Visualizing Uncertainties

For any scientific measurement, **accurate accounting of uncertainties** is nearly **as important,**

if not more so, as accurate reporting of the number itself.

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

Basic Errorbars

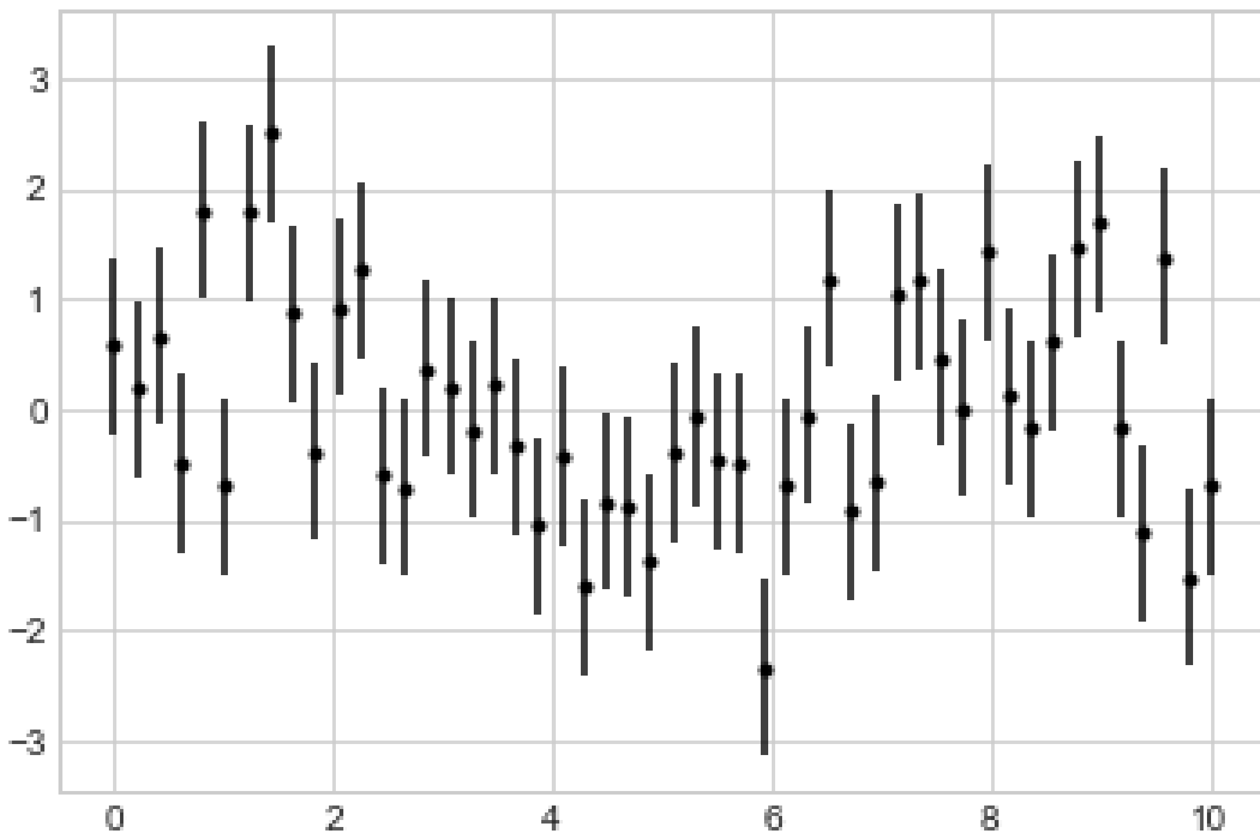
One standard way to visualize uncertainties is using an **errorbar**.

A basic errorbar can be created with a single Matplotlib function call, as shown in the following figure:

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

In [ ]:
```
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 it has the same syntax as the shorthand used in `plt.plot`,

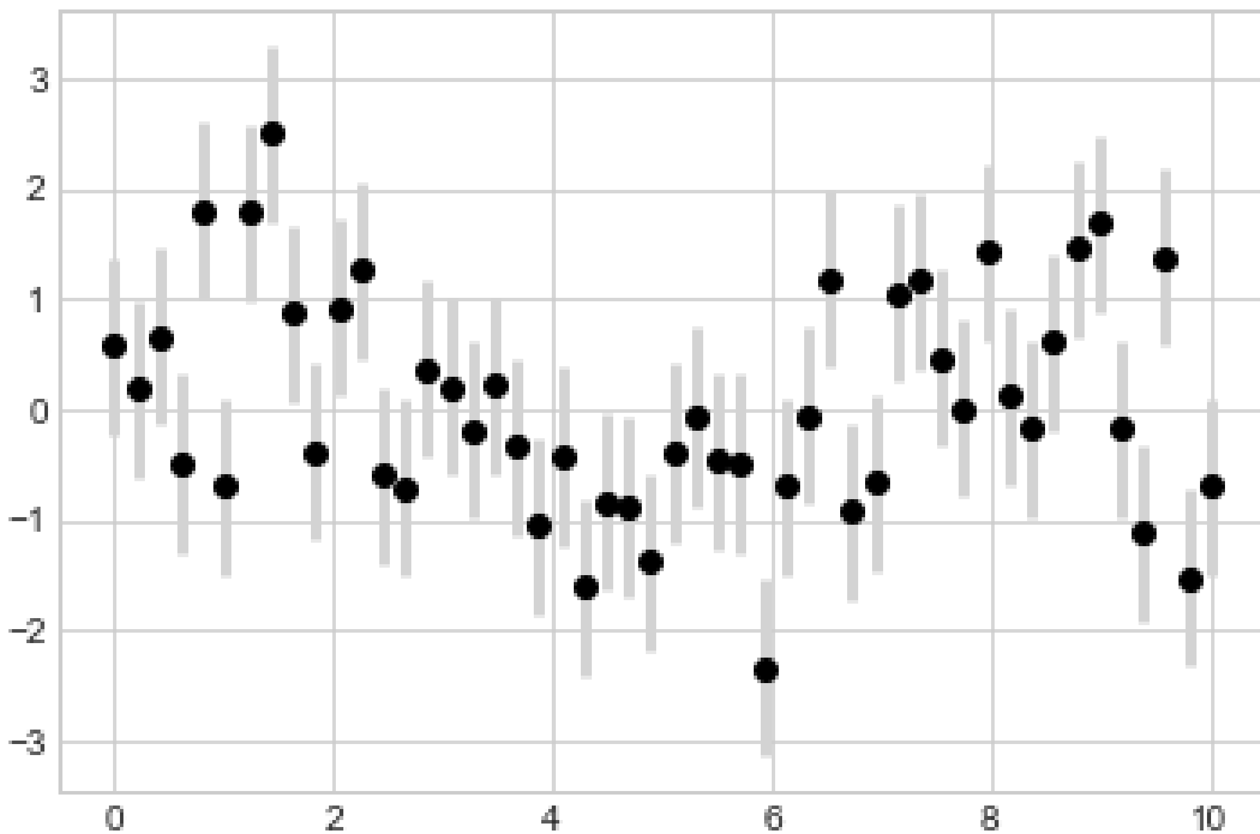
outlined in the previous chapter and earlier in this chapter.

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.

It is helpful, especially in **crowded plots,** to make the **errorbars lighter** than the points themselves (see the following figure):

In [ ]:
```
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, **one-sided** errorbars, and many other variants.

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.

In [ ]:
```
from sklearn.gaussian_process import GaussianProcessRegressor

# 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 = GaussianProcessRegressor()
```

```
gp.fit(xdata[:, np.newaxis], ydata)

xfit = np.linspace(0, 10, 1000)
yfit, dyfit = gp.predict(xfit[:, np.newaxis], return_std=True
```

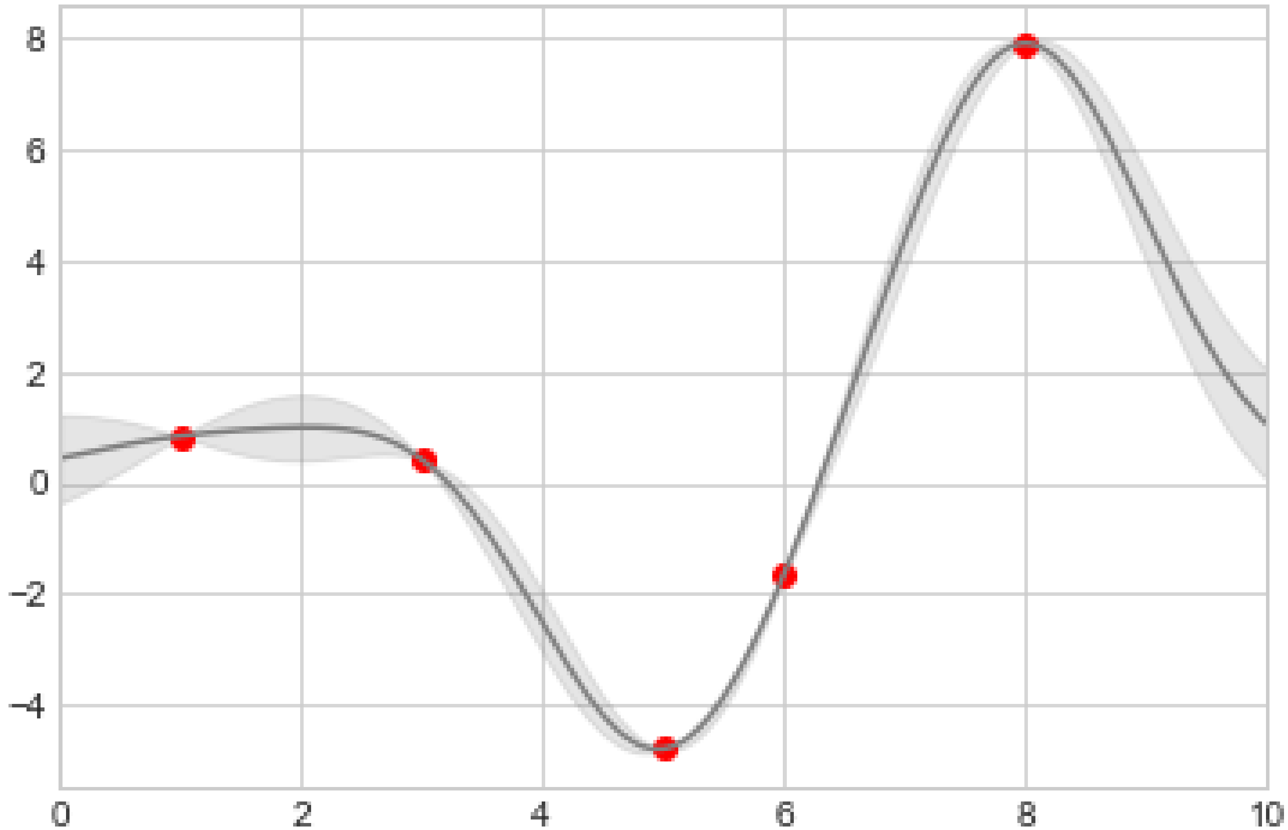
We now have `xfit`, `yfit`, and `dyfit`, which **sample the continuous fit** to our data.

We could pass these to the `plt.errorbar` function as in the previous section, 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** (see the following figure):

In [ ]:

```
# 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);
```



Take a look at the `fill_between` call signature:

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.