# Bios/CS 534 Project 2

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## 1 Problem 1

With perceptron function, the error rate is

0.033333 (1)

#### Python codes of problem 1:

```
import numpy as np
   import pandas as pd
   #define functions of prediction
   def predict(x,w,y):
6
7
       :param x: one row of data samples
8
       :param w: data weight
:param y: one row of data labels
9
       :return: predict label
10
11
12
       y_p = np.dot(x, w)*y
13
       return y_p
   #define function of perceptron
14
15 def perceptron (X, w, Y, lrate):
16
17
        :param X: data samples
       :param w: data weight
:param Y: data labels
18
19
20
        :return: weight vector as a numpy array
21
       flag = True
while(flag):
22
23
24
            total_error = 0
25
            for i, x in enumerate(X):
26
                x = np.insert(x,2,1) \# Add bias = 1 in x
27
                y_p = predict(x, w, Y[i])
28
                 if (y_p <= 0):
29
                     total\_error += 1
30
                     w = w + lrate*x*Y[i] #new weight, lrate = learning rate
31
            if (total_error == 0):
32
                flag = False #loop until all training data are predict correct
33
        return w
34
35
   #prediction of testing data and error rate
36 def Error_rate(X2,w,Y2):
37
38
        :param X2: Testing data samples
        :param w: data weight
39
40
        :param Y: Testing data labels
41
        :return: error_rate
42
43
       s = Y2.shape[0]
44
       n = 0
```

```
45
                                  for i, x in enumerate(X2):
46
                                                      x2 = np.insert(x,2,1)
47
                                                      y2_p = predict(x2, w, Y2[i])
48
                                                      if (y2-p <= 0): #error_rate = #points whose predict class is different
                                 form original one/#total points
49
                                                                      n += 1
50
                                   return n/float(s)
51
              #read files
52
53 \left| \ f \ = \ pd.\, read\_csv\left( \ '/\, Users/\, ccai28 / \, Desktop / \, hw2\_data\_1 \, . \, txt \ ', sep=' \setminus t \ ', \right. \right. \\ \left. header \ = \ None \right| \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right| \\ \left| \ header \ = \ None \right
                                   , skiprows = 1)
54
55
             #read training data
\begin{array}{lll} 56 & X1 = f.loc\,[:69\,,[0\,,1]]\,.\,values \\ 57 & Y1 = f.loc\,[:69\,,[2]]\,.\,values \end{array}
58
59
              #read testing data
60 \mid X2 = f.loc[70:,[0,1]].values
61 \mid Y2 = f.loc[70:,[2]].values
62
63
              #set learning rate and initial weight
64 | lrate = 1
65 | w = np.ones(3)
66
67
              #new weight after training
              w = perceptron(X,w,Y,lrate)
68
69
70
              #Error rate
\begin{array}{c} 71 \\ 72 \end{array}
              error_rate = Error_rate(X2,w,Y2)
               print('perceptron: \nerror rate = {:f} \n'.format(error_rate))
```

With a function of Adaboost, the error rate is shown in Table below

Iteration	3	5	10	20
Error rate	0.167	0.167	0.133	0.133

Plot of Error rate vs iteration is shown as Fig. 1

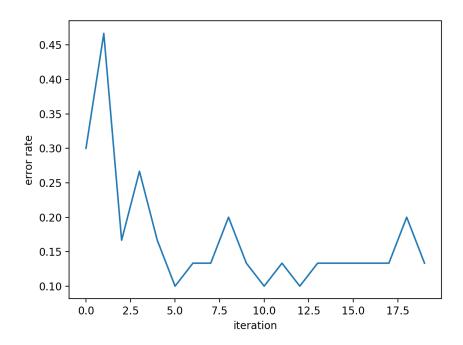


Figure 1: Plots of Adaboost error rate

#### Python codes of problem 2:

```
import numpy as np
   import pandas as pd
   import math
   import matplotlib.pyplot as plt
 4
 6
   #define functions of classifier
 7
   def lineclassify(value,x,label):
 8
 9
         :param value: double, the standard value to compare with
10
         :param x: training data, double, data axis value
11
        : label: 0, left; 1, right
        :left : x \le value: predict y is -1; x > value: predict y is 1 :right: x \le value: predict y is 1; x > value: predict y is -1: return: predict y, int(-1 or -1)
12
13
14
15
16
         if (label == 0):
17
             if (x \le value):
18
                  y_p = -1
19
             else:
                  y_p = 1
20
21
         elif (label == 1):
22
              if (x \le value):
23
                  y_{-}p = 1
24
              else:
\frac{1}{25}
                  y_{-}p = -1
26
27
28
        return y_p
29
   #Classify all training data with one weak classfier (xij)(loop all training
        data with specific xij)
   def Weighterror (value, X, Y, W, label):
32
```

```
:param value: double, the standard value to compare with
        :param X: training data, list (n*1), data set in one axis (eg.X[:,0])
34
35
        :param Y: training data, list (n*1), all data labels
36
        :param W: list (n*1), weight set of data
37
        : label: 0, left; 1, right
        :left : x \le value: predict y is -1; x > value: predict y is 1 :right: x \le value: predict y is 1; x > value: predict y is -1
38
39
40
       :return: double, weighterror = sum(misclassified data's value on one axis
41
42
        weighterror = 0
43
        for i, x in enumerate(X):
44
            y_p = lineclassify (value, x, label)
45
            y_dot = y_p *Y[i]
46
47
            if (y_dot \le 0):
48
                weighterror += W[i]
49
50
       return weighterror
51
52
   #The sum of weight
53 def Sumweight (W):
54
55
        :param W: list (n*1), weight set of data (all equal to 1/N), N is number of
       training data
       :return: double, sum of weight
56
57
58
       sumweight = 0
59
       for i, w in enumerate(W):
60
            sumweight += W[i]
61
        return sumweight
62
63 #new weight after iteration
64
  def changeweight (value, X_line, Y, W, label, a):
65
66
        :param value: double, the best value to compare with
67
        :param X: training data, list (n*1), data set in one axis (eg.X[:,0])
68
        :param Y: training data, list (n*1), all data labels
69
       :param W: list (n*1), weight set of data :para a: alpha wi = wi*exp(a)
70
       :label: 0,left; 1,right
71
72
       :left : x \le value: predict y is -1; x > value: predict y is 1
73
       :right: x \le value: predict y is 1; x > value: predict y is -1
74
       :return: list, new weight
75
76
        for i,x in enumerate(X_line):
            y_p = lineclassify (value, X_line[i], label)
77
78
            y_dot = y_p *Y[i]
79
80
            if (y_dot \ll 0):
            # print W[j], alpha[i]
81
82
               W[i] = W[i] * np.exp(a) # calculate new wi
83
84
            else:
85
                continue
86
        return W
87
88
   #Find the best xij to classify traning data (loop for every possible xij)
89
   def Buildline (X,Y,W):
90
91
        :param X: training data, list (n*2), data set in all axis (X[xi,x2])
92
        :param Y: training data, list (n*1), all data labels
       :param W: list (n*1), weight set of data
93
94
        return: list, best xij with smallest weighterror and its label in 1/r, X1/
95
                 x_{best} = [best value, [l(0)/r(1), X1(0)/X2(1)]
96
        :label: left:0 ; right:1; X1:0 ; X2:1
97
```

```
98
        weight_x1_l = []
99
        weight_x1_r =
100
        weight_x2_l =
101
        weight_x2_r = []
102
        weight_x = []
103
        x_best = []
104
        X_{list} = []
105
106
        X1 = X[:,0] \#all x1
107
        X2 = X[:,1] \#all x2
108
109
        X_list.append(X1)
110
        X_list.append(X1)
111
        X_list.append(X2)
112
        X_{list.append(X2)} \#X_{list} = [[X1], [X1], [X2], [X2]]
113
114
115
        for i, x1 in enumerate(X1):
116
            weighterror1_l = Weighterror(X1[i],X1,Y,W,0) #weighterror of X1, left
117
            weight_x1_l.append(weighterror1_l)
118
119
            weighterror1_r = Weighterror(X1[i],X1,Y,W,1)
120
            weight_x1_r.append(weighterror1_r) #weighterror of X1, right
121
122
        weight_x.append(weight_x1_l) \#put (l,x1) in list, index = 0
        weight_x.append(weight_x1_r) \#put (r,x1) in list, index = 1
123
124
125
126
        for i, x2 in enumerate(X2):
127
            weighterror 2_l = Weighterror (X2[i], X2, Y, W, 0) #weighterror of X2, left
128
            weight_x2_l.append(weighterror2_l)
129
            weighterror2_r = Weighterror(X2[i],X2,Y,W,1) #weighterror of X2, right
130
            weight_x2_r.append(weighterror2_r)
131
132
133
        weight_x.append(weight_x2_l) \#put (1,x2) in list, index = 2
134
        weight_x.append(weight_x2_r) \#put(r,x2) in list, index = 3
135
                                      \#weight_x = [[weight_x1_l], [weight_x1_r], [
        weight_x2_l], [weight_x2_r]]
136
137
        weight_x_min_list = np.min(weight_x, axis=1) \#minimum of every (1/r,x1/x2)
         list
138
                                                      \#weight_x_min_list = [min(
        weight_x1_l),min(weight_x1_r),min(weight_x2_l),min(weight_x2_r)]
139
140
        weight_x_min = min(weight_x_min_list)#minimum in all list, smallest
        weighterror
141
        index_list = np.argmin(weight_x_min_list) #index of four lists who has the
142
         smallest weighterror
143
                                                   \#index_list = the index in
        weight_x_min_list
144
                                                   #= the index in weight_x = best
        value with smallest weighterror in which list, (1/r,x1/x2), between 0 and 3
145
146
        label\_list = [[0,0],[1,0],[0,1],[1,1]] #build label list to represent all
        (1/r, x1/x2)
147
                                                 \#label_list = [[1,X1],[r,X1],[1,X2]]
        ],[r,X2]]
        label = label_list[index_list] #find the label(0 or 1) of smallest
148
        weighterror
149
150
        index = weight_x[index_list].index(weight_x_min)#index of best value,0-69
151
152
        best_value = X_list[index_list][index]
153
154
        x_best.append(best_value)
155
        x_best.append(label) \#x_best = [best value, [l(0)/r(1),X1(0)/X2(1)]
```

```
156
                               \#\text{best value} = x_{\text{best}}[0], 1/r = x_{\text{best}}[1][0], X1/X2 =
         x_best[1][1]
157
158
         return x_best
159
160 #Build Adaboost training
161 def Adaboost (iteration, X, Y, W, X_test, Y_test):
162
163
         :param iteration: times loop weak lineclassify
164
         : param \ X: \ list \ (n*2) \ , training \ data \ set \ in \ all \ axis \ (X[\,xi\,,x2\,])
165
         :param Y: list (n*1), training data, all data labels
         :param X_test: list (n*2), testing data set in all axis (X[xi,x2])
166
         :param Y_test: list (n*1), testing data, all data labels
167
168
         :param W: list (n*1), initial weight set of data (all equal to 1/N), N is
        number of training data
169
         :return: list, error rate, contains every iteration error rate
170
171
         error_rate = []
172
173
         Y_{\text{testp}} = \text{np.zeros}(Y_{\text{test.shape}}[0])
174
         for i in range (iteration):
175
             n = 0
176
             x_best = Buildline(X,Y,W)
177
             value\;,\;\; label\_index \;\;, line\_index \;=\; x\_best\left[0\right], x\_best\left[1\right]\left[0\right], x\_best\left[1\right]\left[1\right]
178
        179
180
181
             weighterror = Weighterror (value, X_line, Y,W, label_index)
182
183
             sumweight = Sumweight (W)
184
             error = weighterror/float(sumweight) #calculate error
185
             print ("errorm:")
186
             print error
187
188
             #print weighterror, sumweight, error
189
             a = np.log((1-error)/float(error)) #calculate alpha
190
             #print error, a, value_best[i]
191
192
             W = changeweight (value, X_line, Y, W, label_index, a) #new weight
193
194
             s_test = X_test.shape[0] #number of data in X_test
195
             for j in range(s_test):
196
                  x_test = X_test[:,line_index][j]
197
                  Y_testp[j] += AdaClassify(a,x_best,x_test)
198
199
                  y_{dot} = Y_{testp}[j] *Y_{test}[j]
200
                  if (y_dot \ll 0):
201
                      n += 1
202
             error_rate.append(n/float(s_test)) #error rate of every iteration
203
             print error_rate[i]
204
205
         return error_rate
206
207 #Adaboost classify (combination of weak classifier)
208 def AdaClassify (alpha, value_best, x_test):
209
210
         :param alpha: to build adaboostc classifier: sum(alpha[i]*Gi(x))
211
         :param value_best: list,= [[best value1,[1(0)/r(1),X1(0)/X2(1)],[[best value1,[1(0)/r(1),X1(0)/X2(1)]]]
        value2, [l(0)/r(1),X1(0)/X2(1)]]...]
212
         : param \ x\_test: \ element \ , testing \ data \ of \ one \ axis
213
         :return: predict y with alpha
214
         value\;,\;\; label\_index\;\;, line\_index\;=\; value\_best\left[0\right]\;, value\_best\left[1\right]\left[0\right]\;, value\_best\;
215
         [1][1] #value, label_index , line_index = best value, 1/r, X1/X2
216
        y_{testp} = lineclassify(value, x_{test}, label_index)*alpha #adaboost
```

```
217
218
        return y_testp
219
220 #read files
221 f = pd.read_csv('/Users/ccai28/Desktop/hw2_data_1.txt',sep='\t', header = None
        , skiprows = 1)
222
    #read training data
223
224 X = f.loc[:69,[0,1]].values
225 | Y = f.loc[:69,[2]].values
226
227
    #read testing data
228 X_{\text{test}} = f.loc[70:,[0,1]].values
229 Y_test = f.loc[70:,[2]].values
230
231 #number of training data
232 s = X. \text{ shape } [0]
233
234 #set initial weight
235 | W = np. full((s,1), 1/float(s))
236
237
238 #iteration
239 iteration = 20
240
241 error_rate = Adaboost(iteration, X, Y, W, X_test, Y_test)
242 print error_rate[iteration -1]
243
244 x_plot = list(range(iteration))
245
246 plt.plot(x_plot, error_rate)
247 plt.xlabel('iteration')
248 plt.ylabel('error rate')
249 plt.show()
```

By using SVM in sklearn, the best parameter and error rate of three kernel methods are shown in Table below

	Radical kernel	Sigmoid kernel	Polynomial kernel
Best parameter (gamma/degree)	0.02	0.06	2
Error rate	0.443	0.493	0.426

Plots of Scores vs gamma or degree of three kernels are shown as Fig. 2, 3, 4

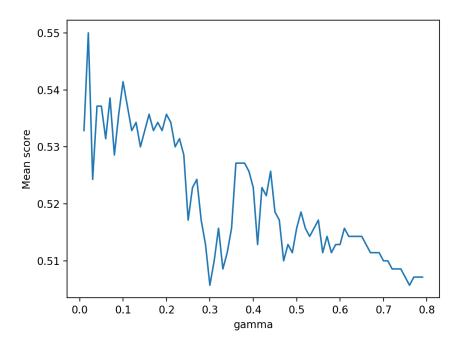


Figure 2: Plots of radical kernel

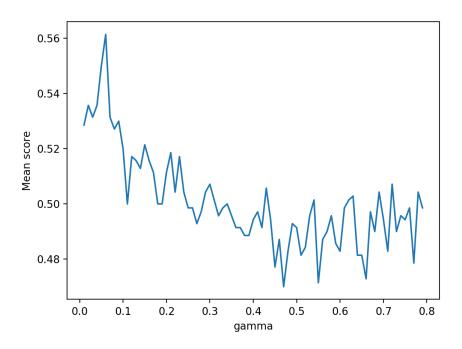


Figure 3: Plots of sigmoid kernel

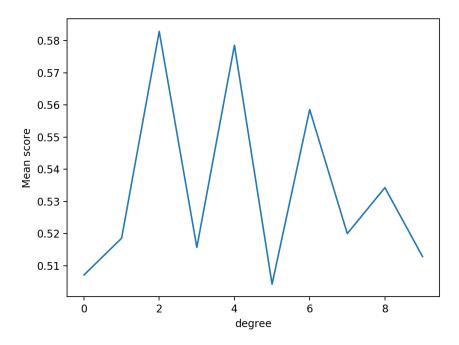


Figure 4: Plots of polynomial kernel

#### Python codes of problem 3:

```
import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
 4
   from sklearn.svm import SVC
 6
   from sklearn.grid_search import GridSearchCV
 7
 8
   def SVM(param_grid , cv , kernel):
 9
10
        :param param_grid: parameter in SVM grid
11
        :param cv : cv-fold
12
        :param kenel: string, thr name of kernel
13
        :return: svm grid
14
15
       grid = GridSearchCV(SVC(kernel=kernel),param_grid,cv = cv)
16
       return grid
17
   def Best_estimator(grid,X,Y):
18
19
        :param grid: SVM grid
20
21
        :param X : Training data X
22
        :param Y : Training data Y
       : return: \ best \ estimator \ after \ fiting \ training \ data. \ It \ has \ smallest \ error \ and \ best \ parameter (gamma \ or \ degree)
23
24
25
        grid.fit(X, Y)
26
        best_estimator = grid.best_estimator_
        print("The best classifier is: ", best_estimator)
27
28
        return best_estimator
29
30
   def plot(grid, C_range, para_range, s):
31
32
       :param grid: SVM grid
```

```
33
        :param C_range : range of C parameter
34
        :param para_range : range of gamma or degree parameter
35
        :param s : string, name of parameter ('gamma' or 'degree')
36
        :return: plot of score vs parameter
37
38
        scores = [x[1]  for  x  in  grid.grid_scores_]
39
40
41
        plt.plot(para_range, scores)
42
43
        plt.legend()
44
        plt.xlabel(s)
45
        plt.ylabel ('Mean score')
46
        plt.show()
47
48
   def Error_rate(X,Y,X2,Y2,best_estimator):
49
50
        :param best_estimator: best_estimator with best parameter
51
        :param X: list (n*20), training data set in all axis (X[xi,x2])
        :param Y: list (n*1), training data, all data labels
:param X2: list (n*20), testing data set in all axis (X[xi,x2])
:param Y2: list (n*1), testing data, all data labels
52
53
54
55
        :return: error_rate
56
57
       s = X2. shape [0]
58
       n = 0
59
        best_estimator.fit(X,Y)
60
        Y_p = best_estimator.predict(X2)
61
        for i, y in enumerate(Y_p):
62
             if (y != Y2[i]): #error_rate = #points whose predict class is different
         form original one/#total points
63
                n += 1
64
        return n/float(s)
65
66
67
   #read files
68 f = pd.read_csv('/Users/ccai28/Desktop/hw2_data_2.txt',sep='\t', header = None
        , skiprows = 1)
69
70
   #read training data
71 | X = f. loc[:699,:19]. values
   Y = f.loc[:699,20]. values
73
   #read testing data
74
   X_{test} = f.loc[700:,:19].values
75
   Y_{test} = f.loc[700:,20].values
76
77
78
79
   #set parameter for Gridsearch
80 C_range = [1]
81 \mid \text{gamma\_range} = \text{np.arange} (0.01, 0.8, 0.01)
   degree\_range = np.arange(0, 10, 1)
83
84
   param_grid_g = dict (gamma=gamma_range)
   param_grid_d = dict (degree=degree_range)
85
86
   cv = 10
87
88
   #radical kernel
89
   grid_r = SVM(param_grid_g, cv, 'rbf')
90
   best_estimator_r = Best_estimator(grid_r,X,Y)
   plot (grid_r, C_range, gamma_range, 'gamma')
92
   \texttt{error\_rate\_r} \ = \ \texttt{Error\_rate} \left( X, Y, X\_test \ , Y\_test \ , \texttt{best\_estimator\_r} \right)
93
94
   print('radical kernel: \nerror rate = {:f} \n'.format(error_rate_r))
95
96
97
   #sigmoid kernel
98 grid_s = SVM(param_grid_g, cv, 'sigmoid')
```

```
99 | best_estimator_s = Best_estimator(grid_s,X,Y)
100
    plot (grid_s, C_range, gamma_range, 'gamma')
101
102
    error_rate_s = Error_rate(X,Y,X_test,Y_test,best_estimator_s)
103
    print('sigmoid kernel: \nerror rate = {:f} \n'.format(error_rate_s))
104
    # polynomial kernel
105
106 grid_p = SVM(param_grid_d, cv, 'poly')
107 best_estimator_p = Best_estimator(grid_p, X, Y)
108
    plot(grid_p, C_range, degree_range, 'degree')
109
110
    \texttt{error\_rate\_p} \ = \ \texttt{Error\_rate}\left(X,Y,X\_test\;,Y\_test\;,best\_estimator\_p\;\right)
    print('polynomial kernel: \nerror rate = {:f} \n'.format(error_rate_p))
```

The plot of OOB error rate and number of trees are shown in Fig. 5,

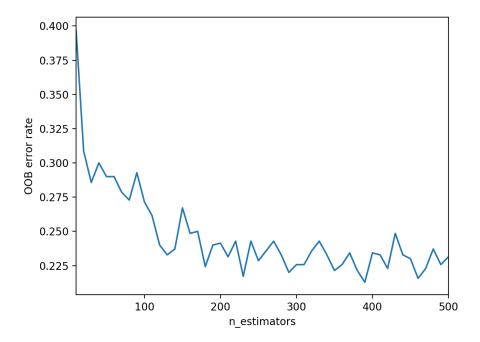


Figure 5: plots of OOB error rate vs number of trees

The selected number of trees is 210, and the error rate is

$$0.223333$$
 (2)

The feature ranking is:

rank	index of variables	importances
1	4	(0.129395)
2	9	(0.119601)
3	14	(0.101843)
4	0	(0.041882)
5	10	(0.041192)
6	2	(0.041054)
7	12	(0.039885)
8	1	(0.039104)
9	16	(0.038682)
10	3	(0.038664)
11	11	(0.038254)
12	7	(0.038123)
13	5	(0.037836)
14	19	(0.037576)
15	18	(0.037312)
16	8	(0.036664)
17	6	(0.036404)
18	13	(0.036342)
19	15	(0.035886)
20	17	(0.034302)

#### Python codes of problem 4:

```
import pandas as pd
   import numpy as np
   import matplotlib.pyplot as plt
 5
   from sklearn.ensemble import RandomForestClassifier
 8
   def Error_rate(X2,Y2,forest):
9
10
        :param forest: forest with best parameter
        :param X2: (n*20), testing data set in all axis (X[xi,x2]):param Y2: (n*1), testing data, all data labels
11
12
        :return: error_rate
13
14
15
        s = X2. shape [0]
16
        n = 0
17
        Y_p = forest.predict(X2)
18
        for i, y in enumerate(Y_p):
         if (y != Y2[i]): \#error\_rate = \#points whose predict class is different form original one/\#total points
19
20
                n += 1
21
        return n/float(s)
22
23
24
   f = pd.read_csv('/Users/ccai28/Desktop/hw2_data_2.txt',sep='\t', header = None
        , skiprows = 1)
26
   #read training data
27 X = f.loc[:699,:19].values
28 | Y = f.loc[:699,20]. values
29
30 #read testing data
31 X_test = f.loc[700:,:19].values
32 Y_test = f.loc[700:,20].values
33
34 # Range of n_estimators values to explore.
35 min_estimators = 10
36 max_estimators = 500
37 | \text{step} = 10
```

```
38 number_estimators = (max_estimators - min_estimators)/step #how many trees are
39
40
   print number_estimators
41
42
  error_rate = []
43 n_estimators = []
44
45
  #use Random Forest
  #oob_score : bool (default=False) :Whether to use out-of-bag samples to
46
       estimate the generalization accuracy
47
  for i in range(min_estimators, max_estimators + step, step):
       clf = RandomForestClassifier(oob_score=True)#warm_start=True
48
49
       clf.set_params(n_estimators=i)
50
       clf.fit(X, Y)
51
52
       # Record the OOB error for each n_estimators=i setting.
53
       oob\_error = 1 - clf.oob\_score
54
       n_estimators.append(i)
55
       error_rate.append(oob_error)
56
       print i,oob_error
57
58
  last_oob_error = error_rate[number_estimators] #oob error of n = 500
59
60 stabilize_estimator = 0
   #number of trees based on when the OOB error rate first stabilizes
61
62 for i in range (number_estimators):
63
       diff_rate = abs((error_rate[i] - last_oob_error)/float(last_oob_error))
64
       print i, diff_rate
65
       if (diff_rate <= 0.002):
66
           stabilize_estimator = n_estimators[i]
67
           print stabilize_estimator
68
           break
69
70
   print stabilize_estimator #the stablize tree number
71
  # Generate the "OOB error rate" vs. "n_estimators" plot.
72
73 plt.plot(n_estimators, error_rate)
74
  plt.xlim(min_estimators, max_estimators)
plt.xlabel("n_estimators")
75
76
  plt.ylabel("OOB error rate")
78
  plt.legend()
79
  plt.show()
80
81
  # Build a forest and compute the feature importances
82 forest = RandomForestClassifier(n_estimators = stabilize_estimator)
83 forest. fit (X,Y)
84
85
  #importance and feature
86 importances = forest.feature_importances_
87
  | indices = np. argsort (importances) [:: -1]
88
89
  # Print the feature ranking
90 print ("Feature ranking:")
91
  for f in range(X_test.shape[1]):
       print ("%d. feature %d (%f)" % (f + 1, indices [f], importances [indices [f]])
92
93
94
  error_rate = Error_rate(X_test, Y_test, forest)
  print('Random Forest: \nerror rate = {:f} \n'.format(error_rate))
```

By running gradient boosting with deviance loss on the training data, the error rate is

$$0.193333$$
 (3)

The feature ranking is:

rank	index of variables	importances
1	9	(0.254537)
2.	4	(0.241189)
3	14	(0.215034)
4	1	(0.034982)
5	10	(0.031280)
6	3	(0.023650)
7	7	(0.023579)
8	6	(0.020974)
9	2	(0.020797)
10	18	(0.020200)
11	5	(0.017700)
12	8	(0.015834)
13	0	(0.015096)
14	17	(0.012983)
15	13	(0.011701)
16	11	(0.010080)
17	19	(0.008941)
18	16	(0.008900)
19	15	(0.007335)
20	12	(0.005209)

#### Python codes of problem 5:

```
import pandas as pd
2
3
   import numpy as np
   from sklearn.ensemble import GradientBoostingClassifier
 4
 5
 6
   def Error_rate(X_test, Y_test, grid):
 7
 8
        :param grid: grid after fit by training data
        :param X_test: (n*20), testing data set in all axis (X[xi,x2]) :param Y_test: (n*1), testing data, all data labels :return: error_rate
9
10
11
12
13
        s = X_test.shape[0]
14
        n = 0
15
        Y_p = grid.predict(X_test)
16
        for i in range(s):
17
             if (Y_p[i]) = Y_{test}[i]): \#error_rate = \#points whose predict class is
        different form original one/#total points
18
                 n += 1
19
        score = grid.score(X_test, Y_test)
20
        return 1-score
21
22
23
   f = pd.read\_csv(\,{}^{,}/Users/ccai28/Desktop/hw2\_data\_2.txt\,{}^{,},sep={}^{,}\backslash t\,{}^{,},\ header = None
        , skiprows = 1)
24
25 #read training data
26 X_train = f.loc[:699,:19].values
   Y_{train} = f.loc[:699,20].values
28
```

```
29 #read testing data
30 X_test = f.loc[700:,:19].values
31 Y_test = f.loc[700:,20].values
32
33 #use gradient boosting with deviance loss
34 grid = GradientBoostingClassifier(loss = 'deviance')
35
  grid.fit (X_train, Y_train)
36
37
  #importance and feature
38 importances = grid.feature_importances_
39
  indices = np. argsort (importances) [::-1]
40
41 # Print the feature ranking
42 print ("Feature ranking:")
43
  for f in range(X_test.shape[1]):
       print ("%d. feature %d (%f)" % (f + 1, indices [f], importances [indices [f]])
44
45
46 error_rate = Error_rate(X_test, Y_test, grid)
47 print ('gradient boosting: \nerror rate = {:f} \n'.format(error_rate))
```

With MARS, the error rate is

$$0.24333$$
 (4)

#### Python codes of problem 6:

```
import pandas as pd
   import numpy as np
   import matplotlib.pyplot as plt
 5
   from pyearth import Earth
 6
 7
   def Error_rate(X_test, Y_test, model):
 8
        :param X_test: (n*20), testing data set in all axis (X[xi,x2]):param Y_test: (n*1), testing data, all data labels
 9
10
11
        :return: error_rate
12
13
        s = X_test.shape[0]
14
        n = 0
15
        Y_p = model.predict(X_test)
        y_{median} = median(Y_p)
16
17
        for i in range(s):
18
             if (Y_p[i] \le y_median):
19
                 y_{-p} = -1
20
             else:
21
                  y_p = 1
22
             if (y-p != Y-test[i]):#error_rate = #points whose predict class is
        different form original one/#total points
23
                 n += 1
24
        return n/float(s)
25
26
   def median(Y_test):
27
        \begin{array}{ll} :param \ Y\_test: & (n*1)\,,predict\ Y, \ all\ data\ labels \\ :return: \ median\ value\ of\ all\ predict\ Y \end{array}
28
29
30
31
        y_median = np.median(Y_test)
32
        return y_median
33
34 #read files
35 | f = pd.read_csv('/Users/ccai28/Desktop/hw2_data_2.txt',sep='\t', header = None
    , skiprows = 1)
```

```
36
37
#read training data
X_train = f.loc[:699,:19].values
Y_train = f.loc[:699,20].values
40
41
#read testing data
X_test = f.loc[700:,:19].values
Y_test = f.loc[700:,20].values
43
44
45
#MARS from earth class
model = Earth() #MARS
model.fit(X_train,Y_train)
48
49
#error_rate
error_rate = Error_rate(X_test,Y_test,model)
print('MARS: \nerror rate = {:f} \n'.format(error_rate))
```