

# 实 验 报 告

(2017 / 2018 学年 第 2 学期)

课程名称	机器学习导论				
实验名称	Support vector machine				
实验时间	2018年6月15日				
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# 1 问题重述

- 给定数据集(文件 data1\_Task.mat) 如下图所示, 参考 Demo 1 和 Demo 2,编程实现一个高斯核 SVM 进行分类。输出训练参数 C, sigma 分别取 0.01, 0.03, 0.1, 0.3, 1, 3, 10, 30 时 (共 64 组 参数组合) 的训练集上的准确率。
- 编程实现一个垃圾邮件 SVM 线性分类器,分别在训练集和测试集上计算准确率。训练数据文件: spamTrain.mat, 要求导入数据时输出样本数和特征维度。测试数据文件: spamTest.mat, 要求导入数据时输出样本数和特征维度。

# 2 Python Code for SVM

#### 2.1 SVM

```
\#-*-coding: utf-8-*-
      @author : Haoran You
 3
 4
      import time
      import numpy as np
      import matplotlib.pyplot as plt
 9
10
      class SVM():
           def name(self):
11
12
                 return 'svm classifier'
13
14
           def svmTrain_SMO(self, X, y, C, kernal_function='linear', tol=le-3, max_iter=5, **kargs):
15
16
                 :param X:
17
                 :param y:
:param C: punishment coefficient
18
                 :param kernal_function: type of kernal function; for nonlinear function, input K directly
20
                 :param tol: error-tolerant rate
21
                 :param max_iter: maximum iterations
                 : param\ kargs:
22
                 :return: model['kernelFunction]: kernal function type
23
                 :return: model['kernelFunction]: kernal function type
:return: model['X']: support vector
:return: model['y']: label
:return: model['alpha']: corresponding lagrange parameters
:return: model['w'], model['b']: model parameters
"""
24
25
27
28
29
                 start_time = time.clock()
30
                 m, n = X.shape
                 X = np.mat(X)
33
                 y = np.mat(y, dtype='float64')
34
                 y[np.where(y==0)] = -1
                 alpha = np.mat(np.zeros((m, 1)))
35
                 b = 0.0
36
37
                 E = np.mat(np.zeros((m, 1)))
                 iters = 0
eta = 0.0
39
                L = 0.0 \\ H = 0.0
40
41
42
43
                 if kernal_function == 'linear':
                      K = X*X.T
44
                 elif kernal_function == 'gaussian':
                      K = \, \mathrm{kargs} \, [\,\, {}^{\backprime}\!K\_{matrix} \,{}^{\backprime}\,]
46
47
                       print('Kernal Error')
48
                       return None
49
                 print('Training ...', end='')
                 dots = 12
52
                 while iters < max_iter:
53
                       num\_changed\_alpha = 0
54
                       \label{eq:continuous_section} \begin{array}{ll} \text{for $i$ in $range(m)$:} \\ \text{E[i]} = b + \text{np.sum(np.multiply(np.multiply(alpha, y), K[:, i])) - y[i]} \\ \text{if $(y[i]^*E[i] < -tol $and $alpha[i] < C)$ or $(y[i]^*E[i] > tol $and $alpha[i] > 0)$:} \end{array}
55
56
58
                                  j = np.random.randint(m)
59
                                   while j == i:
                                        j \; = \; np \, . \, random \, . \, randint \, (m)
60
                                  E[j] = b + np.sum(np.multiply(np.multiply(alpha, y), K[:, j])) - y[j]
61
                                  alpha_i_old = alpha[i].copy()
alpha_j_old = alpha[j].copy()
```

```
 \begin{array}{l} \mbox{if } y[\mbox{i}] == y[\mbox{j}]\colon \\ \mbox{$L = \max(0$, alpha[j] + alpha[i] - C)$} \\ \mbox{$H = \min(C$, alpha[j] + alpha[i])$} \end{array} 
 66
 67
 68
 69
                                                else:
                                                        \begin{array}{l} L = \max(0\,,\; alpha[\,j\,] \; \text{-} \; alpha[\,i\,]) \\ H = \min(C,\; C + \; alpha[\,j\,] \; \text{-} \; alpha[\,i\,]) \end{array} 
  70
  71
  72
 73\\74
                                                \quad \text{if} \ L =\!\!\!\!\!= H:
                                                       continue
  75
                                                eta \, = \, 2 \ * \ K[\,i \;,\;\; j \,] \ - \ K[\,i \;,\;\; i \,] \ - \ K[\,j \;,\;\; j \,]
  76
                                                if eta >= 0:
  78
  79
                                               \begin{array}{l} alpha\left[j\right] = alpha\left[j\right] \; - \; \left(y\left[j\right]^*\left(E\right[i\right] \; - \; E\left[j\right]\right)\right) \; / \; eta \\ alpha\left[j\right] = \min(H, \; alpha\left[j\right]) \\ alpha\left[j\right] = \max(L, \; alpha\left[j\right]) \end{array}
  80
 81
  82
  83
                                                \begin{array}{ll} if & abs(alpha[j] - alpha\_j\_old) < tol: \\ & alpha[j] = alpha\_j\_old \end{array}
  85
 86
                                                       continue
 87
                                                alpha[\,i\,]\,=\,alpha[\,i\,]\,\,+\,\,y[\,i\,]\,\,\,*\,\,\,y[\,j\,]\,\,\,*\,\,\,(alpha\_j\_old\,\,-\,\,alpha[\,j\,])
 88
  90
                                                b1 = b - E[i] \setminus
                                                 - y[i] * (alpha[i] - alpha_i_old) * K[i, j]\
- y[j] * (alpha[j] - alpha_j_old) * K[i, j]
 91
 92
 93
                                               \begin{array}{l} b2 = b \ - E[j] \backslash \\ - \ y[i] \ * \ (alpha[i] \ - \ alpha\_i\_old) \ * \ K[i \ , \ j] \backslash \\ - \ y[j] \ * \ (alpha[j] \ - \ alpha\_j\_old) \ * \ K[i \ , \ j] \end{array}
  94
  95
  96
 97
 98
                                                 if \ (0 < alpha[\,i\,] \ and \ alpha[\,i\,] < C) \colon \\
 99
                                                       b = b1
100
                                                elif (0 < alpha[j] and alpha[j] < C):
                                                      b = b2
101
102
103
                                                       b = (b1 + b2) / 2.0
104
                                                num\_changed\_alpha = num\_changed\_alpha \, + \, 1
105
106
107
                                 if num\_changed\_alpha == 0:
108
                                        iters = iters + 1
109
110
                                        iters = 0
111
                                 print('.', end='')
dots = dots + 1
112
113
                                 if dots > 78:
114
115
                                        dots = 0
116
                                        print()
117
                         print('Done', end='')
118
                         print( Doile , Chel )
end_time = time .clock()
print('( ' + str(end_time - start_time) + 's )')
119
120
121
                         print()
122
123
                         idx = np.where(alpha > 0)
                         124
125
126
                                  'kernelFunction': str(kernal_function),
                                 'b': b,
'alpha':alpha[idx],
128
129
                                 'w': (np.multiply(alpha, y).T * X).T
130
131
132
                         return model
133
134
                  def visualizeBoundaryLinear(self, X, y, model, title=None):
135
                         fig = plt.figure()
                         ax = fig.add\_subplot(111)
136
137
                         w = model['w']

b = model['b']
138
139
                         \begin{array}{l} xp = np. \\ linspace(min(X[:, 0]), \\ max(X[:, 0]), \\ p = np. \\ squeeze(np. \\ array(-(w[0]*xp + b) / w[1])) \end{array} 
140
141
142
143
                         ax.plot(xp, yp)
144
145
                         # scatter
                        X_{pos} = []

X_{neg} = []
147
148
                         \begin{split} & sample Array = np.concatenate((X, y), axis=1) \\ & for array in list(sample Array): \end{split}
149
150
                                 if array[-1]:
151
                                       X_pos.append(array)
153
```

```
154
                                   X_neg.append(array)
155
                     \begin{array}{l} X\_{pos} = \operatorname{np.array}\left(X\_{pos}\right) \\ X\_{neg} = \operatorname{np.array}\left(X\_{neg}\right) \end{array}
156
157
158
159
                      if title: ax.set_title(title)
160
                      \begin{array}{l} pos = plt.scatter(X\_pos[:,\ 0],\ X\_pos[:,\ 1],\ marker='+',\ c='b') \\ neg = plt.scatter(X\_neg[:,\ 0],\ X\_neg[:,\ 1],\ marker='o',\ c='y') \end{array}
161
162
163
                      plt.legend((pos, neg), ('postive', 'negtive'), loc=2)
164
165
166
                      plt.show()
167
               168
169
170
171
172
                      \begin{array}{ccc} \underline{return} & np.\exp(n) \end{array}
173
               \operatorname{\mathtt{def}} gaussianKernel(self, X, sigma):
174
175
                      start = time.clock()
176
                      print('GaussianKernel Computing ...', end='')
178
                      m = X. shape[0]
179
                      X = np.mat(X)
180
                     K = np.mat(np.zeros((m,\ m)))
                      dots = 280
181
                      for i in range(m):
182
                             if dots % 10 == 0: print('.', end='')
183
184
                             dots = dots + 1
185
                             if dots > 780:
186
                                   \mathrm{dots}\,=\,0
                             \label{eq:continuous_continuous} \begin{array}{l} \operatorname{dist} = 0 \\ \operatorname{print}() \\ \text{for } j \text{ in } \operatorname{range}(m) \colon \\ K[i, j] = \operatorname{self.gaussianKernelSub}(X[i, :].T, X[j, :].T, \operatorname{sigma}) \\ K[j, i] = K[i, j].\operatorname{copy}() \end{array}
187
188
189
190
191
                      print('Done', end='')
end = time.clock()
print('(' ' + str(end - start) + 's )')
192
193
                      print('(
print()
194
195
                      return K
196
197
198
               def svmPredict(self, model, X, *arg):
199
                     m = X.shape[0]
                      p = np.mat(np.zeros((m, 1)))
pred = np.mat(np.zeros((m, 1)))
200
201
202
                      \begin{array}{ll} if \ \ model[\,'kernelFunction\,'] == \,'linear\,'\colon \\ p = X \ ^* \ \ model[\,'w'\,] \ + \ model[\,'b'\,] \end{array}
203
204
205
                             for i in range(m):
206
                                   prediction = 0
207
                                   208
209
210
211
212
                                   p[i] = prediction + model['b']
213
214
                      pred[np.where(p >= 0)] = 1
215
                      \operatorname{pred}[\operatorname{np.where}(p < 0)] = 0
216
217
                      return pred
218
219
               {\color{red} \textbf{def} \ visualizeBoundaryGaussian(self, X, y, model, sigma):}
                      fig = plt.figure()
220
                      ax = fig.add\_subplot(111)
221
222
                     \begin{array}{lll} x1plot = np.linspace(min(X[:,\ 0]),\ max(X[:,\ 0]),\ 100) \\ x2plot = np.linspace(min(X[:,\ 1]),\ max(X[:,\ 1]),\ 100) \\ X1,\ X2 = np.meshgrid(x1plot,\ x2plot) \\ X1 = np.mat(X1) \end{array}
223
224
225
226
                      X2 = np.mat(X2)
228
                      vals = np.mat(np.zeros(X1.shape))
229
                      print('Predicting ...', end='')
230
231
                      dots = 14
                      for i in range(X1.shape[1]):
    print('.', end='')
    dots += 1
232
233
234
235
                             if dots == 78:
236
                                   \mathrm{dots}\,=\,0
                             \begin{array}{l} & print() \\ this\_X = np.concatenate((X1[:,\ i],\ X2[:,\ i]),\ axis=1) \\ vals[:,\ i] = self.svmPredict(model,\ this\_X,\ sigma) \end{array}
237
238
239
                      print('Done')
241
```

```
ax.contour(X1, X2, vals, colors='black')
242
243
                  # scatter
                  X_pos = []
X_neg = []
244
245
246
247
                  sampleArray = np.concatenate((X,\ y)\,,\ axis{=}1)
                  for array in list(sampleArray):
    if array[-1]:
248
249
250
                             X_pos.append(array)
251
                        else:
252
                             X_neg.append(array)
253
254
                  X_pos = np.array(X_pos)
255
                  X_{neg} = np.array(X_{neg})
256
                  \begin{array}{l} pos = plt.scatter(X\_pos[:,\ 0],\ X\_pos[:,\ 1],\ marker='+',\ c='b') \\ neg = plt.scatter(X\_neg[:,\ 0],\ X\_neg[:,\ 1],\ marker='o',\ c='y') \end{array}
257
258
259
                  plt.legend((pos, neg), ('postive', 'negtive'), loc=2)
260
261
                  plt.show()
262
```

#### 2.2 data

```
1
     #_*- coding: utf-8-*-
 3
      @author : Haoran You
 4
 6
7
     from scipy.io import loadmat
     import numpy as np
import matplotlib.pyplot as plt
 9
10
     def loadData(filename):
11
           dataDict = loadmat(filename)
12
           return dataDict['X'], dataDict['y']
13
     def plotData(X, y, title=None):
14
          \hat{X}_pos = []

X_neg = []
15
16
18
           sampleArray = np.concatenate((X, y), axis=1)
          for array in list(sampleArray):
   if array[-1]:
19
20
21
                    X_pos.append(array)
22
                else:
                    X_neg.append(array)
23
24
25
          X\_pos = np.array(X\_pos)
26
          X_neg = np.array(X_neg)
27
28
           fig = plt.figure()
29
30
          ax = fig.add\_subplot(111)
31
32
           if title: ax.set_title(title)
33
          \begin{array}{l} pos = plt.scatter(X\_pos[:,\ 0],\ X\_pos[:,\ 1],\ marker='+',\ c='b') \\ neg = plt.scatter(X\_neg[:,\ 0],\ X\_neg[:,\ 1],\ marker='o',\ c='y') \end{array}
34
35
36
37
           plt.legend((pos, neg), ('postive', 'negtive'), loc=2)
38
           plt.show()
39
```

#### 2.3 Main

```
#_*_ coding: utf-8-*_
   3
                @author : Haoran You
   4
                import os
                from data import *
               from SVM import SVM
   9
               file_path = os.getcwd()
10
11
                def Task1():
13
                             # load and visulize data
14
                             svm = SVM()
                            print('Loading and Visualizing Data ...')
X, y = loadData(file_path + '\data1_Task.mat')
plotData(X, y, title='Task 1')
15
16
17
18
 19
                              print('Program paused. Press enter to continue.')
20
                             input()
21
22
                             # Training
                            print ('Training SVM with RBF kernel ...')
param = [0.01, 0.03, 0.1, 0.3, 1, 3, 10, 30]
23
25
                             acc = []
for C in param:
26
27
                                          for sigma in param:
                                                       signa in palan.

model = svm.svmTrain_SMO(X, y, C, kernal_function='gaussian', K_matrix=svm.gaussianKernel(X, sigma))

pred = svm.svmPredict(model, np.mat(X), sigma)

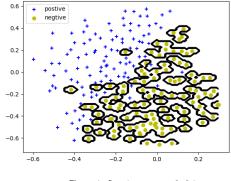
acc.append(1 - np.sum(abs(pred - y)) / len(y))
28
29
31
                             print(acc)
                             f = open('results.txt', 'a+')
f.write('sigma\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.3f\t%.
32
33
34
                             count = 0
35
                             for i in range(len(param)):
    content = '%.3f\t' % param[i]
36
37
                                          for j in range(len(param)):
content += '%.3f\t' % acc[count]
38
39
40
                                          count += 1
content += '\n
41
                                           f.write(content)
42
43
                             f.close()
44
                            # results visualizing # print('Results visualizing ...') # svm.visualizeBoundaryGaussian(X, y, model, sigma)
45
46
47
48
49
                           # load data
print('Loading data ...')
50
51
                            X_train, y_train = loadData(file_path + '\spamTrain.mat')
X_test, y_test = loadData(file_path + '\spamTest.mat')
# plotData(X_train, y_train, title='Task 2')
52
53
54
55
56
                              print('Program paused. Press enter to continue.\n')
57
                             input()
58
                             # trainging
59
                            svm = SVM()
60
                           print('Number of samples: {}'.format(X_train.shape[0]))
print('Number of features: {}'.format(X_train.shape[1]))
print('Training Linear SVM ...')
C = 1; sigma = 0.01;
61
63
64
                           c = 1; sigma = 0.01;
model = svm.svmTrain_SMO(X_train, y_train, C, max_iter=20)
pred_train = svm.svmPredict(model, np.mat(X_train), sigma)
acc_train = 1 - abs(np.sum(pred_train - y_train)) / len(y_train)
print('Train accuracy: {}'.format(acc_train))
65
66
67
68
69
70
                             # test
print('Number of samples: {}'.format(X_test.shape[0]))
print('Number of features: {}'.format(X_test.shape[1]))
pred_test = svm.svmPredict(model, np.mat(X_test), sigma)
acc_test = 1 - abs(np.sum(pred_test - y_test)) / len(y_test)
print('Test accuracy: {}'.format(acc_test))
71
72
73
 74
75
76
                                name
                                                       Task2()
```

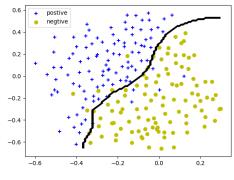
## 2.4 Results

#### 2.4.1 Task1

Table 1: Results for different parameters C & sigma

Table 1. Results for different parameters & & signal								
sigma C	0.01	0.03	0.1	0.3	1	3	10	30
0.01	0.498	0.498	0.502	0.502	0.502	0.498	0.502	0.502
0.03	0.502	0.502	0.502	0.867	0.502	0.498	0.834	0.498
0.1	0.498	0.502	0.943	0.872	0.834	0.81	0.815	0.81
0.3	0.502	0.981	0.948	0.905	0.867	0.81	0.498	0.502
1	1	0.995	0.948	0.934	0.905	0.848	0.815	0.829
3	1	1	0.943	0.943	0.915	0.863	0.825	0.502
10	1	1	0.962	0.934	0.929	0.9	0.848	0.815
30	1	1	0.948	0.943	0.924	0.919	0.867	0.791





C = 1 & sigma = 0.01

C = 1 & sigma = 0.1

Figure 1: Boundary Visualization

### 2.4.2 Task2

• Train accuracy: 0.98775

Number of samples: 4000Number of features: 1899

• Test accuracy: 0.982

Number of samples: 1000Number of features: 1899