TrainTest

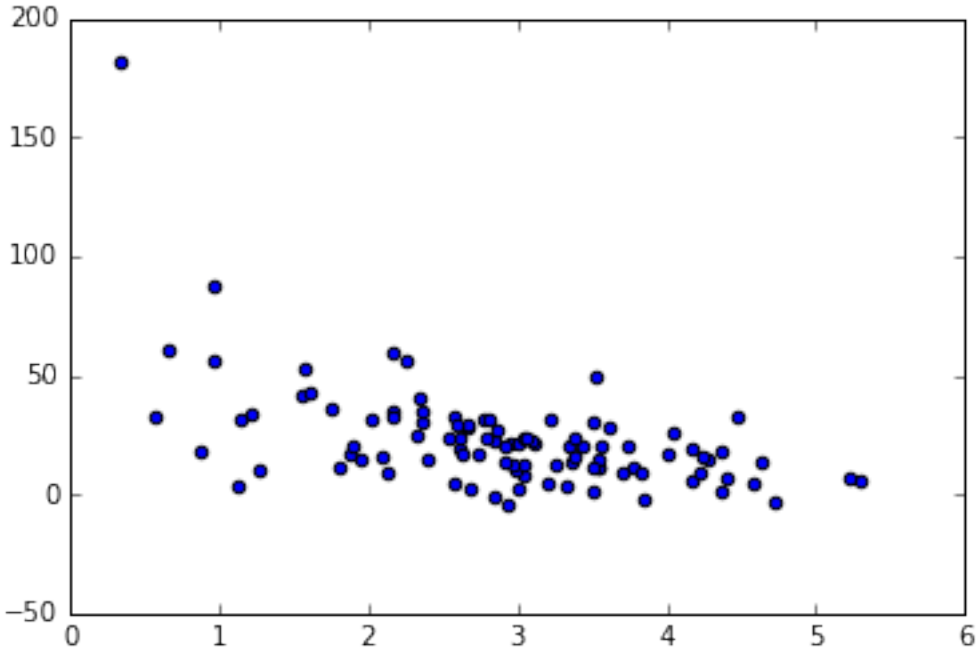
December 20, 2016

1 Train / Test

We'll start by creating some data set that we want to build a model for (in this case a polynomial regression):

In [1]:
```
%matplotlib inline
import numpy as np
from pylab import *

np.random.seed(2)

pageSpeeds = np.random.normal(3.0, 1.0, 100)
purchaseAmount = np.random.normal(50.0, 30.0, 100) / pageSpeeds


scatter(pageSpeeds, purchaseAmount)
```

Out[1]:
```
<matplotlib.collections.PathCollection at 0x7810eb8>
```

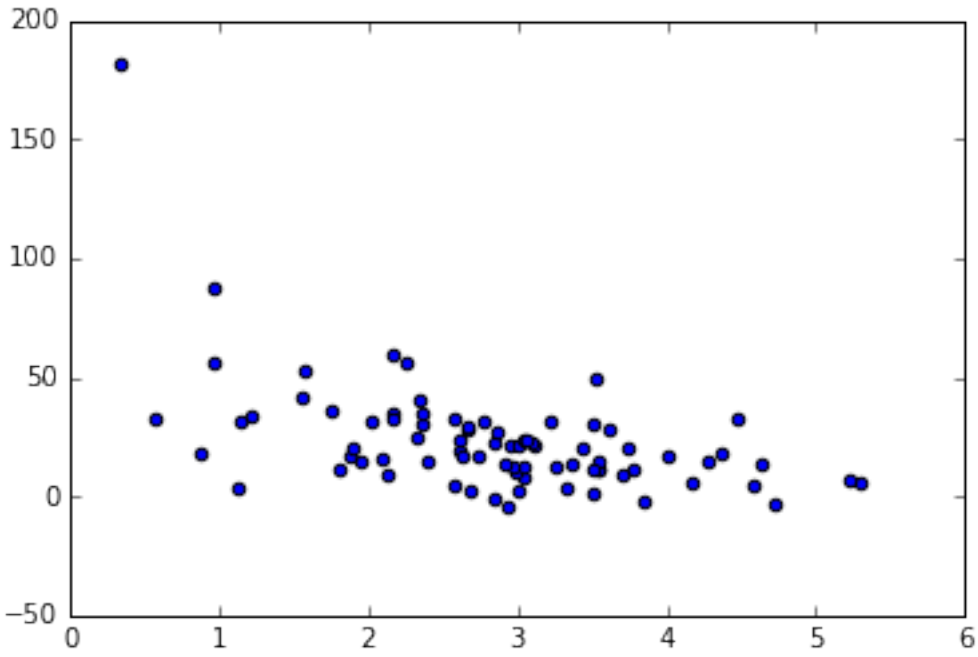


Now we'll split the data in two - 80% of it will be used for "training" our model, and the other 20% for testing it. This way we can avoid overfitting.

```
In [2]: trainX = pageSpeeds[:80]
        testX = pageSpeeds[80:]

        trainY = purchaseAmount[:80]
        testY = purchaseAmount[80:]
```

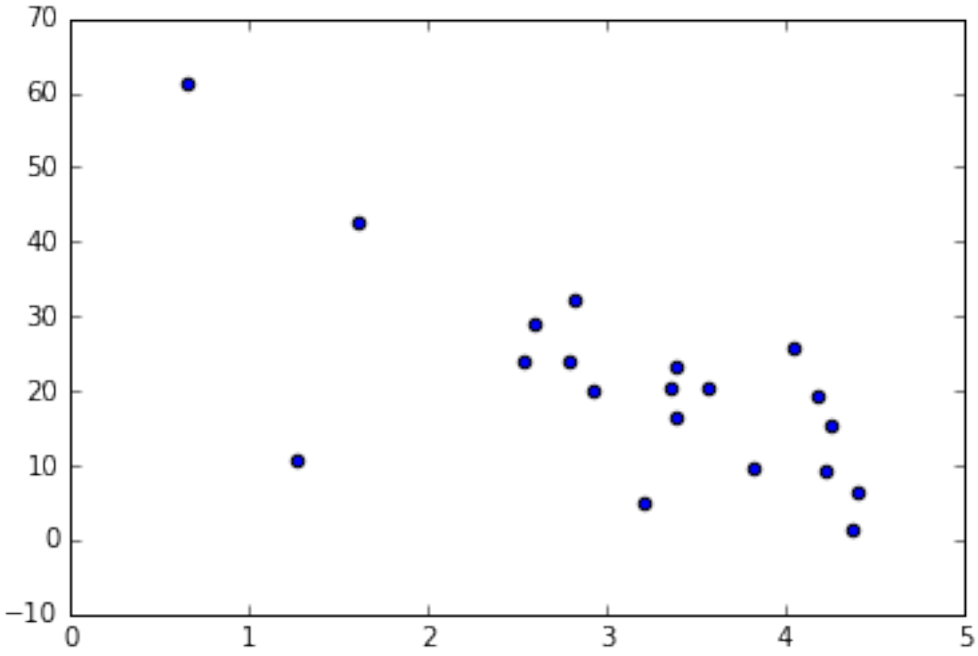
Here's our training dataset:

```
In [3]: scatter(trainX, trainY)

Out[3]: <matplotlib.collections.PathCollection at 0x7a0acf8>
```



And our test dataset:

```
In [4]: scatter(testX, testY)

Out[4]: <matplotlib.collections.PathCollection at 0x85e5c50>
```

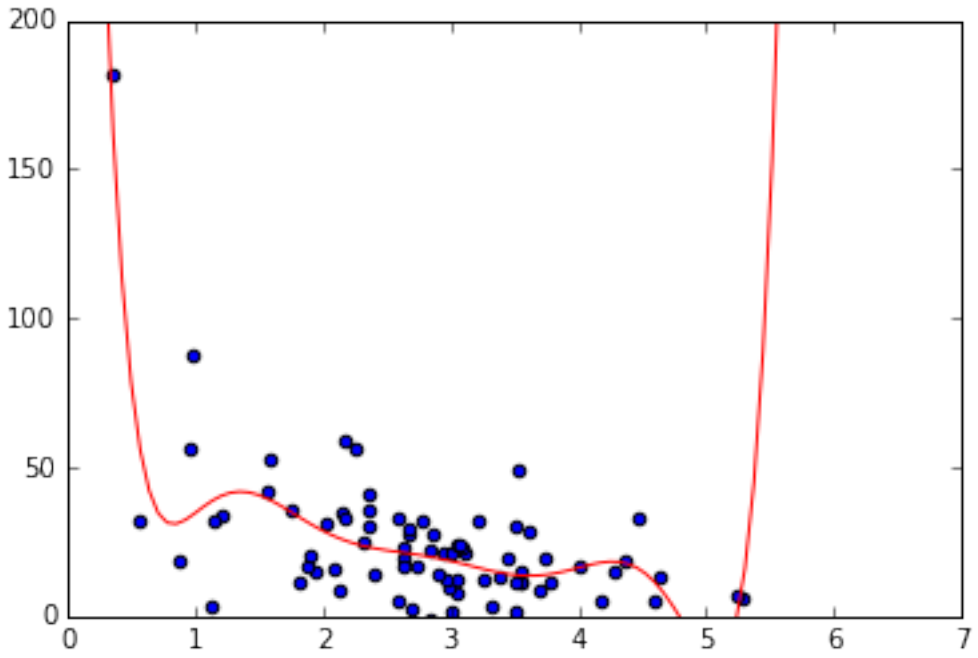


Now we'll try to fit an 8th-degree polynomial to this data (which is almost certainly overfitting, given what we know about how it was generated!)

```
In [5]: x = np.array(trainX)
        y = np.array(trainY)

        p4 = np.poly1d(np.polyfit(x, y, 8))
```

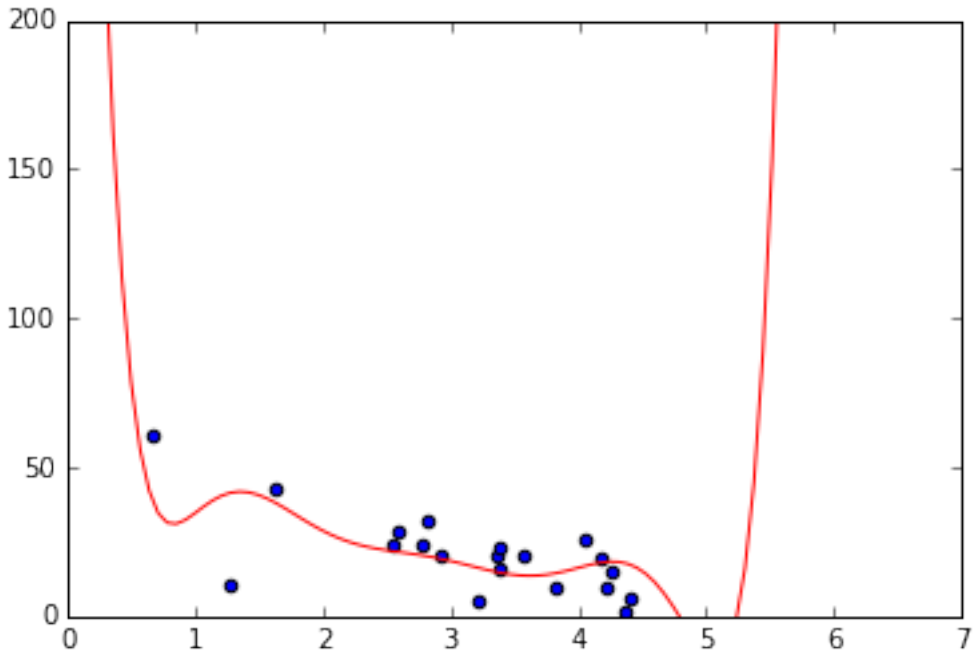
Let's plot our polynomial against the training data:

```
In [6]: import matplotlib.pyplot as plt

        xp = np.linspace(0, 7, 100)
        axes = plt.axes()
        axes.set_xlim([0,7])
        axes.set_ylim([0, 200])
        plt.scatter(x, y)
        plt.plot(xp, p4(xp), c='r')
        plt.show()
```



And against our test data:

```
In [7]: testx = np.array(testX)
        testy = np.array(testY)

        axes = plt.axes()
        axes.set_xlim([0,7])
        axes.set_ylim([0, 200])
        plt.scatter(testx, testy)
        plt.plot(xp, p4(xp), c='r')
        plt.show()
```



Doesn't look that bad when you just eyeball it, but the r-squared score on the test data is kind of horrible! This tells us that our model isn't all that great...

```
In [8]: from sklearn.metrics import r2_score

        r2 = r2_score(testy, p4(testx))

        print(r2)
```

```
0.300181686119
```

...even though it fits the training data better:

```
In [9]: from sklearn.metrics import r2_score

        r2 = r2_score(np.array(trainY), p4(np.array(trainX)))

        print(r2)
```

```
0.642706951469
```

If you're working with a Pandas DataFrame (using tabular, labeled data,) scikit-learn has built-in train_test_split functions to make this easy to do.

Later we'll talk about even more robust forms of train/test, like K-fold cross-validation - where we try out multiple different splits of the data, to make sure we didn't just get lucky with where we split it.

1.1 Activity

Try measuring the error on the test data using different degree polynomial fits. What degree works best?

```
In [ ]:
```