python codes

```
1
   from IPython import display
 2
   from IPython.core.interactiveshell import
   InteractiveShell
   InteractiveShell.ast node interactivity = "all"
   import warnings
   warnings.filterwarnings("ignore")
   import numpy as np
    import matplotlib.pyplot as plt
9
10
   # ## **(b) i**
11
12
13
14
   # define the matrix A and vector b
    def get A b(z, U):
15
        1.1.1
16
17
        params:
            z: the vector of the labels (N, 1)
18
19
            U: the extended features (N, d)
20
        return:
            A: shape (N + 1, 1)
21
22
            b: shape (N + 1, 1)
        1.1.1
23
24
        zTz = z @ z.T
25
        UTU = U @ U.T
        A = np.concatenate((np.concatenate((zTz * UTU, -
26
   z), axis=1),
```

```
27
                             np.concatenate((z.T,
   np.zeros((1, 1))), axis=1)),
                             axis=0)
28
        b = np.concatenate((np.ones((z.shape[0], 1)),
29
    np.zeros((1, 1))), axis=0)
30
        return A, b
31
32
33
    def get_lamda_mu(A, b):
        1.1.1
34
35
        params:
36
            A: matrix shape (N + 1, N + 1)
37
            b: vector shape (N + 1, 1)
        1 \cdot 1 \cdot 1
38
        sol = (np.linalg.inv(A) @ b).ravel()
39
40
        lamda, mu = sol[:A.shape[0]-1], sol[-1]
41
        ## check lamda is greater than zero
42
        while np.any(lamda < 0):
43
            idx1 = [i for i in range(lamda.shape[0]) if
    lamda[i] >= 0]
44
            idx = idx1 + [sol.shape[0] - 1]
            A = A[idx, :][:, idx]
45
            b = b[idx, :]
46
            sol = (np.linalg.inv(A) @ b).ravel()
47
            tmp, mu = sol[:A.shape[0]-1], sol[-1]
48
            lamda[lamda<0] = 0
49
            lamda[idx1] = tmp
50
51
        print("lamda is ", lamda)
52
        print("mu is ", mu)
53
54
55
        return lamda, mu
56
57
```

```
# ## **(b) ii**
58
59
60
61
    def check KKT12(lamda, z):
        1.1.1
62
63
        params:
64
            lamda: lagaurange multiplier. vector shape
    (1, N)
            z: the vector of the labels (N, 1)
65
66
67
        print("KKT conditions 1 is satisfied: ",
    np.allclose(lamda@z, 0))
        print("KKT conditions 2 is satisfied: ",
68
    np.all(lamda>=0) or np.allclose(lamda, 0))
69
70
71
   # ## **(b) iii**
72
73
74
    def get_w_w0(lamda, z, U):
        1.1.1
75
76
        params:
77
            lamda: lagaurange multiplier. vector shape
    (1, N)
78
            z: the vector of the labels (N, 1)
79
            U: the extended features (N, d)
80
        returns:
81
            w: the weights, vector shape (1, N)
82
            w0: the bias, scalar
        I = I = I
83
        W = lamda.reshape((1, -1)) @ (z * U)
84
        w0 = 1 / z[0, 0] - w @ U[0:1].T
85
        print("w is {}, w0 is {}".format(w, w0))
86
87
```

```
88
         return w, w0
 89
 90
     # ## **(b) iv**
 91
 92
 93
 94
     def check_KKT3(z, U, w, w0):
          1.1.1
 95
 96
         params:
97
              z: the vector of the labels (N, 1)
             U: the extended features (N, d)
98
             w: the weights, vector shape (1, N)
99
             w0: the bias, scalar
100
         \mathbf{I} = \mathbf{I} - \mathbf{I}
101
102
         z hat = U @ w.T + w0
         cond3 = z * z_hat - 1
103
104
         if np.all(cond3 >=0) or np.allclose(cond3, 0):
105
              res = True
106
         else:
107
             res = False
108
         print("KKT conditions 3 is satisfied: ", res)
109
110
     # ## **(c)**
111
112
113
     z = np.array([[1], [1], [-1]])
114
     U = np.array([[1, 2], [2, 1], [0, 0]])
115
     A, b = get_A_b(z, U)
116
117
     lamda, mu = get lamda mu(A, b)
     check KKT12(lamda, z)
118
119
     w, w0 = get w w0(lamda, z, U)
120
     check KKT3(z, U, w, w0)
121
```

```
122
123
    # ## **(d)**
124
125
     def plot decision boundary(training, label train, w,
126
     wO):
         # Total number of classes
127
128
         classes = np.unique(label train)
         nclass = len(classes)
129
130
131
         class names = []
132
         for c in classes:
133
             class names.append('Class ' + str(int(c)))
134
135
         # Set the feature range for plotting
136
         \max x1 = \text{np.ceil}(\text{np.max}(\text{training}[:, 0])) + 1.0
137
         min x1 = np.floor(np.min(training[:, 0])) - 1.0
         \max x^2 = \text{np.ceil}(\text{np.max}(\text{training}[:, 1])) + 1.0
138
139
         min x2 = np.floor(np.min(training[:, 1])) - 1.0
140
         xrange = (min x1, max x1)
141
142
         yrange = (min x2, max x2)
143
144
         # step size for how finely you want to visualize
     the decision boundary.
         inc = 0.005
145
146
147
         # generate grid coordinates. This will be the
     basis of the decision boundary visualization.
148
         (x1, x2) = np.meshgrid(np.arange(xrange[0],
     xrange[1] + inc / 100, inc),
149
                                  np.arange(yrange[0],
     yrange[1] + inc / 100, inc))
150
```

```
151
         # size of the (x1, x2) image, which will also be
    the size of the
         # decision boundary image that is used as the
152
     plot background.
153
         image size = x1.shape
         # make (x1, x2) pairs as a bunch of row vectors.
154
         grid 2d = np.hstack((x1.reshape(x1.shape[0] *
155
     x1.shape[1], 1, order='F'),
156
                               x2.reshape(x2.shape[0] *
    x2.shape[1], 1, order='F')))
157
        pred_label = np.where(grid_2d @ w.T + w0 > 0, 1,
158
     -1)
159
         # reshape the idx (which contains the class
     label) into an image.
         decision map = pred label.reshape(image size,
160
     order='F')
161
         # create fig
162
         fig, ax = plt.subplots()
163
         ax.imshow(decision map, vmin=np.min(classes),
164
     vmax=9, cmap='Pastel1',
165
                   extent=[xrange[0], xrange[1],
    yrange[0], yrange[1]],
                   origin='lower')
166
167
         # plot the class training data.
168
         data point styles = ['rx', 'bo', 'g*']
169
         for i in range(nclass):
170
             ax.plot(training[label train == classes[i],
171
    0],
172
                     training[label train == classes[i],
    1],
```

```
173
                     data point styles[int(classes[i]) -
     1],
                      label=class names[i])
174
         ax.legend()
175
176
         plt.tight_layout()
177
        plt.show()
178
179
180
         return fig
181
182
     fig = plot_decision_boundary(U, z.ravel(), w, w0)
183
     fig.savefig("./figs/2d.png", dpi=200)
184
185
186
    # ## **(f)**
187
188
189
     z = np.array([[1], [1], [-1]])
190
    U = np.array([[1, 2], [2, 1], [1, 1]])
191
    A, b = get_A_b(z, U)
192
193
     # (i)
194
     lamda, mu = get_lamda_mu(A, b)
195
196
    # (ii)
197
     check_KKT12(lamda, z)
198
199
     # (iii)
200
    w, w0 = get w w0(lamda, z, U)
201
202
203
    # (iv)
    check KKT3(z, U, w, w0)
204
205
```

```
206
     fig = plot decision boundary(U, z.ravel(), w, w0)
207
208
     fig.savefig("./figs/2f4.png", dpi=200)
209
210
211 # ## **(g)**
212
213
    z = np.array([[1], [1], [-1]])
214
    U = np.array([[1, 2], [2, 1], [0, 1.5]])
215
    A, b = get_A_b(z, U)
216
217
    # (i)
218
219
    lamda, mu = get lamda mu(A, b)
220
221 # (ii)
222
    check KKT12(lamda, z)
223
224 # (iii)
225
    w, w0 = get w w0(lamda, z, U)
226
227 # (iv)
228
    check KKT3(z, U, w, w0)
229
230
     fig = plot decision boundary(U, z.ravel(), w, w0)
231
     fig.savefig("./figs/2g4.png", dpi=200)
232
233
234
235
```