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011499072 CMPE 258 Assignment 2

Import statements

```
In [1]: import numpy as np
   import matplotlib.pyplot as plt
   import pandas as pd
   from math import sqrt
   from sklearn.linear_model import LinearRegression, Ridge, Lasso
   from sklearn.preprocessing import minmax_scale as scale
   from sklearn.model_selection import train_test_split
   from __future__ import division
   import tensorflow as tf
   from sklearn.metrics import mean_squared_error
```

Function for plotting data

```
In [2]: def plot_data(X_test,Y_test,Y_pred):
    result = sorted(zip(X_test, Y_pred))
    X_sorted = []
    Y_pred_sorted = []
    for i in range(0,len(result)):
        X_sorted.append(result[i][0])
        Y_pred_sorted.append(result[i][1])
    plt.scatter(X,Y)
    plt.plot(X_sorted,Y_pred_sorted)
```

Function for Min-Max Normalization

Function definitions for n order regressions without penalty

1 (30pts). Polynomial regression / overfitting / regularization Using Jupyter notebook, load the data (ex2data1.csv).

```
In [5]: data = pd.read_csv('./ex2datal.csv', header=None)
data.shape

Out[5]: (31, 2)

In [6]: data = data.drop(data.index[0]) # Removing Oth row of header x,y
data = data.reset_index(drop=True)
data = data.astype(float)

In [7]: X = data[0]
#X = minmax_normalize(np.power(X,2))
Y = data[1]
m = len(data)
print m

30

In [8]: temp = pd.Series( (1 for i in range(0,m)) )
```

1-1. Fit the data using linear (1st order) regression model (matrix form, gradient descent method).

Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE).

```
In [9]: X_mat = np.asmatrix(np.column_stack((temp,X)))
W_mat = np.asmatrix(np.array([0., 0.])).T
Y_mat = np.asmatrix((np.row_stack((Y))))
learning_rates = [0.01,0.1,0.5]#[0.1,0.01,0.001,0.0001,0.00001,0.000001,0.000001]
```

```
In [10]: for rate in learning rates:
             W_{mat} = np.asmatrix(np.array([0., 0.])).T
             count = 0
             max count = 1000000
             current cost = calculate cost()
             new cost = 0
             while new cost < current cost and count < max count:
                 current cost = calculate cost()
                 calculate_weights(rate)
                 new_cost = calculate_cost()
                 count += 1
                 if(count % 100000 == 0):
                     print "Iterations : %d" % count
             print "Iterations : %d" % count
             print "Last Cost : %lf" % new_cost
             print "Second Last Cost : %f " % current cost
             print "Learning rate : %f " % rate
             print "w0 : %f " % W mat[0]
             print "w1 : %f" % W_mat[1]
             print "RMSE : %f" % sqrt(calculate cost())
             print "\n"
```

```
Iterations: 12551
Last Cost : 0.226805
Second Last Cost: 0.226805
Learning rate: 0.010000
w0 : 1.075811
w1 : -1.188720
RMSE : 0.476240
Iterations: 1345
Last Cost: 0.226805
Second Last Cost: 0.226805
Learning rate: 0.100000
w0 : 1.075811
w1 : -1.188720
RMSE: 0.476240
Iterations : 277
Last Cost: 0.226805
Second Last Cost: 0.226805
Learning rate: 0.500000
w0 : 1.075811
w1 : -1.188720
RMSE: 0.476240
```

Best Result with Learning rate: 0.5

0.2

0.4

0.6

0.8

Iterations: 277

Last Cost: 0.226805

Second Last Cost: 0.226805 Learning rate: 0.500000

-1.0

w0: 1.075811 w1: -1.188720 RMSE: 0.476240

1-2. Fit the data using 2nd order polynomial regression model (matrix form, gradient descent method).

Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE). Note: Do not forget feature normalization.

```
In [14]: X_new = minmax_normalize(np.power(X,2))
In [15]: X_mat = np.asmatrix(np.column_stack((temp,X,X_new)))
W_mat = np.asmatrix(np.array([0., 0., 0.])).T
Y_mat = np.asmatrix((np.row_stack((Y))))
learning_rates = [0.1,0.5,0.6]#[0.1,0.01,0.001,0.0001,0.00001,0.000001,0.0000001]
```

```
In [16]: for rate in learning_rates:
             W mat = np.asmatrix(np.array([0., 0., 0.])).T
             count = 0
             max_count = 1000000
             current_cost = calculate_cost()
             new cost = 0
             while new_cost < current_cost and count < max_count:</pre>
                 current cost = calculate cost()
                 calculate_weights(rate)
                 new_cost = calculate_cost()
                 count += 1
                 if(count % 100000 == 0):
                     print "Iterations : %d" % count
             print "Iterations : %d" % count
             print "Last Cost : %lf" % new cost
             print "Second Last Cost : %f " % current_cost
             print "Learning rate : %f " % rate
             print "w0 : %f " % W_mat[0]
             print "w1 : %f" % W_mat[1]
             print "w2 : %f" % W mat[2]
             print "RMSE : %f" % sqrt(calculate_cost())
             print "\n"
         Iterations: 25214
         Last Cost: 0.081624
         Second Last Cost: 0.081624
```

```
Learning rate: 0.100000
w0: 0.189802
w1: 4.144446
w2 : -4.674276
RMSE: 0.285699
Iterations: 5381
Last Cost: 0.081624
Second Last Cost: 0.081624
Learning rate: 0.500000
w0 : 0.189801
w1: 4.144448
w2 : -4.674278
RMSE: 0.285699
Iterations: 4556
Last Cost: 0.081624
Second Last Cost: 0.081624
Learning rate: 0.600000
w0 : 0.189801
w1: 4.144449
w2 : -4.674278
RMSE: 0.285699
```

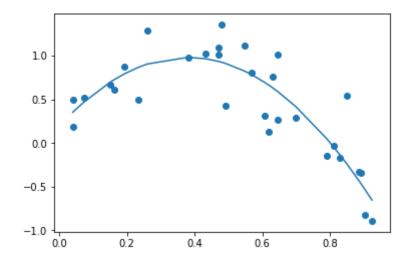
Best Result with Learning rate: 0.6

Iterations: 4556 Last Cost: 0.081624

Second Last Cost: 0.081624 Learning rate: 0.600000

w0: 0.189801 w1: 4.144449 w2: -4.674278 RMSE: 0.285699

```
In [19]: plot_data(X,Y,Y_pred)
```



1-3. Fit the data using 4th order polynomial regression model (matrix form, gradient descent method).

Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE). Note: Do not forget feature normalization.

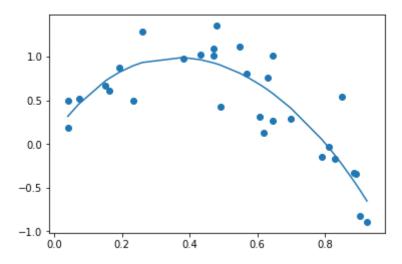
```
In [20]: X2_new = minmax_normalize(np.power(X,2))
X3_new = minmax_normalize(np.power(X,3))
X4_new = minmax_normalize(np.power(X,4))
```

```
In [22]: for rate in learning rates:
             W_{mat} = np.asmatrix(np.array([0., 0., 0., 0., 0.])).T
             count = 0
             max count = 100000
             current_cost = calculate_cost()
             new cost = -878987788
             while new_cost < current_cost and count < max_count:</pre>
                  current_cost = calculate_cost()
                  calculate_weights(rate)
                 new cost = calculate cost()
                 count += 1
                  if(count % 100000 == 0):
                      print "Iterations : %d" % count
             print "Iterations : %d" % count
             print "Last Cost : %lf" % new cost
             print "Second Last Cost : %f " % current cost
             print "Learning rate : %f " % rate
             print "w0 : %f " % W_mat[0]
             print "w1 : %f" % W_mat[1]
             print "w2 : %f " % W mat[2]
             print "w3 : %f " % W mat[3]
             print "w4 : %f " % W mat[4]
             print "RMSE : %f" % sqrt(calculate_cost())
             print "\n"
```

```
Iterations: 100000
Iterations: 200000
Iterations: 300000
Iterations: 400000
Iterations: 500000
Iterations: 600000
Iterations: 700000
Iterations: 800000
Iterations: 900000
Iterations: 1000000
Iterations: 1000000
Last Cost: 0.081329
Second Last Cost: 0.081329
Learning rate: 0.500000
w0 : 0.102319
w1: 5.427704
w2 : -8.801475
w3 : 5.232154
w4 : -2.203128
RMSE: 0.285183
```

```
In [23]: def predict(x,x2_new,x3_new,x4_new):
    return float(W_mat[0]) + float(W_mat[1])*x + float(W_mat[2])*x2_new
+ float(W_mat[3])*x3_new + float(W_mat[4])*x4_new
```

```
In [25]: plot_data(X,Y,Y_pred)
```



Best Result with Learning rate: 0.5

Iterations: 1000000 Last Cost: 0.081329

Second Last Cost: 0.081329 Learning rate: 0.500000

w0: 0.102319 w1: 5.427704 w2: -8.801475 w3: 5.232154 w4: -2.203128 RMSE: 0.285183

1-4. Fit the data using 16th order polynomial regression model (matrix form, gradient descent method).

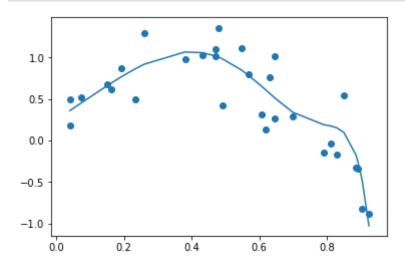
Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE). Note: Do not forget feature normalization.

```
X2 new = minmax_normalize(np.power(X,2))
In [26]:
          X3 \text{ new} = \min\max_{x \in X} \operatorname{normalize}(\operatorname{np.power}(X,3))
          X4_new = minmax_normalize(np.power(X,4))
          X5_new = minmax_normalize(np.power(X,5))
          X6 new = minmax_normalize(np.power(X,6))
          X7_new = minmax_normalize(np.power(X,7))
          X8_new = minmax_normalize(np.power(X,8))
          X9 \text{ new} = \min \max \text{ normalize(np.power(X,9))}
          X10 new = minmax_normalize(np.power(X,10))
          X11_new = minmax_normalize(np.power(X,11))
          X12 new = minmax_normalize(np.power(X,12))
          X13 new = minmax normalize(np.power(X,13))
          X14 new = minmax_normalize(np.power(X,14))
          X15 new = minmax normalize(np.power(X,15))
          X16 new = minmax_normalize(np.power(X,16))
```

```
In [28]: | for rate in learning rates:
            , 0., 0., 0., 0., 0., 0., 0.])).T
            count = 0
            max count = 100000
            current_cost = calculate_cost()
            new cost = 0
            while new cost < current cost and count < max count:</pre>
                current_cost = calculate_cost()
                calculate_weights(rate)
                new_cost = calculate_cost()
                count += 1
                if(count % 100000 == 0):
                    print "Iterations : %d" % count
            print "Iterations : %d" % count
            print "Last Cost : %lf" % new_cost
            print "Second Last Cost : %f " % current cost
            print "Learning rate : %f " % rate
            print "RMSE : %f" % sqrt(calculate_cost())
            print "w0 : %f " % W mat[0]
            print "w1 : %f" % W_mat[1]
            print "w2 : %f" % W_mat[2]
            print "w3 : %f" % W_mat[3]
            print "w4 : %f" % W mat[4]
            print "w5 : %f" % W mat[5]
            print "w6 : %f" % W_mat[6]
            print "w7 : %f" % W mat[7]
            print "w8 : %f" % W mat[8]
            print "w9 : %f" % W mat[9]
            print "w10 : %f" % W mat[10]
            print "w11 : %f" % W mat[11]
            print "w12 : %f" % W mat[12]
            print "w13 : %f" % W mat[13]
            print "w14 : %f" % W mat[14]
            print "w15 : %f" % W_mat[15]
            print "w16 : %f" % W_mat[16]
            print "\n"
```

Iterations: 100000 Iterations : 200000 Iterations: 300000 Iterations: 400000 Iterations: 500000 Iterations: 600000 Iterations: 700000 Iterations: 800000 Iterations: 900000 Iterations: 1000000 Iterations: 1000000 Last Cost: 0.068844 Second Last Cost: 0.068844 Learning rate: 0.330000 RMSE : 0.262381 w0 : 0.255503w1 : 2.653551 w2: 1.030015 w3 : -3.394612w4 : -3.963081w5 : -2.337852w6 : -0.177298w7 : 1.695582 w8 : 2.883656 w9 : 3.229226 w10 : 2.762056 w11 : 1.664585 w12 : 0.229127w13 : -1.186982w14 : -2.200812w15 : -2.434498w16 : -1.536927

In [31]: plot_data(X,Y,Y_pred)



Best Result with Learning rate: 0.6

Iterations: 1000000 Last Cost: 0.068844

Second Last Cost: 0.068844 Learning rate: 0.330000

RMSE: 0.262381

1-5. Fit the data using 16th order polynomial regression model with ridge (L2 penalty) regularization (matrix form, gradient descent method).

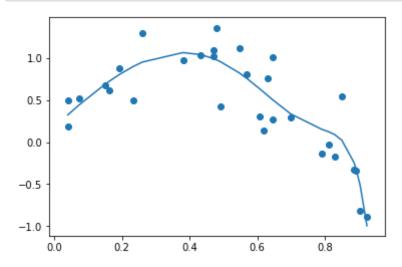
You need to try at least 3 different L2 penalty (for example, $\lambda = 0.1$, 1, 10). Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE) Note: Do not forget feature normalization.

```
In [32]:
         def calculate cost(y):
             result = np.dot((np.matmul(X_mat,W_mat) - Y_mat).T,(np.matmul(X_mat
         ,W mat) - Y mat))
             result /=m
             result += (y/m*np.sum(np.power(W_mat,2)))
             return float(result)
         def cost derivative(y):
             result = (np.matmul(np.matmul(X_mat.T,X_mat),W_mat)-(np.matmul(X_mat
         .T,Y_mat)))
             result *= 2
             result /=m
             result += 2 * (y/m*np.sum(W_mat))
             return result
         def calculate_weights(rate,y):
             global W_mat
             W_mat = W_mat - rate*cost_derivative(y)
```

```
In [34]: for rate in learning rates:
             for y in lambdas:
                , 0., 0., 0., 0., 0., 0., 0., 0.])).T
                count = 0
                max count = 10000
                current_cost = calculate_cost(y)
                new cost = 0
                while new_cost < current_cost and count < max_count:</pre>
                    current_cost = calculate_cost(y)
                    calculate weights(rate,y)
                    new_cost = calculate_cost(y)
                    count += 1
                    if(count % 1000 == 0):
                        print "counter : %d" % count
                print "Penalty : %f" % y
                print "Iterations : %d" % count
                print "Last Cost : %lf" % new cost
                print "Second Last Cost : %f " % current cost
                print "Learning rate : %f " % rate
                print "RMSE : %f" % sqrt(calculate_cost(y))
                print "w0 : %f " % W_mat[0]
                print "w1 : %f" % W_mat[1]
                print "w2 : %f" % W_mat[2]
                print "w3 : %f" % W mat[3]
                print "w4 : %f" % W_mat[4]
                print "w5 : %f" % W mat[5]
                print "w6 : %f" % W mat[6]
                print "w7 : %f" % W mat[7]
                print "w8 : %f" % W mat[8]
                print "w9 : %f" % W mat[9]
                print "w10 : %f" % W mat[10]
                print "w11 : %f" % W mat[11]
                print "w12 : %f" % W mat[12]
                print "w13 : %f" % W_mat[13]
                print "w14 : %f" % W mat[14]
                print "w15 : %f" % W mat[15]
                print "w16 : %f" % W_mat[16]
                print "\n"
             print "\n*********************
```

```
counter: 1000
counter: 2000
counter: 3000
counter: 4000
counter: 5000
counter: 6000
counter: 7000
counter: 8000
counter: 9000
counter: 10000
Penalty: 0.000010
Iterations: 10000
Last Cost: 0.069395
Second Last Cost: 0.069395
Learning rate: 0.380000
RMSE : 0.263429
w0 : 0.173201
w1: 3.806504
w2 : -1.653442
w3 : -3.045987
w4 : -2.229038
w5 : -0.844356
w6: 0.388338
w7: 1.233586
w8 : 1.666024
w9 : 1.738947
w10 : 1.526791
w11: 1.101924
w12 : 0.526626
w13 : -0.148495
w14 : -0.883588
w15 : -1.647884
w16 : -2.417959
```

In [37]: plot_data(X,Y,Y_pred)



Best Result with Learning rate: 0.6

Iterations: 10000 Last Cost: 0.069395

Second Last Cost: 0.069395 Learning rate: 0.380000

RMSE: 0.263429

1-6. Fit the data using 16th order polynomial regression model with scikit-learn Ridge model.

You need to try at least 3 different L2 penalty (for example, $\lambda = 0.1$, 1, 10). Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE)

```
In [61]: Weights = []
    for y in lambdas:
        ridge_model = Ridge(alpha=y)
        ridge_model.fit(X_mat,Y)
        Y_pred = ridge_model.predict(X_mat)
        print "For Penalty : %f" % y
        print "RMSE is %f " % sqrt(mean_squared_error(Y_mat,Y_pred))
        Weights.append(ridge_model.coef_)
        print ""

plt.plot(lambdas,Weights)
    plt.title("Weight Coefficients")
```

For Penalty: 0.000010 RMSE is 0.262312

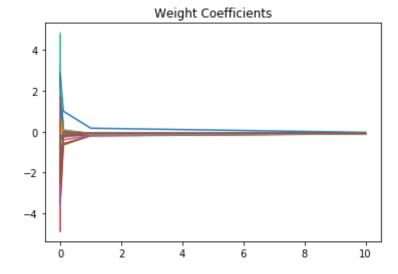
For Penalty : 0.000100 RMSE is 0.262423

For Penalty : 0.100000 RMSE is 0.303637

For Penalty : 1.000000 RMSE is 0.327256

For Penalty : 10.000000 RMSE is 0.350926

Out[61]: Text(0.5,1,u'Weight Coefficients')

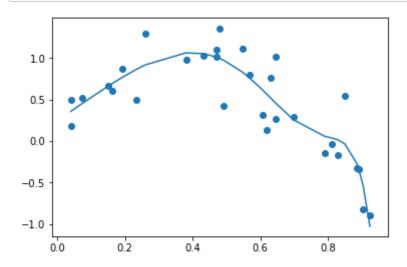


```
In [58]: print "Optimized weights"
         print "w0 : %f" % ridge model.intercept
         print "w1 : %f" % ridge_model.coef_[0]
         print "w2 : %f" % ridge_model.coef_[1]
         print "w3 : %f" % ridge model.coef [2]
         print "w4 : %f" % ridge model.coef [3]
         print "w5 : %f" % ridge model.coef [4]
         print "w6 : %f" % ridge model.coef [5]
         print "w7 : %f" % ridge model.coef [6]
         print "w8 : %f" % ridge_model.coef_[7]
         print "w9 : %f" % ridge model.coef [8]
         print "w10 : %f" % ridge_model.coef [9]
         print "w11 : %f" % ridge model.coef [10]
         print "w12 : %f" % ridge model.coef [11]
         print "w13 : %f" % ridge_model.coef_[12]
         print "w14 : %f" % ridge_model.coef_[13]
         print "w15 : %f" % ridge_model.coef_[14]
         print "w16 : %f" % ridge_model.coef [15]
```

Optimized weights

w0 : 0.247933 w1 : 2.817425 w2 : 0.210606w3 : -2.333924w4 : -3.149074w5 : -3.031167w6 : -1.741198w7 : 0.662601 w8 : 3.242688 w9 : 4.841123 w10 : 4.729656 w11 : 2.868442 w12 : -0.130163w13 : -3.170700w14 : -4.870423w15 : -3.731855w16 : 1.724302

In [59]: plot_data(X,Y,Y_pred.T)



Best result achieved with Penalty: 0.00001

For Penalty : 0.000010 RMSE is 0.262312

1-7. Fit the data using 16th order polynomial regression model with scikit-learn Lasso model.

You need to try at least 3 different L1 penalty (for example, $\lambda = 0.1$, 1, 10). Plot the data with the fitted line. Print optimized weights. Print Root Mean Squared Error (RMSE)

```
In [79]: Weights = []
for y in lambdas:
    lasso_model = Lasso(alpha=y)
    lasso_model.fit(X_mat,Y)
    Y_pred = lasso_model.predict(X_mat)
    Weights.append(lasso_model.coef_)
    print "For Penalty : %f" % y
    print "RMSE is %f " % sqrt(mean_squared_error(Y_mat,Y_pred))
    print ""
    plt.plot(lambdas,Weights)
    plt.title("Weight Coefficients")
```

For Penalty: 0.000010
RMSE is 0.267002

For Penalty: 0.001000
RMSE is 0.290611

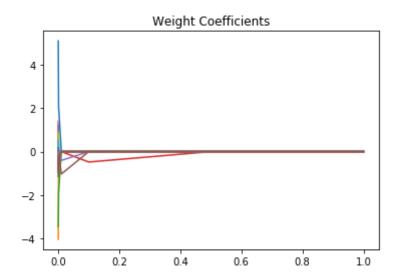
For Penalty: 0.010000
RMSE is 0.331643

For Penalty: 0.100000
RMSE is 0.462805

For Penalty: 0.500000
RMSE is 0.577255

For Penalty: 1.000000
RMSE is 0.577255

Out[79]: Text(0.5,1,u'Weight Coefficients')



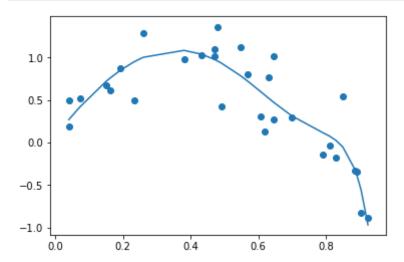
```
In [75]: print "Optimized weights"
         print "w0 : %f" % lasso model.intercept
         print "w1 : %f" % lasso_model.coef_[0]
         print "w2 : %f" % lasso_model.coef_[1]
         print "w3 : %f" % lasso model.coef [2]
         print "w4 : %f" % lasso model.coef [3]
         print "w5 : %f" % lasso model.coef [4]
         print "w6 : %f" % lasso model.coef [5]
         print "w7 : %f" % lasso model.coef [6]
         print "w8 : %f" % lasso_model.coef_[7]
         print "w9 : %f" % lasso model.coef [8]
         print "w10 : %f" % lasso_model.coef [9]
         print "w11 : %f" % lasso model.coef [10]
         print "w12 : %f" % lasso model.coef [11]
         print "w13 : %f" % lasso_model.coef_[12]
         print "w14 : %f" % lasso_model.coef_[13]
         print "w15 : %f" % lasso_model.coef_[14]
         print "w16 : %f" % lasso_model.coef [15]
```

Optimized weights

w0 : 0.066560 w1 : 5.111229 w2 : -4.046053w3 : -3.454817w4 : -0.913061w5 : 0.577025w6: 1.353447 w7: 1.424065 w8: 1.206896 w9 : 0.864756 w10 : 0.488026 w11 : 0.164971 w12 : -0.013095w13 : -0.521554w14 : -0.772556w15 : -0.977965w16 : -1.140289

Best result achieved with Penalty: 0.00001

For Penalty : 0.000010 RMSE is 0.267002 In [76]: plot_data(X,Y,Y_pred)



2 (30pts). Polynomial regression with train/validation/test

Using Jupyter notebook, load the data (ex2data2.csv). The first column is the size of the house (in square feet), the second column is the price of the house. You need to split the data into training/validation/testing data set as 60% / 20% / 20%. Please use np.random.seed(1) to have consistent data for evaluation.

```
data = pd.read csv('./ex2data2.csv', header=None)
In [158]:
          data.shape
Out[158]: (5405, 2)
In [159]:
          data = data.drop(data.index[0]) # Removing 0th row of header x,y
          data = data.reset index(drop=True)
          data = data.astype(float)
In [160]:
          X = data[0]
          \#X = minmax normalize(X)
          Y = data[1]
          m = len(data)
In [161]:
          temp = pd.Series( (1 for i in range(0,m)) )
In [162]:
          X mat = np.asmatrix(np.column stack((temp,X)))
          W_mat = np.asmatrix(np.array([0., 0.])).T
          Y mat = np.asmatrix((np.row stack((Y))))
          learning rates = [0.0000001]
```

Splitting data into Training, Validation and Testing sets

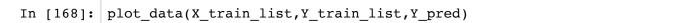
```
In [164]: np.random.seed(1)
    X_train, X_test, Y_train, Y_test = train_test_split(X_mat,Y_mat,train_si
    ze=0.8)
    X_train, X_val, Y_train, Y_val = train_test_split(X_train,Y_train,train_size=.75)
```

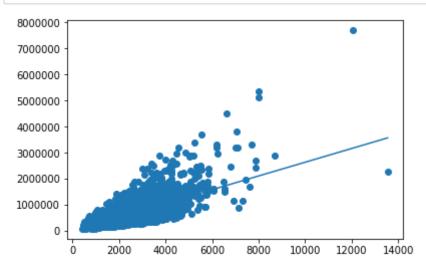
2-1. Fit the data using linear (1st order) regression model (matrix form, gradient descent method).

Plot the training data with the fitted line. Using the optimized weights, please calculated Root Mean Squared Error (RMSE) of training and testing data.

```
In [165]: for rate in learning rates:
              W mat = np.asmatrix(np.array([0., 0.])).T
              count = 0
              max_count = 100000
              current_cost = calculate_cost(X_train,Y_train)
              new cost = 0
              while new_cost < current_cost and count < max_count:</pre>
                  current cost = calculate cost(X train, Y train)
                  calculate_weights(rate, X_train, Y_train)
                  new_cost = calculate_cost(X_train,Y_train)
                  count += 1
                  if(count % 100000 == 0):
                      print "counter : %d" % count
              print "Iterations : %d" % count
              print "Last Cost : %lf" % new cost
              print "Second Last Cost : %f " % current_cost
              print "Learning rate : %f " % rate
              print "w0 : %f " % W mat[0]
              print "w1 : %f" % W_mat[1]
              print "Training RMSE : %1f" % sqrt(calculate cost(X train,Y train))
              print "Validation RMSE : %lf" % sqrt(calculate_cost(X_val,Y_val))
              print "\n"
          counter : 100000
          Iterations: 100000
          Last Cost: 40629415125.450859
          Second Last Cost: 40629415133.811310
          Learning rate: 0.000000
          w0 : -91.426295
          w1 : 263.655422
          Training RMSE: 201567.395988
          Validation RMSE: 134104.927408
In [166]: print "Testing RMSE : %f" % sqrt(calculate cost(X test,Y test))
          Testing RMSE: 118992.237409
In [167]: def predict(x):
              return float(W_mat[0]) + float(W_mat[1])*x
          Y_train_list = Y_train.T[0].tolist()[0]
          X train list = X train[:,1].T.tolist()[0]
          Y pred = []
          for x in X train list:
```

Y pred.append(predict(x))





Best result achieved with Penalty: 0.00001

2-2. Fit the data using 2nd order polynomial regression model (matrix form, gradient descent method).

Plot the training data with the fitted line. Using the optimized weights, please calculated Root Mean Squared Error (RMSE) of training and testing data. Note: Do not forget feature normalization.

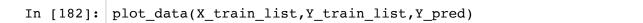
```
In [173]: X = minmax_normalize(X)
X_new = np.power(X,2)

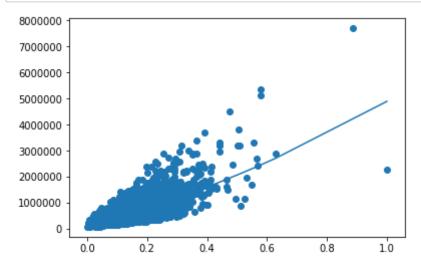
In [177]: X_mat = np.asmatrix(np.column_stack((temp,X,X_new)))
W_mat = np.asmatrix(np.array([0., 0., 0.])).T
Y_mat = np.asmatrix((np.row_stack((Y))))
learning_rates = [0.1]

In [178]: np.random.seed(1)
X_train, X_test, Y_train, Y_test = train_test_split(X_mat,Y_mat,train_si ze=0.8)
X_train, X_val, Y_train, Y_val = train_test_split(X_train,Y_train,train_size=.75)
```

```
In [179]: for rate in learning rates:
              W mat = np.asmatrix(np.array([0., 0., 0.])).T
              count = 0
              max_count = 100000
              current_cost = calculate_cost(X_train,Y_train)
              new cost = 0
              while new_cost < current_cost and count < max_count:</pre>
                  current cost = calculate cost(X train, Y train)
                  calculate weights(rate, X train, Y train)
                  new_cost = calculate_cost(X_train,Y_train)
                  count += 1
                  if(count % 100000 == 0):
                      print "counter : %d" % count
              print "Iterations : %d" % count
              print "Last Cost : %lf" % new cost
              print "Second Last Cost : %f " % current cost
              print "Learning rate : %f " % rate
              print "w0 : %f " % W mat[0]
              print "w1 : %f" % W_mat[1]
              print "w2 : %f" % W mat[2]
              print "Training RMSE : %1f" % sqrt(calculate cost(X train,Y train))
              print "Validation RMSE : %lf" % sqrt(calculate_cost(X_val,Y_val))
              print "\n"
          counter : 100000
          Iterations: 100000
          Last Cost: 39977563876.035477
          Second Last Cost: 39977563893.283493
          Learning rate: 0.100000
          w0: 125936.813323
          w1 : 2997187.284412
          w2: 1771899.453754
          Training RMSE: 199943.901823
          Validation RMSE : 126124.211292
In [180]: print "Testing RMSE: %f" % sqrt(calculate cost(X test,Y test))
          Testing RMSE: 116012.280498
In [181]: def predict(x,x_new):
              return float(W mat[0]) + float(W mat[1])*x + + float(W mat[2])*x new
          Y train list = Y train.T[0].tolist()[0]
          X train list = X train[:,1].T.tolist()[0]
          Y pred = []
          for x,x new in zip(X train list,np.power(X train list,2)):
```

Y pred.append(predict(x,x new))





Best result achieved with Learning rate: 0.1

counter: 100000 Iterations: 100000

Last Cost: 39977563876.035477

Second Last Cost: 39977563893.283493

Learning rate: 0.100000 w0: 125936.813323 w1: 2997187.284412

Training RMSE: 199943.901823 Validation RMSE: 126124.211292 Testing RMSE: 116012.280498

2-3. Fit the data using 4th order polynomial regression model (matrix form, gradient descent method).

Plot the training data with the fitted line. Using the optimized weights, please calculated Root Mean Squared Error (RMSE) of training and testing data. Note: Do not forget feature normalization.

```
In [183]: X2_new = minmax_normalize(np.power(X,2))
X3_new = minmax_normalize(np.power(X,3))
X4_new = minmax_normalize(np.power(X,4))
```

```
In [184]: X_mat = np.asmatrix(np.column_stack((temp,X,X2_new,X3_new,X4_new)))
W_mat = np.asmatrix(np.array([0., 0., 0., 0., 0.])).T
Y_mat = np.asmatrix((np.row_stack((Y))))
learning_rates = [1]
```

In [185]: np.random.seed(1)

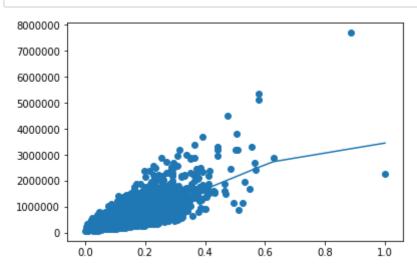
```
X_train, X_test, Y_train, Y_test = train_test_split(X_mat,Y_mat,train_si
          X_train, X_val, Y_train, Y_val = train_test_split(X_train,Y_train,train_
          size=.75)
In [186]: for rate in learning rates:
              W_{mat} = np.asmatrix(np.array([0., 0., 0., 0., 0.])).T
              count = 0
              max count = 10000
              current_cost = calculate_cost(X_train,Y_train)
              new cost = 0
              while new cost < current cost and count < max count:</pre>
                  current cost = calculate cost(X train, Y train)
                  calculate weights(rate, X train, Y train)
                  new cost = calculate cost(X train, Y train)
                  count += 1
              print "Iterations : %d" % count
              print "Last Cost : %lf" % new cost
              print "Second Last Cost : %f " % current cost
              print "Learning rate : %f " % rate
              print "w0 : %f " % W mat[0]
              print "w1 : %f" % W_mat[1]
              print "w2 : %f" % W_mat[2]
              print "w3 : %f" % W mat[3]
              print "w4 : %f" % W mat[4]
              print "Training RMSE : %lf" % sqrt(calculate cost(X train,Y train))
              print "Validation RMSE : %lf" % sqrt(calculate cost(X val,Y val))
              print "\n"
          Iterations: 10000
          Last Cost: 38374780528.962669
          Second Last Cost: 38374895380.947952
          Learning rate: 1.000000
```

```
Last Cost: 38374780528.962669
Second Last Cost: 38374895380.947952
Learning rate: 1.000000
w0: 148814.076829
w1: 2515005.044681
w2: 3794670.119299
w3: -182927.837397
w4: -2817563.714944
Training RMSE: 195894.820067
Validation RMSE: 128888.670561
```

```
In [187]: print "Testing RMSE : %f" % sqrt(calculate_cost(X_test,Y_test))
```

Testing RMSE: 115067.242611

```
In [189]: plot_data(X_train_list,Y_train_list,Y_pred)
```



Best result achieved with Learning rate: 1

Iterations: 10000

Last Cost: 38374780528.962669

Second Last Cost: 38374895380.947952

Learning rate: 1.000000 w0: 148814.076829 w1: 2515005.044681 w2: 3794670.119299 w3: -182927.837397 w4: -2817563.714944

Training RMSE: 195894.820067 Validation RMSE: 128888.670561 Testing RMSE: 115067.242611

2-4. Fit the data using 16th order polynomial regression model (matrix form, gradient descent method).

Plot the training data with the fitted line. Using the optimized weights, please calculated Root Mean Squared Error (RMSE) of training and testing data. Note: Do not forget feature normalization.

```
In [190]:
          X2 \text{ new} = \min \max \text{ normalize(np.power(X,2))}
          X3 \text{ new} = \min\max_{x \in X} \operatorname{normalize}(\operatorname{np.power}(X,3))
          X4_new = minmax_normalize(np.power(X,4))
          X5_new = minmax_normalize(np.power(X,5))
          X6 new = minmax normalize(np.power(X,6))
          X7_new = minmax_normalize(np.power(X,7))
          X8 new = minmax_normalize(np.power(X,8))
          X9 \text{ new} = \min \max \text{ normalize(np.power(X,9))}
          X10 new = minmax_normalize(np.power(X,10))
          X11_new = minmax_normalize(np.power(X,11))
          X12 new = minmax normalize(np.power(X,12))
          X13 new = minmax normalize(np.power(X,13))
          X14 new = minmax_normalize(np.power(X,14))
          X15 new = minmax normalize(np.power(X,15))
          X16 new = minmax normalize(np.power(X,16))
In [191]: X mat = np.asmatrix(np.column stack((temp,X,X2 new,X3 new,X4 new,X5 new,
          X6 new, X7 new, X8 new, X9 new, X10 new, X11 new, X12 new, X13 new, X14 new, X15
          new, X16 new)))
          , 0., 0., 0., 0., 0., 0.])).T
          Y_mat = np.asmatrix((np.row_stack((Y))))
          learning_rates = [1.6]
In [192]: | np.random.seed(1)
          X_train, X_test, Y_train, Y_test = train_test_split(X_mat,Y_mat,train_si
          ze=0.8)
          X train, X val, Y train, Y val = train test split(X train, Y train, train
          size=.75)
```

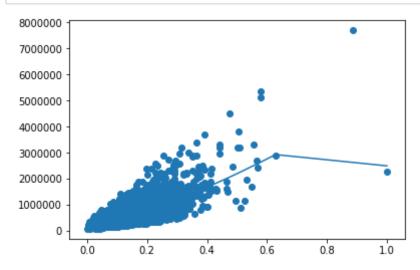
```
In [193]: for rate in learning rates:
             , 0., 0., 0., 0., 0., 0., 0.])).T
             count = 0
             max count = 1000
             current_cost = calculate_cost(X_train,Y_train)
             new cost = 0
             while new cost < current cost and count < max count:</pre>
                 current_cost = calculate_cost(X_train,Y_train)
                 calculate_weights(rate, X_train, Y_train)
                 new_cost = calculate_cost(X_train,Y_train)
                 count += 1
             print "Iterations : %d" % count
             print "Last Cost : %lf" % new cost
             print "Second Last Cost : %f " % current cost
             print "Learning rate : %f " % rate
             print "w0 : %f " % W mat[0]
             print "w1 : %f" % W_mat[1]
             print "w2 : %f" % W mat[2]
             print "w3 : %f" % W mat[3]
             print "w4 : %f" % W mat[4]
             print "w5 : %f" % W_mat[5]
             print "w6 : %f" % W_mat[6]
             print "w7 : %f" % W mat[7]
             print "w8 : %f" % W mat[8]
             print "w9 : %f" % W_mat[9]
             print "w10 : %f" % W mat[10]
             print "w11 : %f" % W mat[11]
             print "w12 : %f" % W mat[12]
             print "w13 : %f" % W mat[13]
             print "w14 : %f" % W mat[14]
             print "w15 : %f" % W mat[15]
             print "w16 : %f" % W mat[16]
             print "Training RMSE : %lf" % sqrt(calculate_cost(X_train,Y_train))
             print "Validation RMSE : %lf" % sqrt(calculate_cost(X_val,Y_val))
             print "Testing RMSE : %f" % sqrt(calculate_cost(X_test,Y_test))
             print "\n"
```

```
Iterations : 1000
Last Cost: 38267044153.940788
Second Last Cost: 38267701364.602348
Learning rate: 1.600000
w0: 118016.137979
w1: 3015301.335410
w2: 1900764.343344
w3: 765766.011798
w4: 186357.980603
w5 : -81680.798105
w6 : -207135.000320
w7 : -268149.724718
w8 : -299023.681177
w9: -315175.768948
w10 : -323848.907232
w11 : -328599.467459
w12 : -331241.164310
w13 : -332727.416927
w14 : -333571.324954
w15 : -334054.065101
w16 : -334331.897824
Training RMSE: 195619.641534
Validation RMSE: 126727.687114
Testing RMSE: 115024.568709
```

print "Testing RMSE : %f" % sqrt(calculate cost(X test,Y test)) In [194]: def predict(x,x2 new,x3 new,x4 new,x5 new,x6 new,x7 new,x8 new,x9 new,x1 0 new, x11 new, x12 new, x13 new, x14 new, x15 new, x16 new): return float(W mat[0]) + float(W mat[1])*x + float(W mat[2])*x2 new + float(W mat[3])*x3 new + float(W mat[4])*x4 new + float(W mat[5])*x5 n ew + float(W mat[6])*x6 new + float(W mat[7])*x7 new + float(W mat[8])*x 8 new + float(W mat[9])*x8 new + float(W mat[10])*x10 new + float(W mat[11])*x11_new + float(W_mat[12])*x12_new + float(W_mat[13])*x13_new + flo at(W mat[14])*x14 new + float(W mat[15])*x15 new + float(W mat[16])*x16 new Y train list = Y train.T[0].tolist()[0] X train list = X train[:,1].T.tolist()[0] Y pred = [] for x,x2,x3,x4,x5,x6,x7,x8,x9,x10,x11,x12,x13,x14,x15,x16 in zip(X train _list,np.power(X_train_list,2),np.power(X_train_list,3),np.power(X_train_ _list,4),np.power(X_train_list,5),np.power(X_train list,6),np.power(X tr ain list,7),np.power(X train list,8),np.power(X train list,9),np.power(X train list,10),np.power(X train list,11),np.power(X train list,12),np.p ower(X train list,13),np.power(X train list,14),np.power(X train list,15),np.power(X train list,16)): Y pred.append(predict(x,x2,x3,x4,x5,x6,x7,x8,x9,x10,x11,x12,x13,x14, x15, x16))

Testing RMSE: 115024.568709

In [195]: plot_data(X_train_list,Y_train_list,Y_pred)



Best result achieved with Learning rate: 1.6

Iterations: 1000

Last Cost: 38267044153.940788

Second Last Cost: 38267701364.602348

Learning rate: 1.600000

Training RMSE: 195619.641534 Validation RMSE: 126727.687114 Testing RMSE: 115024.568709

2-5. Fit the data using 16th order polynomial regression model with ridge (L2 penalty) regularization.

You need to try at least 3 different L2 penalty (for example, λ = 0.1, 1, 10). Plot the training and validation data with the fitted line. Search optimum L2 penalty based on Root Mean Squared Error (RMSE) of validation data. Print optimized weight coefficients. Plot weight coefficients with L2 penalty. Print Root Mean Squared Error (RMSE) for training/validation/test data. Note: Do not forget feature normalization.

```
In [196]: def calculate cost(y, X mat, Y mat):
              result = np.dot((np.matmul(X_mat,W_mat) - Y_mat).T,(np.matmul(X_mat
           ,W mat) - Y mat))
              result /=m
              result += (y/m*np.sum(np.power(W_mat,2)))
              return float(result)
          def cost derivative(y, X mat, Y mat):
              result = (np.matmul(np.matmul(X mat.T, X mat), W mat) - (np.matmul(X mat
           .T,Y_mat)))
              result *= 2
              result /=m
              result += 2 * y/m
              return result
          def calculate_weights(rate,y,X_mat,Y_mat):
              global W mat
              W mat = W mat - rate*cost derivative(y, X mat, Y mat)
```

```
In [207]: np.random.seed(1)
    X_train, X_test, Y_train, Y_test = train_test_split(X_mat,Y_mat,train_si
    ze=0.8)
    X_train, X_val, Y_train, Y_val = train_test_split(X_train,Y_train,train_size=.75)
```

```
In [208]: Weights = []
          for rate in learning rates:
              for y in lambdas:
                 , 0., 0., 0., 0., 0., 0., 0., 0.])).T
                 count = 0
                 max count = 1000
                 current cost = calculate cost(y, X train, Y train)
                 new cost = 0
                 while new_cost < current_cost and count < max_count:</pre>
                      current_cost = calculate_cost(y,X_train,Y_train)
                      calculate_weights(rate,y,X_train,Y_train)
                     new_cost = calculate_cost(y,X_train,Y_train)
                      count += 1
                 Weights.append(list(W_mat.T[0].tolist()[0]))
                 print "Penalty : %f" % y
                 print "Iterations : %d" % count
                 print "Last Cost : %lf" % new cost
                 print "Second Last Cost : %f " % current cost
                 print "Learning rate : %f " % rate
                 print "Training RMSE : %lf" % sqrt(calculate cost(y, X train, Y tr
          ain))
                 print "Validation RMSE : %lf" % sqrt(calculate_cost(y,X_val,Y_va
          1))
                 print "Testing RMSE : %f" % sqrt(calculate_cost(y,X_test,Y_test
          ))
                 print "w0 : %f " % W mat[0]
                 print "w1 : %f" % W mat[1]
                 print "w2 : %f" % W mat[2]
                 print "w3 : %f" % W mat[3]
                 print "w4 : %f" % W mat[4]
                 print "w5 : %f" % W mat[5]
                 print "w6 : %f" % W mat[6]
                 print "w7 : %f" % W mat[7]
                 print "w8 : %f" % W mat[8]
                 print "w9 : %f" % W mat[9]
                 print "w10 : %f" % W mat[10]
                 print "w11 : %f" % W mat[11]
                 print "w12 : %f" % W mat[12]
                 print "w13 : %f" % W mat[13]
                 print "w14 : %f" % W_mat[14]
                 print "w15 : %f" % W mat[15]
                 print "w16 : %f" % W mat[16]
                 print "\n"
              print "\n*********************
```

Penalty : 0.000001 Iterations : 1000

Last Cost : 38308703380.020905

Second Last Cost: 38309337198.841820

Learning rate: 1.500000

Training RMSE: 195726.092742
Validation RMSE: 126935.336170
Testing RMSE: 115104.114733

w0 : 116595.873868 w1 : 3035400.129910

w2: 1854164.443659

w3 : 736441.687879

w4: 174516.232992

w5: -83768.213062

w6: -204268.767799

w7 : -262777.724847

w8 : -292361.006726

w9 : -307834.211135

w10 : -316143.646962

w11 : -320696.460765

w12 : -323229.395185

w13 : -324655.289779

w14 : -325465.467936 w15 : -325929.255820

w16 : -326196.393784

Penalty : 0.001000

Iterations : 1000

Last Cost: 38311340865.985359

Second Last Cost: 38311974271.065613

Learning rate: 1.500000

Training RMSE : 195732.830322 Validation RMSE : 126945.724840

Testing RMSE : 115115.571121

w0 : 116595.873867

w1: 3035400.129929

w2: 1854164.443636

w3: 736441.687830

w4: 174516.232930

w5: -83768.213130

w6 : -204268.767869

w7 : -262777.724920

w8 : -292361.006799

w9 : -307834.211209

w10 : -316143.647036

w11 : -320696.460839

w12 : -323229.395259

w13 : -324655.289853

w14 : -325465.468011

w15 : -325929.255895

w16 : -326196.393858

Penalty : 0.010000 Iterations : 1000

Last Cost: 38335102000.807541

Second Last Cost: 38335731678.494476 Learning rate: 1.500000 Training RMSE : 195793.518792 Validation RMSE: 127039.278157 Testing RMSE: 115218.730464 w0: 116595.873851 w1: 3035400.130108 w2: 1854164.443424 w3: 736441.687387 w4: 174516.232376 w5: -83768.213738 w6 : -204268.768505w7 : -262777.725570w8 : -292361.007458 w9 : -307834.211871w10 : -316143.647702 w11 : -320696.461506 w12 : -323229.395927w13 : -324655.290521w14 : -325465.468679w15 : -325929.256563

Penalty: 0.100000 Iterations: 1000

w16 : -326196.394527

Last Cost: 38572713349.755852

Second Last Cost: 38573305753.509407

Learning rate: 1.500000 Training RMSE : 196399.372071 Validation RMSE: 127971.049811 Testing RMSE: 116245.288951

w0 : 116595.873700 w1: 3035400.131890 w2: 1854164.441303 w3: 736441.682962 w4: 174516.226832 w5: -83768.219825 w6 : -204268.774866w7 : -262777.732076 w8 : -292361.014042 w9 : -307834.218500

w10 : -316143.654356w11 : -320696.468175 w12 : -323229.402604w13 : -324655.297204 w14 : -325465.475365

w15 : -325929.263251w16 : -326196.401215

Penalty: 0.500000 Iterations: 1000

Last Cost: 39628763805.506134

Second Last Cost: 39629190547.329109

Learning rate: 1.500000

Training RMSE: 199069.746083

Validation RMSE: 132032.724165 Testing RMSE: 120702.185896 w0: 116595.873028

w1 : 3035400.139812

w2 : 1854164.431880

w3 : 736441.663293

w4 : 174516.202196

w5 : -83768.246875

w6 : -204268.803137

w7 : -262777.760990

w8 : -292361.043307

w9 : -307834.247962

w10 : -316143.683930

w11 : -320696.497814

w12 : -323229.432281

w13 : -324655.326903

w14 : -325465.505078

w15 : -325929.292972

w16 : -326196.430941

Penalty : 1.000000 Iterations : 1000

Last Cost: 40948826911.882820

Second Last Cost: 40949046576.282272

Learning rate : 1.500000
Training RMSE : 202358.164925

Validation RMSE: 136940.511220 Testing RMSE: 126051.897298

w0 : 116595.872188

w1: 3035400.149714

w2: 1854164.420100

w3 : 736441.638708

w4 : 174516.171399

w5 : -83768.280689

w6 : -204268.838476

w7 : -262777.797132

w8 : -292361.079888

w9 : -307834.284789

w10 : -316143.720897

w11 : -320696.534862

w12 : -323229.469377

w13 : -324655.364028

w14 : -325465.542219

w15 : -325929.330123

w16 : -326196.468099

Penalty : 10.000000 Iterations : 101

Last Cost: 54594969066.124763

Second Last Cost: 54594646312.234482

Learning rate: 1.500000

Training RMSE: 233655.663458
Validation RMSE: 171995.151525
Testing RMSE: 160342.952639

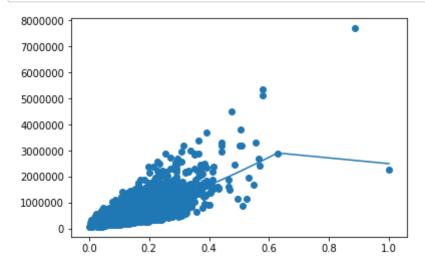
w0 : 255230.119558

```
w1: 2131692.010072
w2: 858002.166318
w3: 318644.691096
w4: 121082.326114
w5: 45041.089423
w6: 13181.742053
w7 : -1316.328854
w8: -8381.384108
w9 : -12009.509321
w10 : -13946.058846
w11 : -15009.251687
w12 : -15605.165640
w13 : -15944.383917
w14 : -16139.787005
w15 : -16253.405274
w16 : -16319.972238
```

```
In [203]: print "Testing RMSE : %f" % sqrt(calculate cost(y, X test, Y test))
          def predict(x,x2_new,x3_new,x4_new,x5_new,x6_new,x7_new,x8_new,x9_new,x1
          0_new,x11_new,x12_new,x13_new,x14_new,x15_new,x16_new):
              return float(W_mat[0]) + float(W_mat[1])*x + float(W_mat[2])*x2 new
          + float(W mat[3])*x3 new + float(W mat[4])*x4 new + float(W mat[5])*x5 n
          ew + float(W mat[6])*x6 new + float(W mat[7])*x7 new + float(W mat[8])*x
          8 new + float(W mat[9])*x8 new + float(W mat[10])*x10 new + float(W mat[
          11])*x11 new + float(W mat[12])*x12 new + float(W mat[13])*x13 new + flo
          at(W mat[14])*x14 new + float(W mat[15])*x15 new + float(W mat[16])*x16
          Y train list = Y train.T[0].tolist()[0]
          X train list = X train[:,1].T.tolist()[0]
          Y pred = []
          for x,x2,x3,x4,x5,x6,x7,x8,x9,x10,x11,x12,x13,x14,x15,x16 in zip(X train
          list,np.power(X train list,2),np.power(X train list,3),np.power(X train
          list,4),np.power(X train list,5),np.power(X train list,6),np.power(X tr
          ain list,7),np.power(X train list,8),np.power(X train list,9),np.power(X
          train list,10),np.power(X train list,11),np.power(X train list,12),np.p
          ower(X train list,13),np.power(X train list,14),np.power(X train list,15
          ),np.power(X train list,16)):
              Y pred.append(predict(x,x2,x3,x4,x5,x6,x7,x8,x9,x10,x11,x12,x13,x14,
          x15, x16))
```

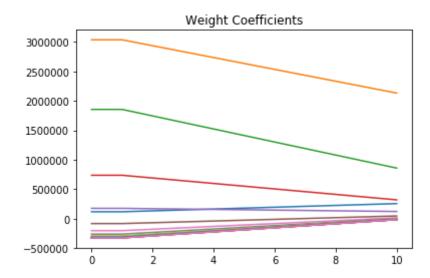
Testing RMSE: 115104.114733

In [204]: plot_data(X_train_list,Y_train_list,Y_pred)



In [209]: plt.plot(lambdas, Weights)
 plt.title("Weight Coefficients")

Out[209]: Text(0.5,1,u'Weight Coefficients')



Best result achieved with Learning rate: 1.5 and Penalty: 0.000001

Penalty: 0.000001 Iterations: 1000

Last Cost: 38308703380.020905

Second Last Cost: 38309337198.841820

Learning rate: 1.500000

Training RMSE: 195726.092742 Validation RMSE: 126935.336170 Testing RMSE: 115104.114733

2-6. Fit the data using 16th order polynomial regression model with scikit-learn Ridge model.

You need to try at least 3 different L2 penalty (for example, $\lambda = 0.1$, 1, 10). Plot the data with the fitted line. Print optimized weight coefficients. Plot weight coefficients with L2 penalty. Print Root Mean Squared Error (RMSE)

```
In [223]: X mat = np.asmatrix(np.column stack((X,X2 new,X3 new,X4 new,X5 new,X6 ne
          w, X7 new, X8 new, X9 new, X10 new, X11 new, X12 new, X13 new, X14 new, X15 new, X
           16 new)))
          Y mat = np.asmatrix((np.row stack((Y))))
           lambdas = [0.001, 0.01, 0.1, 0.5, 1, 10]
          np.random.seed(1)
In [224]:
          X train, X test, Y train, Y test = train test split(X mat,Y mat,train si
           ze=0.8)
          X_train, X_val, Y_train, Y_val = train_test_split(X_train,Y_train,train_
          size=.75)
In [225]:
          ridge_model.coef_[0].tolist()
Out[225]: [665765.6753544116,
           8840151.31867511,
           1315529.311467773,
           -2311763.6565368623,
           -3045537.360111652,
           -2847116.0996238044,
           -2311923.551615864,
           -1646165.3806960688,
           -975526.9670156973,
           -377796.7111575216,
            112826.78280068895,
           492863.246710301,
            775178.3043666402,
           978525.6526114416,
           1121630.1119295966,
            1220560.2061928147]
```

```
In [226]: Weights = []
          for y in lambdas:
              ridge_model = Ridge(alpha=y)
              ridge_model.fit(X_train,Y_train)
              Y pred train = ridge model.predict(X train)
              print "For Penalty : %f" % y
              print "Training RMSE is %f " % sqrt(mean squared error(Y train, Y pre
          d train))
              Y_pred_val = ridge_model.predict(X_val)
              print "Validation RMSE is %f " % sqrt(mean_squared_error(Y_val,Y_pre
          d val))
              Y_pred_test = ridge_model.predict(X_test)
              print "Testing RMSE is %f " % sqrt(mean squared error(Y test,Y pred
          test))
              Weights.append(ridge_model.coef_[0].tolist())
              print "*****"
```

```
For Penalty : 0.001000
Training RMSE is 247033.264775
Validation RMSE is 291390.622584
Testing RMSE is 250848.208917
*****
For Penalty : 0.010000
Training RMSE is 247154.313072
Validation RMSE is 274156.296095
Testing RMSE is 250494.248332
*****
For Penalty : 0.100000
Training RMSE is 247892.814229
Validation RMSE is 266771.588713
Testing RMSE is 250986.546430
*****
For Penalty : 0.500000
Training RMSE is 250264.482379
Validation RMSE is 275070.845456
Testing RMSE is 254294.074698
*****
For Penalty : 1.000000
Training RMSE is 252129.041130
Validation RMSE is 281240.664697
Testing RMSE is 256812.365615
*****
For Penalty : 10.000000
Training RMSE is 272041.229976
Validation RMSE is 315040.501230
Testing RMSE is 279748.466602
*****
```

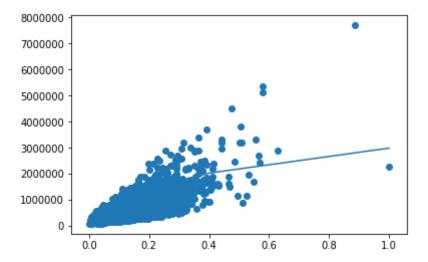
```
In [227]: print "Optimized weights"
          print "w0 : %f" % ridge model.intercept
          print "w1 : %f" % ridge_model.coef_[0][0]
          print "w2 : %f" % ridge_model.coef_[0][1]
          print "w3 : %f" % ridge_model.coef_[0][2]
          print "w4 : %f" % ridge model.coef [0][3]
          print "w5 : %f" % ridge_model.coef_[0][4]
          print "w6 : %f" % ridge model.coef [0][5]
          print "w7 : %f" % ridge_model.coef_[0][6]
          print "w8 : %f" % ridge_model.coef_[0][7]
          print "w9 : %f" % ridge model.coef [0][8]
          print "w10 : %f" % ridge_model.coef [0][9]
          print "w11 : %f" % ridge_model.coef_[0][10]
          print "w12 : %f" % ridge model.coef [0][11]
          print "w13 : %f" % ridge_model.coef_[0][12]
          print "w14 : %f" % ridge_model.coef_[0][13]
          print "w15 : %f" % ridge_model.coef_[0][14]
          print "w16 : %f" % ridge_model.coef_[0][15]
```

w1 : 2099831.709608 w2 : 895726.391701 w3 : 322005.646642 w4 : 96915.418437 w5 : 6212.925388 w6 : -32976.216733 w7 : -51165.974260 w8 : -60134.953940 w9 : -64769.088937 w10 : -67248.231829

w11 : -68608.904666 w12 : -69370.021274 w13 : -69801.914621 w14 : -70049.726503 w15 : -70193.176525 w16 : -70276.815866

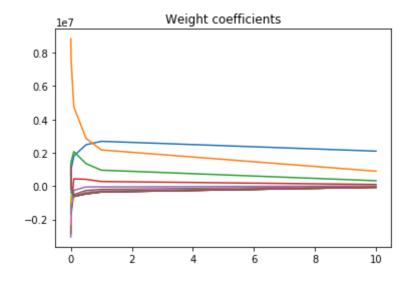
Optimized weights w0: 257876.883126

```
In [228]: Y_train_list = Y_train.T[0].tolist()[0]
X_train_list = X_train[:,1].T.tolist()[0]
plot_data(X_train_list,Y_train_list,Y_pred_train)
```



```
In [229]: plt.plot(lambdas, Weights)
   plt.title("Weight coefficients")
```

Out[229]: Text(0.5,1,u'Weight coefficients')



Best result achieved for penalty: 0.001

For Penalty: 0.001000

Training RMSE is 247033.264775 Validation RMSE is 291390.622584 Testing RMSE is 250848.208917

2-7. Fit the data using 16th order polynomial regression model with scikit-learn Lasso model.

You need to try at least 3 different L1 penalty (for example, λ = 0.1, 1, 10). Plot the data with the fitted line. Print optimized weight coefficients. Plot weight coefficients with L2 penalty. Print Root Mean Squared Error (RMSE) Deep Learning, CMPE 258-01, Spring, 2018 Page 3 of 3

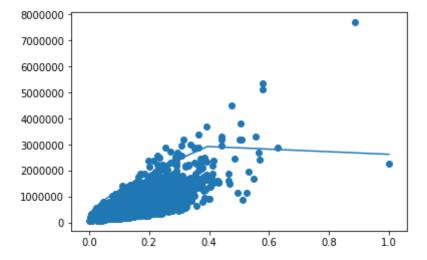
```
Assignment-2_Tanmay_Bhatt_v2
In [232]: Weights = []
          for y in lambdas:
              lasso_model = Ridge(alpha=y)
              lasso_model.fit(X_train,Y_train)
              Y pred train = lasso model.predict(X train)
              print "For Penalty : %f" % y
              print "Training RMSE is %f " % sqrt(mean squared error(Y train, Y pre
          d train))
              Y_pred_val = lasso_model.predict(X_val)
              print "Validation RMSE is %f " % sqrt(mean squared_error(Y_val,Y_pre
          d val))
              Y pred_test = lasso_model.predict(X_test)
              print "Testing RMSE is %f " % sqrt(mean squared error(Y test,Y pred
          test))
              Weights.append(lasso model.coef [0])
              print "*****"
          For Penalty : 0.000010
          Training RMSE is 246926.796974
          Validation RMSE is 515419.686061
          Testing RMSE is 251168.443908
          *****
          For Penalty : 0.000010
          Training RMSE is 246926.796974
          Validation RMSE is 515419.686061
```

Testing RMSE is 251168.443908 ***** For Penalty : 0.001000 Training RMSE is 247033.264775 Validation RMSE is 291390.622584 Testing RMSE is 250848.208917 ***** For Penalty : 0.010000 Training RMSE is 247154.313072 Validation RMSE is 274156.296095 Testing RMSE is 250494.248332 ***** For Penalty : 0.100000 Training RMSE is 247892.814229 Validation RMSE is 266771.588713 Testing RMSE is 250986.546430 ***** For Penalty : 0.500000 Training RMSE is 250264.482379 Validation RMSE is 275070.845456 Testing RMSE is 254294.074698 ***** For Penalty : 1.000000 Training RMSE is 252129.041130 Validation RMSE is 281240.664697 Testing RMSE is 256812.365615 *****

```
In [233]: print "Optimized weights"
          print "w0 : %f" % lasso model.intercept
          print "w1 : %f" % lasso_model.coef_[0][0]
          print "w2 : %f" % lasso_model.coef_[0][1]
          print "w3 : %f" % lasso_model.coef_[0][2]
          print "w4 : %f" % lasso model.coef [0][3]
          print "w5 : %f" % lasso_model.coef_[0][4]
          print "w6 : %f" % lasso model.coef [0][5]
          print "w7 : %f" % lasso_model.coef_[0][6]
          print "w8 : %f" % lasso_model.coef_[0][7]
          print "w9 : %f" % lasso model.coef [0][8]
          print "w10 : %f" % lasso_model.coef_[0][9]
          print "w11 : %f" % lasso model.coef [0][10]
          print "w12 : %f" % lasso model.coef [0][11]
          print "w13 : %f" % lasso_model.coef_[0][12]
          print "w14 : %f" % lasso_model.coef_[0][13]
          print "w15 : %f" % lasso_model.coef_[0][14]
          print "w16 : %f" % lasso_model.coef_[0][15]
```

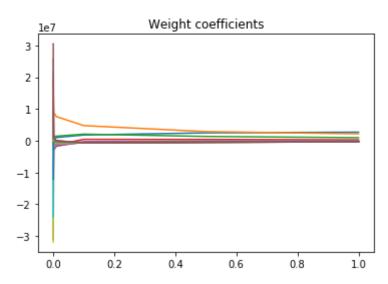
```
Optimized weights
w0 : 152733.737942
w1 : 2689215.825887
w2: 2171559.712919
w3: 957449.929432
w4: 275949.240208
w5 : -48179.228228
w6 : -200798.796796
w7: -274753.922998
w8 : -311850.352944
w9 : -331030.659962
w10 : -341188.198416
w11 : -346666.440737
w12 : -349661.839278
w13 : -351316.712050
w14 : -352238.208628
w15 : -352754.442531
w16 : -353044.997538
```

```
In [234]: Y_train_list = Y_train.T[0].tolist()[0]
X_train_list = X_train[:,1].T.tolist()[0]
plot_data(X_train_list,Y_train_list,Y_pred_train)
```



```
In [235]: plt.plot(lambdas, Weights)
    plt.title("Weight coefficients")
```

Out[235]: Text(0.5,1,u'Weight coefficients')



3 (40pts). Regularization with Tensorflow

Using Jupyter notebook, load the data (ex2data3.csv). This is California housing dataset. The original database is available from http://lib.stat.cmu.edu (http://lib.stat.cmu.edu). The data contains 20,640 observations on 9 variables. This dataset contains the average house value as target variable and the following input variables (features): average income, housing average age, average rooms, average bedrooms, population, average occupation, latitude, and longitude (R. Kelley and Ronald Barry, Sparse Spatial Autoregressions,\ Statistics and Probability Letters, 33 (1997) 291-297). You need to split the data into training/validation/testing data set as 60% / 20% / 20%. Please use np.random.seed(1) to have consistent data for evaluation.

```
In [236]:
          import tensorflow as tf
          from sklearn.datasets import fetch california housing
          housing = fetch_california_housing()
          m = len(housing.data)
In [237]:
          print m
          20640
In [238]:
          temp = pd.Series( (1 for i in range(0,m)) )
In [239]: X = housing.data[:,:-1]
          X = (X - np.mean(X))/np.std(X,axis=0) # Z-score normalization
          #X = minmax normalize(X) # Min-Max Normalization
          Y = housing.data[:,-1]
          X mat = np.asmatrix(np.column_stack((temp,X,np.power(X,2),np.power(X,3),
In [240]:
          np.power(X,4)))
          W_{mat} = np.asmatrix(np.array([0., 0., 0., 0., 0.])).T
          Y mat = np.asmatrix((np.row stack((Y))))
In [241]: np.random.seed(1)
          X train, X test, Y train, Y test = train test split(X mat, Y mat, train si
          ze=0.8,test_size=0.2)
          X train, X val, Y train, Y val = train test split(X train, Y train, train
          size=0.75)
```

3-1. Fit the training data using regression model with ridge (L2 penalty) regularization with scikit-learn Ridge model.

You need to try at least 3 different L2 penalty (for example, λ = 0.1, 1, 10). Search optimum L2 penalty based on Root Mean Squared Error (RMSE) of validation data. Print optimized weight coefficients. Plot weight coefficients with L2 penalty. Print Root Mean Squared Error (RMSE) for training/validation/test data. Note: Do not forget feature normalization

```
lambdas = [0.001, 0.01, 0.1, 0.5, 1, 10]
In [242]:
          Weights = []
          for y in lambdas:
              ridge_model = Ridge(alpha=y)
              ridge_model.fit(X_train,Y_train)
              Y pred train = ridge model.predict(X train)
              print "For Penalty : %f" % y
              print "Training RMSE is %f " % sqrt(mean_squared_error(Y_train,Y_pre
          d_train))
              Y_pred_val = ridge_model.predict(X_val)
              print "Validation RMSE is %f " % sqrt(mean_squared_error(Y_val,Y_pre
          d_val))
              Y_pred_test = ridge_model.predict(X_test)
              print "Testing RMSE is %f " % sqrt(mean_squared_error(Y_test,Y_pred_
          test))
              Weights.append(ridge_model.coef_[0].tolist())
```

For Penalty : 0.001000 Training RMSE is 0.595994 Validation RMSE is 1.262650 Testing RMSE is 0.615572 For Penalty : 0.010000 Training RMSE is 0.596048 Validation RMSE is 1.069546 Testing RMSE is 0.615585 For Penalty : 0.100000 Training RMSE is 0.596186 Validation RMSE is 0.982930 Testing RMSE is 0.615400 For Penalty : 0.500000 Training RMSE is 0.597573 Validation RMSE is 0.983680 Testing RMSE is 0.615853 For Penalty : 1.000000 Training RMSE is 0.599339 Validation RMSE is 0.989856 Testing RMSE is 0.616987 For Penalty : 10.000000 Training RMSE is 0.606051 Validation RMSE is 0.985867 Testing RMSE is 0.622163

Assignment-2_Tanmay_Bhatt_v2 /anaconda2/lib/python2.7/site-packages/scipy/linalg/basic.py:40: Runtim eWarning: scipy.linalg.solve Ill-conditioned matrix detected. Result is not guaranteed to be accurat Reciprocal condition number/precision: 7.09812343614e-25 / 1.1102230246 3e-16 RuntimeWarning) /anaconda2/lib/python2.7/site-packages/scipy/linalg/basic.py:40: Runtim eWarning: scipy.linalg.solve Ill-conditioned matrix detected. Result is not guaranteed to be accurat Reciprocal condition number/precision: 6.64937854392e-24 / 1.1102230246 3e-16 RuntimeWarning) /anaconda2/lib/python2.7/site-packages/scipy/linalg/basic.py:40: Runtim eWarning: scipy.linalg.solve Ill-conditioned matrix detected. Result is not guaranteed to be accurat Reciprocal condition number/precision: 6.6026631313e-23 / 1.11022302463 e-16 RuntimeWarning) /anaconda2/lib/python2.7/site-packages/scipy/linalg/basic.py:40: Runtim eWarning: scipy.linalg.solve Ill-conditioned matrix detected. Result is not guaranteed to be accurat e. Reciprocal condition number/precision: 3.30190324587e-22 / 1.1102230246 3e-16 RuntimeWarning) /anaconda2/lib/python2.7/site-packages/scipy/linalg/basic.py:40: Runtim eWarning: scipy.linalg.solve Ill-conditioned matrix detected. Result is not guaranteed to be accurat Reciprocal condition number/precision: 6.61032603098e-22 / 1.1102230246 3e-16 RuntimeWarning)

/anaconda2/lib/python2.7/site-packages/scipy/linalg/basic.py:40: Runtim eWarning: scipy.linalg.solve

Ill-conditioned matrix detected. Result is not guaranteed to be accurat

Reciprocal condition number/precision: 6.72407587202e-21 / 1.1102230246 3e-16

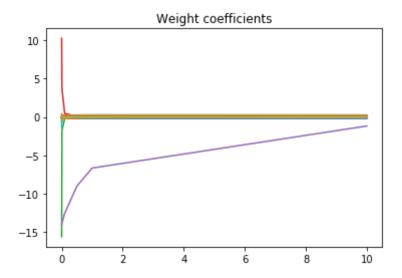
RuntimeWarning)

```
In [243]: print "Optimized weights"
          print "w0 : %f" % ridge model.intercept
          print "w1 : %f" % ridge_model.coef_[0][0]
          print "w2 : %f" % ridge_model.coef_[0][1]
          print "w3 : %f" % ridge_model.coef_[0][2]
          print "w4 : %f" % ridge model.coef [0][3]
          print "w5 : %f" % ridge_model.coef_[0][4]
          print "w6 : %f" % ridge model.coef [0][5]
          print "w7 : %f" % ridge_model.coef_[0][6]
          print "w8 : %f" % ridge_model.coef_[0][7]
          print "w9 : %f" % ridge model.coef [0][8]
          print "w10 : %f" % ridge_model.coef [0][9]
          print "w11 : %f" % ridge model.coef [0][10]
          print "w12 : %f" % ridge model.coef [0][11]
          print "w13 : %f" % ridge_model.coef_[0][12]
          print "w14 : %f" % ridge_model.coef_[0][13]
          print "w15 : %f" % ridge_model.coef_[0][14]
          print "w16 : %f" % ridge_model.coef_[0][15]
```

```
Optimized weights
w0 : -5723.100988
w1 : 0.000000
w2 : 0.000629
w3 : -0.029631
w4 : 0.004126
w5 : -0.000769
w6 : -0.118405
w7 : -0.131393
w8 : 0.020867
w9 : -0.050142
w10 : 0.271262
w11 : -0.169139
w12 : 0.236023
w13 : 0.030443
w14 : -0.000424
w15 : -1.164594
w16 : -0.000279
```

```
In [244]: plt.plot(lambdas, Weights)
   plt.title("Weight coefficients")
```

Out[244]: Text(0.5,1,u'Weight coefficients')



3-2. Fit the training data using regression model with lasso (L1 penalty) regularization with scikit-learn Lasso model.

You need to try at least 3 different L1 penalty (for example, λ = 0.1, 1, 10). Search optimum L1 penalty based on Root Mean Squared Error (RMSE) of validation data. Print optimized weight coefficients. Plot weight coefficients with L2 penalty. Print Root Mean Squared Error (RMSE) for training/validation/test data. Note: Do not forget feature normalization

```
lambdas = [0.001, 0.01, 0.1]
In [245]:
          Weights = []
          for y in lambdas:
              lasso_model = Lasso(alpha=y)
              lasso_model.fit(X_train,Y_train)
              Y_pred_train = lasso_model.predict(X train)
              print "For Penalty : %f" % y
              print "Training RMSE is %f " % sqrt(mean squared error(Y train,Y pre
          d train))
              Y_pred_val = lasso_model.predict(X_val)
              print "Validation RMSE is %f " % sqrt(mean squared error(Y val,Y pre
          d_val))
              Y_pred_test = lasso_model.predict(X_test)
              print "Testing RMSE is %f " % sqrt(mean squared error(Y test,Y pred
          test))
              Weights.append(lasso_model.coef_)
```

For Penalty: 0.001000
Training RMSE is 0.640461
Validation RMSE is 0.636043
Testing RMSE is 0.657463
For Penalty: 0.010000
Training RMSE is 0.643844
Validation RMSE is 0.637571
Testing RMSE is 0.661647
For Penalty: 0.100000
Training RMSE is 0.645881
Validation RMSE is 0.638607
Testing RMSE is 0.661652

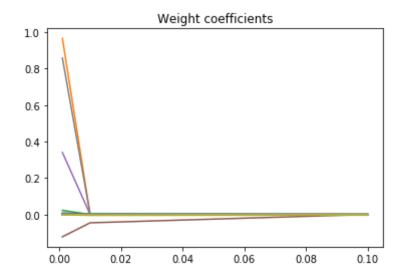
```
In [246]: print "Optimized weights"
          print "w0 : %f" % lasso model.intercept
          print "w1 : %f" % lasso_model.coef_[0]
          print "w2 : %f" % lasso_model.coef_[1]
          print "w3 : %f" % lasso_model.coef_[2]
          print "w4 : %f" % lasso model.coef [3]
          print "w5 : %f" % lasso model.coef [4]
          print "w6 : %f" % lasso model.coef [5]
          print "w7 : %f" % lasso_model.coef_[6]
          print "w8 : %f" % lasso_model.coef_[7]
          print "w9 : %f" % lasso model.coef [8]
          print "w10 : %f" % lasso_model.coef [9]
          print "w11 : %f" % lasso_model.coef_[10]
          print "w12 : %f" % lasso model.coef [11]
          print "w13 : %f" % lasso_model.coef_[12]
          print "w14 : %f" % lasso_model.coef_[13]
          print "w15 : %f" % lasso_model.coef_[14]
          print "w16 : %f" % lasso_model.coef_[15]
```

Optimized weights

```
w0 : -83.200804
w1 : 0.000000
w2 : 0.000000
w3 : -0.000000
w4 : -0.000000
w5 : 0.000000
w6 : -0.000000
w7 : -0.000000
w8 : 0.000000
w9 : -0.003616
w10 : 0.000000
w11 : 0.001032
w12 : -0.000848
w13 : -0.000000
w14 : -0.000000
w15 : -0.001740
w16 : -0.000012
```

```
In [247]: plt.plot(lambdas, Weights)
   plt.title("Weight coefficients")
```

Out[247]: Text(0.5,1,u'Weight coefficients')



3-3. Fit the training data using regression model with ridge (L2 penalty) regularization using TensorFlow.

You need to make gradient descent method instead of open source algorithm. You need to try at least 3 different L2 penalty (for example, λ = 0.1, 1, 10). Search optimum L2 penalty based on Root Mean Squared Error (RMSE) of validation data. Print optimized weight coefficients. Plot weight coefficients with L2 penalty. Print Root Mean Squared Error (RMSE) for training/validation/test data. Note: Do not forget feature normalization.

```
In [249]: x = tf.placeholder(tf.float32,[None,X_train.shape[1]])
y = tf.placeholder(tf.float32,[None,1])
```

```
In [251]: w = tf.zeros([len(housing.data[0])+1, 1], tf.float32)
          lamb = 0.1
          rate = 1
          y_pred = tf.matmul(x, w)
          error = y pred - y
          rmse = tf.sqrt(tf.reduce_mean(tf.square(error), name="rmse"))
          cost = tf.add(rmse, (y/m)* tf.reduce_sum(tf.square(w)))
          gradients = (2/m)*tf.add(tf.matmul(tf.transpose(x), error), (y*w))
          get_new_weights = tf.assign(w, w - rate*gradients)
          learning_rates = [0.0001,0.001,0.01,0.1,1]
          lambdas = [0.01, 0.1, 0.5, 1, 10]
          Weights = []
          n = pochs = 1000
          init = tf.global_variables_initializer()
          with tf.Session() as sess:
              for epoch in range(n_epochs):
                  sess.run(get_new_weights, feed_dict={X:X_train, Y:Y_train})
                  if epoch % 100 == 0:
                      print("Epoch", epoch, "RMSE =", rmse.eval())
              Y pred train = sess.run(y pred, feed dict={X: X train})
              train_rmse = math.sqrt(sess.run(rmse, feed_dict={X:X_train, Y:Y_trai
          n}))
              Y pred val = sess.run(y pred, feed dict={X: X valid tf})
              val rmse = math.sqrt(sess.run(rmse, feed_dict={X:X_val, Y:Y_val}))
              print "Training RMSE is : %f" % train rmse
              print "Validation RMSE is : %f " % val rmse
```

```
Traceback (most recent call 1
ValueError
ast)
<ipython-input-251-8dd25a45c048> in <module>()
      2 \text{ lamb} = 0.1
      3 rate = 1
---> 4 y pred = tf.matmul(x, w)
      5 error = y_pred - y
      6 rmse = tf.sqrt(tf.reduce_mean(tf.square(error), name="rmse"))
/anaconda2/lib/python2.7/site-packages/tensorflow/python/ops/math ops.p
yc in matmul(a, b, transpose a, transpose b, adjoint a, adjoint b, a is
_sparse, b_is_sparse, name)
   1799
            else:
   1800
              return gen_math_ops. mat_mul(
-> 1801
                  a, b, transpose a=transpose a, transpose b=transpose
b, name=name)
   1802
   1803
/anaconda2/lib/python2.7/site-packages/tensorflow/python/ops/gen_math_o
ps.pyc in mat mul(a, b, transpose a, transpose b, name)
   1261
   1262
          result = _op_def_lib.apply_op("MatMul", a=a, b=b, transpose_a
=transpose_a,
-> 1263
                                         transpose b=transpose b, name=n
ame)
          return result
   1264
   1265
/anaconda2/lib/python2.7/site-packages/tensorflow/python/framework/op d
ef library.pyc in apply op(self, op type name, name, **keywords)
    766
                op = g.create op(op type name, inputs, output types, na
me=scope,
    767
                                  input types=input types, attrs=attr pr
otos,
--> 768
                                 op def=op def)
    769
                if output_structure:
    770
                  outputs = op.outputs
/anaconda2/lib/python2.7/site-packages/tensorflow/python/framework/ops.
pyc in create op(self, op type, inputs, dtypes, input types, name, attr
s, op def, compute shapes, compute device)
   2336
                            original op=self. default original op, op d
ef=op def)
   2337
            if compute shapes:
-> 2338
              set shapes for outputs(ret)
   2339
            self. add op(ret)
   2340
            self. record op seen by control dependencies(ret)
/anaconda2/lib/python2.7/site-packages/tensorflow/python/framework/ops.
pyc in set shapes for outputs(op)
   1717
              shape func = call cpp shape fn and require op
   1718
-> 1719
          shapes = shape func(op)
   1720
          if shapes is None:
```

```
1721 raise RuntimeError(
```

```
/anaconda2/lib/python2.7/site-packages/tensorflow/python/framework/ops.
pyc in call with requiring(op)
   1667
   1668
          def call_with_requiring(op):
            return call cpp_shape_fn(op, require_shape_fn=True)
-> 1669
   1670
   1671
          call cpp shape fn and require op = call with requiring
/anaconda2/lib/python2.7/site-packages/tensorflow/python/framework/comm
on shapes.pyc in call cpp shape fn(op, input tensors needed, input tens
ors as shapes needed, debug python shape fn, require shape fn)
            res = call cpp shape fn impl(op, input tensors needed,
    609
                                          input tensors as shapes neede
d,
--> 610
                                          debug python shape fn, requir
e_shape_fn)
            if not isinstance(res, dict):
    611
    612
              # Handles the case where call cpp shape fn impl calls un
known_shape(op).
/anaconda2/lib/python2.7/site-packages/tensorflow/python/framework/comm
on shapes.pyc in call cpp shape fn impl(op, input tensors needed, inpu
t tensors as shapes needed, debug python shape fn, require shape fn)
              missing shape fn = True
    674
    675
            else:
--> 676
              raise ValueError(err.message)
    677
    678
          if missing shape fn:
ValueError: Dimensions must be equal, but are 29 and 9 for 'MatMul' (o
p: 'MatMul') with input shapes: [?,29], [9,1].
```

3-4. Fit the training data using regression model with lasso (L1 penalty) regularization using TensorFlow.

You need to make gradient descent method instead of open source algorithm. You need to try at least 3 different L1 penalty (for example, λ = 0.1, 1, 10). Search optimum L1 penalty based on Root Mean Squared Error (RMSE) of validation data. Print optimized weight coefficients. Plot weight coefficients with L2 penalty. Print Root Mean Squared Error (RMSE) for training/validation/test data. Note: Do not forget feature normalization.