```
1 from numpy import *
 3 class HW3():
 4
 5
       def __init__(self):
           self.data = genfromtxt("crime-train.txt", names=True,
   dtype=float)
 7
           # Do all of this just to get our data into matrix form...
9
           test = []
           for x in self.data.dtype.names:
10
11
               test.append(self.data[x])
12
           test.append(ones(1595)) #include column of all ones
13
14
           self.trainData = array(test)
15
           self.trainData = transpose(self.trainData)
16
           self.t_data = genfromtxt("crime-test.txt", names=True,
17
   dtype=float)
18
19
           # Do all of this just to get our data into matrix form...
20
           test = []
           for x in self.t data.dtype.names:
21
22
               test.append(self.t_data[x])
23
24
           test.append(ones(399)) # Add intercept term
           self.testData = array(test)
25
26
           self.testData = transpose(self.testData)
27
       def linearRegression(self):
29
30
           This function is the implementation of the linear regression
   model. It splits the training/test data set
31
           into matrix X of features and vector Y of outputs.
           The weight vector is calculated as (X.T * X)^{-1} * X.T * Y
34
           Which is then utilized as the weight vector for the prediction
   model of the test data set.
37
           The RSME value is calculated using the costFunction().
           :return: None
39
           Y = self.trainData[:,0]
40
           X = self.trainData[:,1:]
41
42
           Y i = self.testData[:.0]
           X_i = self.testData[:,1:]
43
```

```
44
           W = dot(dot(linalg.inv(dot(transpose(X),X)),transpose(X)),Y)
45
           predict = dot(X_i,transpose(W))
47
           RSME = self.costFunction(Y_i, predict, 399)
49
           print("Linear Regression RSME: {}".format(RSME))
50
51
       def linearRegressionGradientDescent(self):
           This function is the implementation of the linear regression
   model - gradient descent version.
54
           Parameters are initalized to control the model, most
   importantlyy:
           alpha - our step size
           eps - our loss tolerance
59
           theta - Our weight vector, initialized as a random vector of
   Gaussian distribution.
60
           :return: None.
           0.000
61
62
           Y = self.trainData[:, 0]
           X = self.trainData[:, 1:]
63
64
65
           Y_i = self.testData[:, 0]
           X_i = self.testData[:, 1:]
67
68
           grad = None
69
           theta = random.normal(0,1,96)
70
           alpha = 0.01
71
           eps = float('1e-7')
72
           previousLoss = self.costFunction(Y, None, 1595, theta, X)
74
           loss = None
           while True:
77
               # Use training data to calculate the gradient
               h x = dot(X, theta)
79
               grad = theta + ( (alpha * dot(transpose(X), (Y - h_x))) /
   1595)
               # Use training data to calculate the square error loss
81
               loss = self.costFunction(Y, None, 1595, grad, X)
               if abs(loss - previousLoss) < eps: # If |L(w+1) - L(w)| <
84
   0.0001
                   break # Break out of the cycle.
```

```
87
                theta = grad # Update our weight vector
                previousLoss = loss # Set previousLoss to currentLoss so we
    don't have to recalculate this.
            print("Linear Regression Gradient Descent RSME:
    {}".format(self.costFunction(Y_i, None, 399, grad, X_i)))
91
        def ridgeRegressionGradientDescent(self):
94
            This function is the implementation of the ridge regression model

    gradient descent version.

            Parameters are initalized to control the model, most
    importantlyy:
            alpha - our step size
            eps - our loss tolerance
            theta - Our weight vector, initialized as a random vector of
   Gaussian distribution.
            :return: None.
101
            Y = self.trainData[:, 0]
104
105
            X = self.trainData[:, 1:]
            Y_i = self.testData[:, 0]
            X_i = self.testData[:, 1:]
108
109
110
            grad = None
111
            theta = random.normal(0,1,96)
112
            alpha = 0.01
            eps = float('1e-7')
113
114
115
            previousLoss = self.costFunction(Y, None, 1595, theta, X)
            loss = None
116
117
118
            regTerm = self.crossValidation()
119
120
            while True:
121
                h_x = dot(X, theta)
122
                grad = theta + ((alpha * (dot(transpose(X), Y - h_x) -
    regTerm * theta)) / 1595)
123
124
                loss = self.costFunction(Y, None, 1595, grad, X)
125
                if abs(loss - previousLoss) < eps: # If |L(w+1) - L(w)| <
    0.0001
```

```
126
                    break # Break out of the cycle.
127
128
                theta = grad # Update our weight vector
129
                previousLoss = loss # Set previousLoss to currentLoss so we
   don't have to recalculate this.
130
131
            print("Ridge Regression Gradient Descent RSME:
    {}".format(self.costFunction(Y_i, None, 399, grad, X_i)))
132
133
        def costFunction(self, Y_i, predict, n, W = None, X_i = None):
134
135
            This function calculate the square loss for a given set of truth
   values and predicted values.
            :param Y_i: <vector> - A vector of accepted true values.
136
            :param predict: <vector> - A vector of predicted values
137
138
            :param n: <int> - The number of data points used.
139
            :param W: <vector> - A vector of weights used to calculate the
    prediction.
            :param X_i: <matrix> - A matrix of feature values used to
140
   calculate the prediction
141
            :return: RSME: <float> - The root-square loss
142
143
144
            # We can pass in W and X_i if we want the costFunction to just
    calculate the prediction for us.
145
            if W is not None and X_i is not None:
146
                predict = dot(X_i, transpose(W))
147
            # Calculate the RSME.
148
149
            RSME = sqrt(sum(subtract(Y_i, predict) ** 2) / n)
150
151
            return RSME
152
153
        def ridgeRegression(self):
            0.000
154
155
            This function is the implementation of the ridge regression
    model. It splits the training/test data set
156
            into matrix X of features and vector Y of outputs.
157
158
            The weight vector is calculated as (X.T * X + Lambda*I)^{-1} * X.T
  * Y
159
            Which is then utilized as the weight vector for the prediction
   model of the test data set.
161
162
            The RSME value is calculated using the costFunction().
163
            :return: None
```

```
0.000
164
165
166
            regTerm = self.crossValidation()
167
168
            Y = self.trainData[:, 0]
169
            X = self.trainData[:, 1:]
            Y_i = self.testData[:, 0]
170
            X_i = self.testData[:, 1:]
171
172
173
            W = dot(dot(linalg.inv(dot(transpose(X), X) + regTerm *
    identity(96)), transpose(X)), Y)
174
175
            predict = dot(X_i, transpose(W))
176
            RSME = self.costFunction(Y_i, predict, 399)
177
178
            print("Ridge Regression RSME: {}".format(RSME))
179
180
        def ridgeRegressionBase(self, X, Y, regTerm, test):
181
            W = dot(dot(linalg.inv(dot(transpose(X),X) +
    regTerm*identity(96)),transpose(X)),Y)
182
            X_i = test[:,1:]
183
            Y_i = test[:,0]
184
185
            predict = dot(X_i, transpose(W))
186
            RSME = self.costFunction(Y_i, predict, 319)
187
188
189
            return RSME
190
191
        def crossValidation(self):
192
193
            This function performs a k-fold validation to determine the
    lambda value of a ridgeRegression model via repeatedly
            testing a particular lambda value for a given training set. The
    average RSME of a particular k trial cycle
            is used to determine if the lambda value for that cycle is the
    one that produces the smallest average RSME.
196
            :return: minRegTerm: <float> - The lambda value that produces the
197
    smallest average RSME value.
198
            segOne = self.trainData[0:319,:]
199
200
            segTwo = self.trainData[319:638,:]
            segThree = self.trainData[638:957,:]
201
            segFour = self.trainData[957:1276,:]
            segFive = self.trainData[1276:1595,:]
203
204
```

```
regTerm = 400
205
            minRegTerm = None
206
207
            minRSME = None
208
209
            for k in range(10):
210
211
                kOneData = concatenate((segOne, segTwo, segThree, segFour))
212
213
                kOneRSME = self.ridgeRegressionBase(kOneData[:,1:],
    kOneData[:,0], regTerm, segFive)
214
215
                kTwoData = concatenate((segOne, segTwo, segThree, segFive))
216
                kTwoRSME = self.ridgeRegressionBase(kTwoData[:,1:],
217
    kTwoData[:,0], regTerm, segFour)
218
219
                kThreeData = concatenate((segOne, segTwo, segFour, segFive))
220
221
                kThreeRSME = self.ridgeRegressionBase(kThreeData[:, 1:],
    kThreeData[:, ∅], regTerm, segThree)
222
223
                kFourData = concatenate((segOne, segThree, segFour, segFive))
224
                kFourRSME = self.ridgeRegressionBase(kFourData[:, 1:],
    kFourData[:, 0], regTerm, segTwo)
226
227
                kFiveData = concatenate((segTwo, segThree, segFour, segFive))
228
229
                kFiveRSME = self.ridgeRegressionBase(kFiveData[:, 1:],
    kFiveData[:, 0], regTerm, segOne)
230
231
                avgRSME = (k0neRSME + kTwoRSME + kThreeRSME + kFourRSME +
232
    kFiveRSME) / 5
234
                if minRSME is None:
235
                    minRSME = avgRSME
236
                    minRegTerm = regTerm
237
                if avgRSME <= minRSME:</pre>
238
                    minRSME = avgRSME
239
                    minRegTerm = regTerm
240
241
                regTerm /= 2
242
243
            return minRegTerm
244
245 if __name__ == "__main__":
```

```
t = HW3()

t.linearRegression()

t.linearRegressionGradientDescent()

t.ridgeRegressionGradientDescent()

t.ridgeRegressionGradientDescent()

t.ridgeRegressionGradientDescent()
```