index

September 4, 2024

0.1 Overview

This proect aims to develop a predictive model that can determine whether an arrest will be made during a Terry Stop based on various factors. The aim is to provide actionable insights that can help law enforcement agencies optimize their stop-and-search strategies, ensure public safety, and address concerns related to racial profiling and fairness in policing.

0.1.1 Business Understanding: Enhancing Law Enforcement Practices

Terry Stops, based on Terry v. Ohio (1968), are brief stops and searches by police based on reasonable suspicion. These stops raise concerns about fairness and potential bias. The business challenge is to predict the likelihood of an arrest during a Terry Stop to improve decision-making and address potential biases. The business understanding of the project is to enhance law enforcement practices by providing a platform for data-driven decision. This project benefits law enforcement by improving efficiency and fairness, policymakers by providing data-driven insights, and the public by fostering trust and reducing unjustified stops and arrests.

[109]:
```
# importing neccessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

0.1.2 Data

The data has 61050 rows and 23 columns

[110]:
```
# Load the data
terry_df = pd.read_csv('data/Terry_Stops.csv')
terry_df.head()
```

[110]:
```
  Subject Age Group   Subject ID      GO / SC Num  Terry Stop ID  \
0            1 - 17           -1   20170000315550         301338
1           26 - 35           -1   20170000115391         253596
2           18 - 25           -1   20160000036392         123863
3           36 - 45  33919122751   20210000055627    21770133324
4           18 - 25           -1   20160000003522         183376
```

```
  Stop Resolution Weapon Type Officer ID  Officer YOB Officer Gender  \
0  Offense Report         NaN       5489         1964              M
1  Offense Report         NaN       6403         1969              M
2  Offense Report         NaN       7473         1981              M
3   Field Contact           -       6711         1977              M
4   Field Contact         NaN       7090         1981              F

  Officer Race  …     Reported Time  \
0        White  …  00:10:00.0000000
1        White  …  16:04:00.0000000
2        White  …  02:26:00.0000000
3        White  …  14:42:43.0000000
4        White  …  15:49:00.0000000

                        Initial Call Type  \
0                                NUISANCE
1  THEFT (DOES NOT INCLUDE SHOPLIFT OR SVCS)
2    SUSPICIOUS PERSON, VEHICLE, OR INCIDENT
3                       PROPERTY - DAMAGE
4                                       -

                        Final Call Type                 Call Type  \
0          --MISCHIEF OR NUISANCE - GENERAL                       911
1                     --THEFT - ALL OTHER  TELEPHONE OTHER, NOT 911
2  --SUSPICIOUS CIRCUM. - SUSPICIOUS PERSON                       911
3                   --DISTURBANCE - OTHER                       911
4                                       -                         -

                          Officer Squad Arrest Flag Frisk Flag Precinct  \
0             NORTH PCT 3RD W - B/N RELIEF           N          N    North
1      NORTH PCT 2ND W - LINCOLN - PLATOON 1           N          N    North
2             NORTH PCT 3RD W - B/N RELIEF           N          N    North
3  SOUTHWEST PCT 2ND W - WILLIAM - PLATOON 2           N          N        -
4    SOUTHWEST PCT 2ND W - FRANK - PLATOON 2           N          Y        -

  Sector Beat
0      N   N2
1      L   L3
2      B   B3
3      -    -
4      -    -

[5 rows x 23 columns]
```

[111]:
```python
# Data information
terry_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61050 entries, 0 to 61049
Data columns (total 23 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Subject Age Group        61050 non-null  object
 1   Subject ID               61050 non-null  int64
 2   GO / SC Num              61050 non-null  int64
 3   Terry Stop ID            61050 non-null  int64
 4   Stop Resolution          61050 non-null  object
 5   Weapon Type              28485 non-null  object
 6   Officer ID               61050 non-null  object
 7   Officer YOB              61050 non-null  int64
 8   Officer Gender           61050 non-null  object
 9   Officer Race             61050 non-null  object
 10  Subject Perceived Race   61050 non-null  object
 11  Subject Perceived Gender 61050 non-null  object
 12  Reported Date            61050 non-null  object
 13  Reported Time            61050 non-null  object
 14  Initial Call Type        61050 non-null  object
 15  Final Call Type          61050 non-null  object
 16  Call Type                61050 non-null  object
 17  Officer Squad            60489 non-null  object
 18  Arrest Flag              61050 non-null  object
 19  Frisk Flag               61050 non-null  object
 20  Precinct                 61050 non-null  object
 21  Sector                   61050 non-null  object
 22  Beat                     61050 non-null  object
dtypes: int64(4), object(19)
memory usage: 10.7+ MB
```

[112]:
```python
terry_df.shape
```

[112]: (61050, 23)

0.2 Checking for Missing Values

The weapon type column has 32565 missing values and officer squad has 561 missing values.

[113]:
```python
#  check for missing data in the dataset
missing_values = terry_df.isnull().sum()
missing_values
```

[113]:
```
Subject Age Group           0
Subject ID                  0
GO / SC Num                 0
Terry Stop ID               0
Stop Resolution             0
```

```
Weapon Type                  32565
Officer ID                       0
Officer YOB                      0
Officer Gender                   0
Officer Race                     0
Subject Perceived Race           0
Subject Perceived Gender         0
Reported Date                    0
Reported Time                    0
Initial Call Type                0
Final Call Type                  0
Call Type                        0
Officer Squad                  561
Arrest Flag                      0
Frisk Flag                       0
Precinct                         0
Sector                           0
Beat                             0
dtype: int64
```

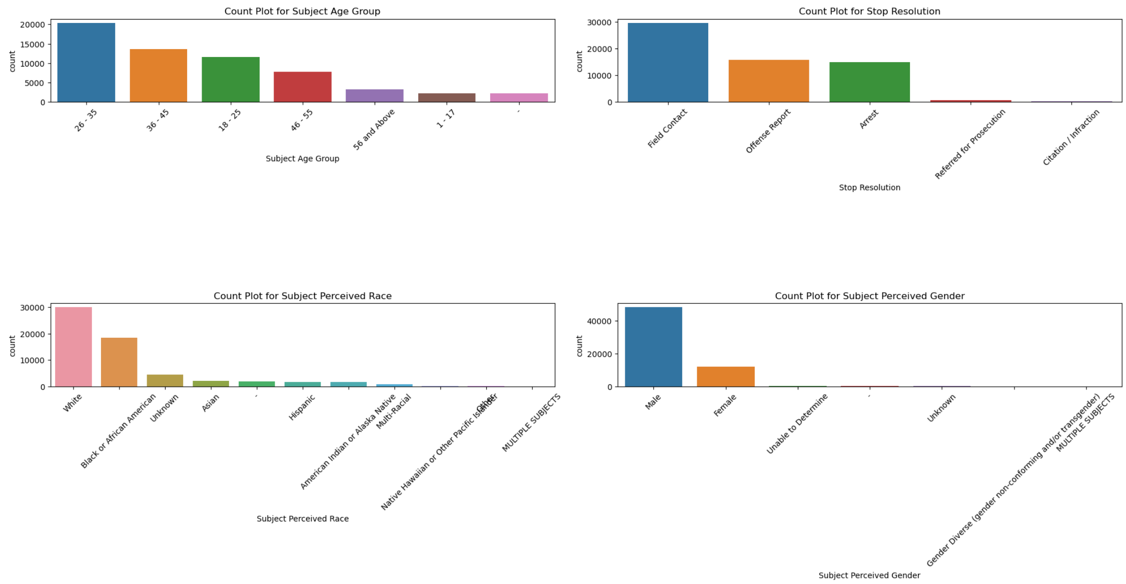
0.3 Analyze the Categorical Features

[114]:

```
# List of categorical columns to analyze
categorical_cols = ['Subject Age Group', 'Stop Resolution', 'Subject Perceived␣
↪Race', 'Subject Perceived Gender']
```

[115]:

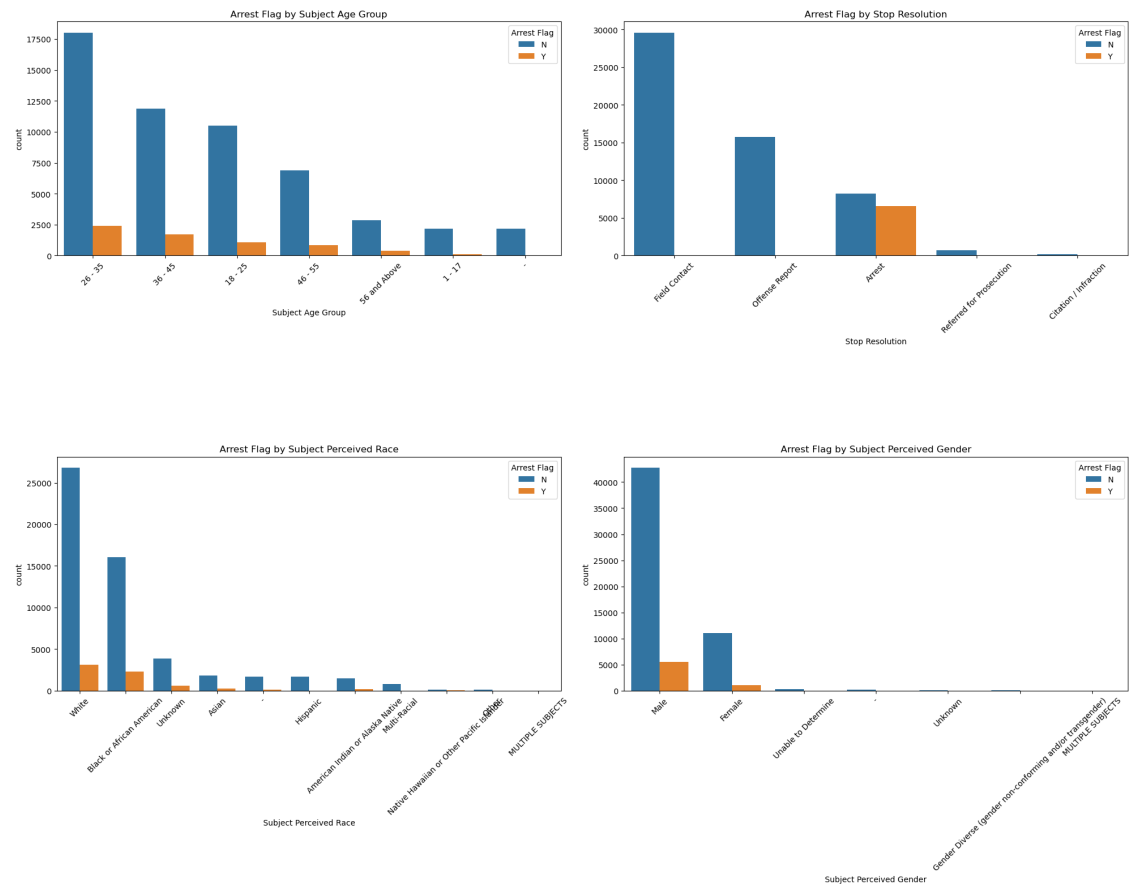
```
# Plot count plots for each categorical feature
plt.figure(figsize=(20, 12))
for i, col in enumerate(categorical_cols, 1):
    plt.subplot(3, 2, i)
    sns.countplot(x=col, data=terry_df, order=terry_df[col].value_counts().
↪index)
    plt.title(f"Count Plot for {col}")
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



0.4 Analyze the Distribution of the Target Variable (Arrest Flag)

We will use crosstabs to summarize the relationship between each categorical feature and the "Arrest Flag" and bar plots to visualize the proportion of arrests within each category of the features.

[116]:
```
# Create bar plots for each categorical feature against the "Arrest Flag"
plt.figure(figsize=(20, 20))
for i, col in enumerate(categorical_cols, 1):
    plt.subplot(3, 2, i)
    sns.countplot(x=col, hue='Arrest Flag', data=terry_df, order=terry_df[col].
 ↪value_counts().index)
    plt.title(f"Arrest Flag by {col}")
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[117]:
```python
# Print crosstab for each categorical feature with "Arrest Flag"
for col in categorical_cols:
    crosstab_result = pd.crosstab(terry_df[col], terry_df['Arrest Flag'])
    print(f"Crosstab for {col} with Arrest Flag:\n", crosstab_result, "\n")
```

```
Crosstab for Subject Age Group with Arrest Flag:
 Arrest Flag           N     Y
Subject Age Group
-                   2160    41
1 - 17              2155   131
18 - 25            10497  1085
26 - 35            18002  2387
36 - 45            11893  1735
46 - 55             6897   845
56 and Above        2856   366

Crosstab for Stop Resolution with Arrest Flag:
 Arrest Flag                  N     Y
Stop Resolution
Arrest                    8210  6588
```

```
Citation / Infraction       219     0
Field Contact             29576     0
Offense Report            15729     0
Referred for Prosecution    726     2

Crosstab for Subject Perceived Race with Arrest Flag:
 Arrest Flag                                   N     Y
Subject Perceived Race
-                                           1718    98
American Indian or Alaska Native            1488   175
Asian                                       1815   273
Black or African American                  16035  2286
Hispanic                                    1684     0
MULTIPLE SUBJECTS                              2     0
Multi-Racial                                 809     0
Native Hawaiian or Other Pacific Islander    117    42
Other                                        152     0
Unknown                                     3851   569
White                                      26789  3147

Crosstab for Subject Perceived Gender with Arrest Flag:
 Arrest Flag                                             N     Y
Subject Perceived Gender
-                                                     243     0
Female                                              11040  1100
Gender Diverse (gender non-conforming and/or tr…      35    10
MULTIPLE SUBJECTS                                       2     0
Male                                                42719  5475
Unable to Determine                                   326     0
Unknown                                                95     5
```

0.5 Statistical tests to validate the significance of observed patterns

We are using Chi-square Test for Independence

[118]:
```python
from scipy.stats import chi2_contingency

# Performing Chi-square test for 'Subject Perceived Race' and 'Arrest Flag'
contingency_table = pd.crosstab(terry_df['Subject Perceived Race'],
 ↪terry_df['Arrest Flag'])
chi2, p, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-square Test Results for 'Subject Perceived Race' and 'Arrest Flag':
 ↪\n Chi2: {chi2}, p-value: {p}")

# Interpretation of p-value
if p < 0.05:
```

```
    print("There is a significant association between 'Subject Perceived Race'␣
↪and 'Arrest Flag'.")
else:
    print("No significant association between 'Subject Perceived Race' and␣
↪'Arrest Flag'.")
```

```
Chi-square Test Results for 'Subject Perceived Race' and 'Arrest Flag':
 Chi2: 503.15362641100324, p-value: 9.353668765101045e-102
There is a significant association between 'Subject Perceived Race' and 'Arrest
Flag'.
```

[119]:
```
# Performing Chi-square test for 'Subject Perceived Gender' and 'Arrest Flag'
contingency_table = pd.crosstab(terry_df['Subject Perceived Gender'],␣
↪terry_df['Arrest Flag'])
chi2, p, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-square Test Results for 'Subject Perceived Gender' and 'Arrest␣
↪Flag':\n Chi2: {chi2}, p-value: {p}")

# Interpretation of p-value
if p < 0.05:
    print("There is a significant association between 'Subject Perceived␣
↪Gender' and 'Arrest Flag'.")
else:
    print("No significant association between 'Subject Perceived Gender' and␣
↪'Arrest Flag'.")
```

```
Chi-square Test Results for 'Subject Perceived Gender' and 'Arrest Flag':
 Chi2: 132.59728273046457, p-value: 3.647072311038753e-26
There is a significant association between 'Subject Perceived Gender' and
'Arrest Flag'.
```

[120]:
```
# Performing Chi-square test for 'Stop Resolution' and 'Arrest Flag'
contingency_table = pd.crosstab(terry_df['Stop Resolution'], terry_df['Arrest␣
↪Flag'])
chi2, p, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-square Test Results for 'Stop Resolution' and 'Arrest Flag':\n Chi2:
↪ {chi2}, p-value: {p}")

# Interpretation of p-value
if p < 0.05:
    print("There is a significant association between 'Stop Resolution' and␣
↪'Arrest Flag'.")
else:
    print("No significant association between 'Stop Resolution' and 'Arrest␣
↪Flag'.")
```

```
Chi-square Test Results for 'Stop Resolution' and 'Arrest Flag':
 Chi2: 23071.40163433658, p-value: 0.0
There is a significant association between 'Stop Resolution' and 'Arrest Flag'.
```

[121]:
```
# Performing Chi-square test for 'Subject Age Group' and 'Arrest Flag'
contingency_table = pd.crosstab(terry_df['Subject Age Group'], terry_df['Arrest␣
↪Flag'])
chi2, p, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-square Test Results for 'Subject Age Group' and 'Arrest Flag':\n␣
↪Chi2: {chi2}, p-value: {p}")

# Interpretation of p-value
if p < 0.05:
    print("There is a significant association between 'Subject Age Group' and␣
↪'Arrest Flag'.")
else:
    print("No significant association between 'Subject Age Group' and 'Arrest␣
↪Flag'.")
```

```
Chi-square Test Results for 'Subject Age Group' and 'Arrest Flag':
 Chi2: 339.60818980749343, p-value: 2.6242186997924706e-70
There is a significant association between 'Subject Age Group' and 'Arrest
Flag'.
```

0.5.1 Data Processing and modelling

We calculate the mode of the "Weapon Type" column and use it to fill any missing values in that column.

After filling the specified column, we drop rows with any remaining missing values in other columns.

[122]:
```
# Drop other null columns
data_cleaned = terry_df.drop(columns=['Weapon Type', 'Officer Squad'])

data_cleaned.shape
```

[122]:
```
(61050, 21)
```

[123]:
```
# Check for missing values
data_cleaned.isnull().sum()
```

[123]:
```
Subject Age Group           0
Subject ID                  0
GO / SC Num                 0
Terry Stop ID               0
Stop Resolution             0
Officer ID                  0
```

```
Officer YOB                 0
Officer Gender              0
Officer Race                0
Subject Perceived Race      0
Subject Perceived Gender    0
Reported Date               0
Reported Time               0
Initial Call Type           0
Final Call Type             0
Call Type                   0
Arrest Flag                 0
Frisk Flag                  0
Precinct                    0
Sector                      0
Beat                        0
dtype: int64
```

0.6 Encode Categorical Variables

I will use Label Encoding for simplicity, which converts each category to a unique integer.

[124]:
```python
from sklearn.preprocessing import LabelEncoder

# Categorical columns to encode
categorical_cols = ['Stop Resolution', 'Subject Perceived Race', 'Subject␣
↪Perceived Gender', 'Subject Age Group']

# Initialize label encoder
label_encoder = LabelEncoder()

# Encode categorical columns
for col in categorical_cols:
    data_cleaned[col] = label_encoder.fit_transform(data_cleaned[col].
↪astype(str))

data_cleaned.head()
```

[124]:
```
   Subject Age Group   Subject ID     GO / SC Num  Terry Stop ID  \
0                  1           -1  20170000315550         301338
1                  3           -1  20170000115391         253596
2                  2           -1  20160000036392         123863
3                  4  33919122751  20210000055627    21770133324
4                  2           -1  20160000003522         183376

   Stop Resolution Officer ID  Officer YOB Officer Gender Officer Race  \
0                3       5489         1964              M        White
1                3       6403         1969              M        White
```

```
2                3       7473          1981                 M        White
3                2       6711          1977                 M        White
4                2       7090          1981                 F        White

   Subject Perceived Race  …          Reported Date      Reported Time  \
0                      10  …   2017-08-26T00:00:00Z  00:10:00.0000000
1                      10  …   2017-04-05T00:00:00Z  16:04:00.0000000
2                      10  …   2016-01-31T00:00:00Z  02:26:00.0000000
3                      10  …   2021-03-06T00:00:00Z  14:42:43.0000000
4                      10  …   2016-08-14T00:00:00Z  15:49:00.0000000

                         Initial Call Type  \
0                                 NUISANCE
1  THEFT (DOES NOT INCLUDE SHOPLIFT OR SVCS)
2    SUSPICIOUS PERSON, VEHICLE, OR INCIDENT
3                        PROPERTY - DAMAGE
4                                        -

                          Final Call Type                 Call Type  \
0         --MISCHIEF OR NUISANCE - GENERAL                      911
1                      --THEFT - ALL OTHER  TELEPHONE OTHER, NOT 911
2  --SUSPICIOUS CIRCUM. - SUSPICIOUS PERSON                      911
3                    --DISTURBANCE - OTHER                      911
4                                       -                        -

  Arrest Flag Frisk Flag Precinct Sector Beat
0           N          N    North      N   N2
1           N          N    North      L   L3
2           N          N    North      B   B3
3           N          N        -      -    -
4           N          Y        -      -    -

[5 rows x 21 columns]
```

0.7 Feature Scaling and Splitting the data

[125]:
```python
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Identify numerical columns
numerical_cols = data_cleaned.select_dtypes(include=[np.number]).columns.
 ↪tolist()
numerical_cols
```

[125]:
```
['Subject Age Group',
 'Subject ID',
 'GO / SC Num',
```

```
 'Terry Stop ID',
 'Stop Resolution',
 'Officer YOB',
 'Subject Perceived Race',
 'Subject Perceived Gender']
```

[126]:
```python
scaler = StandardScaler()

# Scale numerical columns
data_cleaned[numerical_cols] = scaler.
 ↪fit_transform(data_cleaned[numerical_cols])

data_cleaned.head()
```

[126]:
```
   Subject Age Group  Subject ID  GO / SC Num  Terry Stop ID  Stop Resolution  \
0          -1.686045   -0.572752    -0.194557      -0.694398         1.085697
1          -0.195569   -0.572752    -0.194560      -0.694400         1.085697
2          -0.940807   -0.572752    -0.311228      -0.694408         1.085697
3           0.549670    2.090833     0.272110       0.544906         0.186107
4          -0.940807   -0.572752    -0.311229      -0.694404         0.186107

  Officer ID  Officer YOB Officer Gender Officer Race  Subject Perceived Race  \
0       5489    -2.120560              M        White                0.892841
1       6403    -1.592669              M        White                0.892841
2       7473    -0.325732              M        White                0.892841
3       6711    -0.748045              M        White                0.892841
4       7090    -0.325732              F        White                0.892841

   …          Reported Date      Reported Time  \
0  …  2017-08-26T00:00:00Z  00:10:00.0000000
1  …  2017-04-05T00:00:00Z  16:04:00.0000000
2  …  2016-01-31T00:00:00Z  02:26:00.0000000
3  …  2021-03-06T00:00:00Z  14:42:43.0000000
4  …  2016-08-14T00:00:00Z  15:49:00.0000000

                           Initial Call Type  \
0                                  NUISANCE
1  THEFT (DOES NOT INCLUDE SHOPLIFT OR SVCS)
2    SUSPICIOUS PERSON, VEHICLE, OR INCIDENT
3                          PROPERTY - DAMAGE
4                                          -

                            Final Call Type                 Call Type  \
0          --MISCHIEF OR NUISANCE - GENERAL                       911
1                       --THEFT - ALL OTHER  TELEPHONE OTHER, NOT 911
2  --SUSPICIOUS CIRCUM. - SUSPICIOUS PERSON                       911
3                     --DISTURBANCE - OTHER                       911
```

```
4                                        -                         -

  Arrest Flag Frisk Flag Precinct Sector Beat
0           N          N    North      N   N2
1           N          N    North      L   L3
2           N          N    North      B   B3
3           N          N        -      -    -
4           N          Y        -      -    -

[5 rows x 21 columns]
```

[127]:
```
# Split the data into features and target variable
X = data_cleaned[categorical_cols]
y = data_cleaned['Arrest Flag']
```

[128]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

print("Training set size:", X_train.shape)
print("Testing set size:", X_test.shape)
```

```
Training set size: (48840, 4)
Testing set size: (12210, 4)
```

0.8 Model Building

[129]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score

# Initialize models
logistic_regression = LogisticRegression()
decision_tree = DecisionTreeClassifier()

# Train Logistic Regression model
logistic_regression.fit(X_train, y_train)

# Train Decision Tree model
decision_tree.fit(X_train, y_train)
```

[129]:
```
DecisionTreeClassifier()
```

[130]:
```
# Predict on the test set with Logistic Regression
y_pred_lr = logistic_regression.predict(X_test)
```

[131]:
```python
# Predict on the test set with Decision Tree
y_pred_dt = decision_tree.predict(X_test)
```

[132]:
```python
# Evaluate Logistic Regression model
print("Logistic Regression Model Evaluation:")
print("Accuracy:", accuracy_score(y_test, y_pred_lr))
print("Classification Report:\n", classification_report(y_test, y_pred_lr))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_lr))
```

```
Logistic Regression Model Evaluation:
Accuracy: 0.8925470925470925
Classification Report:
               precision    recall  f1-score   support

           N       0.91      0.98      0.94     10921
           Y       0.47      0.16      0.24      1289

    accuracy                           0.89     12210
   macro avg       0.69      0.57      0.59     12210
weighted avg       0.86      0.89      0.87     12210

Confusion Matrix:
 [[10696   225]
 [ 1087   202]]
```

[133]:
```python
# Evaluate Decision Tree model
print("\nDecision Tree Model Evaluation:")
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test, y_pred_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
```

```

Decision Tree Model Evaluation:
Accuracy: 0.9013923013923014
Classification Report:
               precision    recall  f1-score   support

           N       0.93      0.96      0.95     10921
           Y       0.55      0.40      0.46      1289

    accuracy                           0.90     12210
   macro avg       0.74      0.68      0.70     12210
weighted avg       0.89      0.90      0.89     12210

Confusion Matrix:
 [[10492   429]
 [  775   514]]
```

0.9 Hyperparameter Tuning

[134]:
```
# Import GridSearch library
from sklearn.model_selection import GridSearchCV
```

[135]:
```
# Iterative Development: Grid Search for Hyperparameter Tuning for Decision Tree
param_grid = {'max_depth': [None, 10, 20, 30], 'min_samples_split': [2, 5, 10]}
grid_search_dt = GridSearchCV(decision_tree, param_grid, cv=5)
grid_search_dt.fit(X_train, y_train)
```

[135]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'max_depth': [None, 10, 20, 30],
                         'min_samples_split': [2, 5, 10]})
```

[136]:
```
# Best model from Grid Search
best_dt = grid_search_dt.best_estimator_
```

[137]:
```
# Predict using the best Decision Tree model
y_pred_best_dt = best_dt.predict(X_test)
```

[138]:
```
# Evaluate the best Decision Tree model
print("\nBest Decision Tree Model Evaluation after Grid Search:")
print("Accuracy:", accuracy_score(y_test, y_pred_best_dt))
print("Classification Report:\n", classification_report(y_test, y_pred_best_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_best_dt))
```

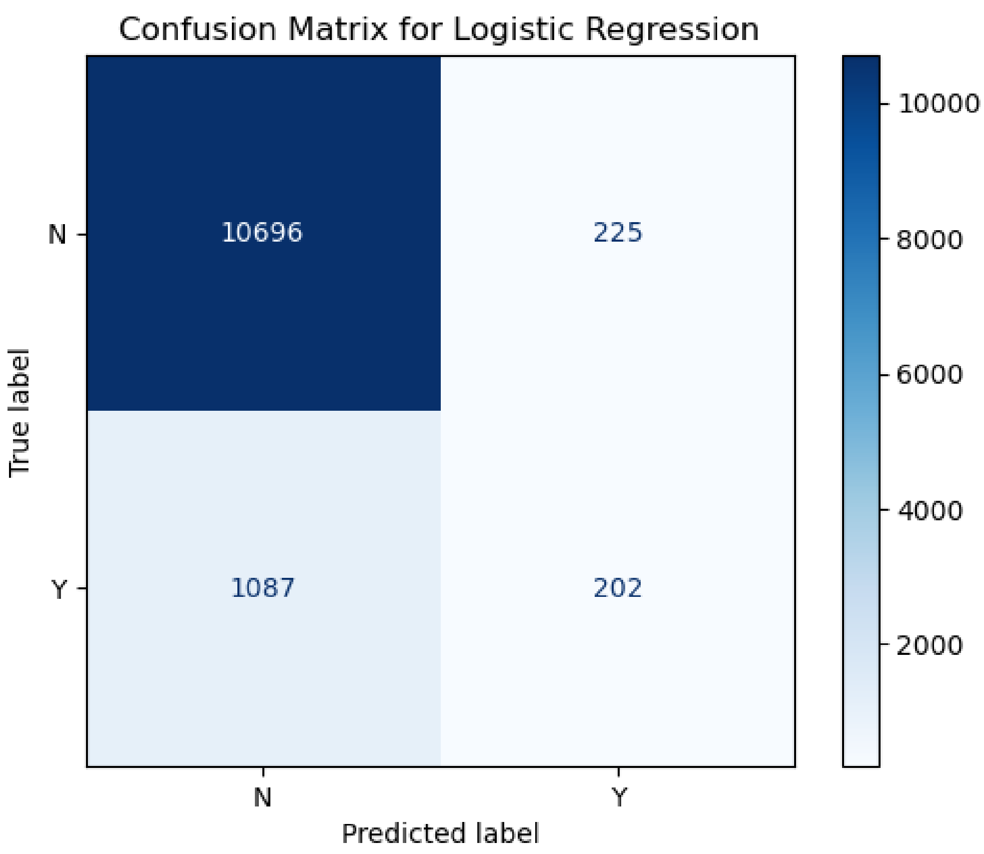
```
Best Decision Tree Model Evaluation after Grid Search:
Accuracy: 0.9013104013104013
Classification Report:
               precision    recall  f1-score   support

           N       0.93      0.96      0.95     10921
           Y       0.54      0.40      0.46      1289

    accuracy                           0.90     12210
   macro avg       0.74      0.68      0.70     12210
weighted avg       0.89      0.90      0.89     12210

Confusion Matrix:
 [[10491   430]
 [  775   514]]
```

0.10 Visualizations

[139]:
```
# Import libraries
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import roc_curve, roc_auc_score
```

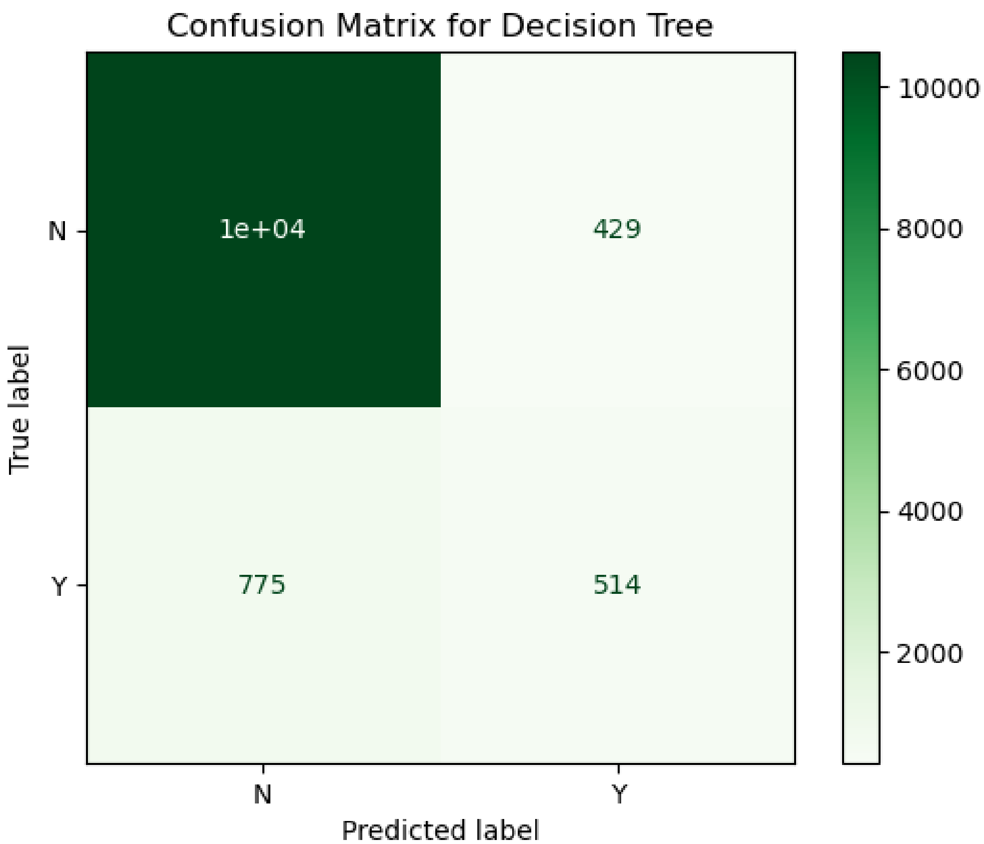
0.10.1 Confusion Matrix for both models

[140]:
```
# Confusion Matrix for Logistic Regression
cm_lr = confusion_matrix(y_test, y_pred_lr)
disp_lr = ConfusionMatrixDisplay(confusion_matrix=cm_lr,␣
 ↪display_labels=logistic_regression.classes_)
disp_lr.plot(cmap='Blues')
plt.title('Confusion Matrix for Logistic Regression')
plt.show()
```



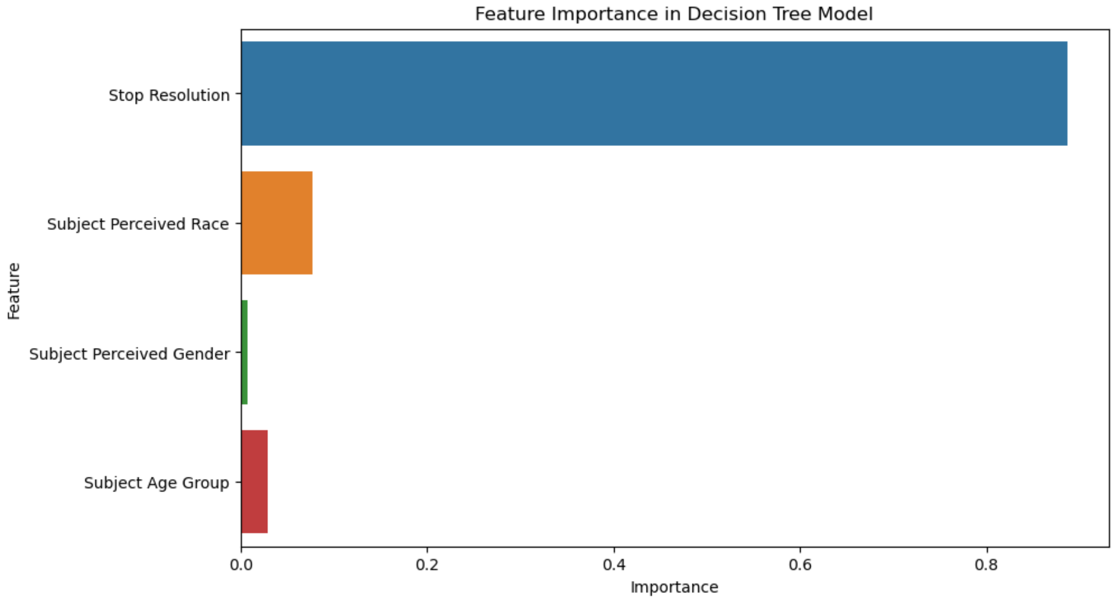
[141]:
```
# Confusion Matrix for Decision Tree
cm_dt = confusion_matrix(y_test, y_pred_dt)
disp_dt = ConfusionMatrixDisplay(confusion_matrix=cm_dt,␣
 ↪display_labels=decision_tree.classes_)
```

```
disp_dt.plot(cmap='Greens')
plt.title('Confusion Matrix for Decision Tree')
plt.show()
```



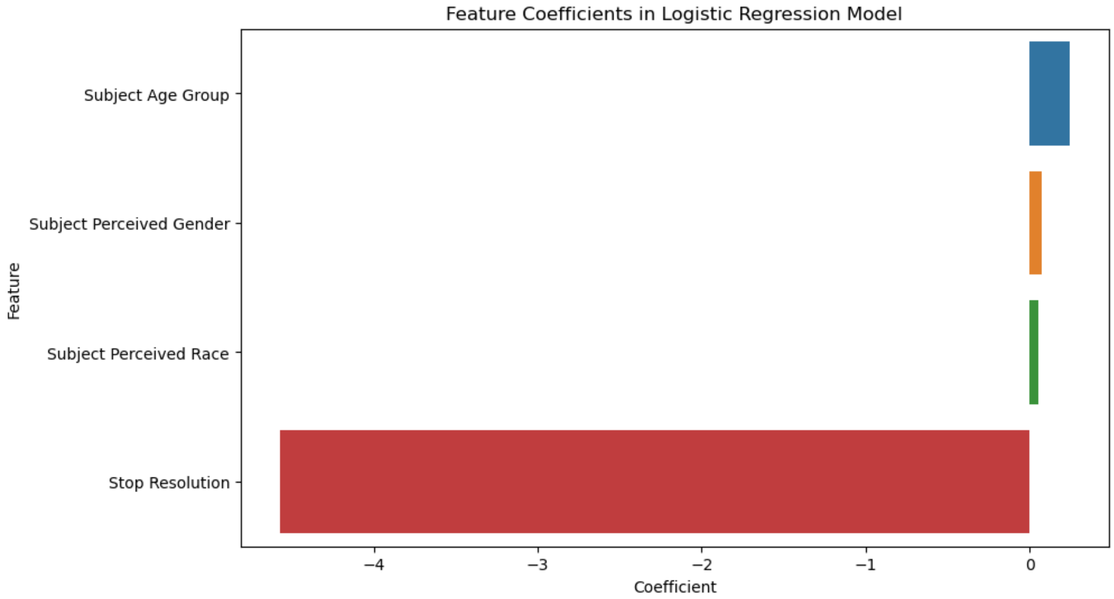
0.10.2 Feature Importance for Decision Tree

[142]:
```
# Feature Importance for Decision Tree
plt.figure(figsize=(10, 6))
sns.barplot(x=decision_tree.feature_importances_, y=categorical_cols)
plt.title('Feature Importance in Decision Tree Model')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```



0.10.3 Coefficients for Logistic Regression

[143]:
```
# Coefficients for Logistic Regression
coefficients = pd.DataFrame({'Feature': X_train.columns, 'Coefficient':␣
↪logistic_regression.coef_[0]})
coefficients = coefficients.sort_values(by='Coefficient', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(x='Coefficient', y='Feature', data=coefficients)
plt.title('Feature Coefficients in Logistic Regression Model')
plt.xlabel('Coefficient')
plt.ylabel('Feature')
plt.show()
```

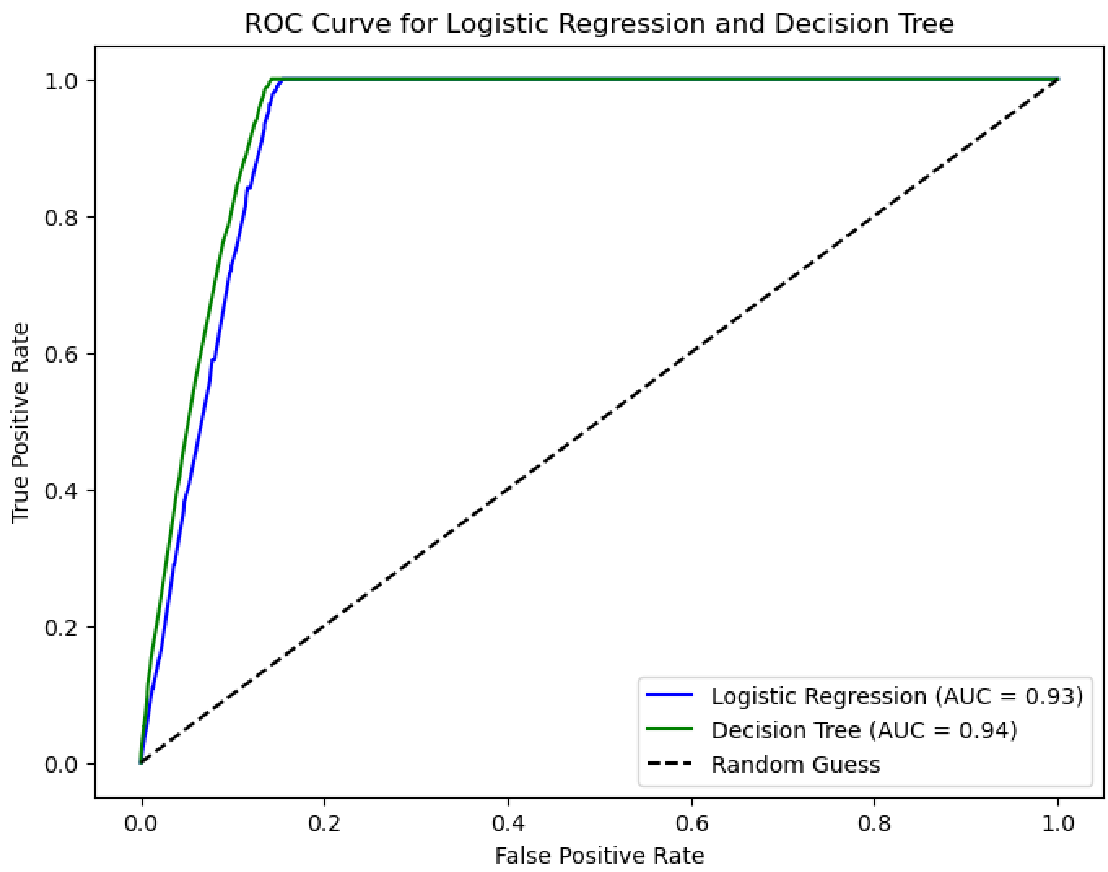


0.10.4 ROC Curve

[144]:
```
# Convert 'No' to 0 and 'Yes' to 1 in y_test and predictions
y_test_binary = y_test.map({'N': 0, 'Y': 1})
y_pred_prob_lr = logistic_regression.predict_proba(X_test)[:, 1]
y_pred_prob_dt = decision_tree.predict_proba(X_test)[:, 1]
```

[145]:
```
# Prediction probabilities for Logistic Regression
y_pred_prob_lr = logistic_regression.predict_proba(X_test)[:, 1]

# Prediction probabilities for Decision Tree
y_pred_prob_dt = decision_tree.predict_proba(X_test)[:, 1]

# ROC Curve for Logistic Regression
fpr_lr, tpr_lr, _ = roc_curve(y_test_binary, y_pred_prob_lr)
roc_auc_lr = roc_auc_score(y_test_binary, y_pred_prob_lr)

# ROC Curve for Decision Tree
fpr_dt, tpr_dt, _ = roc_curve(y_test_binary, y_pred_prob_dt)
roc_auc_dt = roc_auc_score(y_test_binary, y_pred_prob_dt)

# Plotting the ROC curves on a single graph
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC = {roc_auc_lr:.2f})',␣
↪color='blue')
plt.plot(fpr_dt, tpr_dt, label=f'Decision Tree (AUC = {roc_auc_dt:.2f})',␣
↪color='green')
```

```
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Logistic Regression and Decision Tree')
plt.legend(loc='lower right')
plt.show()
```



0.11 Cross-Validation

[146]:
```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
↪recall_score, f1_score
```

[147]:
```
# Define scoring metrics
scoring = {'accuracy': make_scorer(accuracy_score),
           'precision': make_scorer(precision_score, pos_label='Y'),
           'recall': make_scorer(recall_score, pos_label='Y'),
           'f1': make_scorer(f1_score, pos_label='Y')}
```

[148]:
```python
# Cross-validation for Logistic Regression
cv_scores_lr = cross_val_score(logistic_regression, X_train, y_train, cv=5,␣
 ↪scoring='accuracy')
print(f"Cross-Validation Scores for Logistic Regression (Accuracy):␣
 ↪{cv_scores_lr}")
print(f"Average Cross-Validation Score for Logistic Regression (Accuracy):␣
 ↪{cv_scores_lr.mean()}")

# If you want to calculate multiple metrics at once:
from sklearn.model_selection import cross_validate
cv_results_lr = cross_validate(logistic_regression, X_train, y_train, cv=5,␣
 ↪scoring=scoring)

# Print detailed cross-validation results
print("\nDetailed Cross-Validation Results for Logistic Regression:")
for key in scoring.keys():
    print(f"{key.capitalize()} Scores: {cv_results_lr['test_' + key]}")
    print(f"Average {key.capitalize()} Score: {cv_results_lr['test_' + key].
 ↪mean()}")
```

```
Cross-Validation Scores for Logistic Regression (Accuracy): [0.89209664
0.89045864 0.89250614 0.89322277 0.88841114]
Average Cross-Validation Score for Logistic Regression (Accuracy):
0.8913390663390663

Detailed Cross-Validation Results for Logistic Regression:
Accuracy Scores: [0.89209664 0.89045864 0.89250614 0.89322277 0.88841114]
Average Accuracy Score: 0.8913390663390663
Precision Scores: [0.505      0.4872449  0.50853242 0.52449568 0.45797101]
Average Precision Score: 0.4966488025787116
Recall Scores: [0.28584906 0.18018868 0.28113208 0.17169811 0.14891612]
Average Recall Score: 0.21355680827983567
F1 Scores: [0.36506024 0.2630854  0.36208991 0.25870647 0.22475107]
Average F1 Score: 0.2947386179752469
```

[149]:
```python
# Cross-validation for Decision Tree
cv_scores_dt = cross_val_score(decision_tree, X_train, y_train, cv=5,␣
 ↪scoring='accuracy')
print(f"\nCross-Validation Scores for Decision Tree (Accuracy): {cv_scores_dt}")
print(f"Average Cross-Validation Score for Decision Tree (Accuracy):␣
 ↪{cv_scores_dt.mean()}")

# Calculate multiple metrics at once:
cv_results_dt = cross_validate(decision_tree, X_train, y_train, cv=5,␣
 ↪scoring=scoring)

# Print detailed cross-validation results
```

```
print("\nDetailed Cross-Validation Results for Decision Tree:")
for key in scoring.keys():
    print(f"{key.capitalize()} Scores: {cv_results_dt['test_' + key]}")
    print(f"Average {key.capitalize()} Score: {cv_results_dt['test_' + key].
 ↪mean()}")
```

```
Cross-Validation Scores for Decision Tree (Accuracy): [0.90120803 0.89946765
0.8996724  0.90284603 0.90120803]
Average Cross-Validation Score for Decision Tree (Accuracy): 0.9008804258804259

Detailed Cross-Validation Results for Decision Tree:
Accuracy Scores: [0.90120803 0.89946765 0.8996724  0.90284603 0.90120803]
Average Accuracy Score: 0.9008804258804259
Precision Scores: [0.56129032 0.54779412 0.55899705 0.58295964 0.56282723]
Average Precision Score: 0.5627736713523384
Recall Scores: [0.41037736 0.42169811 0.35754717 0.36792453 0.40527804]
Average Recall Score: 0.3925650418793235
F1 Scores: [0.47411444 0.47654584 0.43613349 0.45112782 0.47123288]
Average F1 Score: 0.4618308933323954
```