classification-regression-1

February 6, 2024

```
[82]: import pandas as pd
      github_url = 'https://raw.githubusercontent.com/aniruddhachoudhury/
       →Red-Wine-Quality/master/winequality-red.csv'
      wine_data = pd.read_csv(github_url)
      print('Wine Quality Dataset:')
      print(wine_data.head())
      display(wine_data)
     Wine Quality Dataset:
        fixed acidity volatile acidity citric acid residual sugar
                                                                       chlorides
     0
                  7.4
                                    0.70
                                                 0.00
                                                                   1.9
                                                                            0.076
                  7.8
                                    0.88
                                                 0.00
                                                                   2.6
     1
                                                                            0.098
                  7.8
                                    0.76
                                                 0.04
                                                                   2.3
     2
                                                                            0.092
     3
                  11.2
                                    0.28
                                                 0.56
                                                                   1.9
                                                                            0.075
                  7.4
                                    0.70
                                                 0.00
                                                                   1.9
                                                                            0.076
        free sulfur dioxide total sulfur dioxide density
                                                               рΗ
                                                                  sulphates
     0
                       11.0
                                              34.0
                                                     0.9978 3.51
                                                                         0.56
                       25.0
                                              67.0
                                                     0.9968 3.20
                                                                         0.68
     1
                                                     0.9970 3.26
                                              54.0
                                                                         0.65
     2
                        15.0
     3
                        17.0
                                              60.0
                                                     0.9980 3.16
                                                                         0.58
     4
                        11.0
                                              34.0
                                                     0.9978 3.51
                                                                         0.56
        alcohol quality
     0
            9.4
                        5
            9.8
     1
                       5
     2
            9.8
                       5
                        6
     3
            9.8
            9.4
           fixed acidity volatile acidity citric acid residual sugar chlorides \
                     7.4
                                      0.700
                                                    0.00
                                                                      1.9
                                                                               0.076
     0
                                                    0.00
     1
                     7.8
                                      0.880
                                                                      2.6
                                                                               0.098
     2
                     7.8
                                      0.760
                                                    0.04
                                                                      2.3
                                                                               0.092
     3
                     11.2
                                      0.280
                                                    0.56
                                                                      1.9
                                                                               0.075
     4
                     7.4
                                      0.700
                                                    0.00
                                                                      1.9
                                                                               0.076
```

```
1594
                     6.2
                                      0.600
                                                    0.08
                                                                      2.0
                                                                               0.090
     1595
                     5.9
                                      0.550
                                                    0.10
                                                                      2.2
                                                                               0.062
     1596
                     6.3
                                      0.510
                                                    0.13
                                                                      2.3
                                                                               0.076
     1597
                     5.9
                                      0.645
                                                    0.12
                                                                      2.0
                                                                               0.075
                     6.0
                                                                      3.6
     1598
                                      0.310
                                                    0.47
                                                                               0.067
           free sulfur dioxide total sulfur dioxide density
                                                                  pH sulphates \
     0
                           11.0
                                                 34.0 0.99780 3.51
                                                                            0.56
     1
                           25.0
                                                 67.0 0.99680 3.20
                                                                            0.68
     2
                           15.0
                                                 54.0 0.99700 3.26
                                                                            0.65
     3
                           17.0
                                                 60.0 0.99800 3.16
                                                                            0.58
     4
                           11.0
                                                 34.0 0.99780 3.51
                                                                            0.56
                                                 44.0 0.99490 3.45
                                                                            0.58
     1594
                           32.0
     1595
                           39.0
                                                 51.0 0.99512 3.52
                                                                            0.76
                           29.0
                                                 40.0 0.99574 3.42
                                                                            0.75
     1596
     1597
                           32.0
                                                 44.0 0.99547 3.57
                                                                            0.71
     1598
                           18.0
                                                 42.0 0.99549 3.39
                                                                            0.66
           alcohol quality
               9.4
     0
                           5
               9.8
     1
                           5
     2
               9.8
                           5
                           6
     3
               9.8
     4
               9.4
                           5
              10.5
                           5
     1594
              11.2
                           6
     1595
              11.0
                           6
     1596
     1597
              10.2
                           5
     1598
              11.0
                           6
     [1599 rows x 12 columns]
[83]: import pandas as pd
      # Assuming redWine is a pandas DataFrame that has been previously loaded
      quality_counts = wine_data['quality'].value_counts()
      print(quality_counts)
      wine_data['quality_binary'] = wine_data['quality'].apply(lambda x: 0 if x in_
       \Rightarrow[3, 4, 5] else (1 if x in [6, 7, 8] else None))
      quality_binary_counts = wine_data['quality_binary'].value_counts()
      print(quality binary counts)
     quality
```

5

681

```
6
          638
     7
          199
     4
           53
     8
           18
           10
     3
     Name: count, dtype: int64
     quality_binary
     1
          855
          744
     Name: count, dtype: int64
[84]: pip install scikit-learn
     Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.11/site-
     packages (1.4.0)
     Requirement already satisfied: numpy<2.0,>=1.19.5 in
     /opt/conda/lib/python3.11/site-packages (from scikit-learn) (1.26.2)
     Requirement already satisfied: scipy>=1.6.0 in /opt/conda/lib/python3.11/site-
     packages (from scikit-learn) (1.12.0)
     Requirement already satisfied: joblib>=1.2.0 in /opt/conda/lib/python3.11/site-
     packages (from scikit-learn) (1.3.2)
     Requirement already satisfied: threadpoolctl>=2.0.0 in
     /opt/conda/lib/python3.11/site-packages (from scikit-learn) (3.2.0)
     Note: you may need to restart the kernel to use updated packages.
[85]: pip install matplotlib
     Requirement already satisfied: matplotlib in /opt/conda/lib/python3.11/site-
     packages (3.8.2)
     Requirement already satisfied: contourpy>=1.0.1 in
     /opt/conda/lib/python3.11/site-packages (from matplotlib) (1.2.0)
     Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.11/site-
     packages (from matplotlib) (0.12.1)
     Requirement already satisfied: fonttools>=4.22.0 in
     /opt/conda/lib/python3.11/site-packages (from matplotlib) (4.47.2)
     Requirement already satisfied: kiwisolver>=1.3.1 in
     /opt/conda/lib/python3.11/site-packages (from matplotlib) (1.4.5)
     Requirement already satisfied: numpy<2,>=1.21 in /opt/conda/lib/python3.11/site-
     packages (from matplotlib) (1.26.2)
     Requirement already satisfied: packaging>=20.0 in
     /opt/conda/lib/python3.11/site-packages (from matplotlib) (23.2)
     Requirement already satisfied: pillow>=8 in /opt/conda/lib/python3.11/site-
     packages (from matplotlib) (10.2.0)
     Requirement already satisfied: pyparsing>=2.3.1 in
     /opt/conda/lib/python3.11/site-packages (from matplotlib) (3.1.1)
     Requirement already satisfied: python-dateutil>=2.7 in
     /opt/conda/lib/python3.11/site-packages (from matplotlib) (2.8.2)
     Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.11/site-
```

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packages (from python-dateutil>=2.7->matplotlib) (1.16.0) Note: you may need to restart the kernel to use updated packages.
```

[86]: pip install seaborn

```
Requirement already satisfied: seaborn in /opt/conda/lib/python3.11/site-
packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in
/opt/conda/lib/python3.11/site-packages (from seaborn) (1.26.2)
Requirement already satisfied: pandas>=1.2 in /opt/conda/lib/python3.11/site-
packages (from seaborn) (2.0.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in
/opt/conda/lib/python3.11/site-packages (from seaborn) (3.8.2)
Requirement already satisfied: contourpy>=1.0.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(1.2.0)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.11/site-
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(4.47.2)
Requirement already satisfied: kiwisolver>=1.3.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(1.4.5)
Requirement already satisfied: packaging>=20.0 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(23.2)
Requirement already satisfied: pillow>=8 in /opt/conda/lib/python3.11/site-
packages (from matplotlib!=3.6.1,>=3.4->seaborn) (10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.11/site-
packages (from pandas>=1.2->seaborn) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.11/site-
packages (from pandas>=1.2->seaborn) (2023.4)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.11/site-
packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

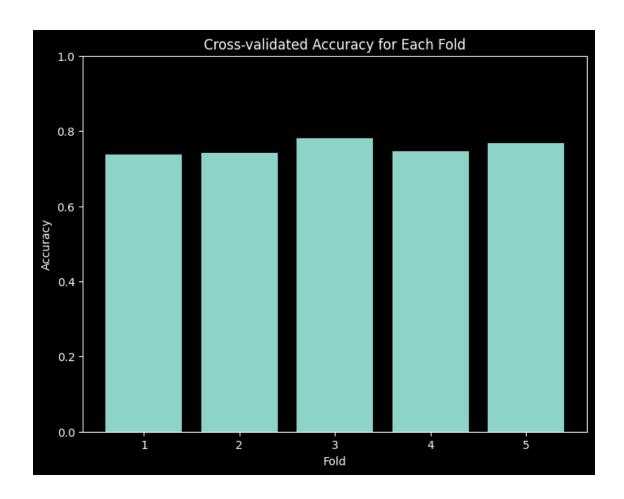
```
[87]: import numpy as np
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

```
# Assuming 'redWine' is a pandas DataFrame and 'quality binary' is a column in
 \hookrightarrow it
# Set the random seed
np.random.seed(123)
# Split the data into training and test sets
train_data, test_data = train_test_split(wine_data, test_size=0.3)
# Prepare the data for logistic regression
# Assuming 'quality' is a column to be excluded from the model
X_train = train_data.drop(columns=['quality', 'quality_binary'])
y_train = train_data['quality_binary']
X_test = test_data.drop(columns=['quality', 'quality_binary'])
y_test = test_data['quality_binary']
# Create and fit the logistic regression model
logistic_model_no_quality = LogisticRegression(max_iter=1000)
logistic_model_no_quality.fit(X_train, y_train)
# Print the summary of the model
# Note: There's no direct equivalent of R's summary function in sklearn; we_
 ⇔print the coefficients instead
#print(logistic_model_no_quality.coef_)
# Make predictions on the test data
predictions_no_quality = logistic_model_no_quality.predict_proba(X_test)[:, 1]
# Convert probabilities to class predictions
predicted_classes_no_quality = (predictions_no_quality > 0.5).astype(int)
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score,
 ⇔recall_score, f1_score
# Assuming test_data['quality_binary'] and predicted_classes_no_quality are__
 \hookrightarrow defined
conf_matrix_no_quality = confusion_matrix(test_data['quality_binary'],_
 predicted_classes_no_quality)
print(conf_matrix_no_quality)
accuracy_no_quality = accuracy_score(test_data['quality_binary'],_
→predicted_classes_no_quality)
precision_no_quality = precision_score(test_data['quality_binary'],_
 →predicted_classes_no_quality)
recall_no_quality = recall_score(test_data['quality_binary'],__
 →predicted_classes_no_quality)
```

```
f1_score_no_quality = f1_score(test_data['quality_binary'],_
       ⇒predicted_classes_no_quality)
     print("Model without 'quality' - Accuracy:", accuracy_no_quality)
     print("Model without 'quality' - Precision:", precision_no_quality)
     print("Model without 'quality' - Recall:", recall no quality)
     print("Model without 'quality' - F1 Score:", f1_score_no_quality)
     [[158 74]
      [ 62 186]]
     Model without 'quality' - Accuracy: 0.7166666666666667
     Model without 'quality' - Precision: 0.7153846153846154
     Model without 'quality' - Recall: 0.75
     Model without 'quality' - F1 Score: 0.7322834645669292
[88]: from sklearn.model_selection import cross_val_score
     scores = cross_val_score(logistic_model_no_quality, X_train, y_train, cv=5,_

scoring='accuracy')
     print("Cross-validated Accuracy:", np.mean(scores))
```

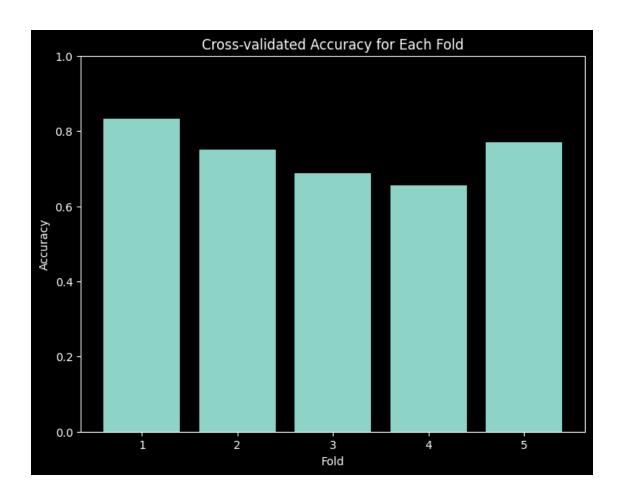
Cross-validated Accuracy: 0.7542560858424088

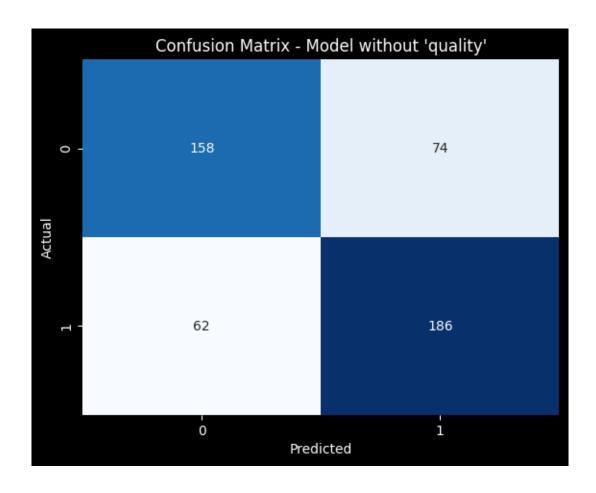


```
[468]: import matplotlib.pyplot as plt

# Perform cross-validation
scores = cross_val_score(logistic_model_no_quality, X_test, y_test, cv=5,u_scoring='accuracy')

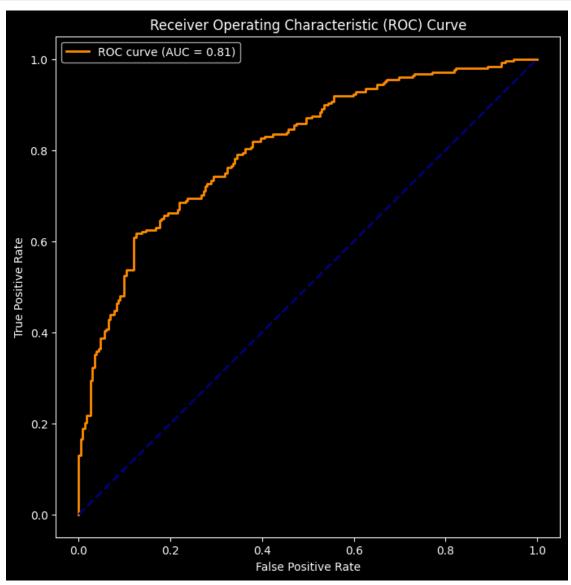
# Create a bar plot of cross-validated accuracy for each fold
plt.figure(figsize=(8, 6))
plt.bar(range(1, len(scores) + 1), scores)
plt.title('Cross-validated Accuracy for Each Fold')
plt.xlabel('Fold')
plt.ylabel('Accuracy')
plt.ylim([0, 1])
plt.show()
```

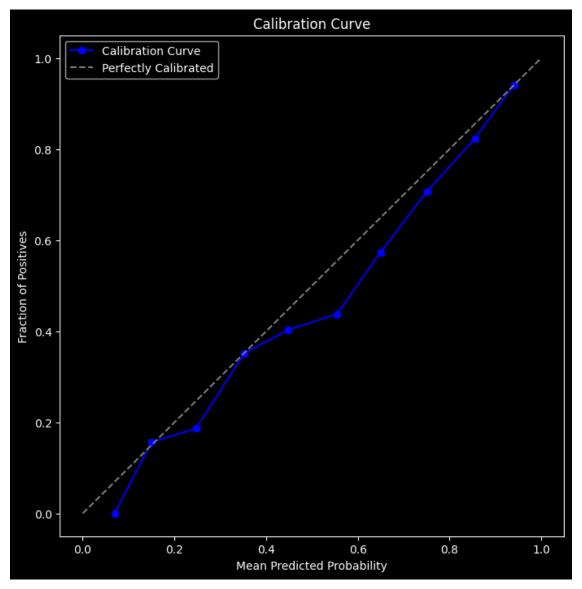




```
[90]: import matplotlib.pyplot as plt
      import seaborn as sns
      from sklearn.metrics import roc_curve, roc_auc_score
      # Assuming logistic_model is your fitted scikit-learn LogisticRegression model
      \# Assuming X_{test} is your test data and y_{test} is the corresponding true labels
      # Predict probabilities
      probabilities = logistic_model_no_quality.predict_proba(X_test)[:, 1]
      # ROC curve
      fpr, tpr, thresholds = roc_curve(y_test, probabilities)
      roc_auc = roc_auc_score(y_test, probabilities)
      plt.figure(figsize=(8, 8))
     plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = {:.2f})'.
       →format(roc auc))
      plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
      plt.xlabel('False Positive Rate')
      plt.ylabel('True Positive Rate')
```

```
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```

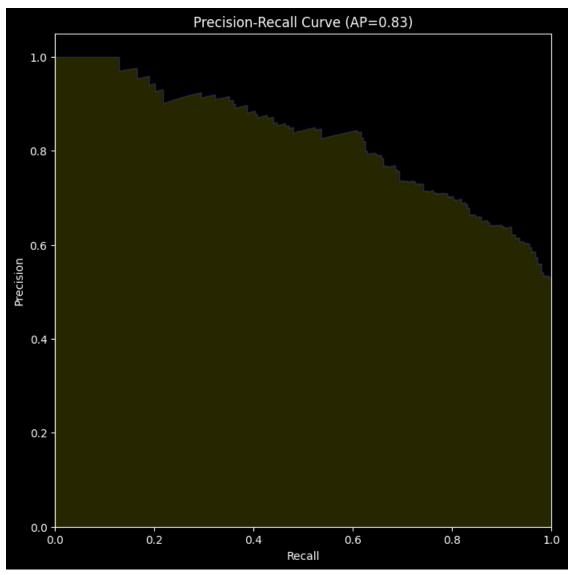




[92]: from sklearn.metrics import precision_recall_curve, average_precision_score

```
# Compute precision-recall curve and area the curve
precision, recall, _ = precision_recall_curve(y_test, predictions_no_quality)
average_precision = average_precision_score(y_test, predictions_no_quality)

# Plot precision-recall curve
plt.figure(figsize=(8, 8))
plt.step(recall, precision, color='b', alpha=0.2, where='post')
plt.fill_between(recall, precision, step='post', alpha=0.2, color='y')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.05])
plt.title('Precision-Recall Curve (AP={:.2f})'.format(average_precision))
plt.show()
```



[]:[