PolynomialRegression

December 20, 2016

1 Polynomial Regression

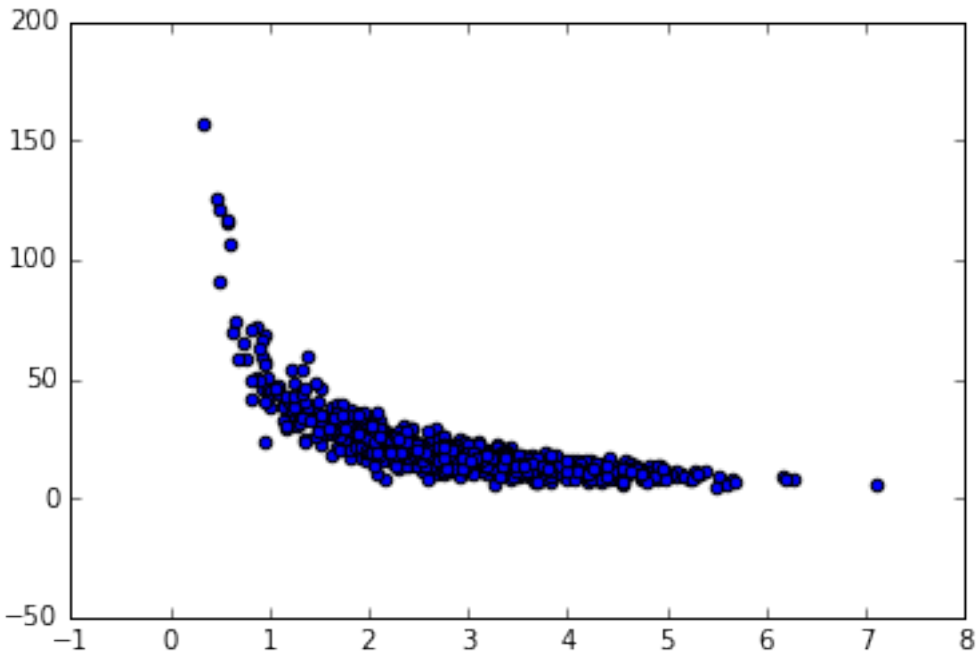
What if your data doesn't look linear at all? Let's look at some more realistic-looking page speed / purchase data:

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

np.random.seed(2)
pageSpeeds = np.random.normal(3.0, 1.0, 1000)
purchaseAmount = np.random.normal(50.0, 10.0, 1000) / pageSpeeds

scatter(pageSpeeds, purchaseAmount)
```

Out[1]:
```
<matplotlib.collections.PathCollection at 0x723aeb8>
```



numpy has a handy polyfit function we can use, to let us construct an nth-degree polynomial model of our data that minimizes squared error. Let's try it with a 4th degree polynomial:

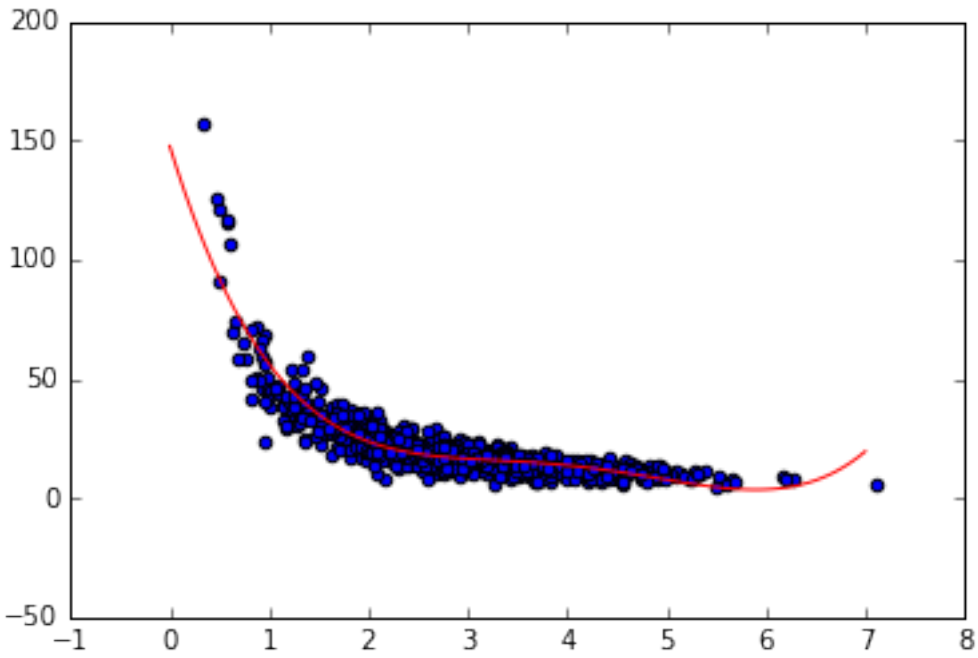
```
In [2]: x = np.array(pageSpeeds)
        y = np.array(purchaseAmount)

        p4 = np.poly1d(np.polyfit(x, y, 4))
```

We'll visualize our original scatter plot, together with a plot of our predicted values using the polynomial for page speed times ranging from 0-7 seconds:

```
In [3]: import matplotlib.pyplot as plt

        xp = np.linspace(0, 7, 100)
        plt.scatter(x, y)
        plt.plot(xp, p4(xp), c='r')
        plt.show()
```



Looks pretty good! Let's measure the r-squared error:

```
In [4]: from sklearn.metrics import r2_score

        r2 = r2_score(y, p4(x))

        print(r2)
```

```
0.82937663963
```

1.1 Activity

Try different polynomial orders. Can you get a better fit with higher orders? Do you start to see overfitting, even though the r-squared score looks good for this particular data set?

In [ ]: