```
#!/usr/bin/env python3
    # -*- coding: utf-8 -*-
 3
 4
    Example 2.2
 5
    Polynomial regression
    Machine Learning for Engineering Problem Solving
 7
    @author: Austin Downey
 8
 9
10
     import IPython as IP
11
     IP.get ipython().run line magic('reset', '-sf')
12
13
     import numpy as np
14
     import scipy as sp
15
     import matplotlib as mpl
16
     import matplotlib.pyplot as plt
17
     import sklearn as sk
18
    from sklearn import linear model
19
20
    plt.close('all')
21
22
    #%% build the data sets
23
   np.random.seed(2) # 2 and 6 are pretty good
24
    m = 100
25
    X = 6 * np.random.rand(m,1) - 3
26
    Y = 0.5 * X**2 + X + 2 + np.random.randn(m,1)
27
28
    # plot the data
29
   plt.figure()
30 plt.grid(True)
31
    plt.scatter(X,Y)
32
    plt.xlabel('x')
33
    plt.ylabel('y')
34
35
    #%% perform polynomial regression
36
37
     # generate x^2 as we use the model y = a*x^2* + b*x + c
38
    X \text{ poly manual} = \text{np.hstack}((X, X**2))
39
40
     # or use the code as this does lots of features for multi-feature data sets.
41
     poly features = sk.preprocessing.PolynomialFeatures(degree=2, include bias=False)
42
    X poly sk = poly features.fit transform(X)
43
44
     # they do do same thing as shown below, so select one to carry forward.
    print(X poly manual == X poly sk)
45
46
    X poly = X poly manual
47
48
    # In essence, we now have two data sets. We can plot that here
49
   plt.figure()
50
   plt.grid(True)
51
    plt.scatter(X poly[:,0],Y,label = 'data for x')
52
    plt.scatter(X poly[:,1],Y,marker='s',label = 'data for $x^2$')
53
    plt.legend()
54
    plt.xlabel('x')
55
    plt.ylabel('y')
56
57
    # and fit linear models to these data sets
58 model = sk.linear model.LinearRegression() # Select a linear model
59
    model.fit(X poly,Y) # Train the model
60
    X model 1 = np.linspace (-3,3)
61
    X \mod 2 = np.linspace(0,9)
62
63
    # the model parameters are:
64
   model coefficients = model.coef
65
   model intercept = model.intercept
66
    print(model coefficients)
67
    print(model intercept)
```

```
68
 69
     Y X1 = model coefficients[0][0]*X model 1 + model intercept
     Y_X2 = model_coefficients[0][1]*X_model_2 + model_intercept
70
71
72
     # now if we plot the linear models on the extended set of features.
73 plt.figure()
74 plt.grid(True)
75
    plt.scatter(X_poly[:,0],Y,label = 'data for x')
76
     plt.scatter(X poly[:,1],Y,marker='s',label = 'data for $x^2$')
77
     plt.plot(X model 1,Y X1,'--',label='inear fit $x$')
78
    plt.plot(X model 2,Y X2,':',label='linear fit for $x^2$',)
79
    plt.legend()
80
    plt.xlabel('x')
81
    plt.ylabel('y')
82
     plt.savefig('example 6 fig 1',dpi=300)
83
84
     \# now that we have a parameter for x and x^2, these can be recombined into a single
85
     \# \text{ model}, y = x^2*a + x*b + c.
    Y_polynominal = model_coefficients[0][1]*X_model_1**2 + model coefficients[0][0]*\
86
87
         X model 1 + model intercept
88
89
    plt.figure()
90 plt.grid(True)
91
     plt.scatter(X,Y,label='data')
92
    plt.plot(X model 1,Y polynominal,'r--',label='polynominal fit')
93
    plt.xlabel('x')
94
    plt.ylabel('y')
95
    plt.legend()
96
    plt.savefig('example 6 fig 2',dpi=300)
97
98
99
100
```

101