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1  """
2  Example 4.2 1D Decision boundary for the Iris dataset
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4  """
5
6  import IPython as IP
7  IP.get_ipython().run_line_magic('reset', '-sf')
8
9  import numpy as np
10 import matplotlib.pyplot as plt
11 import sklearn as sk
12
13
14 cc = plt.rcParams['axes.prop_cycle'].by_key()['color']
15 plt.close('all')
16
17
18 %% Load your data
19
20 # We will use the Iris data set. This dataset was created by biologist Ronald
21 # Fisher in his 1936 paper "The use of multiple measurements in taxonomic
22 # problems" as an example of linear discriminant analysis
23
24 iris = sk.datasets.load_iris()
25
26 # for simplicity, extract some of the data sets
27 X = iris['data'] # this contains the length of the pedals and sepals
28 Y = iris['target'] # contains what type of flower it is
29 Y_names = iris['target_names'] # contains the name that aligns with the type of the
30 flower
31 feature_names = iris['feature_names'] # the names of the features
32
33 # plot the Sepal data
34 plt.figure(figsize=(6.5,3))
35 plt.subplot(121)
36 plt.grid(True)
37 plt.scatter(X[Y==0,0],X[Y==0,1],marker='o')
38 plt.scatter(X[Y==1,0],X[Y==1,1],marker='s')
39 plt.scatter(X[Y==2,0],X[Y==2,1],marker='d')
40 plt.xlabel(feature_names[0])
41 plt.ylabel(feature_names[1])
42
43
44 plt.subplot(122)
45 plt.grid(True)
46 plt.scatter(X[Y==0,2],X[Y==0,3],marker='o',label=Y_names[0])
47 plt.scatter(X[Y==1,2],X[Y==1,3],marker='s',label=Y_names[1])
48 plt.scatter(X[Y==2,2],X[Y==2,3],marker='d',label=Y_names[2])
49 plt.xlabel(feature_names[2])
50 plt.ylabel(feature_names[3])
51 plt.legend(framealpha=1)
52 plt.tight_layout()
53
54 %% Train a Logistic Regression model
55
56 # define the features (X) and the output (Y)
57 X_pedal = iris["data"][:, 3:] # consider just the petal width
58 y_pedal = iris["target"] == 2 # 1 if Iris-Virginica, else 0
59
60 # Build the logistic Regression model and train it.
61 log_reg = sk.linear_model.LogisticRegression(C=1)
62 log_reg.fit(X_pedal, y_pedal)
63 # Note: The hyper-parameter controlling the regularization strength of a
64 # Scikit-Learn LogisticRegression model is not alpha (as in other linear models),
65 # but its inverse: C. The higher the value of C, the less the model is regularized.
66

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67 # Build a range of the feature (X) to predict over. Here we just consider pedal width.
68 X_new = np.linspace(0, 3, 1000)
69 X_new = np.expand_dims(X_new, axis=1)
70
71 # Use the Logistic Regression Model to predict the pedal type based on pedal width
72 y_proba = log_reg.predict_proba(X_new)
73
74 # plot the probability plots
75 plt.figure(figsize=(6.5,3))
76 plt.grid(True)
77
78 # plot the data used for training, set at 0 and 1
79 plt.scatter(X[Y==0,3],np.zeros(50),marker='o',label=Y_names[0],zorder=10)
80 plt.scatter(X[Y==1,3],np.zeros(50),marker='s',label=Y_names[1],zorder=10)
81 plt.scatter(X[Y==2,3],np.ones(50),marker='d',label=Y_names[2],zorder=10)
82
83 # plot the probability
84 plt.plot(X_new,y_proba[:,0], '--',color=cc[3],label='Not Iris - Virgincia')
85 plt.plot(X_new,y_proba[:,1],color=cc[2], label='Iris - Virgincia')
86
87 # find and plot the 50% decision boundary
88 x_at_50 = X_new[np.argmin(np.abs(y_proba[:,0] - 0.5))]
89 plt.vlines(x_at_50,0,1,color='k',linestyles=':',label='Decision Boundary')
90
91 plt.xlabel('pedal width (cm)')
92 plt.ylabel('probability')
93 plt.legend(framealpha=1)
94 plt.tight_layout()
95
96 # make predictions on the model trained on the data.
97 log_reg.predict([[1.7]])

```