1. Introduction

The Seattle Police Department (SPD) conducts Terry Stops as part of their law enforcement efforts to address public safety concerns. Terry Stops involve stopping, questioning, and sometimes frisking individuals based on reasonable suspicion of involvement in criminal activity. However, the effectiveness and fairness of these stops have been scrutinized, particularly regarding potential biases and the frequency of resulting arrests.

To address these concerns, this analysis aims to build a predictive model that can estimate the likelihood of an arrest occurring during a Terry Stop. By leveraging historical data, we can identify patterns and factors that are most indicative of an arrest outcome, which can inform policy decisions and improve the fairness and efficiency of law enforcement practices.

2. Problem Statement

The goal of this analysis is to develop a predictive model using historical Terry Stops data from the Seattle Police Department to estimate the likelihood of an arrest during these stops. The primary challenge lies in accurately predicting arrests in a dataset that exhibits significant class imbalance, with most stops not resulting in an arrest. Addressing this imbalance and ensuring the model's predictions are both accurate and fair are critical to the success of this project.

3. Objectives

Major Objective:

a. Derive the most important features in predicting an arrest:

Over and above getting insights into why officers make arrests, this is important to assess whether the future arrest trends are being influenced by changing dynamics.

Minor Objectives

b.Develop a Predictive Model for Arrests During Terry Stops:

Create a predictive classification model that accurately predicts whether a Terry Stop will result in an arrest or no arrest, using features derived from the dataset. This task is a classification problem because we would like to predict categorical outcomes—in this case, whether a Terry Stop will result in an arrest (True) or not (False). Classification problems involve predicting discrete labels or categories based on input features, and in this scenario, the model is being trained to classify each stop into one of these two possible outcomes.

c. EDA and Feature Engineering:

- Perform an exploratory data analysis (EDA) to identify the distribution, relationships, and potential issues with the variables, such as missing values, which could impact model performance.

- Implement and compare different encoding techniques (one-hot encoding for low cardinality features and target encoding for high cardinality features) to effectively incorporate categorical variables into the model without increasing dimensionality.

d. Class Imbalance Management:

Evaluate and apply resampling techniques like SMOTE to address the class imbalance in the dataset, ensuring that the model can reliably predict both outcomes (arrests and non-arrests) without bias toward the majority class.

4. Data Understanding

Imports & Data Loading

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,
roc_curve, roc_auc_score


import pandas as pd

df = pd.read_csv('Terry_Stops_20240819.csv')
df.head()

  Subject Age Group   Subject ID     GO / SC Num  Terry Stop ID  \
0            1 - 17           -1  20150000002502          47107
1           36 - 45  32643034540  20220000318696    38698204851
2           18 - 25           -1  20180000003995         497654
3           46 - 55           -1  20150000299600         109376
4           26 - 35           -1  20160000438879         219794

  Stop Resolution Weapon Type Officer ID  Officer YOB Officer
Gender  \
0  Offense Report        None       6358         1970              M

1          Arrest           -       7560         1986              M

2   Field Contact        None       7428         1963              M
```

```
3   Field Contact        None       6805         1973              M

4  Offense Report        None       5781         1963              M


                Officer Race  ...     Reported Time  \
0                      White  ...  23:52:00.0000000
1                      White  ...  12:24:59.0000000
2         Hispanic or Latino  ...  16:18:00.0000000
3                      White  ...  15:53:00.0000000
4  Black or African American  ...  15:51:00.0000000

                              Initial Call Type  \
0                                             -
1  ORDER - CRITICAL VIOLATION OF DV COURT ORDER
2                                             -
3    SUSPICIOUS STOP - OFFICER INITIATED ONVIEW
4     THEFT (DOES NOT INCLUDE SHOPLIFT OR SVCS)

                                Final Call Type                 Call
Type  \
0                                             -
-
1  --DV - ENFORCE COURT ORDER (ARREST MANDATED)  TELEPHONE OTHER, NOT
911
2                                             -
-
3                         --DISTURBANCE - OTHER
ONVIEW
4                            --THEFT - SHOPLIFT
ONVIEW

                          Officer Squad Arrest Flag Frisk Flag
Precinct  \
0     WEST PCT 3RD W - MARY - PLATOON 1           N          N
-
1          SOUTH PCT 1ST W - R/S RELIEF           Y          N
South
2                    WEST PCT OPS - CPT           N          N
-
3    WEST PCT 2ND W - DAVID - PLATOON 1           N          N
West
4  SOUTHWEST PCT 2ND WATCH - F/W RELIEF           N          N
Southwest

  Sector Beat
0      -    -
1      S   S1
2      -    -
```

```
3       D   D3
4       W   W2

[5 rows x 23 columns]
```

Exploratory Data Analysis (EDA) & Feature Engineering

```
df.shape
```

```
(60962, 23)
```

```
df.describe()
```

```
         Subject ID   GO / SC Num  Terry Stop ID   Officer YOB
count  6.096200e+04  6.096200e+04   6.096200e+04  60962.000000
mean   7.246509e+09  2.018660e+13   1.213135e+10   1984.077474
std    1.265918e+10  8.575239e+10   1.749055e+10      9.472551
min   -8.000000e+00 -1.000000e+00   2.802000e+04   1900.000000
25%   -1.000000e+00  2.017000e+13   2.387742e+05   1979.000000
50%   -1.000000e+00  2.018000e+13   5.086870e+05   1986.000000
75%    7.752270e+09  2.021000e+13   1.953036e+10   1991.000000
max    5.845336e+10  2.024000e+13   5.845333e+10   2002.000000
```

Given the shape and description of our data, most of our features seem non-numeric

Our data has 23 columns and 609562 rows

```
df.columns
```

```
Index(['Subject Age Group', 'Subject ID', 'GO / SC Num', 'Terry Stop
ID',
       'Stop Resolution', 'Weapon Type', 'Officer ID', 'Officer YOB',
       'Officer Gender', 'Officer Race', 'Subject Perceived Race',
       'Subject Perceived Gender', 'Reported Date', 'Reported Time',
       'Initial Call Type', 'Final Call Type', 'Call Type', 'Officer
Squad',
       'Arrest Flag', 'Frisk Flag', 'Precinct', 'Sector', 'Beat'],
      dtype='object')
```

These are the columns in our data and their descriptions based on a review of our data and information from our data source: (https://data.seattle.gov/Public-Safety/Terry-Stops/28ny-9ts8/about_data):

1. Subject Age Group - Subject Age Group (10 year increments) as reported by the officer (Text)

2. Subject ID - Key, generated daily, identifying unique subjects in the dataset using a character to character match of first name and last name. "Null" values indicate an "anonymous" or "unidentified" subject. Subjects of a Terry Stop are not required to present identification. (Text)

3. GO / SC Num - General Offense or Street Check number, relating the Terry Stop to the parent report. This field may have a one to many relationship in the data. (Text)
4. Terry Stop ID - Key identifying unique Terry Stop reports. (Text)
5. Stop Resolution - Resolution of the stop as reported by the officer. (Text)
6. Weapon Type - Type of weapon, if any, identified during a search or frisk of the subject. Indicates "None" if no weapons was found. (Text)
7. Officer ID - Key identifying unique officers in the dataset. (Text)
8. Officer YOB - Year of birth, as reported by the officer. (Text)
9. Officer Gender - Gender of the officer, as reported by the officer. (Text)
10. Officer Race - Race of the officer, as reported by the officer. (Text)
11. Subject Perceived Race - Perceived race of the subject, as reported by the officer. (Text)
12. Subject Perceived Gender - Perceived gender of the subject, as reported by the officer. (Text)
13. Reported Date - Date the report was filed in the Records Management System (RMS). Not necessarily the date the stop occurred but generally within 1 day. (Floating Timestamp)
14. Reported Time - Time the stop was reported in the Records Management System (RMS). Not the time the stop occurred but generally within 10 hours. (Text)
15. Initial Call Type - Initial classification of the call as assigned by 911. (Text)
16. Final Call Type - Final classification of the call as assigned by the primary officer closing the event. (Text)
17. Call Type - How the call was received by the communication center. (Text)
18. Officer Squad - Functional squad assignment (not budget) of the officer as reported by the Data Analytics Platform (DAP). (Text)
19. Arrest Flag - Indicator of whether a "physical arrest" was made, of the subject, during the Terry Stop. Does not necessarily reflect a report of an arrest in the Records Management System (RMS). (Text)
20. Frisk Flag - Indicator of whether a "frisk" was conducted, by the officer, of the subject, during the Terry Stop. (Text)
21. Precint - Precinct of the address associated with the underlying Computer Aided Dispatch (CAD) event. Not necessarily where the Terry Stop occurred. (Text)

22. Sector - Sector of the address associated with the underlying Computer Aided Dispatch (CAD) event. Not necessarily where the Terry Stop occurred. (Text)

23. Beat - Beat of the address associated with the underlying Computer Aided Dispatch (CAD) event. Not necessarily where the Terry Stop occurred. (Text)

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60962 entries, 0 to 60961
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Subject Age Group          60962 non-null  object
 1   Subject ID                 60962 non-null  int64
 2   GO / SC Num                60962 non-null  int64
 3   Terry Stop ID              60962 non-null  int64
 4   Stop Resolution            60962 non-null  object
 5   Weapon Type                60962 non-null  object
 6   Officer ID                 60962 non-null  object
 7   Officer YOB                60962 non-null  int64
 8   Officer Gender             60962 non-null  object
 9   Officer Race               60962 non-null  object
 10  Subject Perceived Race     60962 non-null  object
 11  Subject Perceived Gender   60962 non-null  object
 12  Reported Date              60962 non-null  object
 13  Reported Time              60962 non-null  object
 14  Initial Call Type          60962 non-null  object
 15  Final Call Type            60962 non-null  object
 16  Call Type                  60962 non-null  object
 17  Officer Squad              60401 non-null  object
 18  Arrest Flag                60962 non-null  object
 19  Frisk Flag                 60962 non-null  object
 20  Precinct                   60962 non-null  object
 21  Sector                     60962 non-null  object
 22  Beat                       60962 non-null  object
dtypes: int64(4), object(19)
memory usage: 10.7+ MB
```

We seem to have a mix of numerical and non-numerical data. However, the numeric data seems to be related to identifiers vs actual numerical data

```
df.isna().sum()
```

```
Subject Age Group            0
Subject ID                   0
GO / SC Num                  0
Terry Stop ID                0
Stop Resolution              0
```

```
Weapon Type                    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
Officer Squad                561
Arrest Flag                    0
Frisk Flag                     0
Precinct                       0
Sector                         0
Beat                           0
dtype: int64
```

We have missing data in the Officer Squad column. We will impute this column with a placeholder 'Unknown' Value

```
df_imputed = df.fillna('Unknown')
df_imputed.head()

  Subject Age Group   Subject ID     GO / SC Num  Terry Stop ID  \
0            1 - 17           -1  20150000002502          47107
1           36 - 45  32643034540  20220000318696    38698204851
2           18 - 25           -1  20180000003995         497654
3           46 - 55           -1  20150000299600         109376
4           26 - 35           -1  20160000438879         219794

  Stop Resolution Weapon Type Officer ID  Officer YOB Officer
Gender  \
0  Offense Report        None       6358         1970              M

1          Arrest           -       7560         1986              M

2   Field Contact        None       7428         1963              M

3   Field Contact        None       6805         1973              M

4  Offense Report        None       5781         1963              M


                Officer Race  ...      Reported Time  \
0                      White  ...  23:52:00.0000000
1                      White  ...  12:24:59.0000000
2         Hispanic or Latino  ...  16:18:00.0000000
```

```
3                      White  ...  15:53:00.0000000
4  Black or African American  ...  15:51:00.0000000

                              Initial Call Type  \
0                                             -
1  ORDER - CRITICAL VIOLATION OF DV COURT ORDER
2                                             -
3    SUSPICIOUS STOP - OFFICER INITIATED ONVIEW
4     THEFT (DOES NOT INCLUDE SHOPLIFT OR SVCS)

                                Final Call Type                 Call
Type  \
0                                             -
-
1  --DV - ENFORCE COURT ORDER (ARREST MANDATED)  TELEPHONE OTHER, NOT
911
2                                             -
-
3                        --DISTURBANCE - OTHER
ONVIEW
4                           --THEFT - SHOPLIFT
ONVIEW

                          Officer Squad Arrest Flag Frisk Flag
Precinct  \
0     WEST PCT 3RD W - MARY - PLATOON 1           N          N
-
1          SOUTH PCT 1ST W - R/S RELIEF           Y          N
South
2                    WEST PCT OPS - CPT           N          N
-
3    WEST PCT 2ND W - DAVID - PLATOON 1           N          N
West
4  SOUTHWEST PCT 2ND WATCH - F/W RELIEF           N          N
Southwest

  Sector Beat
0      -    -
1      S   S1
2      -    -
3      D   D3
4      W   W2

[5 rows x 23 columns]
```

```
df_imputed.duplicated().sum()
```

```
0
```

Our data does not have any duplicated rows

We also seem to have rows filled with '-'. We will treat these as missing values. First we need to convert these to NaN

```
for column in df_imputed.columns:
    df_imputed[column] = df_imputed[column].replace('-', np.nan)

df_imputed.isna().sum()
```

```
Subject Age Group              2200
Subject ID                        0
GO / SC Num                       0
Terry Stop ID                     0
Stop Resolution                   0
Weapon Type                   24528
Officer ID                       24
Officer YOB                       0
Officer Gender                    0
Officer Race                      0
Subject Perceived Race         1816
Subject Perceived Gender        243
Reported Date                     0
Reported Time                     0
Initial Call Type             13473
Final Call Type               13473
Call Type                     13473
Officer Squad                     0
Arrest Flag                       0
Frisk Flag                      478
Precinct                      10617
Sector                        10768
Beat                          10762
dtype: int64
```

After deeper analysis of our data, we have several more columns with missing data.

We will handle these columns separately to preserve the quality of our data.

1. Subject Age Group - we can impute this with mode to preserve the shape of our data.
2. Weapon Type - Given that a large portion is missing, it’s possible that in many cases, no weapon was found. Imputing missing values with "None" is most logical.
3. Officer ID - Since only 24 out of 60,962 entries are affected, we will drop these rows.
4. Subject Perceived Race - Replacing missing values with "Unknown" maintains the data structure without introducing bias.
5. Subject Perceived Gender - Replacing missing values with "Unknown" maintains the data structure without introducing bias.

6. Initial Call Type, Final Call Type, Call Type - Missing call types might suggest a lack of information or a specific condition (e.g., not applicable since no call was made and the incident just transpired). Imputing with "Unknown" preserves this possibility.

7. Frisk Flag - Since the missing values are minimal, using the most frequent value could be effective.

8. Precint, Sector, Beat - Geographic information might be missing due to unreported locations. We will fill with "Unknown" allows us to retain these rows.

```
columns_to_fill_with_mode = ['Subject Age Group', 'Frisk Flag']
columns_to_fill_with_unkown = ['Subject Perceived Race', 'Subject
Perceived Gender', 'Initial Call Type'
, 'Final Call Type', 'Call Type', 'Precinct', 'Sector', 'Beat']
columns_to_fill_with_none = ['Weapon Type']
columns_to_drop = ['Officer ID']

for column in columns_to_fill_with_mode:
    df_imputed[column] =
df_imputed[column].fillna(df_imputed[column].mode()[0])

for column in columns_to_fill_with_unkown:
    df_imputed[column] = df_imputed[column].fillna('Unknown')

for column in columns_to_fill_with_none:
    df_imputed[column] = df_imputed[column].fillna('None')

for column in columns_to_drop:
    df_imputed.dropna(inplace=True)

df_imputed.isna().sum()
```

```
Subject Age Group           0
Subject ID                  0
GO / SC Num                 0
Terry Stop ID               0
Stop Resolution             0
Weapon Type                 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
Officer Squad               0
```

```
Arrest Flag                  0
Frisk Flag                   0
Precinct                     0
Sector                       0
Beat                         0
dtype: int64
```

Our dataset no longer contains missing values.

We can use Officer YOB - Officer Year of Birth to extract Age and put it into bins similar to our Subject Age Group by subtracting their year of birth from the year of the stop.

```
bins = df_imputed['Subject Age Group'].unique()
bins

array(['1 - 17', '36 - 45', '18 - 25', '46 - 55', '26 - 35',
       '56 and Above'], dtype=object)


# Calculate Officer Age and add this to a new column
report_year = df_imputed['Reported Date'].str[:4].astype(int)
df_imputed['Officer Age'] = report_year - df_imputed['Officer YOB']
df_imputed.head()

  Subject Age Group   Subject ID     GO / SC Num  Terry Stop ID  \
0            1 - 17           -1  20150000002502          47107
1           36 - 45  32643034540  20220000318696    38698204851
2           18 - 25           -1  20180000003995         497654
3           46 - 55           -1  20150000299600         109376
4           26 - 35           -1  20160000438879         219794

  Stop Resolution Weapon Type Officer ID  Officer YOB Officer
Gender  \
0  Offense Report        None       6358         1970              M

1          Arrest        None       7560         1986              M

2   Field Contact        None       7428         1963              M

3   Field Contact        None       6805         1973              M

4  Offense Report        None       5781         1963              M


                Officer Race  ...  \
0                      White  ...
1                      White  ...
2         Hispanic or Latino  ...
3                      White  ...
4  Black or African American  ...
```

```
                              Initial Call Type  \
0                                       Unknown
1  ORDER - CRITICAL VIOLATION OF DV COURT ORDER
2                                       Unknown
3    SUSPICIOUS STOP - OFFICER INITIATED ONVIEW
4     THEFT (DOES NOT INCLUDE SHOPLIFT OR SVCS)

                                Final Call Type                 Call
Type  \
0                                       Unknown
Unknown
1  --DV - ENFORCE COURT ORDER (ARREST MANDATED)  TELEPHONE OTHER, NOT
911
2                                       Unknown
Unknown
3                         --DISTURBANCE - OTHER
ONVIEW
4                            --THEFT - SHOPLIFT
ONVIEW

                          Officer Squad Arrest Flag Frisk Flag
Precinct  \
0     WEST PCT 3RD W - MARY - PLATOON 1           N          N
Unknown
1          SOUTH PCT 1ST W - R/S RELIEF           Y          N
South
2                    WEST PCT OPS - CPT           N          N
Unknown
3    WEST PCT 2ND W - DAVID - PLATOON 1           N          N
West
4  SOUTHWEST PCT 2ND WATCH - F/W RELIEF           N          N
Southwest

    Sector     Beat Officer Age
0  Unknown  Unknown          45
1        S       S1          36
2  Unknown  Unknown          55
3        D       D3          42
4        W       W2          53

[5 rows x 24 columns]
```

```python
df_imputed['Officer Age'].describe()
```

```
count    60938.000000
mean        34.590666
std          8.793464
min         21.000000
25%         28.000000
50%         33.000000
```

```
75%          39.000000
max         121.000000
Name: Officer Age, dtype: float64
```

It's unlikely we have on duty officers above the age of 65 so we can drop rows with officers above this age

```
df_imputed = df_imputed[df_imputed['Officer Age'] <= 65]

df_imputed.head()

  Subject Age Group   Subject ID     GO / SC Num  Terry Stop ID  \
0            1 - 17           -1  20150000002502          47107
1           36 - 45  32643034540  20220000318696    38698204851
2           18 - 25           -1  20180000003995         497654
3           46 - 55           -1  20150000299600         109376
4           26 - 35           -1  20160000438879         219794

  Stop Resolution Weapon Type Officer ID  Officer YOB Officer
Gender  \
0  Offense Report        None       6358         1970              M

1          Arrest        None       7560         1986              M

2   Field Contact        None       7428         1963              M

3   Field Contact        None       6805         1973              M

4  Offense Report        None       5781         1963              M


                Officer Race  ...  \
0                      White  ...
1                      White  ...
2         Hispanic or Latino  ...
3                      White  ...
4  Black or African American  ...

                              Initial Call Type  \
0                                       Unknown
1  ORDER - CRITICAL VIOLATION OF DV COURT ORDER
2                                       Unknown
3    SUSPICIOUS STOP - OFFICER INITIATED ONVIEW
4     THEFT (DOES NOT INCLUDE SHOPLIFT OR SVCS)

                                Final Call Type                  Call
Type  \
0                                       Unknown
Unknown
1  --DV - ENFORCE COURT ORDER (ARREST MANDATED)  TELEPHONE OTHER, NOT
```

```
911
2                                        Unknown
Unknown
3                          --DISTURBANCE - OTHER
ONVIEW
4                             --THEFT - SHOPLIFT
ONVIEW

                          Officer Squad Arrest Flag Frisk Flag
Precinct  \
0     WEST PCT 3RD W - MARY - PLATOON 1           N          N
Unknown
1          SOUTH PCT 1ST W - R/S RELIEF           Y          N
South
2                    WEST PCT OPS - CPT           N          N
Unknown
3    WEST PCT 2ND W - DAVID - PLATOON 1           N          N
West
4  SOUTHWEST PCT 2ND WATCH - F/W RELIEF           N          N
Southwest

    Sector     Beat Officer Age
0  Unknown  Unknown          45
1        S       S1          36
2  Unknown  Unknown          55
3        D       D3          42
4        W       W2          53

[5 rows x 24 columns]
```

```
df_imputed['Officer Age'].describe()
```

```
count    60835.000000
mean        34.469467
std          8.238621
min         21.000000
25%         28.000000
50%         33.000000
75%         39.000000
max         65.000000
Name: Officer Age, dtype: float64
```

The distribution of Officer Age now makes more sense

```
# Initialize bin_edges list and handle bins, setting the lower bound
for the last bin to 56 (similar to Subject Age Group)
bin_edges = []
for bin in bins:
    if bin == '56 and Above':
        bin_edges.append(56)
```

```
    else:
        lower_bound = int(bin.split(' - ')[0])
        bin_edges.append(lower_bound)


# Add the upper bound from the last bin
max_age = df_imputed['Officer Age'].max()
bin_edges.append(max_age)

# Remove duplicates and sort bin_edges
bin_edges = sorted(set(bin_edges))

bin_edges
```

```
[1, 18, 26, 36, 46, 56, 65]
```

```
# We will use labels similar to those in Subject Age Group
labels = df_imputed['Subject Age Group'].unique().tolist()
labels
```

```
['1 - 17', '36 - 45', '18 - 25', '46 - 55', '26 - 35', '56 and Above']
```

```
print('length of bin_edges: ', len(bin_edges)-1)
print('length of labels: ', len(labels))
```

```
length of bin_edges:  6
length of labels:  6
```

```
# Use pd.cut to create the bins for Officer Age
df_imputed['Officer Age Group'] = pd.cut(df_imputed['Officer Age'],
bins=bin_edges, labels=labels, right=True)

print('Officer Age Group:', bins)
print('Subject Age Group:', labels)
df_imputed.head()
```

```
Officer Age Group: ['1 - 17' '36 - 45' '18 - 25' '46 - 55' '26 - 35'
'56 and Above']
Subject Age Group: ['1 - 17', '36 - 45', '18 - 25', '46 - 55', '26 -
35', '56 and Above']
```

```
  Subject Age Group   Subject ID     GO / SC Num  Terry Stop ID  \
0            1 - 17           -1  20150000002502          47107
1           36 - 45  32643034540  20220000318696    38698204851
2           18 - 25           -1  20180000003995         497654
3           46 - 55           -1  20150000299600         109376
4           26 - 35           -1  20160000438879         219794

  Stop Resolution Weapon Type Officer ID  Officer YOB Officer
Gender  \
0  Offense Report        None       6358         1970              M
```

```
1          Arrest        None       7560          1986              M

2   Field Contact        None       7428          1963              M

3   Field Contact        None       6805          1973              M

4  Offense Report        None       5781          1963              M


                Officer Race  ...  \
0                      White  ...
1                      White  ...
2         Hispanic or Latino  ...
3                      White  ...
4  Black or African American  ...

                                Final Call Type                 Call
Type  \
0                                       Unknown
Unknown
1  --DV - ENFORCE COURT ORDER (ARREST MANDATED)  TELEPHONE OTHER, NOT
911
2                                       Unknown
Unknown
3                         --DISTURBANCE - OTHER
ONVIEW
4                            --THEFT - SHOPLIFT
ONVIEW

                          Officer Squad Arrest Flag Frisk Flag
Precinct  \
0     WEST PCT 3RD W - MARY - PLATOON 1           N          N
Unknown
1          SOUTH PCT 1ST W - R/S RELIEF           Y          N
South
2                    WEST PCT OPS - CPT           N          N
Unknown
3    WEST PCT 2ND W - DAVID - PLATOON 1           N          N
West
4  SOUTHWEST PCT 2ND WATCH - F/W RELIEF           N          N
Southwest

    Sector     Beat Officer Age Officer Age Group
0  Unknown  Unknown          45           46 - 55
1        S       S1          36           18 - 25
2  Unknown  Unknown          55           26 - 35
3        D       D3          42           46 - 55
4        W       W2          53           26 - 35
```

```
[5 rows x 25 columns]
```

Columns to drop:

Next, we will drop some columns that do not provide useful information for our analysis. From a review of the column descriptions, we can ignore the following columns:

1. Subject ID: This is a unique identifier for each subject, not useful for modeling.
2. GO / SC Num: Unique identifier for reports, irrelevant for prediction.
3. Terry Stop ID: Another unique identifier.
4. Officer ID: Identifies each officer; may introduce bias and is not necessary.
5. Reported Date & Reported Time: Since they represent when the report was filed, not when the stop occurred, they may not be useful.

```
#change the datatype so Officer Age Group and Subject Age Group to
ordinal categorical values.
df_imputed['Officer Age Group'] = pd.Categorical(df_imputed['Officer
Age Group'],
                                          categories=bins,
                                          ordered=True)
df_imputed['Subject Age Group'] = pd.Categorical(df_imputed['Subject
Age Group'],
                                          categories=labels,
                                          ordered=True)

columns_to_drop = ['Subject ID', 'GO / SC Num', 'Terry Stop ID',
'Officer ID', 'Reported Date', 'Reported Time','Officer Age','Officer
YOB']

df_preprocessed = df_imputed.drop(columns=columns_to_drop, axis =1)

df_preprocessed.head()

  Subject Age Group Stop Resolution Weapon Type Officer Gender  \
0            1 - 17  Offense Report        None              M
1           36 - 45          Arrest        None              M
2           18 - 25   Field Contact        None              M
3           46 - 55   Field Contact        None              M
4           26 - 35  Offense Report        None              M

                 Officer Race            Subject Perceived Race  \
0                       White                           Unknown
1                       White                           Unknown
2          Hispanic or Latino                             White
3                       White  American Indian or Alaska Native
```

```
4  Black or African American                              White

  Subject Perceived Gender                             Initial Call
Type  \
0                   Female
Unknown
1                     Male  ORDER - CRITICAL VIOLATION OF DV COURT
ORDER
2                     Male
Unknown
3                   Female    SUSPICIOUS STOP - OFFICER INITIATED
ONVIEW
4                   Female     THEFT (DOES NOT INCLUDE SHOPLIFT OR
SVCS)

                                Final Call Type                 Call
Type  \
0                                        Unknown
Unknown
1  --DV - ENFORCE COURT ORDER (ARREST MANDATED)  TELEPHONE OTHER, NOT
911
2                                        Unknown
Unknown
3                          --DISTURBANCE - OTHER
ONVIEW
4                             --THEFT - SHOPLIFT
ONVIEW

                          Officer Squad Arrest Flag Frisk Flag
Precinct  \
0     WEST PCT 3RD W - MARY - PLATOON 1           N          N
Unknown
1          SOUTH PCT 1ST W - R/S RELIEF           Y          N
South
2                    WEST PCT OPS - CPT           N          N
Unknown
3    WEST PCT 2ND W - DAVID - PLATOON 1           N          N
West
4  SOUTHWEST PCT 2ND WATCH - F/W RELIEF           N          N
Southwest

    Sector     Beat Officer Age Group
0  Unknown  Unknown           46 - 55
1        S       S1           18 - 25
2  Unknown  Unknown           26 - 35
3        D       D3           46 - 55
4        W       W2           26 - 35
```

We have dropped 6 columns 'Subject ID', 'Officer YOB', 'GO / SC Num', 'Terry Stop ID', 'Officer ID', 'Reported Date',and 'Reported Time' from our original dataset and added one new column - Officer Age Group

Let us look at what our dataset looks like now

```
df_preprocessed.shape
```

```
(60835, 17)
```

```
df_preprocessed.duplicated().sum()
```

```
5967
```

Let's drop our duplicated rows - these may be rows entered multiple times under different IDs that we dropped

```
df_preprocessed.drop_duplicates(inplace = True)

print('Shape: ',df_preprocessed.shape)
print('Duplicates: ',df_preprocessed.duplicated().sum())
```

```
Shape:  (54868, 17)
Duplicates:  0
```

Our dataset now has 17 columns and 54,868 rows and no duplicates

```
df_preprocessed.columns
```

```
Index(['Subject Age Group', 'Stop Resolution', 'Weapon Type', 'Officer
Gender',
       'Officer Race', 'Subject Perceived Race', 'Subject Perceived
Gender',
       'Initial Call Type', 'Final Call Type', 'Call Type', 'Officer
Squad',
       'Arrest Flag', 'Frisk Flag', 'Precinct', 'Sector', 'Beat',
       'Officer Age Group'],
      dtype='object')
```

```
df_preprocessed.describe()
```

```
       Subject Age Group Stop Resolution Weapon Type Officer Gender  \
count              54868           54868       54868          54868
unique                 6               5          22              2
top              26 - 35   Field Contact        None              M
freq               20144           25055       51063          48582

       Officer Race Subject Perceived Race Subject Perceived Gender  \
count         54868                  54868                    54868
unique            8                     10                        6
top           White                  White                     Male
```

```
freq          38884                      26448                         43031

       Initial Call Type Final Call Type Call Type  \
count              54868           54868     54868
unique               180             196         7
top              Unknown         Unknown       911
freq                9769            9769     27519

                          Officer Squad Arrest Flag Frisk Flag
Precinct  \
count                             54868       54868      54868
54868
unique                              271           2          2
8
top     TRAINING - FIELD TRAINING SQUAD           N          N
West
freq                               5801       48364      40928
15917

         Sector     Beat Officer Age Group
count     54868    54868             54868
unique       20       55                 5
top     Unknown  Unknown           18 - 25
freq       7324     7318             29457
```

We are left with only categorical data from a review of the description.

Types of Variables:

Next we will look at the types of variables in our dataset.

We have three columns with binary data - officer gender, arrest flag and frisk flag. We will convert these data to booleans

```
binary_columns = ['Arrest Flag', 'Frisk Flag', 'Officer Gender']

for column in binary_columns:
    df_preprocessed[column] = df_preprocessed[column] == 'Y' if column
in ['Arrest Flag', 'Frisk Flag'] else df_preprocessed[column] == 'M'

df_preprocessed[binary_columns].head()

   Arrest Flag  Frisk Flag  Officer Gender
0        False       False            True
1         True       False            True
2        False       False            True
3        False       False            True
4        False       False            True
```

The goal of our analysis is to predict whether an arrest was made during a Terry Stop. Therefore , our target will be "Arrest Flag".

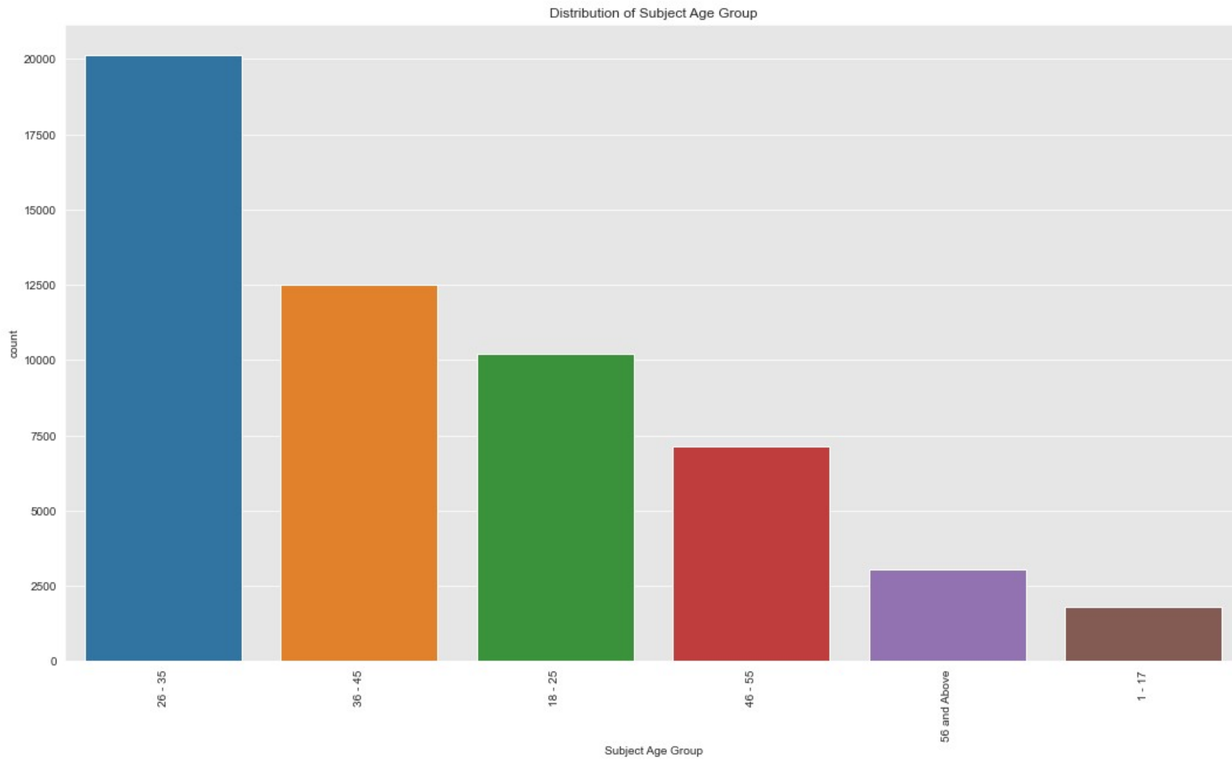
```
X = df_preprocessed.drop('Arrest Flag', axis = 1)
y = df_preprocessed['Arrest Flag']

# Identify categorical and numerical features
categorical = [var for var in X.columns if X[var].dtype in ['O',
'category', 'bool']]
numerical = [var for var in X.columns if X[var].dtype not in ['O',
'category','bool']]

print('Summary of Features\n')
print('There are {} numerical variables\n'.format(len(numerical)))
print('The numerical variables are :', numerical)

print('There are {} categorical variables\n'.format(len(categorical)))
print('The categorical variables are :', categorical)
```

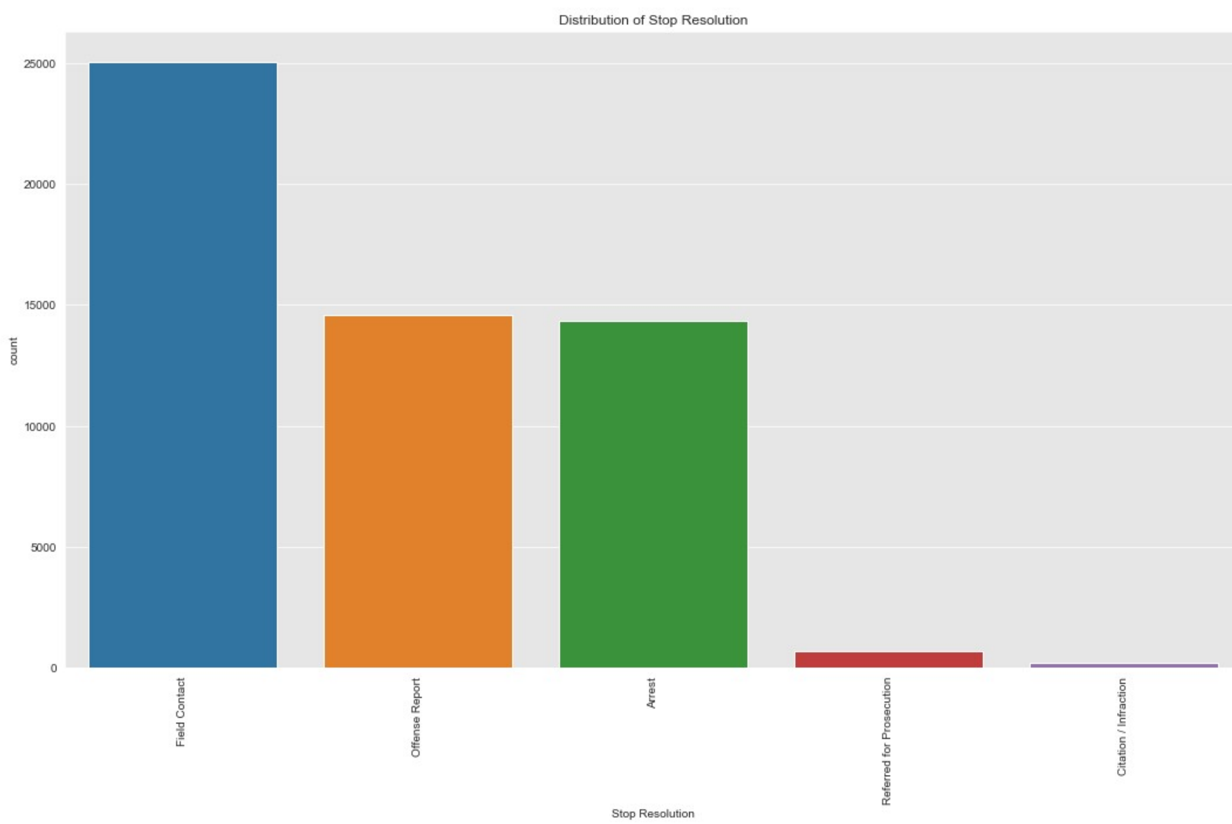
```
Summary of Features

There are 0 numerical variables

The numerical variables are : []
There are 16 categorical variables

The categorical variables are : ['Subject Age Group', 'Stop
Resolution', 'Weapon Type', 'Officer Gender', 'Officer Race', 'Subject
Perceived Race', 'Subject Perceived Gender', 'Initial Call Type',
'Final Call Type', 'Call Type', 'Officer Squad', 'Frisk Flag',
'Precinct', 'Sector', 'Beat', 'Officer Age Group']
```

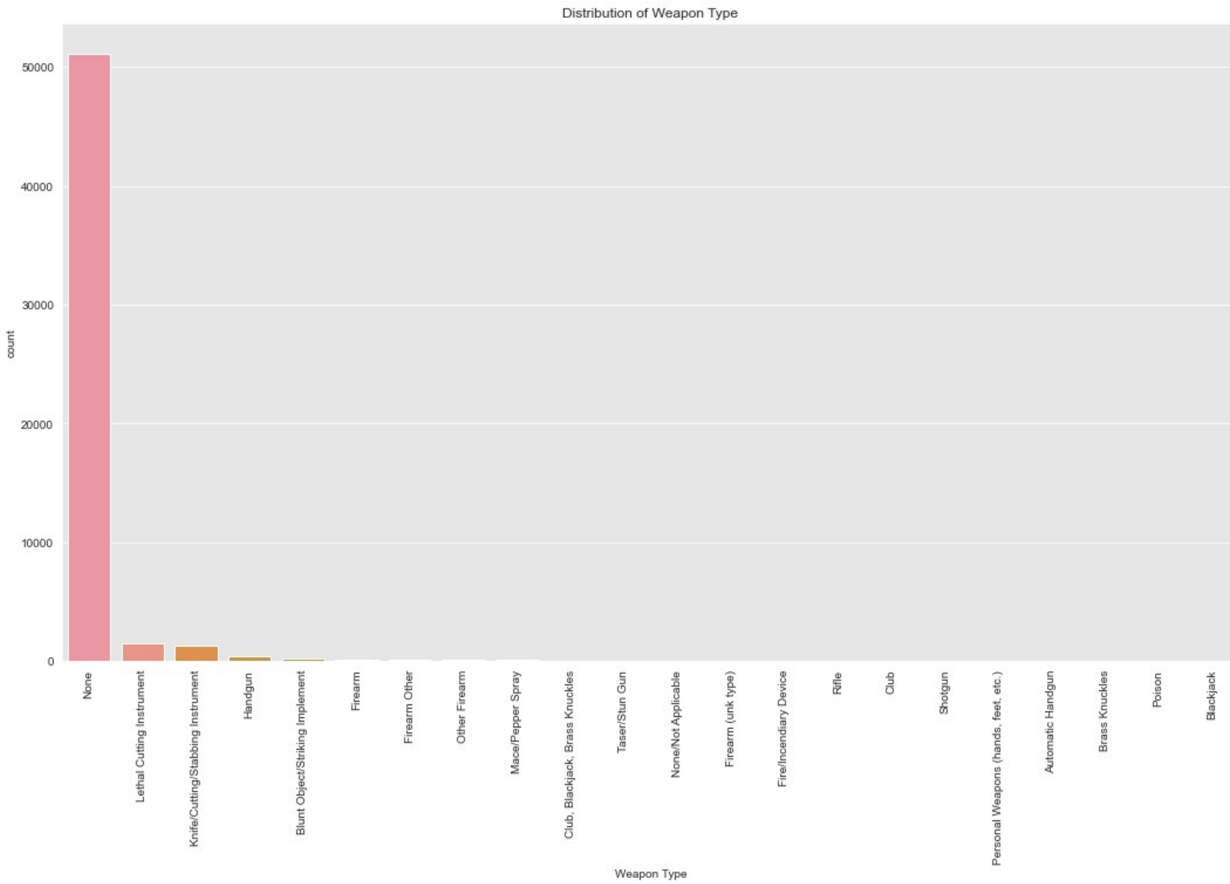
All our features are categorical variables.

Visualizing the distribution of our dataset

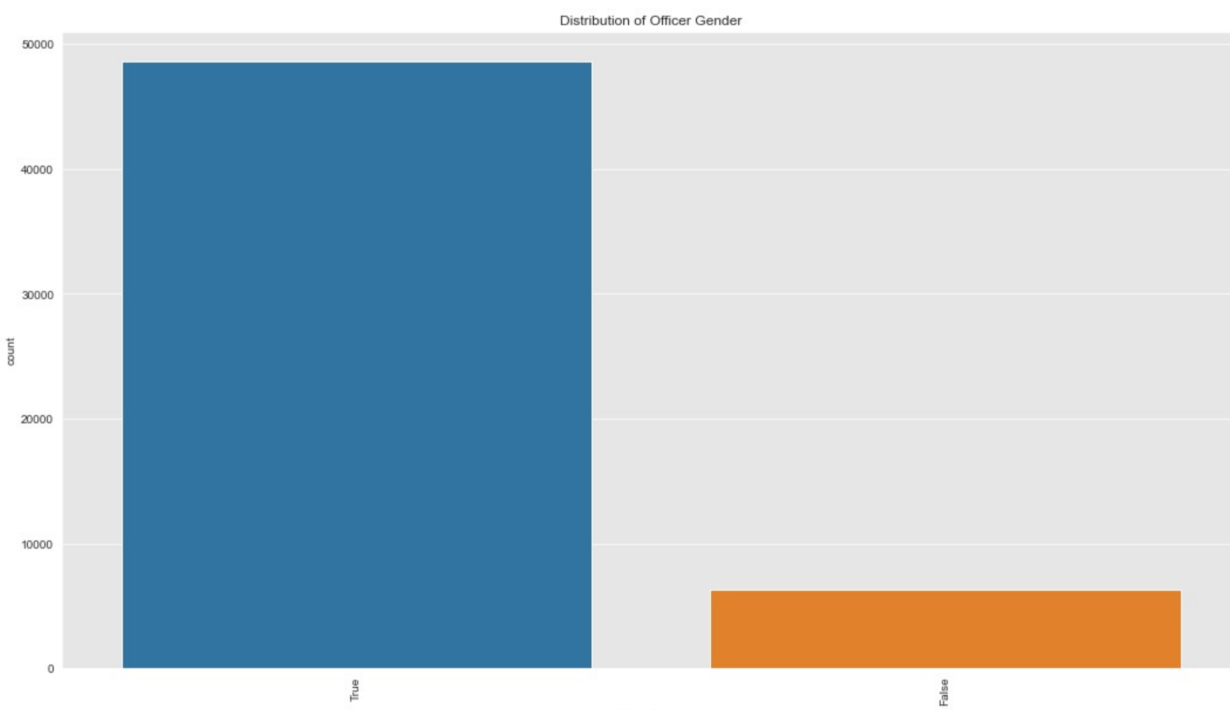
```
for column in df_preprocessed.columns:
    plt.figure(figsize = (18,10))
    sns.countplot(data=df_preprocessed, x=column,
order=df_preprocessed[column].value_counts().index)
    plt.xticks(rotation=90)
    plt.title(f'Distribution of {df_preprocessed[column].name}')
    plt.show;
```


Distribution of Subject Age Group
count
20000
17500
15000
12500
10000
7500
5000
2500
0
26 - 35
36 - 45
18 - 25
46 - 55
56 and Above
1 - 17
Subject Age Group

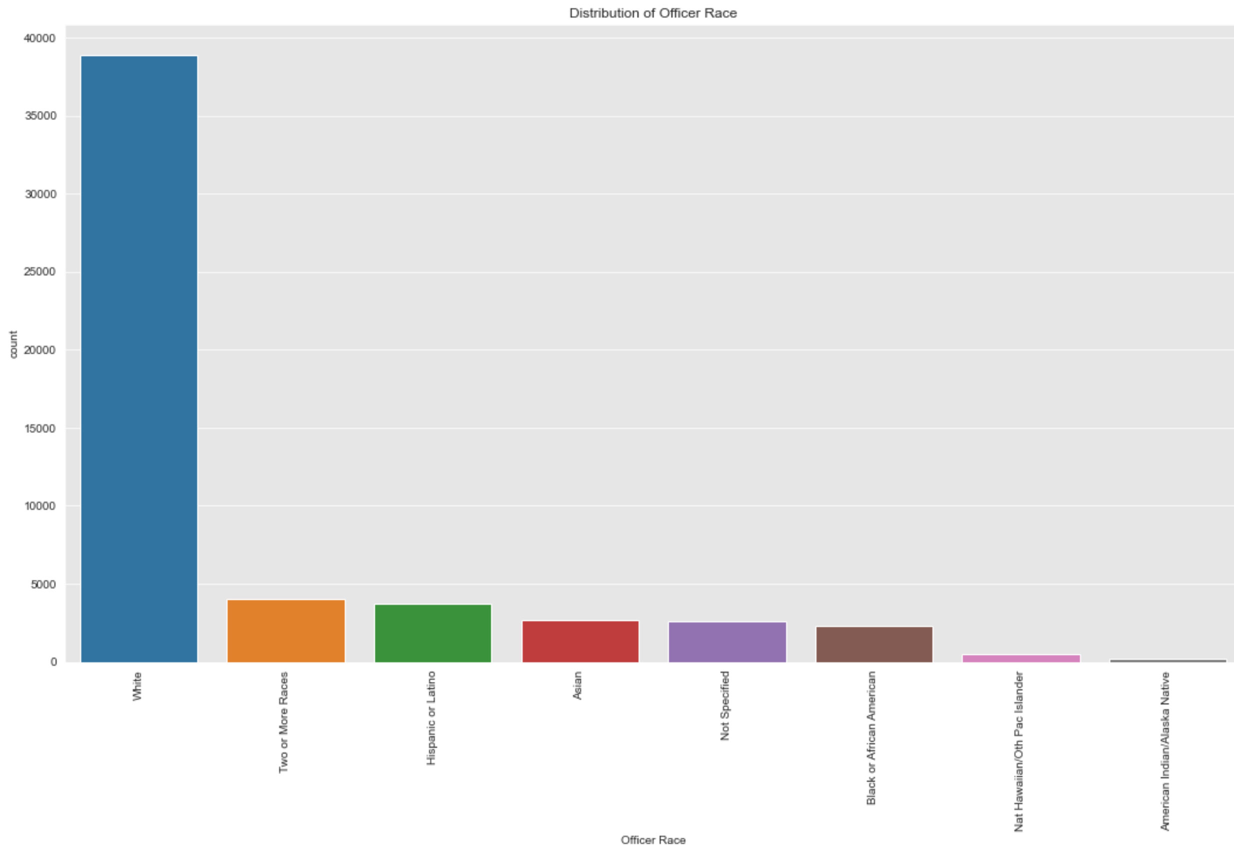

Distribution of Stop Resolution
count
25000
20000
15000
10000
5000
0
Field Contact
Offense Report
Arrest
Referred for Prosecution
Citation / Infraction
Stop Resolution



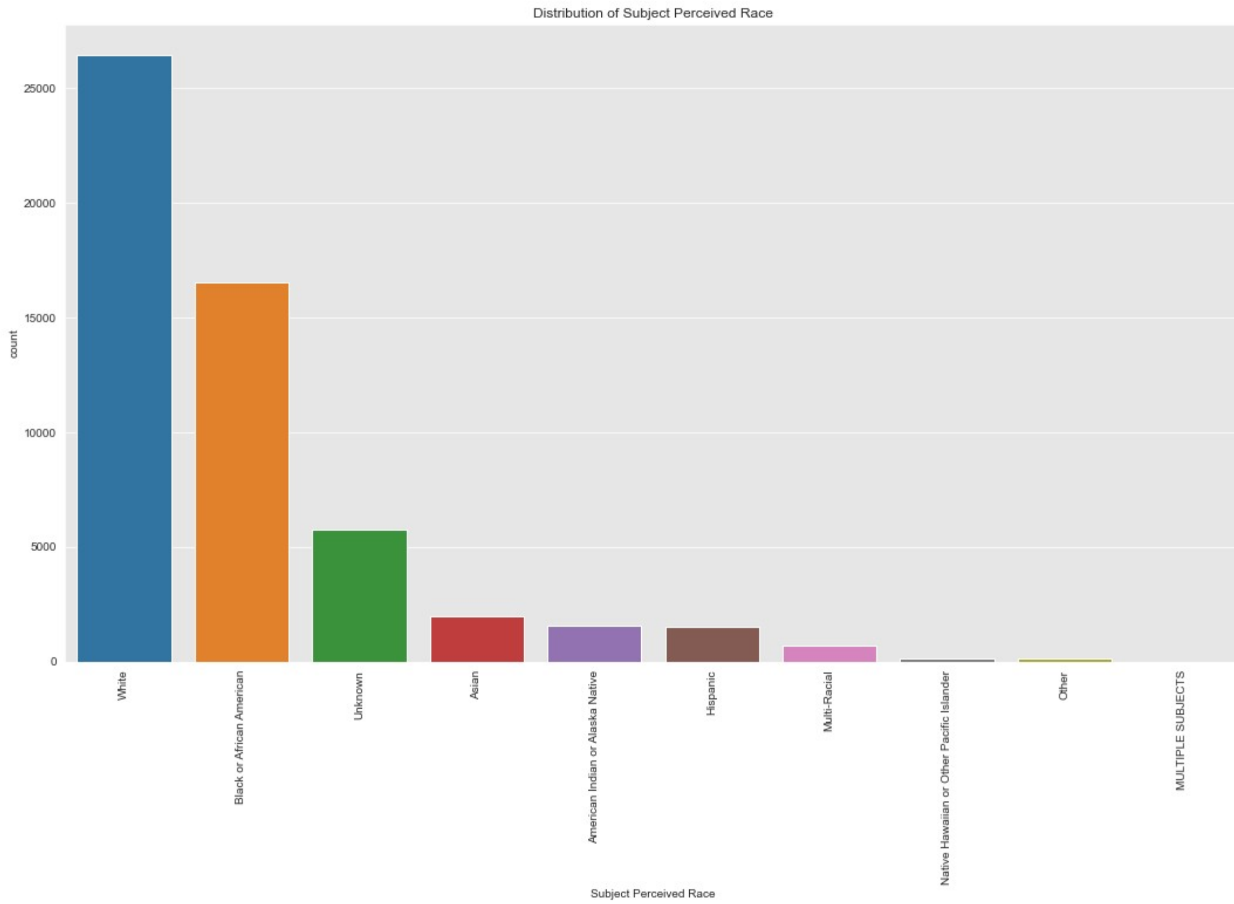
Distribution of Weapon Type
count
50000
40000
30000
20000
10000
0
None
Lethal Cutting Instrument
Knife/Cutting/Stabbing Instrument
Handgun
Blunt Object/Striking Implement
Firearm
Firearm Other
Other Firearm
Mace/Pepper Spray
Club, Blackjack, Brass Knuckles
Taser/Stun Gun
None/Not Applicable
Firearm (unk type)
Fire/Incendiary Device
Rifle
Club
Shotgun
Personal Weapons (hands, feet, etc.)
Automatic Handgun
Brass Knuckles
Poison
Blackjack
Weapon Type



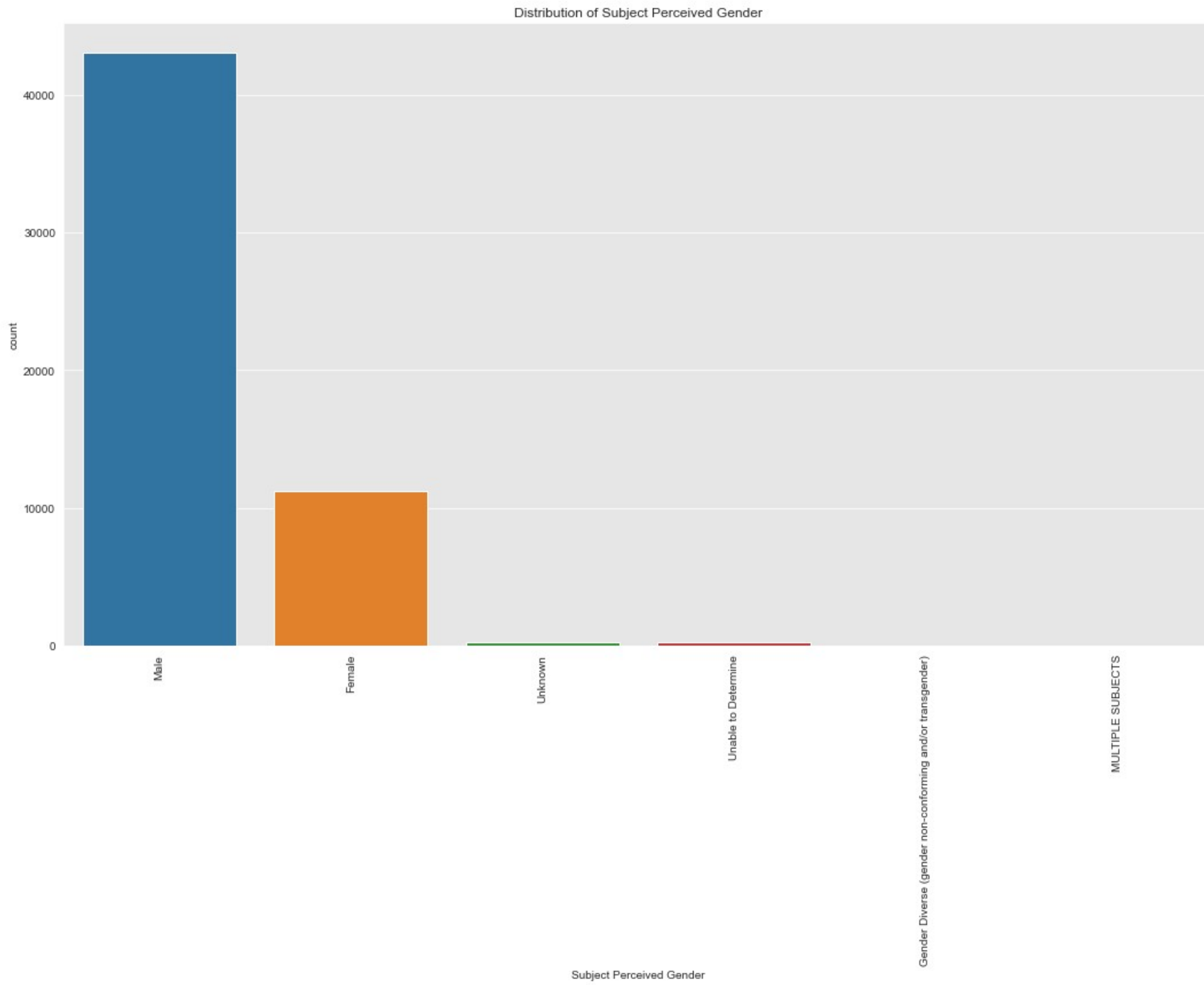
Distribution of Officer Gender
count
50000
40000
30000
20000
10000
0
True
False
Officer Gender

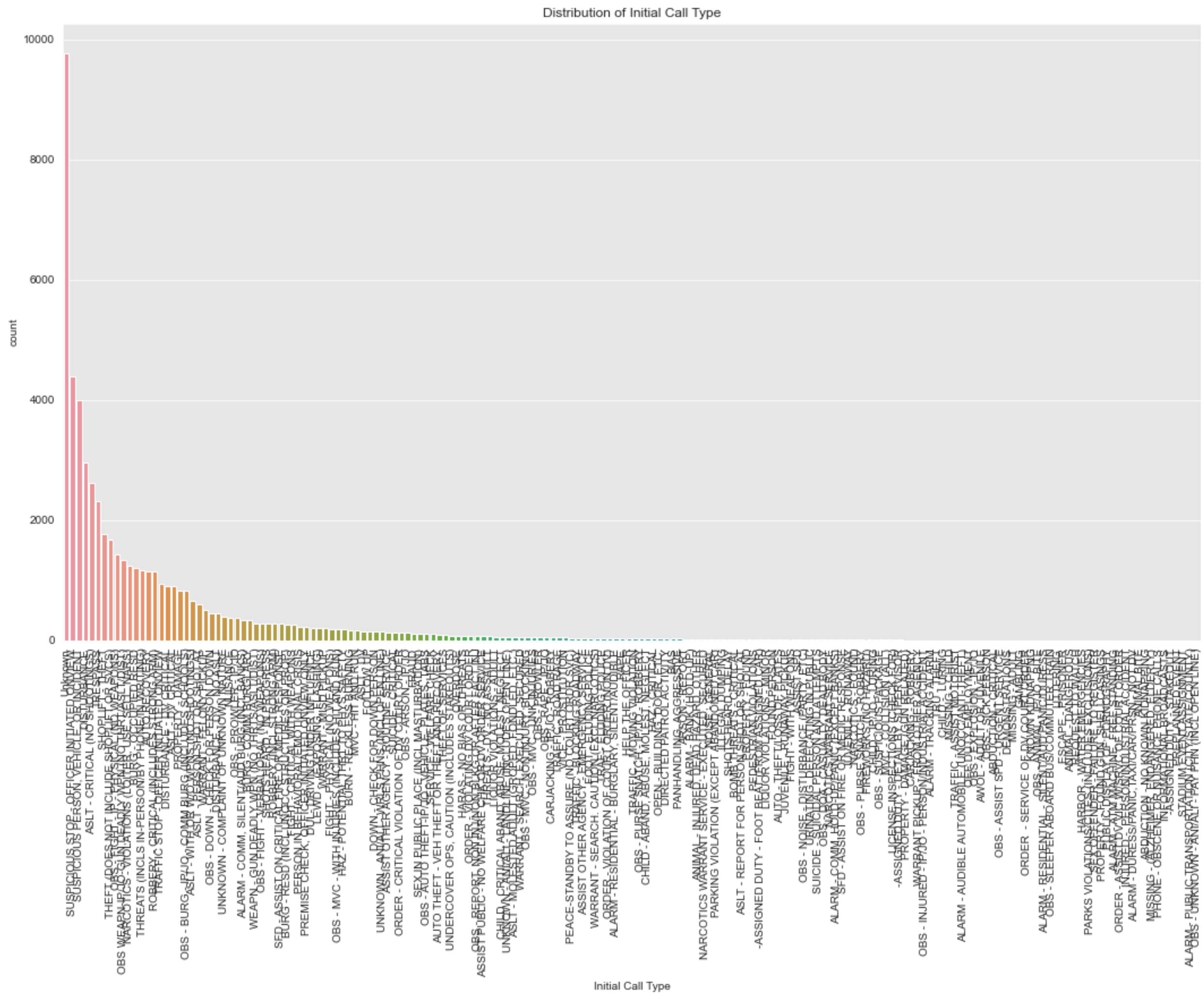


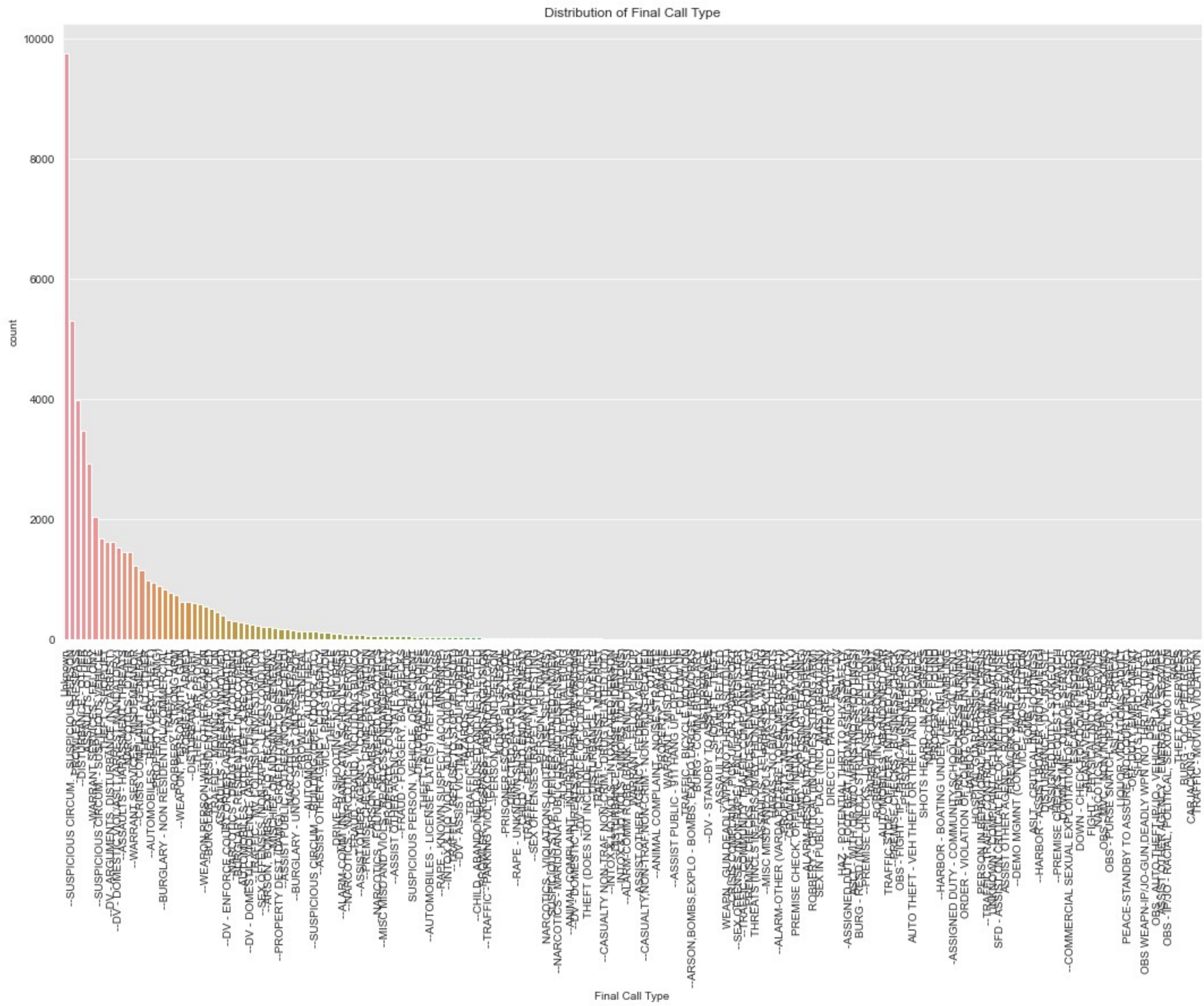
Distribution of Officer Race
count
40000
35000
30000
25000
20000
15000
10000
5000
0
White
Two or More Races
Hispanic or Latino
Asian
Not Specified
Black or African American
Nat Hawaiian/Oth Pac Islander
American Indian/Alaska Native
Officer Race

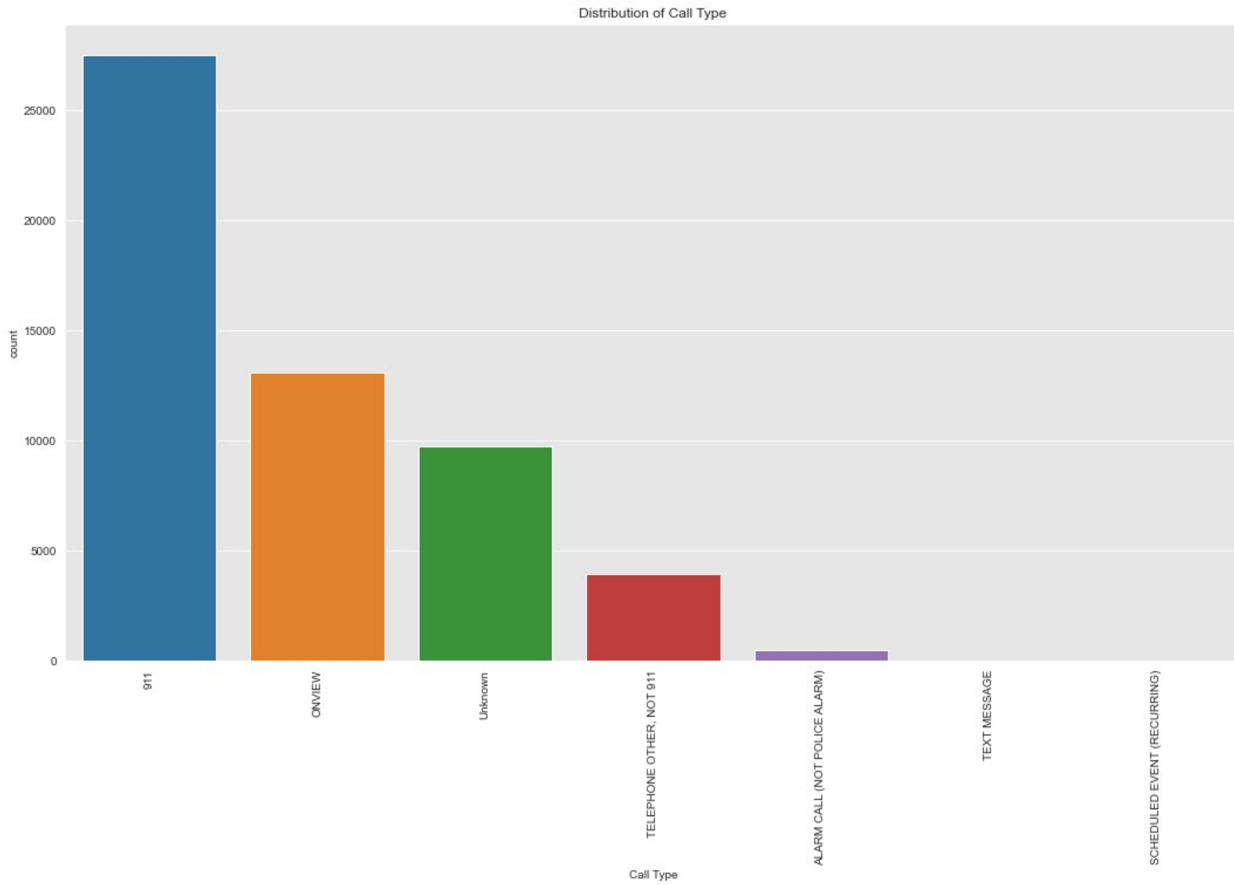


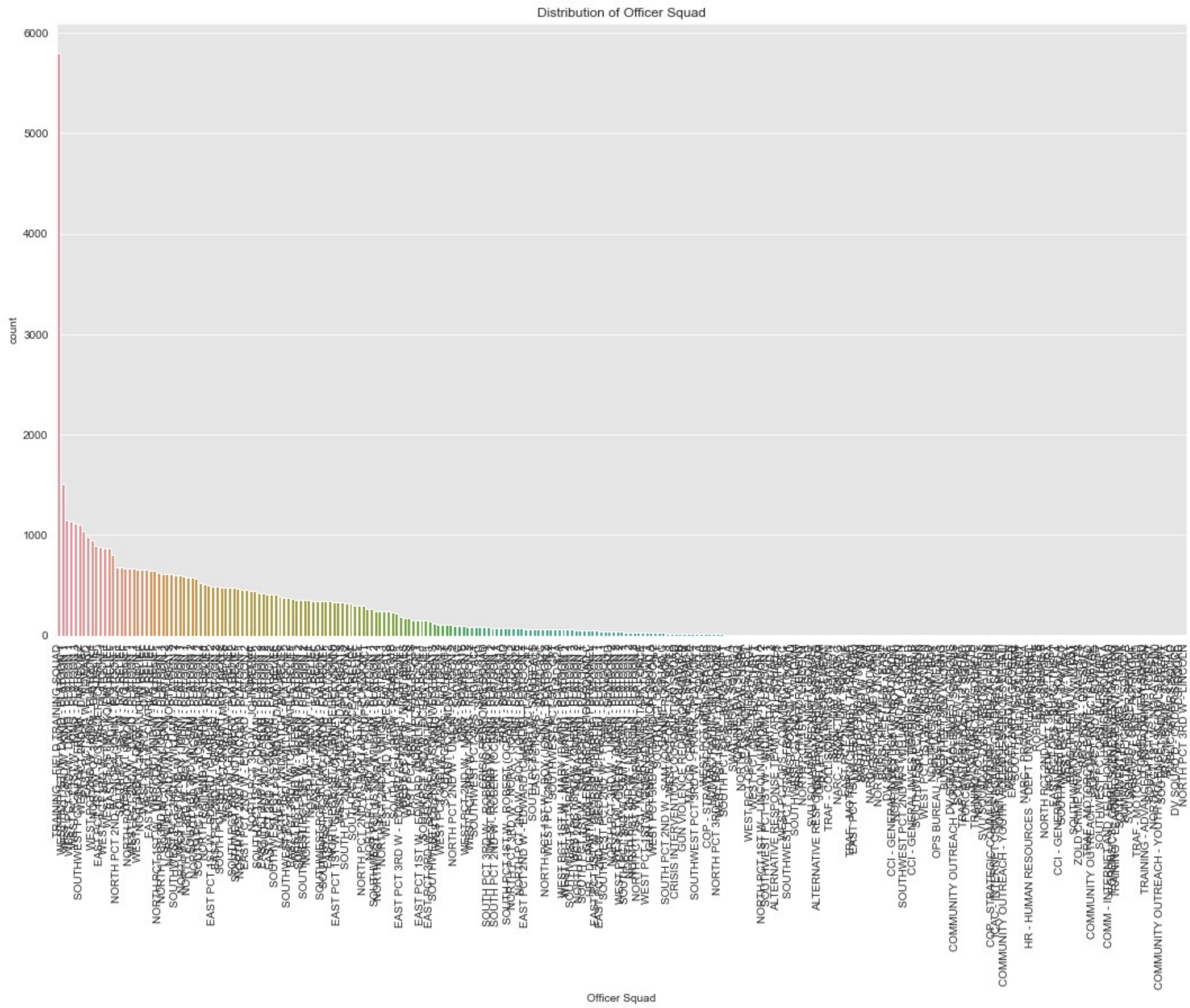
Distribution of Subject Perceived Race
count
25000
20000
15000
10000
5000
0
White
Black or African American
Unknown
Asian
American Indian or Alaska Native
Hispanic
Multi-Racial
Native Hawaiian or Other Pacific Islander
Other
MULTIPLE SUBJECTS
Subject Perceived Race

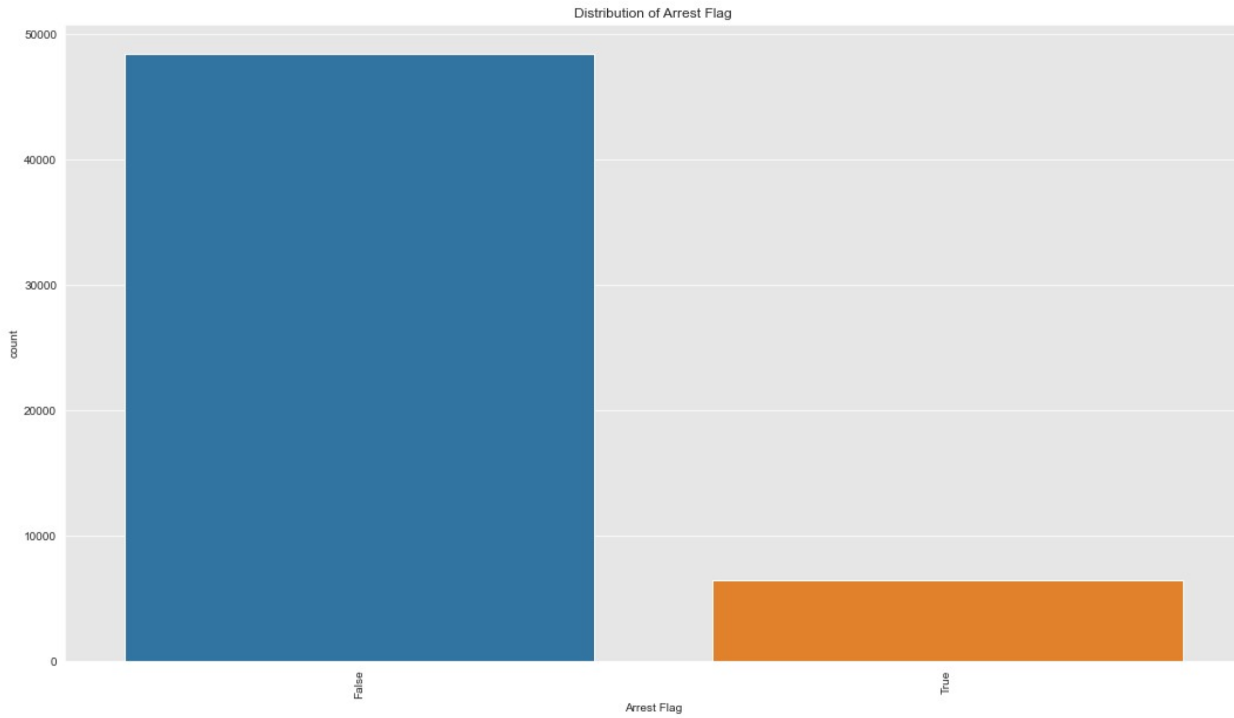

Distribution of Subject Perceived Gender
40000
30000
20000
10000
0
count
Male
Female
Unknown
Unable to Determine
Gender Diverse (gender non-conforming and/or transgender)
MULTIPLE SUBJECTS
Subject Perceived Gender

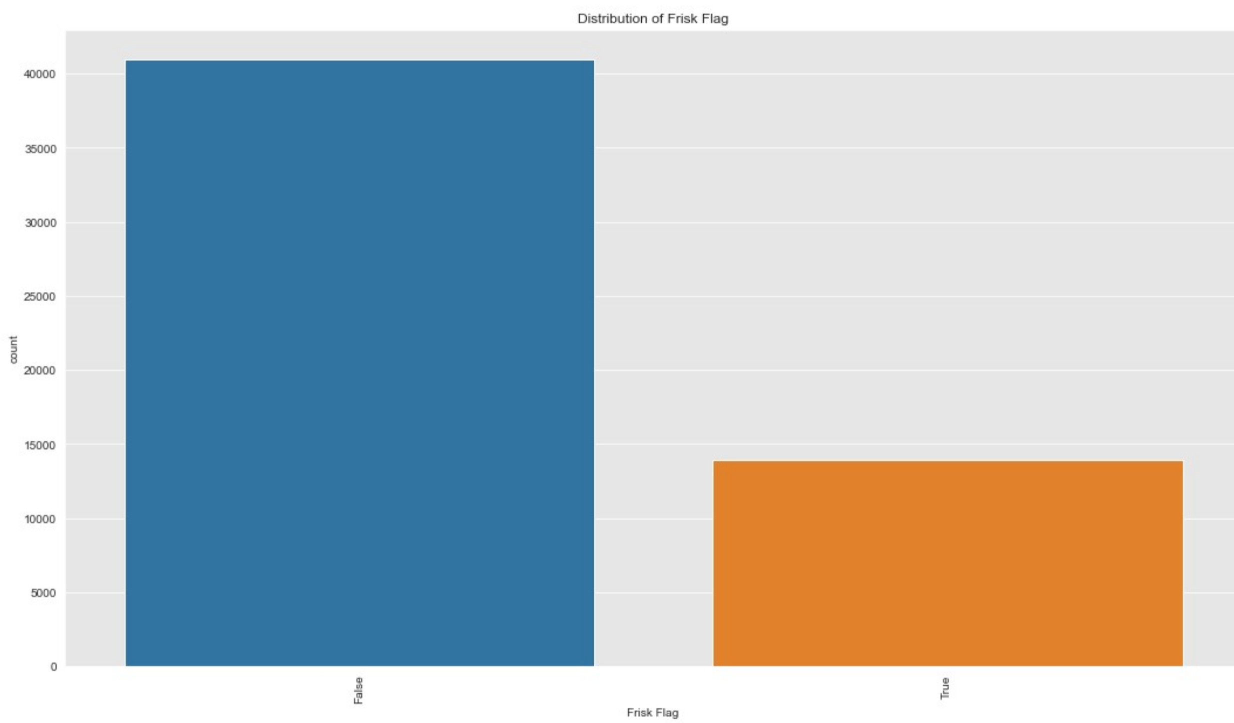

Distribution of Initial Call Type
count
10000
8000
6000
4000
2000
0
Initial Call Type

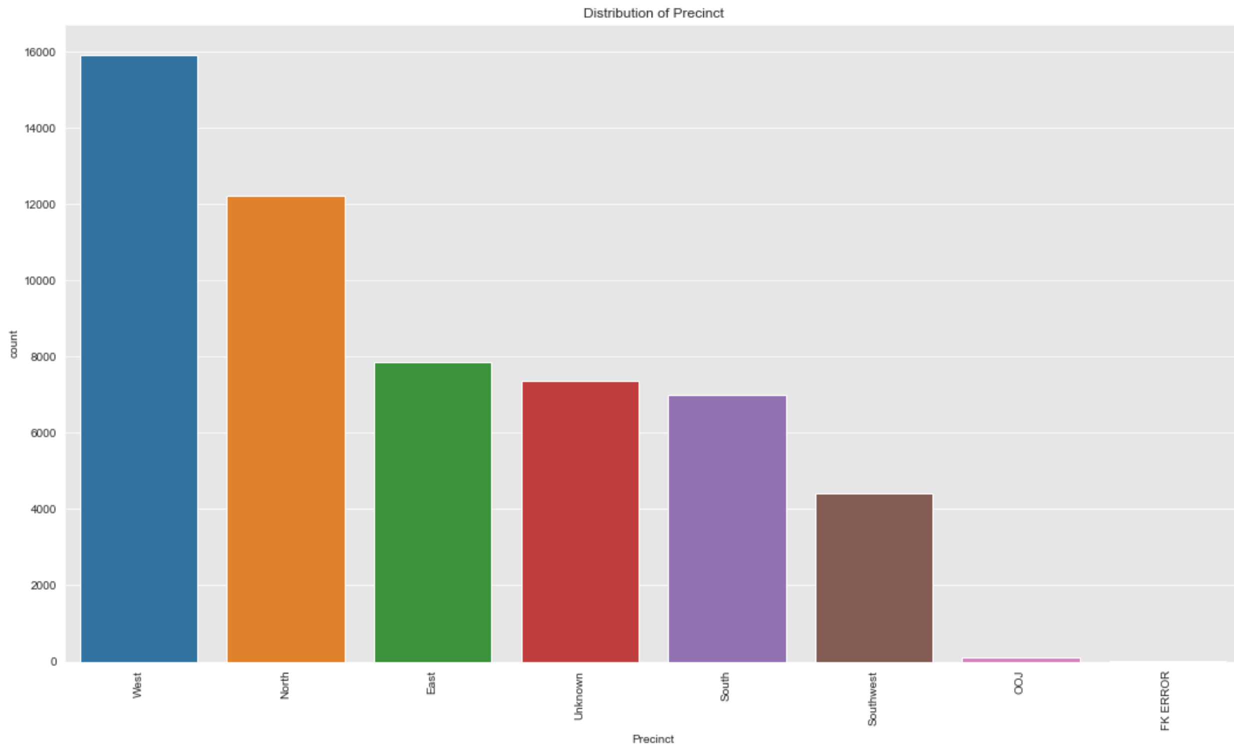

Distribution of Final Call Type
10000
8000
6000
4000
2000
0
count
Final Call Type


Distribution of Call Type
count
25000
20000
15000
10000
5000
0
911
ONVIEW
Unknown
TELEPHONE OTHER, NOT 911
ALARM CALL (NOT POLICE ALARM)
TEXT MESSAGE
SCHEDULED EVENT (RECURRING)
Call Type

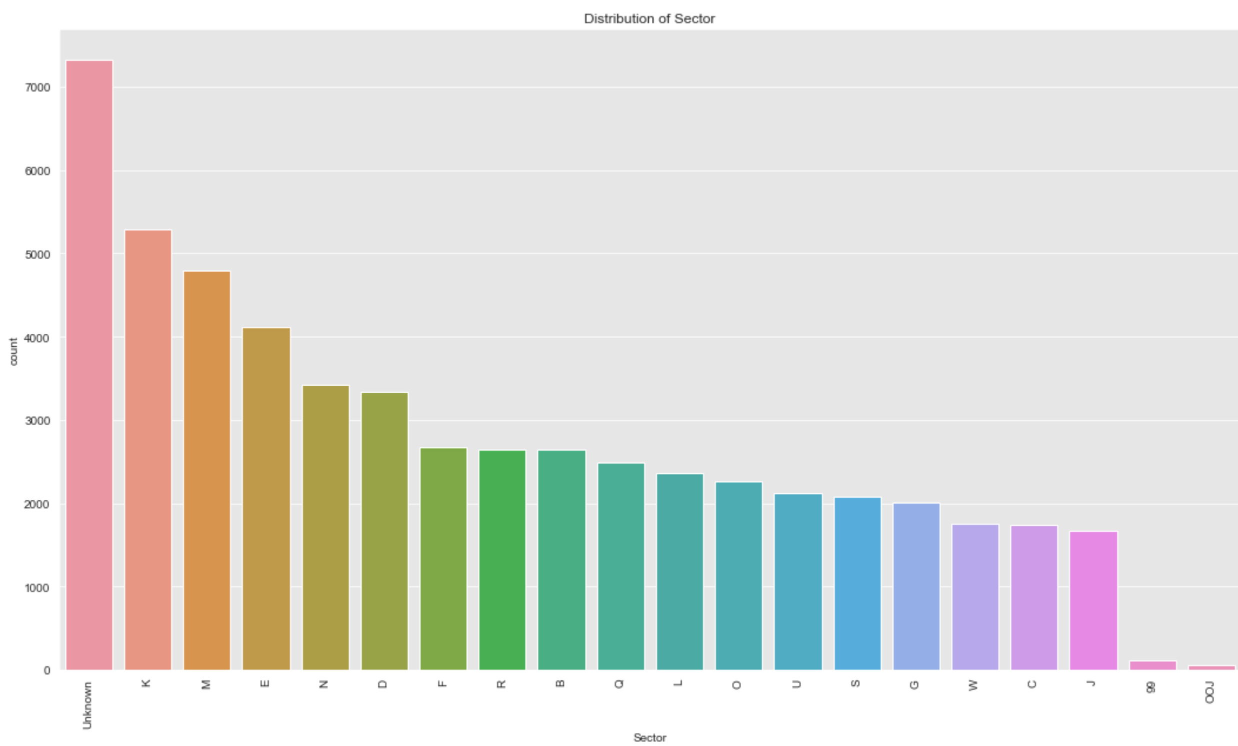

Distribution of Officer Squad
count
Officer Squad
0
1000
2000
3000
4000
5000
6000


Distribution of Arrest Flag
50000
40000
30000
20000
10000
0
count
False
True
Arrest Flag

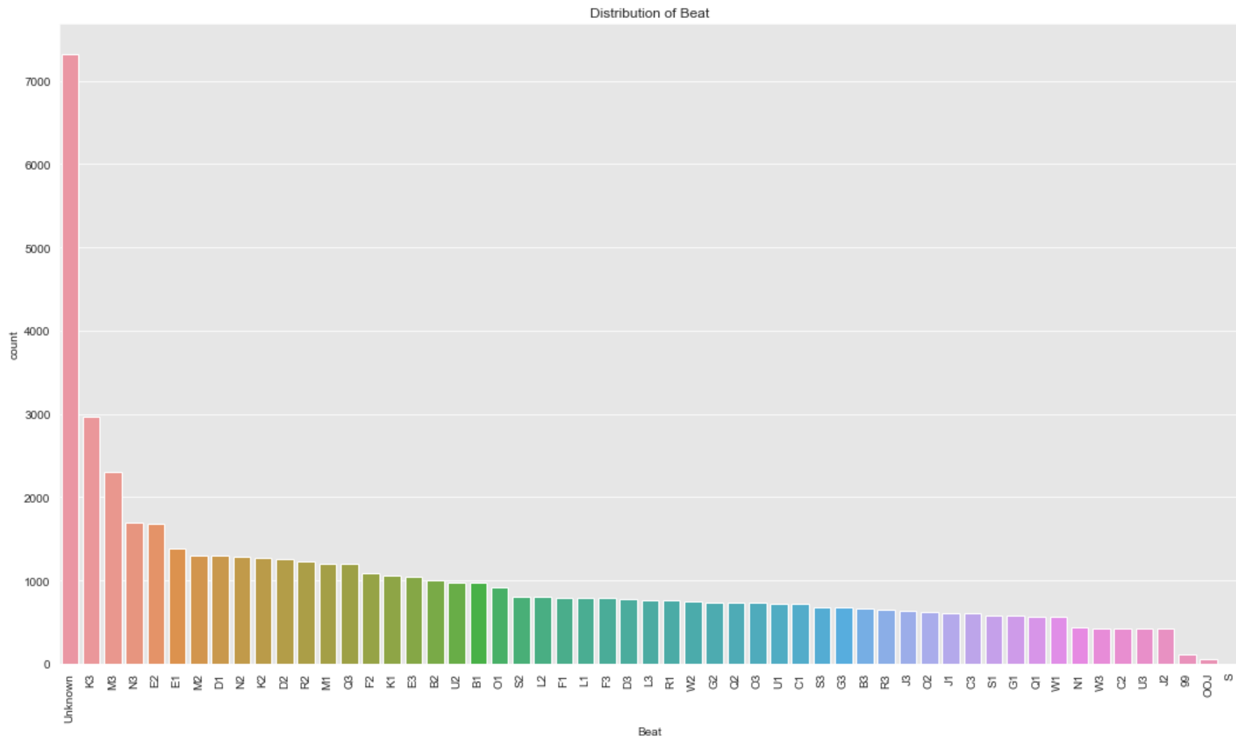

Distribution of Frisk Flag
40000
35000
30000
25000
20000
15000
10000
5000
0
count
False
True
Frisk Flag

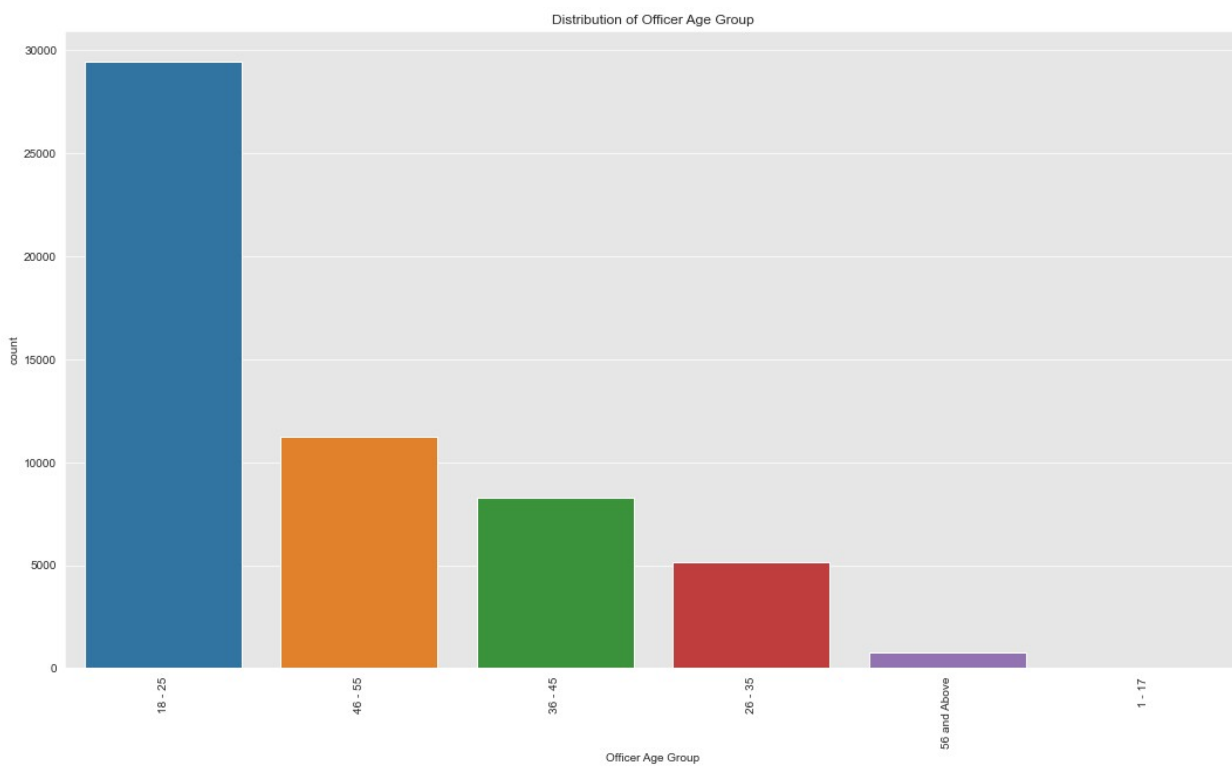


Distribution of Precinct
count
16000
14000
12000
10000
8000
6000
4000
2000
0
West
North
East
Unknown
South
Southwest
OOJ
FK ERROR
Precinct



Distribution of Sector
count
7000
6000
5000
4000
3000
2000
1000
0
Unknown
K
M
E
N
D
F
R
B
Q
L
O
U
S
G
W
C
J
99
OOJ
Sector






```python
print('Summary of Frequency Distribution in our Features\n')
for column in X.columns:
    print(f'{column} has {X[column].nunique()} unique values')
```

```
Summary of Frequency Distribution in our Features

Subject Age Group has 6 unique values
Stop Resolution has 5 unique values
Weapon Type has 22 unique values
Officer Gender has 2 unique values
Officer Race has 8 unique values
Subject Perceived Race has 10 unique values
Subject Perceived Gender has 6 unique values
Initial Call Type has 180 unique values
Final Call Type has 196 unique values
Call Type has 7 unique values
Officer Squad has 271 unique values
Frisk Flag has 2 unique values
Precinct has 8 unique values
Sector has 20 unique values
Beat has 55 unique values
Officer Age Group has 5 unique values
```

Some of our features have high cardinality as exhibited by their high frequency:

High Cardinality Features

1. Initial Call Type: 180 unique values
2. Final Call Type: 196 unique values
3. Officer Squad: 271 unique values
4. Beat: 55 unique values
5. Weapon Type: 22 unique value
6. Sector: 20 unique values

These features could lead to a high dimensional feature space if we apply one hot encoding (OHE) directly to our entire feature set.

Low Cardinality Features

1. Subject Age Group: 6 unique values
2. Stop Resolution: 5 unique values
3. Officer Gender: 2 unique values
4. Officer Race: 8 unique values
5. Subject Perceived Race: 10 unique values
6. Subject Perceived Gender: 6 unique values
7. Call Type: 7 unique values
8. Frisk Flag: 2 unique values
9. Precinct: 8 unique values
10. Officer Age Group: 5 unique values

5. Data Preparation

We will start by splitting our data into a training and test set before proceeding to avoid any data leakage

```
X_train, X_test, y_train, y_test = train_test_split(X, y, 
test_size=0.35, random_state=42)
```

Target Encoding

We will use target encoding to deal with our high cardinality features.

Target encoding replaces each category with the mean of the target variable for that category. This reduces the dimensionality by not increasing the number of features, which can help in preventing overfitting. Example: If a category is frequently associated with positive outcomes (e.g., arrests), the encoding will reflect that association. Target encoding should not alter the shape of our data

```
from category_encoders.target_encoder import TargetEncoder

high_cardinality_cols = ['Initial Call Type', 'Final Call Type', 'Call 
Type', 'Officer Squad', 'Beat', 'Weapon Type','Sector']

target_encoder = TargetEncoder(cols = high_cardinality_cols)

#fit the target encoder to the high cardinality features
target_encoder.fit(X_train[high_cardinality_cols], y_train)

#transform the high cardinality features
X_train_te = target_encoder.transform(X_train[high_cardinality_cols])
X_test_te = target_encoder.transform(X_test[high_cardinality_cols])

#assign the transform values into a dataframe
X_train_te_df = pd.DataFrame(X_train_te, 
columns=X_train[high_cardinality_cols].columns)
X_test_te_df = pd.DataFrame(X_test_te, 
columns=X_test[high_cardinality_cols].columns)

#drop the original low cardinality features from our train and test 
set
X_train = X_train.drop(columns=high_cardinality_cols)
X_test = X_test.drop(columns=high_cardinality_cols)

# reset index of Train and Test
X_train = X_train.reset_index(drop=True)
X_test = X_test.reset_index(drop=True)

#reset index of te df
X_train_te_df = X_train_te_df.reset_index(drop=True)
```

```
X_test_te_df = X_test_te_df.reset_index(drop=True)

#update train and test feature set with the encoded values
X_train = pd.concat([X_train, X_train_te_df], axis=1)
X_test = pd.concat([X_test, X_test_te_df], axis=1)



X_train.head()
```

```
  Subject Age Group Stop Resolution  Officer Gender       Officer Race  \
0           36 - 45          Arrest            True              White

1           26 - 35   Field Contact            True              White

2            1 - 17  Offense Report            True  Two or More Races

3           36 - 45   Field Contact           False              White

4           26 - 35  Offense Report            True              White


      Subject Perceived Race Subject Perceived Gender  Frisk Flag
Precinct  \
0  Black or African American                     Male        True
South
1  Black or African American                   Female       False
West
2                    Unknown                     Male       False
Unknown
3                      White                     Male       False
Unknown
4                      White                     Male       False
East

  Officer Age Group  Initial Call Type  Final Call Type  Call Type  \
0           18 - 25           0.128431         0.322581   0.160678
1           46 - 55           0.021691         0.021691   0.021691
2           18 - 25           0.021691         0.021691   0.021691
3           46 - 55           0.021691         0.021691   0.021691
4           18 - 25           0.194543         0.275972   0.160678

   Officer Squad      Beat  Weapon Type    Sector
0       0.141276  0.092308     0.111332  0.105186
1       0.004854  0.202670     0.111332  0.181354
2       0.170673  0.046371     0.111332  0.046333
3       0.004854  0.046371     0.111332  0.046333
4       0.095122  0.145492     0.111332  0.135931
```

```
X_test.head()
```

```
  Subject Age Group Stop Resolution  Officer Gender Officer Race  \
0           18 - 25   Field Contact            True        White
1           36 - 45  Offense Report            True        White
2           26 - 35  Offense Report            True        White
3           26 - 35          Arrest            True        White
4      56 and Above          Arrest            True        White

      Subject Perceived Race Subject Perceived Gender  Frisk Flag
Precinct  \
0  Black or African American                     Male       False
Unknown
1                      White                     Male       False
South
2                      Asian                     Male       False
East
3  Black or African American                     Male       False
West
4  Black or African American                     Male       False
North

  Officer Age Group  Initial Call Type  Final Call Type  Call Type  \
0           46 - 55           0.021691         0.021691   0.021691
1           46 - 55           0.101512         0.045058   0.160678
2           18 - 25           0.093209         0.042056   0.099681
3           46 - 55           0.054414         0.092455   0.099681
4           18 - 25           0.116041         0.213333   0.160678

   Officer Squad      Beat  Weapon Type    Sector
0       0.145540  0.046371     0.111332  0.046333
1       0.074074  0.140957     0.111332  0.105186
2       0.146520  0.127660     0.111332  0.130906
3       0.063291  0.141104     0.111332  0.144683
4       0.025000  0.035971     0.111332  0.079111
```

We will do some checks on our data to make sure we have preserved the integrity of our data

```
print(X_train.index[:5])
print(X_train_te_df.index[:5])
```

```
RangeIndex(start=0, stop=5, step=1)
RangeIndex(start=0, stop=5, step=1)
```

```
print(X_test.index[:5])
print(X_test_te_df.index[:5])
```

```
RangeIndex(start=0, stop=5, step=1)
RangeIndex(start=0, stop=5, step=1)
```

```
X_train.isna().sum()
```

```
Subject Age Group            0
Stop Resolution              0
Officer Gender               0
Officer Race                 0
Subject Perceived Race       0
Subject Perceived Gender     0
Frisk Flag                   0
Precinct                     0
Officer Age Group            0
Initial Call Type            0
Final Call Type              0
Call Type                    0
Officer Squad                0
Beat                         0
Weapon Type                  0
Sector                       0
dtype: int64
```

Let's compare the shape of our encoded data with the original data.

```
print('No. of rows in encoded data:',
(X_train.shape[0]+X_test.shape[0]))
print('No. of rows in original data:', (df_preprocessed.shape[0]))
print(f'No of features in encoded data {X_train.shape[1]} in Train Set
and {X_test.shape[1]} in test set:')
print('No. of features in original data:',
(df_preprocessed.drop('Arrest Flag', axis=1).shape[1]))

No. of rows in encoded data: 54868
No. of rows in original data: 54868
No of features in encoded data 16 in Train Set and 16 in test set:
No. of features in original data: 16
```

As expected, target encoding does not change the shape of our data, we did not alter the shape of our data or create missing values

One Hot Encoding

Next, we will one hot encode our low cardinality features. Unlike with target encoding, one hot encoding will alter the shape of our data by creating additional columns for each unique value of our low cardinality features (and dropping the first column of each category since it does not add any new information that we cannot get by aggregating the rest of the columns for similar categories).

```
#select low cardinality features from our dataframe and drop the
target
low_cardinality_cols = df_preprocessed.drop(columns =
high_cardinality_cols +['Arrest Flag']).columns
```

```
#fit the ohe
ohe = OneHotEncoder(handle_unknown="ignore")
ohe.fit(X_train[low_cardinality_cols])

#transform our train and test feature set
X_train_ohe = ohe.transform(X_train[low_cardinality_cols])
X_test_ohe = ohe.transform(X_test[low_cardinality_cols])

#assign the transform values into a dataframe
X_train_ohe_df = pd.DataFrame(X_train_ohe.toarray(),
columns=ohe.get_feature_names_out(X_train[low_cardinality_cols].column
s))
X_test_ohe_df = pd.DataFrame(X_test_ohe.toarray(),
columns=ohe.get_feature_names_out(X_test[low_cardinality_cols].columns
))

#drop the original low cardinality features from our train and test
set
X_train = X_train.drop(low_cardinality_cols, axis=1)
X_test = X_test.drop(low_cardinality_cols, axis=1)

# reset index of Train and Test
X_train = X_train.reset_index(drop=True)
X_test = X_test.reset_index(drop=True)

#reset index of ohe
X_train_ohe_df = X_train_ohe_df.reset_index(drop=True)
X_test_ohe_df = X_test_ohe_df.reset_index(drop=True)


#update train and test feature set with the encoded values
X_train = pd.concat([X_train, X_train_ohe_df], axis=1 )
X_test = pd.concat([X_test, X_test_ohe_df], axis=1)

X_train.head()
```

```
   Initial Call Type  Final Call Type  Call Type  Officer Squad
Beat  \
0           0.128431         0.322581   0.160678       0.141276
0.092308
1           0.021691         0.021691   0.021691       0.004854
0.202670
2           0.021691         0.021691   0.021691       0.170673
0.046371
3           0.021691         0.021691   0.021691       0.004854
0.046371
4           0.194543         0.275972   0.160678       0.095122
0.145492

   Weapon Type    Sector  Subject Age Group_1 - 17  Subject Age
```

```
Group_18 - 25  \
0     0.111332  0.105186                       0.0
0.0
1     0.111332  0.181354                       0.0
0.0
2     0.111332  0.046333                       1.0
0.0
3     0.111332  0.046333                       0.0
0.0
4     0.111332  0.135931                       0.0
0.0

   Subject Age Group_26 - 35  ...  Precinct_OOJ  Precinct_South  \
0                        0.0  ...           0.0             1.0
1                        1.0  ...           0.0             0.0
2                        0.0  ...           0.0             0.0
3                        0.0  ...           0.0             0.0
4                        1.0  ...           0.0             0.0

   Precinct_Southwest  Precinct_Unknown  Precinct_West  \
0                 0.0               0.0            0.0
1                 0.0               0.0            1.0
2                 0.0               1.0            0.0
3                 0.0               1.0            0.0
4                 0.0               0.0            0.0

   Officer Age Group_18 - 25  Officer Age Group_26 - 35  \
0                        1.0                        0.0
1                        0.0                        0.0
2                        1.0                        0.0
3                        0.0                        0.0
4                        1.0                        0.0

   Officer Age Group_36 - 45  Officer Age Group_46 - 55  \
0                        0.0                        0.0
1                        0.0                        1.0
2                        0.0                        0.0
3                        0.0                        1.0
4                        0.0                        0.0

   Officer Age Group_56 and Above
0                             0.0
1                             0.0
2                             0.0
3                             0.0
4                             0.0

[5 rows x 57 columns]

X_test.head()
```

```
   Initial Call Type  Final Call Type  Call Type  Officer Squad
Beat  \
0           0.021691         0.021691   0.021691       0.145540
0.046371
1           0.101512         0.045058   0.160678       0.074074
0.140957
2           0.093209         0.042056   0.099681       0.146520
0.127660
3           0.054414         0.092455   0.099681       0.063291
0.141104
4           0.116041         0.213333   0.160678       0.025000
0.035971

   Weapon Type    Sector  Subject Age Group_1 - 17  Subject Age
Group_18 - 25  \
0     0.111332  0.046333                       0.0
1.0
1     0.111332  0.105186                       0.0
0.0
2     0.111332  0.130906                       0.0
0.0
3     0.111332  0.144683                       0.0
0.0
4     0.111332  0.079111                       0.0
0.0

   Subject Age Group_26 - 35  ...  Precinct_OOJ  Precinct_South  \
0                        0.0  ...           0.0             0.0
1                        0.0  ...           0.0             1.0
2                        1.0  ...           0.0             0.0
3                        1.0  ...           0.0             0.0
4                        0.0  ...           0.0             0.0

   Precinct_Southwest  Precinct_Unknown  Precinct_West  \
0                 0.0               1.0            0.0
1                 0.0               0.0            0.0
2                 0.0               0.0            0.0
3                 0.0               0.0            1.0
4                 0.0               0.0            0.0

   Officer Age Group_18 - 25  Officer Age Group_26 - 35  \
0                        0.0                        0.0
1                        0.0                        0.0
2                        1.0                        0.0
3                        0.0                        0.0
4                        1.0                        0.0

   Officer Age Group_36 - 45  Officer Age Group_46 - 55  \
0                        0.0                        1.0
1                        0.0                        1.0
```

```
2                       0.0                        0.0
3                       0.0                        1.0
4                       0.0                        0.0

   Officer Age Group_56 and Above
0                             0.0
1                             0.0
2                             0.0
3                             0.0
4                             0.0

[5 rows x 57 columns]
```

As above, we will do some checks on our data to make sure we have preserved the integrity of our data

```
X_train.isna().sum()
```

```
Initial Call Type
0
Final Call Type
0
Call Type
0
Officer Squad
0
Beat
0
Weapon Type
0
Sector
0
Subject Age Group_1 - 17
0
Subject Age Group_18 - 25
0
Subject Age Group_26 - 35
0
Subject Age Group_36 - 45
0
Subject Age Group_46 - 55
0
Subject Age Group_56 and Above
0
Stop Resolution_Arrest
0
Stop Resolution_Citation / Infraction
0
Stop Resolution_Field Contact
```

```
0
Stop Resolution_Offense Report
0
Stop Resolution_Referred for Prosecution
0
Officer Gender_False
0
Officer Gender_True
0
Officer Race_American Indian/Alaska Native
0
Officer Race_Asian
0
Officer Race_Black or African American
0
Officer Race_Hispanic or Latino
0
Officer Race_Nat Hawaiian/Oth Pac Islander
0
Officer Race_Not Specified
0
Officer Race_Two or More Races
0
Officer Race_White
0
Subject Perceived Race_American Indian or Alaska Native
0
Subject Perceived Race_Asian
0
Subject Perceived Race_Black or African American
0
Subject Perceived Race_Hispanic
0
Subject Perceived Race_Multi-Racial
0
Subject Perceived Race_Native Hawaiian or Other Pacific Islander
0
Subject Perceived Race_Other
0
Subject Perceived Race_Unknown
0
Subject Perceived Race_White
0
Subject Perceived Gender_Female
0
Subject Perceived Gender_Gender Diverse (gender non-conforming and/or
transgender)    0
Subject Perceived Gender_Male
0
```

```
Subject Perceived Gender_Unable to Determine
0
Subject Perceived Gender_Unknown
0
Frisk Flag_False
0
Frisk Flag_True
0
Precinct_East
0
Precinct_FK ERROR
0
Precinct_North
0
Precinct_OOJ
0
Precinct_South
0
Precinct_Southwest
0
Precinct_Unknown
0
Precinct_West
0
Officer Age Group_18 - 25
0
Officer Age Group_26 - 35
0
Officer Age Group_36 - 45
0
Officer Age Group_46 - 55
0
Officer Age Group_56 and Above
0
dtype: int64
```

```
print(X_train.index[:5])
print(X_train_ohe_df.index[:5])
```

```
RangeIndex(start=0, stop=5, step=1)
RangeIndex(start=0, stop=5, step=1)
```

```
print(X_test.index[:5])
print(X_test_ohe_df.index[:5])
```

```
RangeIndex(start=0, stop=5, step=1)
RangeIndex(start=0, stop=5, step=1)
```

```
print('No. of rows in encoded data:',
(X_train.shape[0]+X_test.shape[0]))
```

```
print('No. of rows in original data:', (df_preprocessed.shape[0]))
print(f'No of features in encoded data {X_train.shape[1]} in Train Set
and {X_test.shape[1]} in test set:')
print('No. of features in original data:',
(df_preprocessed.drop('Arrest Flag', axis=1).shape[1]))
```

```
No. of rows in encoded data: 54868
No. of rows in original data: 54868
No of features in encoded data 57 in Train Set and 57 in test set:
No. of features in original data: 16
```

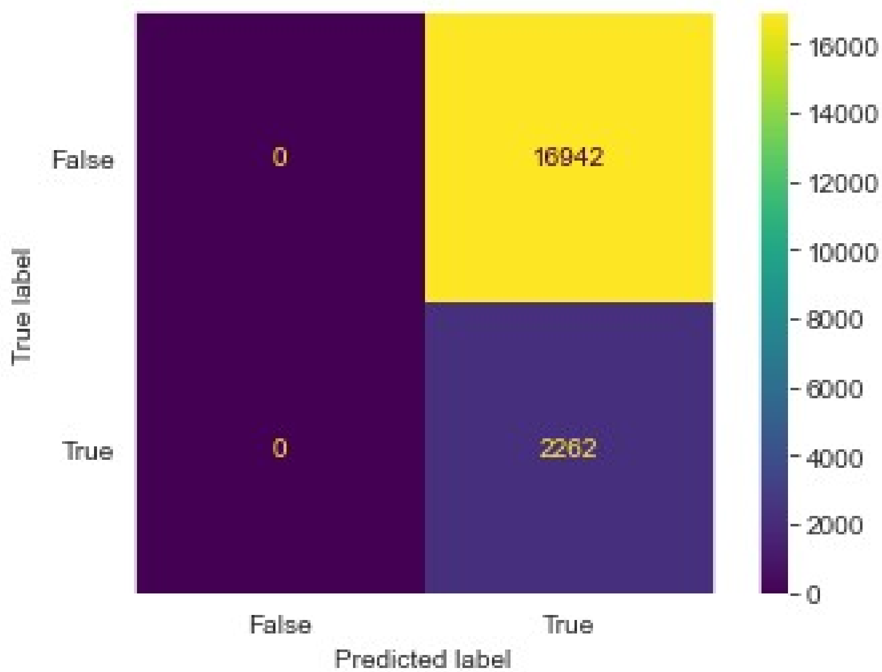
As expected, our rows are preserved but our encoded data now has additional columns

6. Modeling

A. Baseline Model

We will create a baseline model that always predicts the positive class. We will use the model's score to evaluate our logistic models.

```
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.dummy import DummyClassifier

ConfusionMatrixDisplay.from_estimator(estimator=DummyClassifier(strate
gy='constant', constant=1).fit(X_train, y_train),
                                       X=X_test, y=y_test)


plt.grid(False);
```




```
# Fit the DummyClassifier (baseline model)
dummy_clf = DummyClassifier(strategy='constant', constant=1)
dummy_clf.fit(X_train, y_train)

# Predict using the baseline model on the test set
y_pred_baseline = dummy_clf.predict(X_test)

# Calculate accuracy score
accuracy_baseline = accuracy_score(y_test, y_pred_baseline)
print(f"Baseline Model Accuracy: {accuracy_baseline:.4f}")

# Generate the classification report
print("\nBaseline Model Classification Report:")
print(classification_report(y_test, y_pred_baseline, zero_division=0,
target_names=['False', 'True']));
```

```
Baseline Model Accuracy: 0.1178

Baseline Model Classification Report:
              precision    recall  f1-score   support

       False       0.00      0.00      0.00     16942
        True       0.12      1.00      0.21      2262

    accuracy                           0.12     19204
   macro avg       0.06      0.50      0.11     19204
weighted avg       0.01      0.12      0.02     19204
```

Baseline Model Results

Baseline Model Accuracy: 0.118: This indicates that the baseline model, which always predicts the positive class (Arrest), has an accuracy of about 11.84%. This is expected since the positive class makes up only a small fraction of the total cases in the dataset.

Classification Report:

False Class (No Arrest): The model's precision, recall, and F1-score are all 0.00 because it never predicts the negative class (No Arrest). Hence, the precision and F1-score are undefined (zero)

True Class (Arrest):

- Precision: 0.12 — This is low because the model predicts the positive class (Arrest) regardless of the actual outcome, which means it gets all the negatives wrong.
- Recall: 1.00 — This is perfect because, by always predicting the positive class, the model captures all actual positive instances.
- F1-Score: 0.21 — This is the harmonic mean of precision and recall, and it's low due to the very poor precision.

B. Logistic Regression

We will start by training our model by fitting the training data to a logistic regression model.

1. Model 1

- ***C***: This parameter controls the regularization strength. A higher C reduces the penalty on the model for large coefficients allowing to fit the data more optimally but with additional risk of overfitting.
- ***solver***: This parameter specifies the algorithm used to optimize the model. 'lbfgs' is a limited-memory solver that can be efficient for large datasets.
- ***random_state***: This parameter sets the random seed for the model, ensuring reproducibility.
- ***max_iter***: This parameter sets the maximum number of iterations for the solver.

```
# train a logistic regression model on the training set
from sklearn.linear_model import LogisticRegression


# instantiate the model
logreg_1 = LogisticRegression(C = 100, solver='lbfgs', random_state=0,
max_iter=100_000)


# fit the model
model_1 = logreg_1.fit(X_train, y_train)
```

Next, we apply the model to our test set to see its predictive performance

```
y_pred_test = logreg_1.predict(X_test)

y_pred_test

array([False, False, False, ..., False, False, False])
```

Let us to see the no. of unique values in our target again before assessing the perfomance of our model.

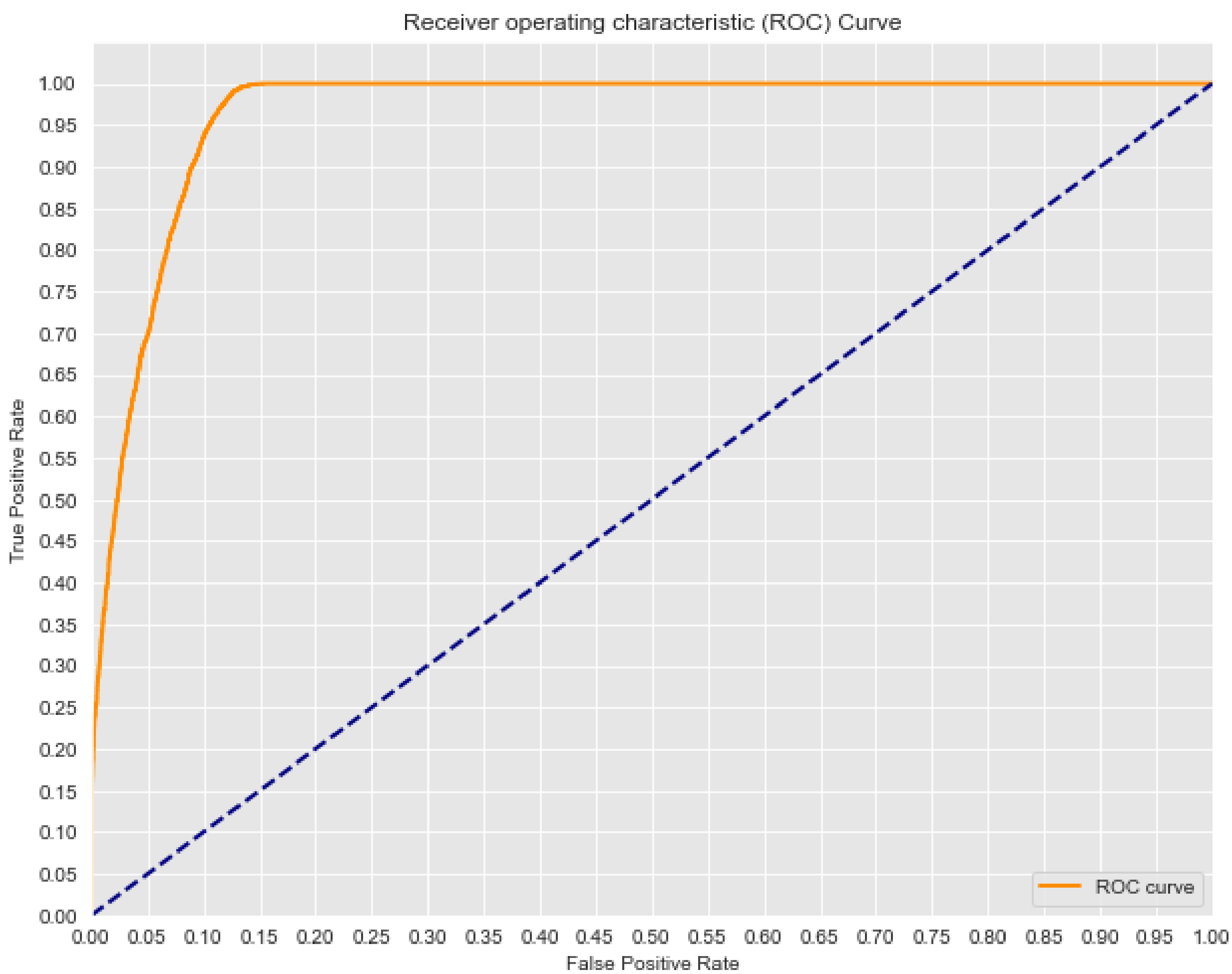
```
true_proportion = y_test.value_counts(normalize=True)[1]


false_proportion = y_test.value_counts(normalize=True)[0]
print(f"True: {true_proportion:.2f}")
print(f"False: {false_proportion:.2f}")

True: 0.12
False: 0.88
```

The data summary shows that the 'Arrest Flag' is imbalanced, with the 'False' class (no arrest) comprising 88% and the 'True' class (arrest) only 12% of the dataset. This means that most stops do not result in an arrest.

```
from sklearn.metrics import accuracy_score, classification_report

print('Model 1 accuracy score: {0:0.4f}'.
format(accuracy_score(y_test, y_pred_test)))
print(classification_report(y_test,y_pred_test))

Model 1 accuracy score: 0.9227
              precision    recall  f1-score   support

       False       0.95      0.96      0.96     16942
        True       0.70      0.61      0.65      2262

    accuracy                           0.92     19204
   macro avg       0.82      0.79      0.80     19204
weighted avg       0.92      0.92      0.92     19204


# print the scores on training and test set

print('Training set score: {:.4f}'.format(model_1.score(X_train,
y_train)))

print('Test set score: {:.4f}'.format(model_1.score(X_test, y_test)))

Training set score: 0.9273
Test set score: 0.9227
```

```python
from sklearn.metrics import roc_curve, auc

# First calculate the probability scores of each of the datapoints:
y_score = model_1.decision_function(X_test)


%matplotlib inline

fpr, tpr, thresholds = roc_curve(y_test, y_score)
sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

print('AUC: {}'.format(auc(fpr, tpr)))
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
AUC: 0.9652426659594115
```



Model 1 Analysis

Model 1 Performance:

****a. Overall Model Accuracy:**** Our training set score of 92.7% and test set score of 92.3% imply that our model is highly accurate. The minimal difference between the test and training scores suggest our model generalizies well ie. not overfitting or undefitting.

****b. Classification Report:**** Precision and Recall for the False Class:

- Precision: 0.95
- Recall: 0.96
- F1-Score: 0.96

These scores indicate the model performs very well in predicting the majority class (False).

Precision and Recall for the True Class:

- Precision: 0.70
- Recall: 0.61
- F1-Score: 0.65

This shows the model struggles to accurately predict the minority class (True), missing 39% of the actual positives.

****c. ROC Curve:**** The ROC curve shows a high True Positive Rate (TPR) or Sensitivity against a low False Positive Rate (FPR) across the threshold range, indicating strong performance in distinguishing between the classes.The curve is close to the top-left corner, which represents excellent performance.

Comparison vs Baseline Model:

Our model shows general improvement from our baseline model.

Accuracy: The logistic regression model's accuracy (92.13%) is significantly higher than the baseline (11.84%), indicating our logistic regression model performs much better at correctly classifying instances overall.

Precision: For the baseline model, precision is 0 for the False class, as it never predicts False. For the True class, precision is 0.12, which is very low and reflects a high number of False Positives. Precision is notably higher in our logistic regression, especially for the True class (0.69), suggesting that when the logistic regression predicts True, it is correct about 69% of the time, which is a substantial improvement.

Recall: The baseline model has perfect recall (1.00) for the True class because it predicts True for all cases, but it misses all False cases (recall = 0 for False). The logistic regression has balanced recall between False (0.96) and True (0.61), showing it is capable of detecting both classes, albeit less so for True cases due to class imbalance.

F1 Score: The F1-score is low overall in our baseline model, with the False class scoring 0 and the True class at 0.21, reflecting poor precision and recall balance. In comparison, in our logistic regression mode, the F1-score for both classes is significantly improved (False: 0.96, True: 0.61), indicating a better balance between precision and recall.

****Implications of Class Imbalance:****

- Biased Model Predictions: Class imbalance can cause our logistic regression model to be biased towards predicting the majority class ('False' for no arrest) because predicting the majority class more frequently would still yield a high accuracy. In law enforcement, accurately predicting the 'Arrest Flag' is crucial. Misclassifying an actual arrest situation (False Negative) could have serious implications, such as failing to appropriately flag an encounter where an arrest should have occured.

- Underperformance on Minority Class: As seen in the classification report, the precision and recall for the 'True' class (arrest) are significantly lower than for the 'False' class. This suggests that the model struggles to correctly identify and predict arrests, which is the minority class. Overpredicting 'False' (no arrest) could lead to missed opportunities for police intervention, which might not align with the goals of public safety and proper law enforcement.

****Using SMOTE to Address Class Imbalance****

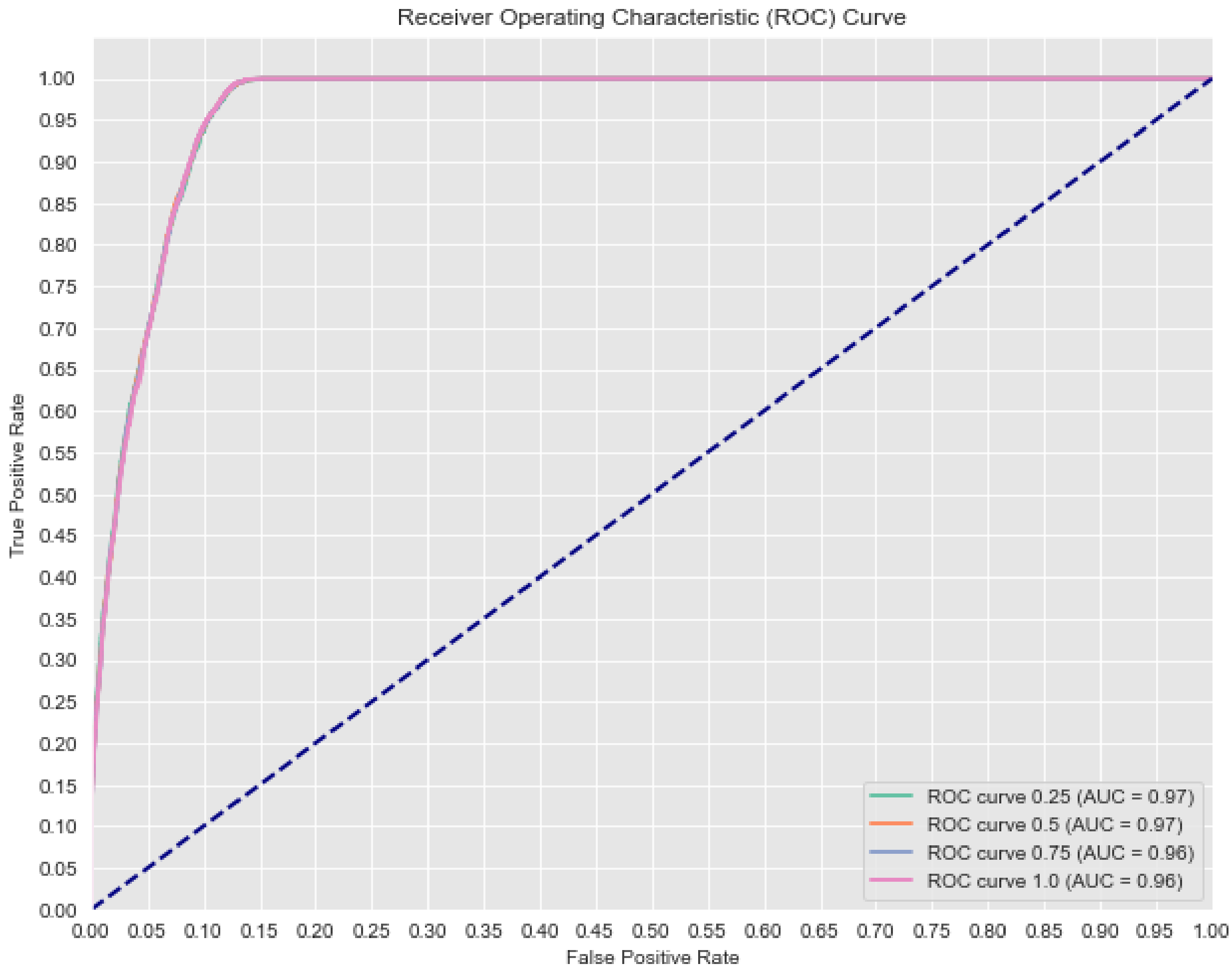
SMOTE (Synthetic Minority Oversampling) generates new sample data using 'synthetic' data from our original dataset, this reduces class imbalance by increasing the number of minority class instances in our dataset.

2. Model 2

```
from imblearn.over_sampling import SMOTE

print('Original class distribution: \n')
print(y_train.value_counts())
colors = sns.color_palette('Set2')
# Initialize SMOTE and resample the data
smote = SMOTE()
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)

# Preview synthetic sample class distribution
print('-----------------------------------------------------------------
----------------------')
print('SMOTE class distribution: \n')
print(pd.Series(y_train_resampled).value_counts())
print('-----------------------------------------------------------------
----------------------')




# Now let's compare a few different ratios of minority class to
majority class
ratios = [0.25, 0.5, 0.75, 1.0]
names = ['0.25', '0.5', '0.75', '1.0']


plt.figure(figsize=(10, 8))

for n, ratio in enumerate(ratios):
    # Fit a model using different SMOTE ratios
    smote = SMOTE(sampling_strategy=ratio)
    X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)
    logreg = LogisticRegression(fit_intercept=False, C=100,
solver='lbfgs', max_iter = 100_000)
    model_log = logreg.fit(X_train_resampled, y_train_resampled)

    # Predict on the test set
    y_hat_test = logreg.predict(X_test)
    y_score = logreg.decision_function(X_test)

    # Compute ROC curve and AUC
    fpr, tpr, thresholds = roc_curve(y_test, y_score)
    auc_score = auc(fpr, tpr)
```

```
    # Print the AUC for the current ratio
    print(f'AUC for {names[n]}: {auc_score}')

print('-----------------------------------------------------------------------
----------------------')

    # Plot the ROC curve
    lw = 2
    plt.plot(fpr, tpr, color=colors[n], lw=lw, label=f'ROC curve
{names[n]} (AUC = {auc_score:.2f})')

# Plot settings
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
Original class distribution:

False    31422
True      4242
Name: Arrest Flag, dtype: int64
----------------------------------------------------------------------
---------------
SMOTE class distribution:

False    31422
True     31422
Name: Arrest Flag, dtype: int64
----------------------------------------------------------------------
---------------
AUC for 0.25: 0.9651404291815391
----------------------------------------------------------------------
---------------
AUC for 0.5: 0.9650625904096162
----------------------------------------------------------------------
---------------
AUC for 0.75: 0.9649214472928441
----------------------------------------------------------------------
---------------
AUC for 1.0: 0.9647739893980618
----------------------------------------------------------------------
---------------
```



Let us also generate a classification report to our model performance using a SMOTE ratio of 1

```
# Fit a model using the highest SMOTE ratio
smote = SMOTE(sampling_strategy=1.0)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)
logreg_2 = LogisticRegression(fit_intercept=False, C=100,
solver='lbfgs', max_iter = 100_000)
model_log = logreg_2.fit(X_train_resampled, y_train_resampled)

# Predict on the test set
y_hat_test = logreg_2.predict(X_test)
y_score = model_log.decision_function(X_test)

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test,
y_hat_test)))
print(classification_report(y_test,y_hat_test))

Model accuracy score: 0.8937
              precision    recall  f1-score   support
```

```
       False       1.00      0.88      0.94     16942
        True       0.53      0.98      0.68      2262

    accuracy                           0.89     19204
   macro avg       0.76      0.93      0.81     19204
weighted avg       0.94      0.89      0.91     19204
```

Model 2 Analysis

****Before SMOTE:****

- Accuracy: 0.9227
- Precision (True): 0.70
- Recall (True): 0.61
- F1-score (True): 0.65

****After SMOTE:****

- Accuracy: 0.8934
- Precision (True): 0.53
- Recall (True): 0.98
- F1-score (True): 0.68

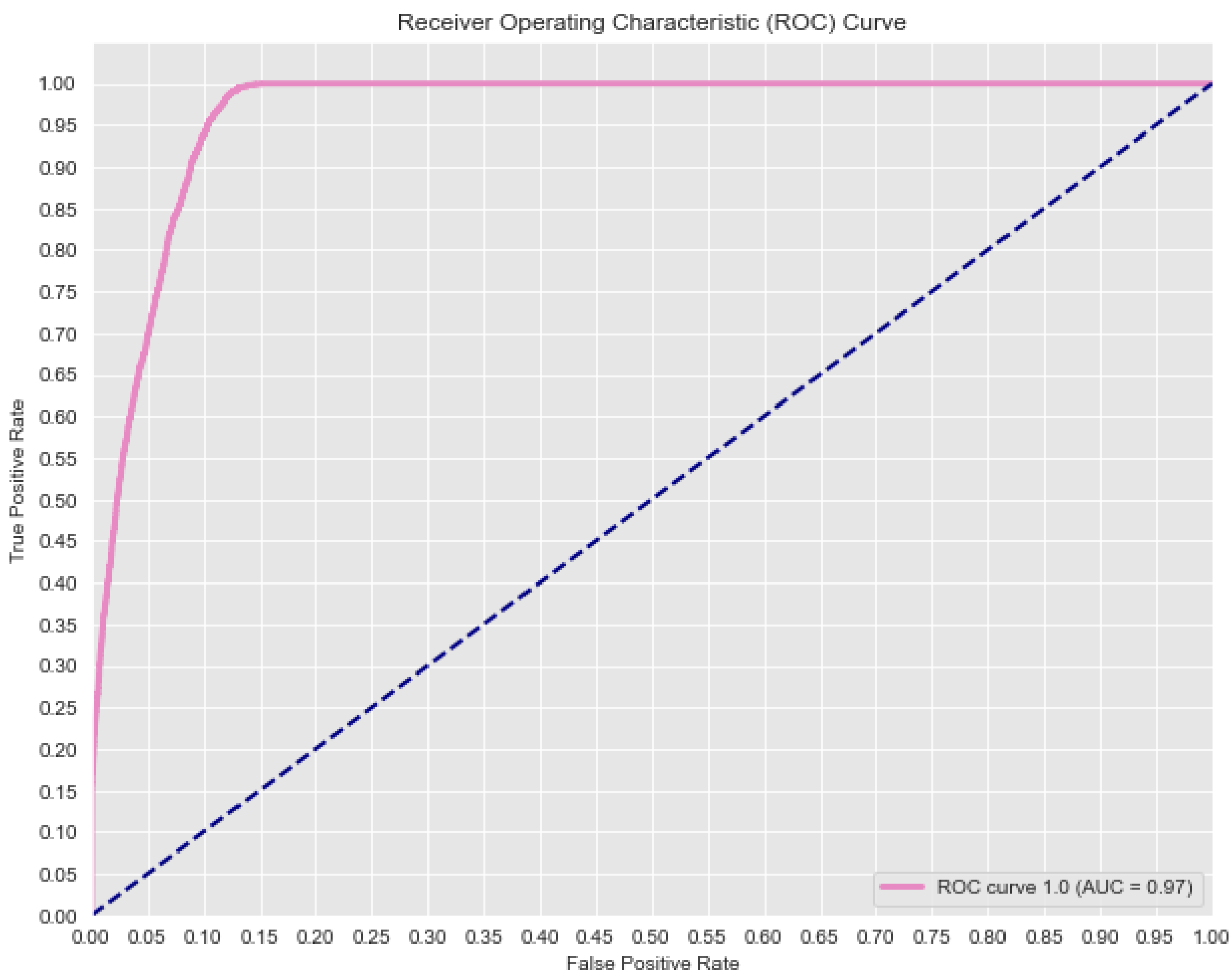
While our model's recall has improved greatly, meaning we are able to predict true postives(actual arrests) significantly better based on an improvement from 0.61 to 0.98, our precision has suffered as is evident from the drop from 0.69 to 0.53. Our overall model accuracy has also dropped from 0.9227 to 0.8938. Let's try a different SMOTE ratio to see if we can limit the impact on precision i.e. reduce the amount of false positives (or incorrectly predicted arrests).

3. Model 3

```
# fir a model using the lowest SMOTE ratio
smote = SMOTE(sampling_strategy=0.25)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, 
y_train)
logreg_3 = LogisticRegression(fit_intercept=False, C=100, 
solver='lbfgs', max_iter = 100_000)
model_log =logreg_3.fit(X_train_resampled, y_train_resampled)

# Predict on the test set
y_hat_test = logreg_3.predict(X_test)
y_score = model_log.decision_function(X_test)

# Compute ROC curve and AUC
fpr, tpr, thresholds = roc_curve(y_test, y_score)
auc_score = auc(fpr, tpr)
print('AUC Score: {:.4f}'.format(auc_score))
```

```python
print('Model 3 accuracy score: {0:0.4f}'.
format(accuracy_score(y_test, y_hat_test)))
print(classification_report(y_test,y_hat_test))

fig = plt.figure(figsize=(10, 8))


# Plot the ROC curve
lw = 3
plt.plot(fpr, tpr, color=colors[n], lw=lw, label=f'ROC curve
{names[n]} (AUC = {auc_score:.2f})')

# Plot settings
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
AUC Score: 0.9651
Model 3 accuracy score: 0.9169
              precision    recall  f1-score   support

       False       0.98      0.93      0.95     16942
        True       0.61      0.82      0.70      2262

    accuracy                           0.92     19204
   macro avg       0.79      0.88      0.83     19204
weighted avg       0.93      0.92      0.92     19204
```



Model 3 Analysis

****Model 2:****

- Accuracy: 0.9227
- Precision (True): 0.70
- Recall (True): 0.61
- F1-score (True): 0.65

****Model 3:****

- Accuracy: 0.9171
- Precision (True): 0.61
- Recall (True): 0.82
- F1-score (True): 0.70

****Key Observations:**** The scores for the False class remain high overall

a. Recall for predicting arrests improved significantly from 0.61 to 0.82. This means the model is now much better at identifying true positives (actual arrests), which is crucial in scenarios where failing to predict an arrest correctly might have serious consequences.

b. Precision for the minority class dropped from 0.70 to 0.61(Model 1) after SMOTE. This decrease implies that the model now has more false positives, i.e., it incorrectly predicts arrests more frequently. However, the decline is not material and this is a trade off we are willing to make given the improvements in predicting actual arrests.

c. The F1-score for predicting arrests increased from 0.65 to 0.70. This balanced metric of precision and recall suggests an overall improvement in predicting the minority class

d. The overall accuracy slightly decreased from 0.9223 to 0.9171 This is a minor reduction and is acceptable given the other improvements in model performance.

C. Decision Tree Classifier

In this step, we initiate a Decision Tree classifier using the entropy criterion for information gain. The random_state parameter ensures reproducibility, allowing consistent results across different runs. We will compare the performance of this model with our existing Logistic Regression model to determine which is more effective for our classification task.

```
from sklearn import tree

dt = DecisionTreeClassifier(criterion='entropy', random_state = 0)
dt.fit(X_train, y_train)
```

```
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

The Decision Tree classifier has been successfully initialized. Next, we will evaluate its performance across various metrics and determine the optimal depth for the tree to avoid overfitting.

We proceed by calculating the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) for our Decision Tree model.

```
# Make predictions using test set
y_pred = dt.predict(X_test)

# Check the AUC of predictions
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
auc_score = auc(fpr, tpr)
print('AUC score: ', auc_score)
```

```
AUC score:  0.8167847008272151
```

The initial AUC score for the Decision Tree is approximately 0.8109. While this score indicates a reasonable ability to distinguish between classes, there is room for improvement, especially compared to our Logistic Regression model.

To enhance the performance of our Decision Tree, we experiment with varying the tree depth and identify the optimal depth that maximizes the AUC score on the test set. This step helps us balance model complexity and performance, avoiding overfitting by selecting an appropriate depth.

```
# Lists to store AUC scores
max_depths = list(range(1, 15))
train_results = []
test_results = []

for max_depth in max_depths:
    # Initialize and train the Decision Tree model
    dt = DecisionTreeClassifier(criterion='entropy',
max_depth=max_depth, random_state=0)
    dt.fit(X_train, y_train)

    # Predict probabilities for ROC AUC computation
    y_train_pred_prob = dt.predict_proba(X_train)[:, 1]
    y_test_pred_prob = dt.predict_proba(X_test)[:, 1]

    # Compute AUC score for train and test sets
    train_auc = roc_auc_score(y_train, y_train_pred_prob)
    test_auc = roc_auc_score(y_test, y_test_pred_prob)

    # Append the results
    train_results.append(train_auc)
    test_results.append(test_auc)


# Initialize variables to track the best max_depth and corresponding
AUC score
optimal_train_auc = 0
optimal_max_depth = 0

# Loop through the train_results to find the best AUC score and
corresponding max_depth
for i in range(len(train_results)):
    if train_results[i] > optimal_train_auc:
        optimal_train_auc = train_results[i]
        optimal_max_depth = max_depths[i]

# Initialize variables to track the best max_depth and corresponding
AUC score
optimal_test_auc = 0
optimal_max_depth = 0

# Loop through the test_results to find the best AUC score and
corresponding max_depth
for i in range(len(test_results)):
    if test_results[i] > optimal_test_auc:
        optimal_test_auc = test_results[i]
        optimal_max_depth = max_depths[i]

print('Optimal test AUC score: ',optimal_test_auc)
print('Optimal train AUC score: ', optimal_train_auc)
```

```
print('Optimal max depth: ',optimal_max_depth)
```

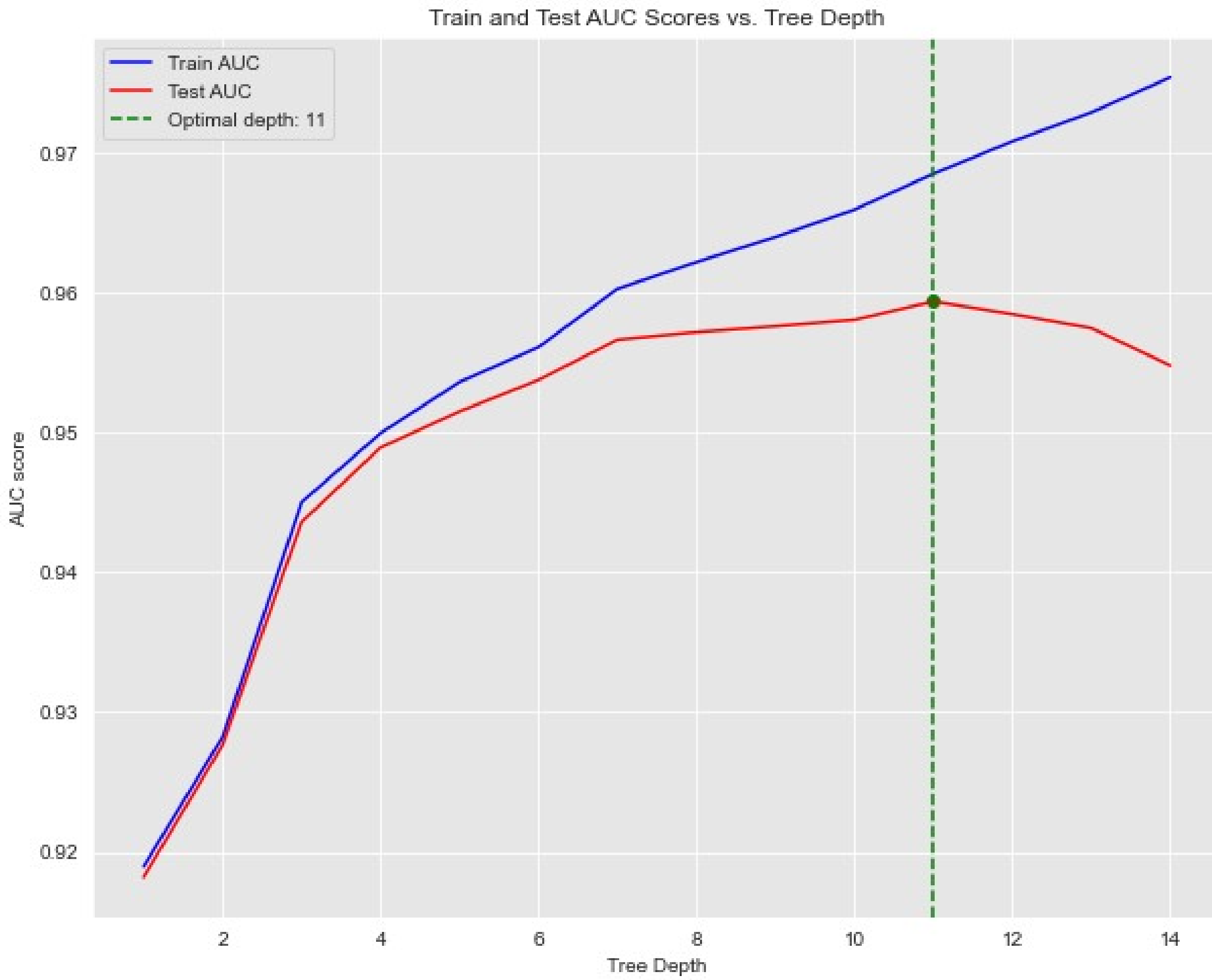
```
Optimal test AUC score:  0.9593548269589042
Optimal train AUC score:  0.9753750529176052
Optimal max depth:  11
```

Optimal Tree Depth Analysis

The plot shows the relationship between the tree depth and the AUC scores for both the training and test datasets.

- Train AUC (Blue Line): As expected, the AUC score on the training set increases as the tree depth increases. This indicates that the model becomes increasingly complex, allowing it to fit the training data more closely.
- Test AUC (Red Line): The AUC score on the test set initially increases with tree depth, reaches a peak at a depth of 11, and then begins to decrease. This suggests that beyond a depth of 11, the model begins to overfit the training data, leading to a decrease in performance on unseen data.
- Optimal Depth: The green vertical line highlights the optimal tree depth, which is 11 in this case. This depth offers the best balance between model complexity and generalization performance, as it maximizes the test AUC score.

```
# Plot the AUC scores with the optimal depth highlighted
plt.figure(figsize=(10, 8))
plt.plot(max_depths, train_results, 'b', label='Train AUC')
plt.plot(max_depths, test_results, 'r', label='Test AUC')

# Highlight the optimal depth on the plot
plt.axvline(x=optimal_max_depth, color='green', linestyle='--',
label=f'Optimal depth: {optimal_max_depth}')
plt.scatter(optimal_max_depth, optimal_test_auc, color='green')

plt.ylabel('AUC score')
plt.xlabel('Tree Depth')
plt.legend()
plt.title('Train and Test AUC Scores vs. Tree Depth')
plt.show()
```

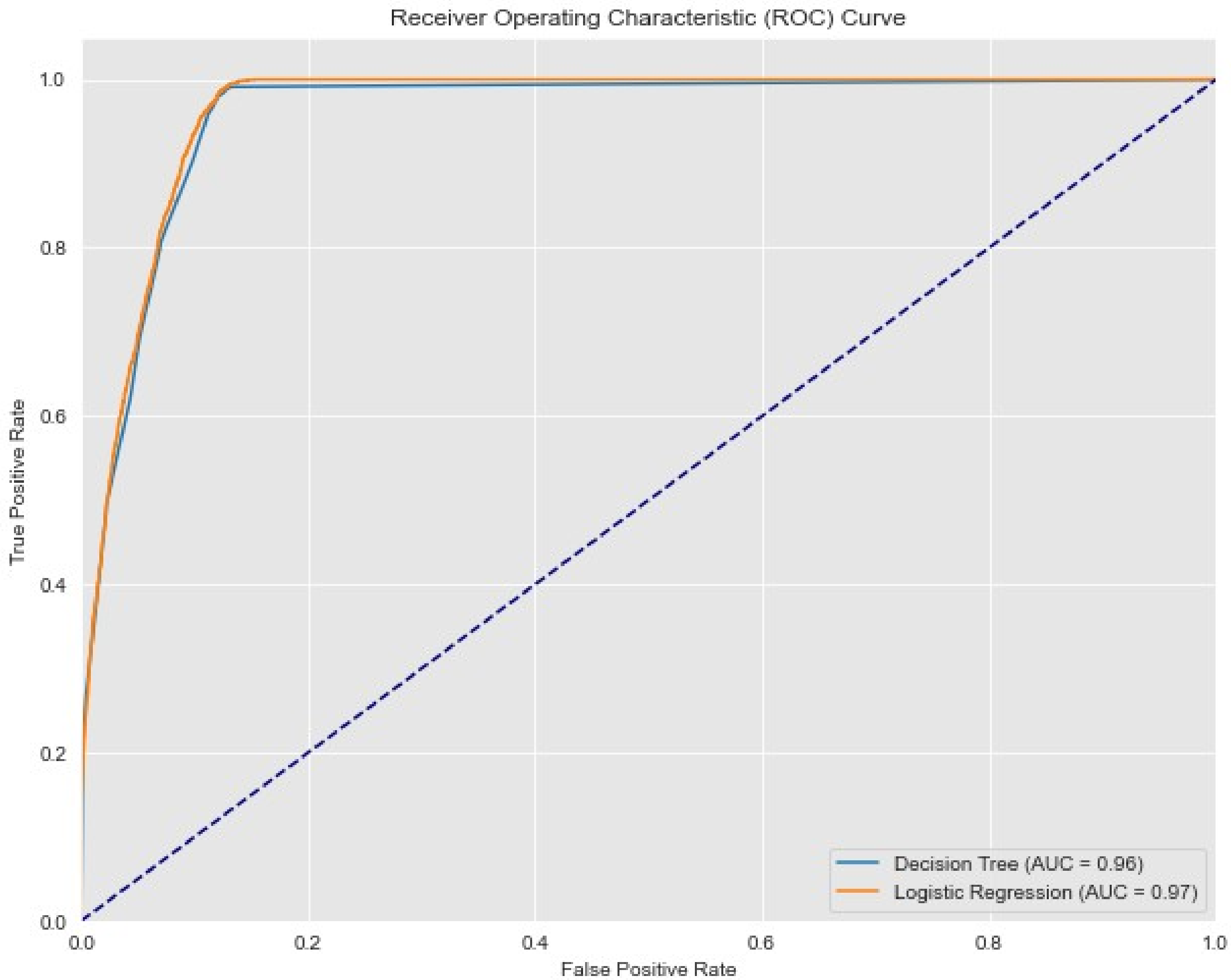


With the optimal depth established, we now evaluate the Decision Tree's performance using standard classification metrics: Accuracy, Precision, Recall, F1 Score, and AUC. We then compare these results with those from our Logistic Regression model to determine the best model for our classification task.

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, roc_auc_score, roc_curve

# Decision Tree Model
dt = DecisionTreeClassifier(max_depth = optimal_max_depth,
criterion='entropy', random_state=0)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
y_pred_proba_dt = dt.predict_proba(X_test)[:, 1]

# Logistic Regression Model
y_pred_lr = logreg_3.predict(X_test)
y_pred_proba_lr = logreg_3.predict_proba(X_test)[:, 1]

# Metrics Calculation
```

```
models = {'Decision Tree': {'y_pred': y_pred_dt, 'y_proba':
y_pred_proba_dt},
          'Logistic Regression': {'y_pred': y_pred_lr, 'y_proba':
y_pred_proba_lr}}

for model_name, preds in models.items():
    print(f'--- {model_name} ---')
    print(f'Accuracy: {accuracy_score(y_test, preds["y_pred"]):.2f}')
    print(f'Precision: {precision_score(y_test, preds["y_pred"],
average="binary"):.2f}')
    print(f'Recall: {recall_score(y_test, preds["y_pred"],
average="binary"):.2f}')
    print(f'F1 Score: {f1_score(y_test, preds["y_pred"],
average="binary"):.2f}')
    print(f'AUC: {roc_auc_score(y_test, preds["y_proba"]):.4f}')
    print()

# ROC Curve Comparison
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 8))
for model_name, preds in models.items():
    fpr, tpr, _ = roc_curve(y_test, preds['y_proba'])
    plt.plot(fpr, tpr, label=f'{model_name} (AUC =
{roc_auc_score(y_test, preds["y_proba"]):.2f})')

plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
--- Decision Tree ---
Accuracy: 0.92
Precision: 0.75
Recall: 0.49
F1 Score: 0.59
AUC: 0.9594

--- Logistic Regression ---
Accuracy: 0.92
Precision: 0.61
Recall: 0.82
F1 Score: 0.70
AUC: 0.9651
```



Overall Performance

Both models demonstrate excellent performance with AUC scores above 0.95, which suggests that they are both effective at distinguishing between arrests and non-arrests in this dataset.

The Decision Tree classifier demonstrates strong performance, particularly in terms of AUC (0.9594). However, the Logistic Regression model outperforms it in most metrics, including AUC (0.9652), Recall (0.8236), and F1 Score (0.6986). The higher recall and F1 score of the Logistic Regression model indicate that it is better at correctly identifying positive instances, making it the preferred choice for our final model.

Decision to Select the Logistic Regression Model

After a thorough comparison between the Decision Tree and Logistic Regression models, I decided to select the Logistic Regression model as my final choice for the following reasons:

Higher Accuracy and Performance Metrics:

The Logistic Regression model achieved a slightly higher accuracy (0.9170) compared to the Decision Tree (0.9163). More importantly, the Logistic Regression model significantly outperformed the Decision Tree in Recall (0.8218 vs. 0.65486658) and F1 Score (0.7001 vs. 0.6519), making it more reliable in correctly identifying positive instances in our dataset.

Better Generalization:

Logistic Regression is inherently less prone to overfitting, especially with high-dimensional data, as it assumes a linear relationship between the features and the target variable. This helps it generalize better to unseen data. Our analysis of the Decision Tree model revealed that while it could be optimized by tuning the tree depth, it was more susceptible to overfitting, as indicated by the divergence between the train and test AUC scores at deeper tree depths.

Interpretability:

Logistic Regression provides clear coefficients that indicate the direction and magnitude of the impact of each feature on the prediction. This transparency is crucial for our target audience, who may need to understand the model's decision-making process for legal, ethical, or operational reasons. Decision Trees, while interpretable can become complex and less intuitive especially at higher depths. This complexity can make it harder for stakeholders to grasp the logic behind predictions, especially in a high-stakes environment like law enforcement.

Alignment with Objectives:

Our primary objective is to create a predictive model that accurately identifies positive outcomes (e.g., arrests) while maintaining interpretability and robustness. The Logistic Regression model meets these criteria more effectively than the Decision Tree. Additionally, the model's strong performance on Recall and F1 Score is aligned with the need to minimize false negatives, ensuring that our system is effective at identifying true positive cases.

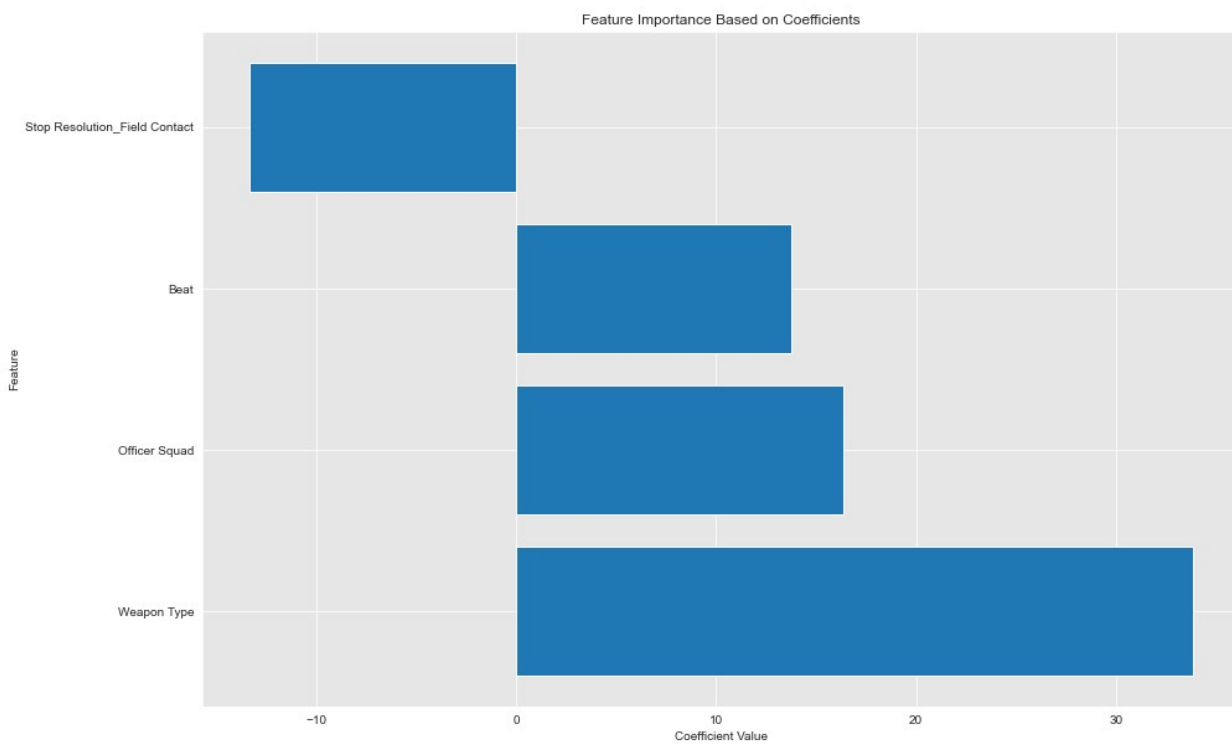
7. Conclusion

a. Major Objective: Derive the most important features in predicting an arrest:

```
feature_names = X_train.columns

coefficients = logreg.coef_[0]

#add feature names and coefficients to a dataframe
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

# Sort features by absolute value of the coefficient
coef_df['Abs_Coefficient'] = coef_df['Coefficient'].abs()
coef_df = coef_df.sort_values(by='Abs_Coefficient', ascending=False)

print(coef_df[['Feature', 'Coefficient']][:4])
```

```
plt.figure(figsize=(15, 10))
plt.barh(coef_df['Feature'][:4], coef_df['Coefficient'][:4])
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.title('Feature Importance Based on Coefficients')
plt.show()
```

	Feature	Coefficient
5	Weapon Type	33.861240
3	Officer Squad	16.376071
4	Beat	13.773122
15	Stop Resolution_Field Contact	-13.337051



Our most important features are the following:

1. Stop Resolution_Field Contact (coefficient: -13.3) - this is a feature that arose because of one hot encoding our data but signals that most stops arising naturally in the field end up with no arrests as signalled by the negative coefficient.

2. Beat (Coefficient: 13.8)- The Beat feature has a significant positive coefficient, indicating that certain beats are more associated with arrests. This could be related to specific crime rates, community issues, or patrol patterns in those beats.

3. Officer Squad (coefficient: 16.4) - The positive coefficient for Officer Squad indicates that the specific squad or team involved in the stop is a significant factor in predicting arrests. This may reflect differences in squad practices, experience, or operational focus.

4. Weapon Type (Coefficient: 33.9) -The high positive coefficient for Weapon Type suggests that the presence of a weapon is a strong predictor of an arrest. This is intuitive, as encounters involving weapons are more likely to escalate to an arrest due to safety concerns and legal considerations.

b. Develop a Predictive Model for Arrests During Terry Stops

Our final model generally improves upon the baseline model and earlier iterations.

Accuracy Score: 91.69%. This indicates that the model performs well overall.

Precision and Recall:

- Precision: 0.6072
- Recall: 0.8223
- F1 Score: 0.6986
- AUC: 0.9651

Precision: 0.6072 - Precision indicates that when the model predicts a positive outcome (arrest), it is correct about 60.7% of the time. This suggests a moderate rate of false positives, where the model incorrectly predicts an arrest when there is none.

Recall: 0.8223 - Recall shows that the model correctly identifies about 82.2% of all actual positive cases (arrests). This high recall means that the model is effective at catching most of the true arrests, which is crucial for scenarios where missing an arrest prediction could have significant consequences.

F1 Score: 0.6986 - The F1 Score is the harmonic mean of precision and recall. A score of 0.6986 reflects a good balance between precision and recall, ensuring that the model is reasonably accurate in both detecting arrests and minimizing false alarms.

AUC: 0.9651 - The Area Under the ROC Curve (AUC) of 0.9651 indicates excellent performance in distinguishing between the positive class (arrests) and the negative class. A high AUC score means the model is very effective at ranking cases so that the positive instances (arrests) have a higher prediction probability than negative instances.

Overall, these metrics suggest that the logistic regression model performs very well, particularly in terms of distinguishing between classes (high AUC) and correctly identifying true arrests (high recall). The slightly lower precision indicates that there is some trade-off between catching all possible arrests and minimizing false positives, but this is a tradeoff we have to make. The F1 Score also indicates that the model maintains a good balance between precision and recall, making it robust for practical application in predicting arrests.

c. EDA and Feature Engineering:

Our exploratory data analysis (EDA) highlighted some issues with missing values where some rows had blank values and others had been filled in with a placeholder value ('-').

Handling of missing values:

1. Subject Age Group - we imputed this with mode to preserve the shape of our data.

2. Weapon Type - Imputed with 'None" given that a since several rows were blank, it's possible that in many cases, no weapon was found.
3. Officer ID - Since only 24 out of 60,962 entries are affected, we dropped these rows.
4. Subject Perceived Race - We replaced missing values with "Unknown" to maintain the data structure without introducing bias.
5. Subject Perceived Gender - We replaced missing values with "Unknown" to maintain the data structure without introducing bias..
6. Initial Call Type, Final Call Type, Call Type - We imputed this with "Unknown" since missing call types might suggest a lack of information or a specific condition (e.g., not applicable since no call was made and the incident just transpired).
7. Frisk Flag - We imputed missing values with the mode since the missing values are minimal.
8. Precint, Sector, Beat - We filled missing values with "Unknown" allowing us to retain the rows.
9. Officer Squad - imputed with "Unknown" to retain the rows

Enchoding Techniques

We used 'Target Encoding' to replace each feature that exhibited high cardinality with the mean of the target variable for that category. This reduced the dimensionality by not increasing the number of features, which can help in preventing overfitting. One hot encoding would not have been suitable for such features as they would have increased the number of features in our dataset by a significant magnitude.

We used 'One Hot Encoding' for features in our dataset with low cardinality One-hot encoding transforms categorical variables into a format that can be easily interpreted by our logistic regression model. Each category is represented by a binary feature (0 or 1), preserving the information contained in the categorical features.

d. Class Imbalance Management:

We used SMOTE to address the class imbalance in our target variable.

Addressing class imbalance using SMOTE (Synthetic Minority Over-sampling Technique) was important in our logistic regression modeling process due to the following reasons:

1. Improvement in Minority Class Recall: In the initial logistic regression model without addressing class imbalance, the recall for the True class (minority class) was relatively low (0.61), meaning that a significant portion of the actual True cases were being missed. After applying SMOTE, the recall for the True class improved significantly (0.81), indicating that the model became much better at detecting the minority class instances (i.e., Arrests), which is a critical goal in our main objective

2. Balanced Performance Across Classes: Without addressing the imbalance, the logistic regression model performed extremely well on the majority class (False) but poorly on the minority class (True). This imbalance in performance was reflected in the F1-score and recall differences. Applying SMOTE balanced the dataset, allowing the logistic regression model to learn equally well from both classes. As a result, the F1-score for the True class improved, leading to a more balanced performance that reflects a model capable of handling both True and False outcomes more equitably.

3. Mitigation of Bias Towards Majority Class: Imbalanced datasets cause models to be biased towards predicting the majority class e.g., the baseline model's constant prediction of the majority class (No Arrests) resulted in low precision and F1-scores. SMOTE helped mitigate this bias by synthetically oversampling the minority class, providing the model with a more representative training set. This change encouraged our model to learn the features distinguishing Arrests and No Arrests more effectively resulting in the models overall predictive ability given identifying minority class instances (arrests) is crucial, as false negatives (missed True cases) can have significant real-world implications.**

7. Recommendations

1. Enhance Training and Protocols for Weapon-Related Stops

Given the strong positive correlation between the presence of a weapon (Weapon Type) and the likelihood of an arrest, SPD should emphasize comprehensive training for officers on handling stops involving weapons. This training can include creating specific modules addressing the handling of weapon-related encounters including simulations and scenario-based derived from the predictions of the model to prepare officers for real-world situations.

Additionally, SPD should continuously monitor the outcomes of weapon-related stops comparing them to the outcomes predicted by the model.

2. Evaluate and Optimize Squad Practices

SPD should analyze practices across different squads to identify successful strategies and areas for improvement. This can be done in the following ways:

- Conduct Performance Reviews: Analyze arrest data and performance metrics for each squad to identify best practices and discrepancies in arrest rates.
- Share Best Practices: Develop a best practices guide based on high-performing squads and distribute it across the department.
- Targeted Training: Provide additional training or support to squads with lower arrest rates to align their practices with successful strategies observed in other squads.

3. Adjust Resource Allocation Based on Beats

The analysis of beat features indicates varying likelihoods of arrests across different areas. SPD should adjust resource allocation and patrol strategies based on these insights to optimize effectiveness. This can be done in the following ways

- Resource Reallocation: Adjust patrol patterns and allocate resources based on crime rates and arrest patterns observed in different beats.

- Community Engagement: Increase community policing efforts in beats and beats with higher arrest rates to build relationships and address underlying issues that may contribute to higher arrest rates.
- Beat-Specific Strategies: Develop targeted strategies for beats with lower arrest rates to understand if there are specific challenges or factors affecting law enforcement outcomes.

4. Review and Standardize Field Contact Procedures

The negative coefficient for Stop Resolution_Field Contact suggests that stops resulting in field contacts are less likely to lead to arrests. SPD should continue to review the outcomes of actual stops to those predicted by the model to ensure that field contacts are well-justified and in line with department policies.

5. Use Model to Improve Law Enforcement Practices

- Implement Decision-Making Frameworks: Use the model as one tool among many in decision-making processes. Combine model predictions with officer judgment and contextual information to make balanced decisions.
- Continuous Model Improvement: Regularly update and refine the model to improve performance on predicting arrests. Consider exploring other advanced techniques for class imbalance management, such as different sampling methods.
- Evaluation and Feedback: Continuously evaluate the impact of the predictive model on real-world outcomes and gather feedback from officers to make necessary adjustments and improvements.