## Assignment-2\_Machine\_Learning\_Valapadasu\_UdayBhaskar

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[142]: #Assignment 2: Machine Learning
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[143]: #Import Statements
       import pandas as pd
       import seaborn as sns
       import matplotlib.pyplot as plt
       from sklearn.model_selection import train_test_split
       import warnings
       # Suppress the FutureWarning
       warnings.simplefilter(action='ignore', category=FutureWarning)
[144]: # Using the diabetes_df.csv created from assignment - 1 & Created a Pandas_
        →dataframe from diabetes_df.csv and named it assignment2_df
       assignment2_df = pd.read_csv("diabetes_df.csv")
       assignment2_df
[144]:
            Pregnancies
                         Glucose
                                  BloodPressure
                                                  SkinThickness
                                                                  Insulin
                                                                            BMI
       0
                      6
                              148
                                              72
                                                              35
                                                                      150 33.6
                                                                      150 26.6
       1
                      1
                               85
                                              66
                                                              29
       2
                      8
                              183
                                              64
                                                               0
                                                                      150 23.3
       3
                      1
                               89
                                              66
                                                              23
                                                                       94 28.1
       4
                      0
                                              40
                                                              35
                                                                      168 43.1
                              137
                                                                      180 32.9
       763
                     10
                              101
                                              76
                                                              48
       764
                      2
                              122
                                              70
                                                              27
                                                                      150 36.8
       765
                      5
                              121
                                              72
                                                              23
                                                                      112 26.2
       766
                      1
                              126
                                              60
                                                               0
                                                                      150 30.1
       767
                      1
                               93
                                              70
                                                              31
                                                                      150 30.4
            DiabetesPedigreeFunction
                                            Target
                                       Age
                                0.627
       0
                                        50
       1
                                0.351
                                        31
                                                 0
       2
                                0.672
                                        32
                                                 1
       3
                                0.167
                                        21
                                                 0
```

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4
                               2.288
                                       33
                                                 1
       763
                               0.171
                                       63
                                                 0
       764
                               0.340
                                       27
                                                 0
      765
                               0.245
                                       30
                                                0
      766
                               0.349
                                       47
                                                 1
      767
                               0.315
                                       23
                                                0
       [768 rows x 9 columns]
[145]: # Setup the Machine Learning Model:
       #Dividing the data into features (X) array and target (y) array.
       #features array
       X = assignment2_df.drop(['Target'], axis=1)
       #target array
       y = assignment2_df['Target']
[146]: | # Splitting the dataset into 80-20, 70-30, and 60-40 ratios. (Example: <math>80-20_{\square}
        →means, 80% training data, 20% testing data, and so on.)
       #Split-1 into 80-20
       X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y, test_size=0.2,_
        →random_state=42)
       #Split-2 into 70-30
       X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.3,_
        ⇔random_state=42)
       #Split-3 into 60-40
       X_train3, X_test3, y_train3, y_test3 = train_test_split(X, y, test_size=0.4,_
        →random state=42)
[147]: # For each data split, apply logistic regression machine learning model to
       ⇒build confusion matrix and accuracy estimates.
       # So, importing the necessary accordinhly.
       from sklearn.linear_model import LogisticRegression
       from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score
[148]: # Performing Logistic Regression & Building Confusion Matrix and Accuracy for
       →Split-1 Training:Test(80:20) Ratio
       lr_split_1 = LogisticRegression(random_state=42, max_iter=1000)
       lr_split_1.fit(X_train1, y_train1)
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y\_pred1 = lr\_split\_1.predict(X\_test1)

y\_pred\_proba1 = lr\_split\_1.predict\_proba(X\_test1)[:, 1]

cm\_split\_1 = confusion\_matrix(y\_test1, y\_pred1)

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accuracy_split_1 = accuracy_score(y_test1, y_pred1)
       auc_split_1 = roc_auc_score(y_test1, y_pred_proba1)
       # Displaying the Confusion Matrix, Accuracy, and AUC
       print("Confusion Matrix and Accuracy for Split-1 Training:Test(80:20)")
       print("Confusion Matrix:")
       print(cm_split_1)
       print("Accuracy:", accuracy_split_1)
       print("AUC:", auc_split_1)
      Confusion Matrix and Accuracy for Split-1 Training:Test(80:20)
      Confusion Matrix:
      [[80 19]
       [19 36]]
      Accuracy: 0.7532467532467533
      AUC: 0.8165289256198347
[149]: # Performing Logistic Regression & Building Confusion Matrix, Accuracy, and AUC
       ⇔for Split-2 Training:Test(70:30) Ratio
       lr_split_2 = LogisticRegression(solver='lbfgs', random_state=42, max_iter=1000)
       lr_split_2.fit(X_train2, y_train2)
       y_pred2 = lr_split_2.predict(X_test2)
       y_pred_proba2 = lr_split_2.predict_proba(X_test2)[:, 1]
       cm_split_2 = confusion_matrix(y_test2, y_pred2)
       accuracy_split_2 = accuracy_score(y_test2, y_pred2)
       auc_split_2 = roc_auc_score(y_test2, y_pred_proba2)
       # Displaying the Confusion Matrix, Accuracy, and AUC
       print("Confusion Matrix, Accuracy, and AUC for Split-2 Training:Test(70:30)")
       print("Confusion Matrix:")
       print(cm_split_2)
       print("Accuracy:", accuracy_split_2)
       print("AUC:", auc_split_2)
      Confusion Matrix, Accuracy, and AUC for Split-2 Training: Test (70:30)
      Confusion Matrix:
      [[121 30]
       [ 30 50]]
      Accuracy: 0.7402597402597403
      AUC: 0.7964403973509934
[150]: # Performing Logistic Regression & Building Confusion Matrix, Accuracy, and AUC
       →for Split-3 Training:Test(60:40) Ratio
       lr split 3 = LogisticRegression(random state=42, max iter=1000)
       lr_split_3.fit(X_train3, y_train3)
       y pred3 = lr split 3.predict(X test3)
       y_pred_proba3 = lr_split_3.predict_proba(X_test3)[:, 1]
       cm_split_3 = confusion_matrix(y_test3, y_pred3)
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accuracy_split_3 = accuracy_score(y_test3, y_pred3)
       auc_split_3 = roc_auc_score(y_test3, y_pred_proba3)
       # Displaying the Confusion Matrix, Accuracy, and AUC
       print("Confusion Matrix, Accuracy, and AUC for Split-3 Training:Test(60:40)_{\sqcup}
        →Ratio")
       print("Confusion Matrix:")
       print(cm_split_3)
       print("Accuracy:", accuracy_split_3)
       print("AUC:", auc_split_3)
      Confusion Matrix, Accuracy, and AUC for Split-3 Training: Test (60:40) Ratio
      Confusion Matrix:
      [[166 40]
       [ 36 66]]
      Accuracy: 0.7532467532467533
      AUC: 0.8213401865600609
[151]: #Which data split is providing you the best accuracy?
       #Ans: As, we observe split_1(80-20), split_3(60-40) ratio are on a tie giving
        → the best accuracy of 75% when compared to data split_2(70:30)
       # Here, I am selecting split_3 (60:40) for the further analysis, because AUC_{\sqcup}
        ⇔score for Split-3 is higher than i.e 82% than other splits.
[152]: # Importing all the necessary libraries
       from sklearn.utils import resample
       import numpy as np
       import matplotlib.pyplot as plt
       from sklearn.metrics import roc_curve, roc_auc_score
[153]: #Performing bootstrap analysis on the selected data split to calculate.
       ⇔accuracy, p-value, confidence intervals, and
       #ROC threshold, and generate a histogram of the confidence intervals
       # No of bootstrap iterations
       noofitr = 1000
       # Initialized bootstrap results storing arrays
       bs_accuracylist = []
       bs thresholdslist = []
       bs_auc_scoreslist = []
       # Bootstrap iterations are performed below
       for _ in range(noofitr):
          # Using the resampled data to train the LR model
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X_train_resampled, y_train_resampled = resample(X_train3, y_train3, u
 →replace=True, n_samples=len(X_train3))
    # Training the LR model on the resampled data
   lr_bootstrap = LogisticRegression(random_state=42, max_iter=1000)
   lr bootstrap.fit(X train resampled, y train resampled)
    # Predict using the test set.
   y_pred_bootstrap = lr_bootstrap.predict(X_test3)
   y pred_proba_bootstrap = lr_bootstrap.predict_proba(X_test3)[:, 1]
    # Determine the current bootstrap iteration's accuracy.
   accuracy_bootstrap = accuracy_score(y_test3, y_pred_bootstrap)
   bs_accuracylist.append(accuracy_bootstrap)
    # Determine the current bootstrap iteration's threshold and ROC curve.
   fpr, tpr, thresholds = roc_curve(y_test3, y_pred_proba_bootstrap)
   optimal_idx = np.argmax(tpr - fpr)
   optimal threshold = thresholds[optimal idx]
   bs_thresholdslist.append(optimal_threshold)
    # Determine the current bootstrap iteration's AUC score.
   auc_score = roc_auc_score(y_test3, y_pred_proba_bootstrap)
   bs_auc_scoreslist.append(auc_score)
# Determine the confidence intervals and the p-value.
p_value = np.mean(np.array(bs_accuracylist) > accuracy_split_3)
accuracy_ci = np.percentile(bs_accuracylist, [2.5, 97.5])
threshold_ci = np.percentile(bs_thresholdslist, [2.5, 97.5])
auc_ci = np.percentile(bs_auc_scoreslist, [2.5, 97.5])
# Produce the report.
report = f"""
Logistic Regression Report (Split-3: 60:40 ratio)
Accuracy: {accuracy_split_3:.4f}
P-value: {p_value:.4f}
Accuracy 95% Confidence Interval: [{accuracy_ci[0]:.4f}, {accuracy_ci[1]:.4f}]
Threshold (ROC): {np.mean(bs_thresholdslist):.4f}
Threshold 95% Confidence Interval: [{threshold_ci[0]:.4f}, {threshold_ci[1]:.
⊶4f}]
AUC Score: {np.mean(bs_auc_scoreslist):.4f}
AUC Score 95% Confidence Interval: [{auc_ci[0]:.4f}, {auc_ci[1]:.4f}]
0.00
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print(report)
# Plot the confidence interval histogram.
plt.figure(figsize=(10, 4))
plt.subplot(1, 3, 1)
plt.hist(bs_accuracylist, bins=20, edgecolor='black')
plt.xlabel('Accuracy')
plt.ylabel('Frequency')
plt.title('Accuracy Confidence Interval')
plt.subplot(1, 3, 2)
plt.hist(bs_thresholdslist, bins=20, edgecolor='black')
plt.xlabel('Threshold')
plt.ylabel('Frequency')
plt.title('Threshold Confidence Interval')
plt.subplot(1, 3, 3)
plt.hist(bs_auc_scoreslist, bins=20, edgecolor='black')
plt.xlabel('AUC Score')
plt.ylabel('Frequency')
plt.title('AUC Score Confidence Interval')
plt.tight_layout()
plt.show()
```

Logistic Regression Report (Split-3: 60:40 ratio)

Accuracy: 0.7532 P-value: 0.5360

Accuracy 95% Confidence Interval: [0.7273, 0.7857]

Threshold (ROC): 0.3601

Threshold 95% Confidence Interval: [0.2415, 0.5325]

AUC Score: 0.8132

AUC Score 95% Confidence Interval: [0.7866, 0.8334]





