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

July 1, 2024

```
[37]: #Assignment 2: Machine Learning
      #Name: Uday Bhaskar Valapadasu
      #ID: 11696364
[38]: #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)
[39]: # 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
[39]:
           Pregnancies
                        Glucose
                                 BloodPressure
                                                 SkinThickness
                                                                 Insulin
                                                                           BMI
      0
                     6
                            148
                                             72
                                                            35
                                                                     150 33.6
                                                                     150 26.6
      1
                     1
                             85
                                             66
                                                            29
                     8
      2
                            183
                                             64
                                                             0
                                                                     150 23.3
      3
                     1
                             89
                                             66
                                                            23
                                                                      94 28.1
                     0
      4
                            137
                                             40
                                                             35
                                                                     168 43.1
                                                                     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
                                       50
      0
      1
                               0.351
                                       31
                                                0
      2
                               0.672
                                       32
                                                1
      3
                               0.167
                                       21
                                                0
```

```
4
                              2.288
                                      33
                                               1
                                ... ...
      763
                              0.171
                                      63
                                               0
      764
                              0.340
                                      27
                                               0
     765
                              0.245
                                      30
                                               0
                              0.349
     766
                                      47
                                               1
     767
                              0.315
                                      23
                                               0
      [768 rows x 9 columns]
[40]: # 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']
[41]: \# Splitting the dataset into 80-20, 70-30, and 60-40 ratios. (Example: 80-20.
       →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,_u
       →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)
[42]: # 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
[43]: # 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)
```

y\_pred1 = lr\_split\_1.predict(X\_test1)

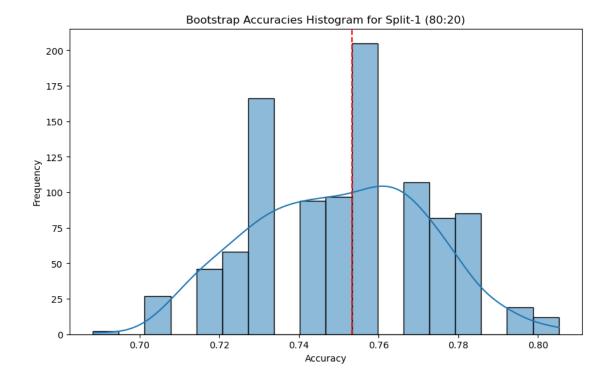
y\_pred\_proba1 = lr\_split\_1.predict\_proba(X\_test1)[:, 1]

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

```
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
[44]: # 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
[45]: # 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)
```

```
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) ∪
       →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
[46]: #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_1(80-20) for the further analysis.
[47]: # 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
[48]: # Compute ROC curve and ROC area for Split-1
      fpr_split1, tpr_split1, thresholds_split1 = roc_curve(y_test1, y_pred_proba1)
      roc_auc_split1 = auc(fpr_split1, tpr_split1)
      # Bootstrap analysis for Split-1 (80:20)
      n_iterations = 1000
      bootstrap_accuracies = []
      # Perform bootstrap sampling
      for i in range(n_iterations):
          X_resampled, y_resampled = resample(X_train1, y_train1, replace=True,__
       →random state=i)
          lr_split_1.fit(X_resampled, y_resampled) # Fit logistic regression on_
       ⇔resampled data
          y_pred_resampled = lr_split_1.predict(X_test1) # Predict on test set
          accuracy_resampled = accuracy_score(y_test1, y_pred_resampled) # Calculate_
       \rightarrowaccuracy
```

```
bootstrap_accuracies.append(accuracy_resampled) # Store accuracy from each_
 \rightarrow iteration
# Calculate p-value and confidence intervals
p_value_split1 = np.mean(np.array(bootstrap_accuracies) >= accuracy_split_1)
confidence interval split1 = np.percentile(bootstrap accuracies, [2.5, 97.5])
# Plot histogram of bootstrap accuracies
plt.figure(figsize=(10, 6))
sns.histplot(bootstrap_accuracies, kde=True)
plt.axvline(accuracy_split_1, color='r', linestyle='--')
plt.xlabel('Accuracy')
plt.ylabel('Frequency')
plt.title('Bootstrap Accuracies Histogram for Split-1 (80:20)')
plt.show()
# Write the report with metrics for Split-1 (80:20)
report_split1 = f"""
Selected Data Split Ratio (80:20) Metrics:
  Confusion Matrix:
{cm split 1}
 Accuracy: {accuracy_split_1}
 AUC: {auc_split_1}
 ROC AUC: {roc_auc_split1}
 ROC Thresholds: {thresholds_split1}
Bootstrap Analysis for Split-1:
 P-Value: {p_value_split1}
 Confidence Interval: {confidence_interval_split1}
print(report_split1)
```



```
Selected Data Split Ratio (80:20) Metrics:
```

Confusion Matrix:

[[80 19] [19 36]]

> Accuracy: 0.7532467532467533 AUC: 0.8165289256198347 ROC AUC: 0.8165289256198347

ROC Thresholds: [1.97062516 0.97062516 0.96040546 0.87284274 0.87075569

0.78031972

Bootstrap Analysis for Split-1:

P-Value: 0.51

Confidence Interval: [0.70779221 0.79220779]