ECGR 4105 HW2

October 9, 2022

```
[1]: import numpy as np
     import matplotlib.pyplot as plt
     import pandas as pd
     import seaborn as sns
     from sklearn.model_selection import KFold
     from sklearn.model selection import cross val score
     from sklearn.linear_model import LogisticRegression
     from sklearn import datasets
     from sklearn.preprocessing import Normalizer
     from sklearn.preprocessing import StandardScaler
     from sklearn.model_selection import train_test_split
     from sklearn import metrics
     from sklearn.metrics import confusion_matrix,accuracy_score
     from sklearn.metrics import classification_report
     from sklearn.datasets import load_breast_cancer
[2]: diabset = pd.read_csv(r'C:\Users\homer\OneDrive\Documents\School_
      →Folder\diabetes.csv')
[3]: diabset.head()
[3]:
        Pregnancies
                     Glucose
                              BloodPressure SkinThickness
                                                             Insulin
                                                                        BMI
                         148
                                                         35
                                                                       33.6
     0
                  6
                                          72
     1
                  1
                          85
                                          66
                                                         29
                                                                    0
                                                                       26.6
     2
                  8
                         183
                                          64
                                                          0
                                                                    0 23.3
     3
                                          66
                                                         23
                                                                   94
                                                                       28.1
                  1
                          89
                  0
                         137
                                          40
                                                         35
                                                                  168 43.1
        DiabetesPedigreeFunction
                                  Age
                                        Outcome
     0
                           0.627
                                    50
                                              1
                           0.351
                                    31
                                              0
     1
     2
                           0.672
                                    32
                                              1
     3
                           0.167
                                    21
                                              0
     4
                           2.288
                                    33
                                              1
[4]: diabset.shape
```

[4]: (768, 9)

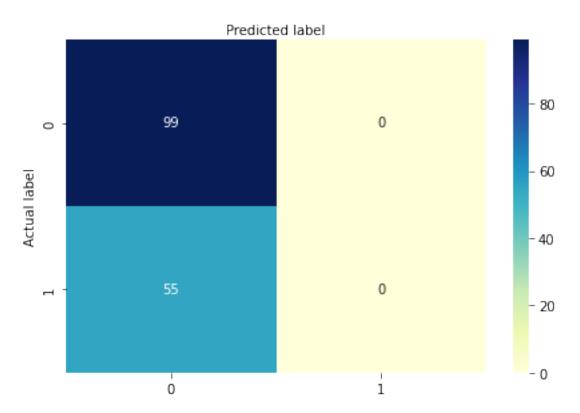
```
[5]: diab_index = diabset.index.values
     diab_index.shape
 [5]: (768,)
 [6]: diab_labels = np.reshape(diab_index, (768,1))
 [7]: diab_data = np.concatenate([diabset,diab_labels],axis=1)
     diab_data.shape
 [8]: (768, 10)
 [9]: diab_dataset = pd.DataFrame(diab_data)
[10]: diab dataset.head()
[10]:
                                          5
                                                       7
                                                                 9
                       2
                             3
                                    4
                                                 6
                                                            8
                 1
     0 6.0 148.0 72.0
                          35.0
                                  0.0 33.6 0.627
                                                    50.0
                                                          1.0
                                                               0.0
     1 1.0
             85.0 66.0
                          29.0
                                  0.0 26.6 0.351
                                                    31.0
                                                          0.0
                                                               1.0
     2 8.0 183.0 64.0
                                  0.0 23.3 0.672
                           0.0
                                                    32.0
                                                          1.0
                                                               2.0
     3 1.0
             89.0
                    66.0
                          23.0
                                 94.0 28.1 0.167
                                                    21.0
                                                          0.0
                                                               3.0
     4 0.0 137.0 40.0 35.0 168.0 43.1 2.288
                                                    33.0 1.0 4.0
[11]: diab_X = diab_dataset.values[:, 9]
     diab_Y = diab_dataset.values[:, 8]
[12]: diab X_train, diab_X_test, diab_Y_train, diab_Y_test = train_test_split(diab_X,__

diab_Y, test_size=0.2, random_state=42)
[13]: sc = StandardScaler()
     diab_X_reshape = diab_X_train.reshape(-1, 1)
     diab_X_std = sc.fit_transform(diab_X_reshape)
     diab_Xtest_reshape = diab_X_test.reshape(-1, 1)
     diab Xtest std = sc.transform(diab Xtest reshape)
[14]: diab_logreg = LogisticRegression(solver = 'liblinear', random_state=0)
     diab_logreg.fit(diab_X_std, diab_Y_train)
[14]: LogisticRegression(random state=0, solver='liblinear')
[15]: diab_Y_pred = diab_logreg.predict(diab_Xtest_std)
[16]: diab_cnf_matrix = confusion_matrix(diab_Y_test, diab_Y_pred)
     diab_cnf_matrix
[16]: array([[99, 0],
             [55, 0]], dtype=int64)
```

```
[17]: print("Accuracy:",metrics.accuracy_score(diab_Y_test, diab_Y_pred))
      print("Precision:",metrics.precision_score(diab_Y_test, diab_Y_pred))
      print("Recall:",metrics.recall_score(diab_Y_test, diab_Y_pred))
     Accuracy: 0.6428571428571429
     Precision: 0.0
     Recall: 0.0
     C:\Users\homer\anaconda3\lib\site-
     packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
     Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
     `zero_division` parameter to control this behavior.
       _warn_prf(average, modifier, msg_start, len(result))
[18]: class_names = [0,1]
      fig, ax = plt.subplots()
      tick_marks = np.arange(len(class_names))
      plt.xticks(tick_marks, class_names)
      plt.yticks(tick_marks, class_names)
      sns.heatmap(pd.DataFrame(diab_cnf_matrix), annot=True, cmap="YlGnBu", fmt='g')
      ax.xaxis.set_label_position("top")
      plt.tight_layout()
      plt.title('Confusion matrix', y=1.1)
      plt.ylabel('Actual label')
      plt.xlabel('Predicted label')
```

[18]: Text(0.5, 257.44, 'Predicted label')

Confusion matrix



```
[19]: diab_kfold = KFold(n_splits=5, random_state=42, shuffle=True)
model = LogisticRegression(solver='liblinear')
results = cross_val_score(model, diab_X.reshape(-1, 1), diab_Y, cv=diab_kfold)
print("Accuracy: %.3f%% (%.3f%%)" % (results.mean()*100.0, results.std()*100.0))
```

Accuracy: 65.106% (3.703%)

```
[20]: diab_kfold = KFold(n_splits=10, random_state=42, shuffle=True)
model = LogisticRegression(solver='liblinear')
results = cross_val_score(model, diab_X.reshape(-1, 1), diab_Y, cv=diab_kfold)
print("Accuracy: %.3f%% (%.3f%%)" % (results.mean()*100.0, results.std()*100.0))
```

Accuracy: 65.096% (4.779%)

```
[21]: cancer = load_breast_cancer()
```

```
[22]: cancer_data = cancer.data
cancer_data.shape
```

[22]: (569, 30)

```
[23]: cancer_input = pd.DataFrame(cancer_data)
     cancer_input.head()
[23]:
           0
                  1
                          2
                                  3
                                           4
                                                   5
                                                           6
                                                                    7
                                                                            8
                             1001.0
        17.99
               10.38
                     122.80
                                     0.11840
                                              0.27760 0.3001
                                                              0.14710
                                                                        0.2419
     1 20.57
               17.77 132.90
                             1326.0 0.08474
                                              0.07864 0.0869
                                                              0.07017
                                                                        0.1812
     2 19.69 21.25 130.00
                             1203.0 0.10960
                                              0.15990
                                                       0.1974
                                                               0.12790
                                                                        0.2069
     3 11.42 20.38
                       77.58
                               386.1
                                     0.14250
                                              0.28390 0.2414
                                                               0.10520 0.2597
     4 20.29 14.34 135.10
                             1297.0 0.10030 0.13280 0.1980 0.10430 0.1809
                       20
                              21
                                      22
                                                     24
             9
                                              23
                                                             25
                                                                     26
                                                                             27
                    25.38
     0 0.07871
                          17.33
                                 184.60
                                         2019.0
                                                 0.1622
                                                         0.6656
                                                                 0.7119
                                                                         0.2654
     1 0.05667
                    24.99
                          23.41
                                  158.80
                                         1956.0 0.1238
                                                         0.1866
                                                                 0.2416 0.1860
     2 0.05999 ...
                    23.57
                           25.53 152.50
                                         1709.0 0.1444
                                                         0.4245
                                                                 0.4504 0.2430
                                          567.7
     3 0.09744 ...
                    14.91
                           26.50
                                   98.87
                                                 0.2098
                                                         0.8663
                                                                 0.6869 0.2575
     4 0.05883 ...
                    22.54 16.67 152.20
                                         1575.0 0.1374 0.2050
                                                                 0.4000 0.1625
            28
                     29
     0 0.4601 0.11890
     1 0.2750 0.08902
     2 0.3613 0.08758
     3 0.6638 0.17300
     4 0.2364 0.07678
      [5 rows x 30 columns]
[24]: cancer_labels = cancer.target
[25]: cancer_labels.shape
[25]: (569,)
[26]: labels = np.reshape(cancer_labels, (569,1))
[27]: |final_cancer_data = np.concatenate([cancer_data,labels],axis=1)
[28]: final_cancer_data.shape
[28]: (569, 31)
[29]: cancer_dataset = pd.DataFrame(final_cancer_data)
[30]: features = cancer.feature_names
     features
[30]: array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
             'mean smoothness', 'mean compactness', 'mean concavity',
             'mean concave points', 'mean symmetry', 'mean fractal dimension',
```

```
'smoothness error', 'compactness error', 'concavity error',
             'concave points error', 'symmetry error',
             'fractal dimension error', 'worst radius', 'worst texture',
             'worst perimeter', 'worst area', 'worst smoothness',
             'worst compactness', 'worst concavity', 'worst concave points',
             'worst symmetry', 'worst fractal dimension'], dtype='<U23')
[31]: features_labels = np.append(features, 'label')
[32]: cancer_dataset.columns = features_labels
[33]: cancer_dataset.head()
[33]:
         mean radius mean texture mean perimeter mean area mean smoothness \
      0
               17.99
                              10.38
                                             122.80
                                                        1001.0
                                                                         0.11840
      1
               20.57
                             17.77
                                             132.90
                                                        1326.0
                                                                         0.08474
      2
               19.69
                             21.25
                                             130.00
                                                        1203.0
                                                                         0.10960
      3
               11.42
                             20.38
                                             77.58
                                                                         0.14250
                                                         386.1
      4
               20.29
                             14.34
                                             135.10
                                                        1297.0
                                                                         0.10030
                           mean concavity mean concave points
         mean compactness
                                                                 mean symmetry \
      0
                  0.27760
                                    0.3001
                                                        0.14710
                                                                         0.2419
      1
                  0.07864
                                    0.0869
                                                        0.07017
                                                                         0.1812
      2
                  0.15990
                                    0.1974
                                                        0.12790
                                                                         0.2069
      3
                  0.28390
                                    0.2414
                                                        0.10520
                                                                         0.2597
      4
                  0.13280
                                    0.1980
                                                        0.10430
                                                                         0.1809
         mean fractal dimension ... worst texture worst perimeter worst area
      0
                        0.07871
                                             17.33
                                                                          2019.0
                                                              184.60
      1
                        0.05667 ...
                                             23.41
                                                             158.80
                                                                          1956.0
                                             25.53
                                                             152.50
                                                                          1709.0
      2
                        0.05999
      3
                        0.09744 ...
                                             26.50
                                                              98.87
                                                                           567.7
                        0.05883 ...
                                             16.67
                                                             152.20
                                                                          1575.0
         worst smoothness worst compactness worst concavity worst concave points
      0
                   0.1622
                                       0.6656
                                                        0.7119
                                                                               0.2654
                   0.1238
                                                        0.2416
      1
                                       0.1866
                                                                               0.1860
      2
                   0.1444
                                       0.4245
                                                        0.4504
                                                                               0.2430
      3
                   0.2098
                                       0.8663
                                                        0.6869
                                                                               0.2575
                   0.1374
                                       0.2050
                                                        0.4000
                                                                               0.1625
         worst symmetry worst fractal dimension label
      0
                 0.4601
                                          0.11890
                                                     0.0
                                                     0.0
      1
                 0.2750
                                          0.08902
                 0.3613
                                          0.08758
                                                     0.0
      3
                 0.6638
                                                     0.0
                                          0.17300
```

'radius error', 'texture error', 'perimeter error', 'area error',

4 0.2364 0.07678 0.0

[5 rows x 31 columns]

```
[34]: cancer dataset['label'].replace(0, 'Benign', inplace=True)
      cancer_dataset['label'].replace(1, 'Malignant', inplace=True)
[35]: cancer_dataset.tail()
[35]:
           mean radius mean texture mean perimeter mean area mean smoothness \
      564
                 21.56
                                22.39
                                               142.00
                                                           1479.0
                                                                            0.11100
      565
                 20.13
                                28.25
                                                131.20
                                                           1261.0
                                                                            0.09780
                 16.60
                                28.08
      566
                                               108.30
                                                            858.1
                                                                            0.08455
                                29.33
      567
                 20.60
                                               140.10
                                                           1265.0
                                                                            0.11780
      568
                  7.76
                                24.54
                                                47.92
                                                            181.0
                                                                            0.05263
           mean compactness mean concavity mean concave points
                                                                    mean symmetry
      564
                    0.11590
                                     0.24390
                                                           0.13890
                                                                            0.1726
      565
                                                                            0.1752
                    0.10340
                                     0.14400
                                                           0.09791
      566
                                     0.09251
                                                                            0.1590
                    0.10230
                                                           0.05302
      567
                    0.27700
                                     0.35140
                                                           0.15200
                                                                            0.2397
      568
                    0.04362
                                     0.00000
                                                           0.00000
                                                                            0.1587
           mean fractal dimension ... worst texture
                                                      worst perimeter worst area
      564
                           0.05623 ...
                                               26.40
                                                                166.10
                                                                             2027.0
      565
                                               38.25
                                                                155.00
                           0.05533 ...
                                                                             1731.0
      566
                           0.05648 ...
                                               34.12
                                                                126.70
                                                                             1124.0
      567
                           0.07016 ...
                                                                             1821.0
                                                39.42
                                                                184.60
      568
                           0.05884 ...
                                                30.37
                                                                 59.16
                                                                              268.6
           worst smoothness worst compactness worst concavity \
                                        0.21130
                                                           0.4107
      564
                    0.14100
      565
                    0.11660
                                        0.19220
                                                           0.3215
      566
                    0.11390
                                        0.30940
                                                           0.3403
      567
                                        0.86810
                                                           0.9387
                    0.16500
      568
                    0.08996
                                        0.06444
                                                           0.0000
           worst concave points worst symmetry worst fractal dimension
                                                                                 label
      564
                         0.2216
                                          0.2060
                                                                   0.07115
                                                                                Benign
                                          0.2572
      565
                         0.1628
                                                                   0.06637
                                                                                Benign
      566
                         0.1418
                                          0.2218
                                                                   0.07820
                                                                                Benign
      567
                          0.2650
                                          0.4087
                                                                   0.12400
                                                                                Benign
      568
                                          0.2871
                         0.0000
                                                                   0.07039 Malignant
```

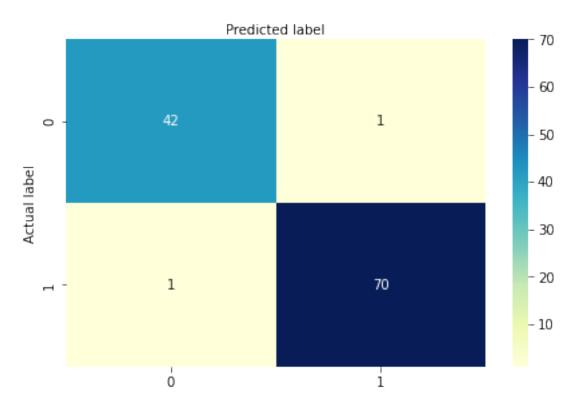
[5 rows x 31 columns]

```
[36]: cancer_X = cancer_dataset.iloc[:,0:29].values
      cancer_Y = cancer_dataset.iloc[:,30].values
[37]: cancer_X_train, cancer_X_test, cancer_Y_train, cancer_Y_test =
       otrain_test_split(cancer_X, cancer_Y, test_size=0.2, random_state=42)
[38]: sc_X = StandardScaler()
      cancer X trainstd = sc X.fit transform(cancer X train)
      cancer_X_teststd = sc_X.transform(cancer_X_test)
[39]: cancerClass = LogisticRegression(random_state=42)
      cancerClass.fit(cancer_X_trainstd, cancer_Y_train)
[39]: LogisticRegression(random_state=42)
[40]: cancer_Y_pred = cancerClass.predict(cancer_X_teststd)
[41]: cancer_Y_pred[0:9]
[41]: array(['Malignant', 'Benign', 'Benign', 'Malignant', 'Malignant',
             'Benign', 'Benign', 'Malignant'], dtype=object)
[42]: cancer_cnf_matrix = confusion_matrix(cancer_Y_test, cancer_Y_pred)
      cancer_cnf_matrix
[42]: array([[42, 1],
             [ 1, 70]], dtype=int64)
[43]: print("Accuracy:",metrics.accuracy_score(cancer_Y_test, cancer_Y_pred))
      print("Precision:",metrics.precision_score(cancer_Y_test, cancer_Y_pred,__
       ⇔pos_label="Benign"))
      print("Recall:",metrics.recall score(cancer Y test, cancer Y pred, ...
       →pos_label="Benign"))
     Accuracy: 0.9824561403508771
     Precision: 0.9767441860465116
     Recall: 0.9767441860465116
[44]: class_names = [0,1]
      fig, ax = plt.subplots()
      tick_marks = np.arange(len(class_names))
      plt.xticks(tick_marks, class_names)
      plt.yticks(tick_marks, class_names)
      sns.heatmap(pd.DataFrame(cancer_cnf_matrix), annot=True, cmap="YlGnBu", fmt='g')
      ax.xaxis.set_label_position("top")
      plt.tight_layout()
      plt.title('Confusion matrix', y=1.1)
      plt.ylabel('Actual label')
```

```
plt.xlabel('Predicted label')
```

[44]: Text(0.5, 257.44, 'Predicted label')

Confusion matrix



```
[48]: C = [10, 1, .1, .001]
for c in C:
    clf = LogisticRegression(penalty ='l1', C=c, solver='liblinear')
    clf.fit(cancer_X_trainstd, cancer_Y_train)
    print('C:', c)
    print('Training accuracy: ', clf.score(cancer_X_trainstd, cancer_Y_train))
    print('Test accuracy: ', clf.score(cancer_X_teststd, cancer_Y_test))
    print(' ')
```

C: 10

Training accuracy: 0.9912087912087912 Test accuracy: 0.956140350877193

C: 1

Training accuracy: 0.989010989010989 Test accuracy: 0.9736842105263158

```
Training accuracy: 0.9802197802197802
     Test accuracy: 0.9649122807017544
     C: 0.001
     Training accuracy: 0.37142857142857144
     Test accuracy: 0.37719298245614036
[49]: cancer_kfold = KFold(n_splits=5, random_state=42, shuffle=True)
      model = LogisticRegression(solver='liblinear')
      results = cross_val_score(model, cancer_X, cancer_Y, cv=cancer_kfold)
      print("Accuracy: %.3f%% (%.3f%%)" % (results.mean()*100.0, results.std()*100.0))
     Accuracy: 94.723% (2.675%)
[50]: cancer_kfold = KFold(n splits=10, random state=42, shuffle=True)
      model = LogisticRegression(solver='liblinear')
      results = cross_val_score(model, cancer_X, cancer_Y, cv=cancer_kfold)
      print("Accuracy: %.3f%% (%.3f%%)" % (results.mean()*100.0, results.std()*100.0))
     Accuracy: 94.897% (3.477%)
[51]: for c in C:
          cancer_kfold = KFold(n_splits=5, random_state=42, shuffle=True)
          model = LogisticRegression(penalty = '11', C=c, solver='liblinear')
          results = cross_val_score(model, cancer_X, cancer_Y, cv=cancer_kfold)
          print("Accuracy: %.3f%% (%.3f%%)" % (results.mean()*100.0, results.
       ⇒std()*100.0))
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\ base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     Accuracy: 96.479% (2.097%)
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
```

C: 0.1

```
ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     Accuracy: 94.898% (3.219%)
     Accuracy: 93.316% (3.760%)
     Accuracy: 91.559% (3.039%)
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
[52]: for c in C:
          cancer_kfold = KFold(n_splits=10, random_state=42, shuffle=True)
          model = LogisticRegression(penalty ='11', C=c, solver='liblinear')
          results = cross_val_score(model, cancer_X, cancer_Y, cv=cancer_kfold)
          print("Accuracy: %.3f%% (%.3f%%)" % (results.mean()*100.0, results.

std()*100.0))
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     Accuracy: 95.949% (2.966%)
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
     iterations.
       warnings.warn(
     C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206:
     ConvergenceWarning: Liblinear failed to converge, increase the number of
```

iterations.

warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(Accuracy: 94.721% (3.346%) C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations. warnings.warn(

C:\Users\homer\anaconda3\lib\site-packages\sklearn\svm_base.py:1206:

ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

warnings.warn(

Accuracy: 93.318% (4.636%) Accuracy: 91.557% (5.090%)

[]: