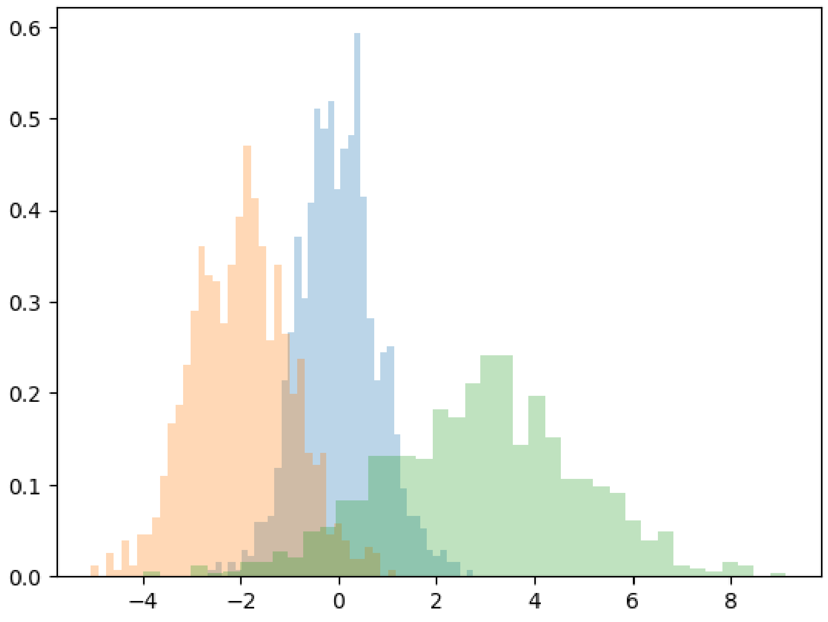
The `hist()` function has many options to tune both the calculation and the display; here's an example of a more customized histogram:

[27]:
```python
plt.hist(data, bins=30, density=True, 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:

[28]:
```python
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:

[29]:
```python
counts, bin_edges = np.histogram(data, bins=5)
print(counts)
```

```
[ 27 205 485 244  39]
```

5 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 this section we'll explore four routines for creating subplots in Matplotlib.

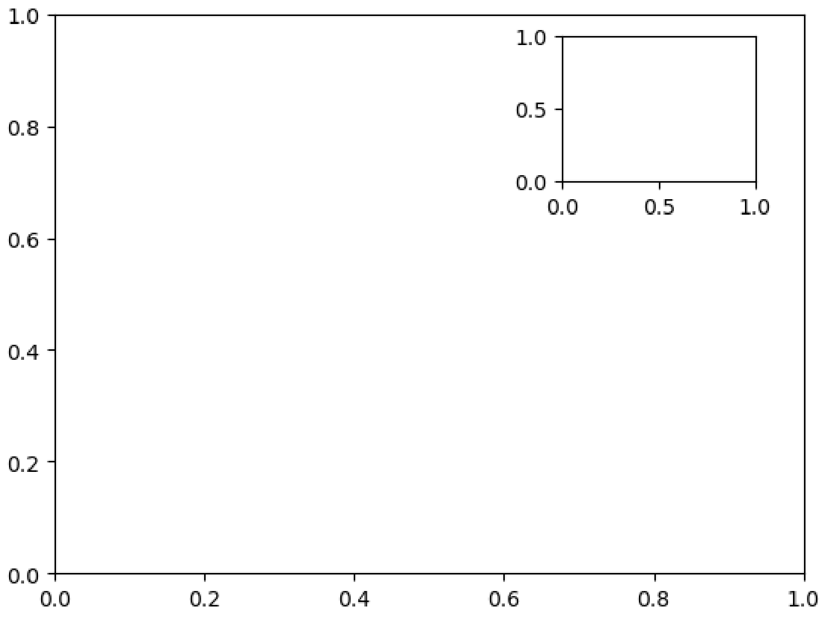
[30]:
```python
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
```

5.1 `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.

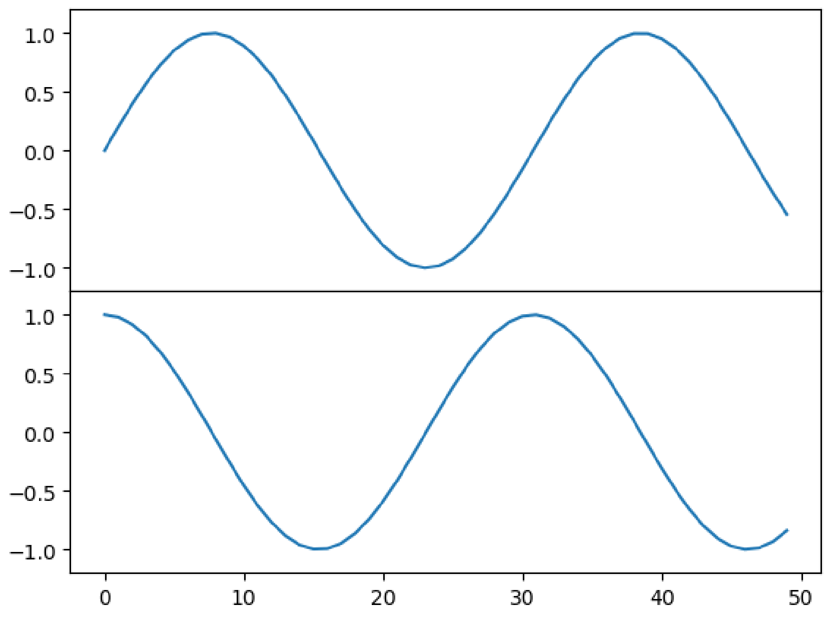
For example, we might create an inset axes at the top-right corner of another axes by setting the x and y position to 0.65 (that is, starting at 65% of the width and 65% of the height of the figure) and the x and y extents to 0.2 (that is, the size of the axes is 20% of the width and 20% of the height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

[31]:
```python
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:

[32]:
```python
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));
```



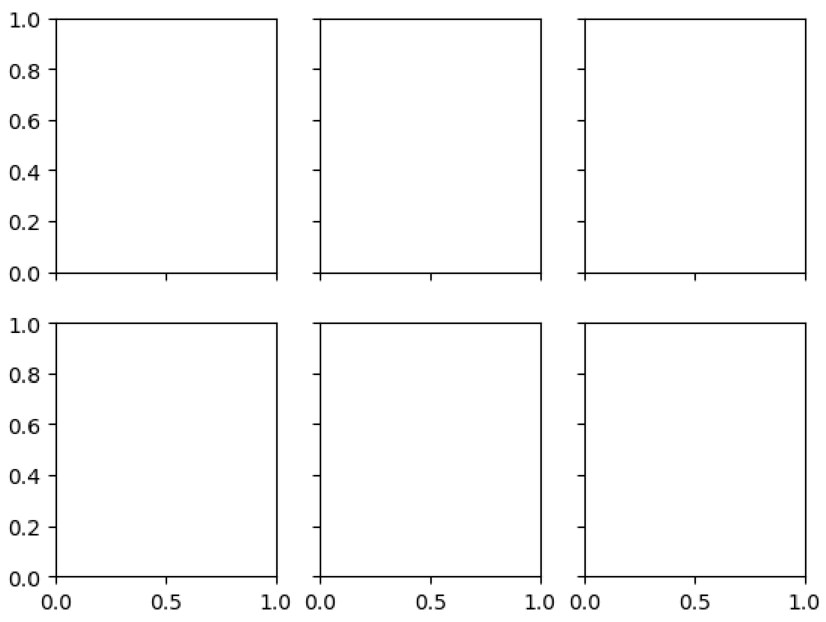
We now have two axes (the top with no tick labels) that are just touching: the bottom of the upper panel (at position 0.5) matches the top of the lower panel (at position 0.1 + 0.4).

5.2 `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:

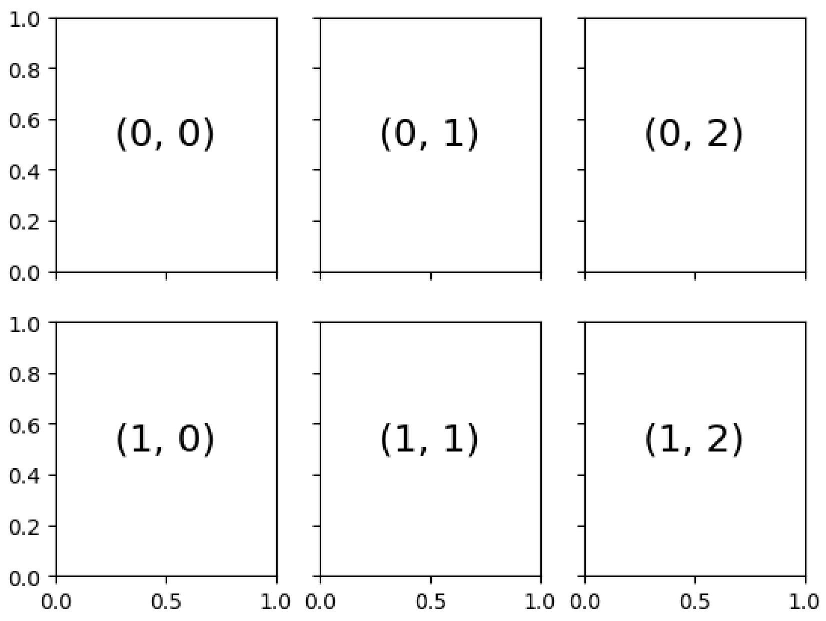
```
[33]: fig, ax = plt.subplots(2, 3, sharex='col', sharey='row')
```



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:

[34]:
```python
# 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
```

[34]:



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

6 Further Resources

6.1 Matplotlib Resources

A single handout can never hope to cover all the available features and plot types available in Matplotlib. As with other packages we've seen, liberal use of IPython's tab-completion and help functions can be very helpful when exploring Matplotlib's API. In addition, Matplotlib's online documentation can be a helpful reference. See in particular the Matplotlib gallery linked on that page: it shows thumbnails of hundreds of different plot types, each one linked to a page with the Python code snippet used to generate it. In this way, you can visually inspect and learn about a wide range of different plotting styles and visualization techniques.

For a book-length treatment of Matplotlib, I would recommend *Interactive Applications Using Matplotlib*, written by Matplotlib core developer Ben Root.

6.2 Other Python Graphics Libraries

Although Matplotlib is the most prominent Python visualization library, there are other more modern tools that are worth exploring as well. I'll mention a few of them briefly here:

- Bokeh is a JavaScript visualization library with a Python frontend that creates highly interactive visualizations capable of handling very large and/or streaming datasets. The Python front-end outputs a JSON data structure that can be interpreted by the Bokeh JS engine.
- Plotly is the eponymous open source product of the Plotly company, and is similar in spirit to Bokeh. Because Plotly is the main product of a startup, it is receiving a high level of development effort. Use of the library is entirely free.
- Vispy is an actively developed project focused on dynamic visualizations of very large datasets. Because it is built to target OpenGL and make use of efficient graphics processors in your computer, it is able to render some quite large and stunning visualizations.
- Vega and Vega-Lite are declarative graphics representations, and are the product of years of research into the fundamental language of data visualization. The reference rendering implementation is JavaScript, but the API is language agnostic. There is a Python API under development in the Altair package. Though as of summer 2016 it's not yet fully mature, I'm quite excited for the possibilities of this project to provide a common reference point for visualization in Python and other languages.

The visualization space in the Python community is very dynamic, and I fully expect this list to be out of date as soon as it is published. Keep an eye out for what's coming in the future!