Terry Stops

Overview

In Terry v. OhioLinks to an external site., a landmark Supreme Court case in 1967-8, the court found that a police officer was not in violation of the "unreasonable search and seizure" clause of the Fourth Amendment, even though he stopped and frisked a couple of suspects only because their behavior was suspicious. Thus was born the notion of "reasonable suspicion", according to which an agent of the police may e.g. temporarily detain a person, even in the absence of clearer evidence that would be required for full-blown arrests etc. Terry Stops are stops made of suspicious drivers.

Problem Statement

This project aims to build a model that can accurately predict the result of a Terry Stop i.e Arrest or No Arrest. By applying the features from the dataset, this model will learn patterns and relationships that will help to differentiate those two outcomes.

Objective

Build a model that will classify or predict whether an arrest was made or not after a Terry Stop conducted by law enforcement officers.

Methodology

1. `Data Exploration` : Examine the data structure and content, identify relevant variables and understand their meaning and distribution.

2. `Analysis` : Generate descriptive statistics and visualizations to gain insight into the patterns of Terry stops.

3. `Predictive Modeling` : Create models that will predict whether an arrest was made after a Terry stop.

Data Understanding

The dataset contains various attributes related to the stops, including demographic information, stop location, stop reasoning, and outcomes. his data represents records of police reported stops under Terry v. Ohio, 392 U.S. 1 (1968). Each row represents a unique stop.

- Each record contains perceived demographics of the subject, as reported by the officer making the stop and officer demographics as reported to the Seattle Police Department, for employment purposes. ### Data description

`Subject Age Group` : Subject Age Group (10 year increments) as reported by the officer.

`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.

`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.

`Terry Stop ID` : Key identifying unique Terry Stop reports.

`Stop Resolution` : Resolution of the stop as reported by the officer.

`Weapon Type` : Type of weapon, if any, identified during a search or frisk of the subject. Indicates "None" if no weapons was found.

`Officer ID` : Key identifying unique officers in the dataset.

`Officer YOB` : Year of birth, as reported by the officer.

`Officer Gender` : Gender of the officer, as reported by the officer.

`Officer Race` : Race of the officer, as reported by the officer.

`Subject Perceived Race` : Perceived race of the subject, as reported by the officer.

`Subject Perceived Gender` : Perceived gender of the subject, as reported by the officer.

`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.

`Reported Time` : Time the stop was reported in the Records Management System (RMS). Not the time the stop occurred but generally within 10 hours.

`Initial Call Type` : Initial classification of the call as assigned by 911.

`Final Call Type` : Final classification of the call as assigned by the primary officer closing the event.

`Call Type` : How the call was received by the communication center.

`Officer Squad` : Functional squad assignment (not budget) of the officer as reported by the Data Analytics Platform (DAP).

`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).

`Frisk Flag` : Indicator of whether a "frisk" was conducted, by the officer, of the subject, during the Terry Stop.

`Precinct` : Precinct of the address associated with the underlying Computer Aided Dispatch (CAD) event. Not necessarily where the Terry Stop occurred.

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

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

In [2]:
```
# importing libraries
from imports.functions import *
%matplotlib inline
```

In [3]:
```python
# creating a dataframe
df = pd.read_csv('data/Terry_Stops.csv')
df.head()
```

Out[3]:

	Subject Age Group	Subject ID	GO / SC Num	Terry Stop ID	Stop Resolution	Weapon Type	Officer ID	Officer YOB	Officer Gender	Officer
0	36 - 45	7726342469	20200000112069	12803715000	Field Contact	-	6953	1968	M	\
1	46 - 55	17544297314	20210000007572	19456101086	Field Contact	-	6678	1970	M	\
2	26 - 35	-1	20150000005079	88327	Field Contact	None	6382	1958	M	Hawaiia Pac Isl
3	-	31307974123	20220000015393	31308022368	Field Contact	-	6799	1976	M	Hispa L
4	26 - 35	7727242683	20190000195849	8258954520	Field Contact	-	6953	1968	M	\

5 rows × 23 columns

In [4]:
```python
# checking data details
info(df)
```

Out[4]:

	Column	Missing Percentage	Missing Values	Length	Data type
17	Officer Squad	38.8	930838	2399030	object
0	Subject Age Group	0.0	0	2399030	object
12	Reported Date	0.0	0	2399030	object
21	Sector	0.0	0	2399030	object
20	Precinct	0.0	0	2399030	object
19	Frisk Flag	0.0	0	2399030	object
18	Arrest Flag	0.0	0	2399030	object
16	Call Type	0.0	0	2399030	object
15	Final Call Type	0.0	0	2399030	object
14	Initial Call Type	0.0	0	2399030	object
13	Reported Time	0.0	0	2399030	object
11	Subject Perceived Gender	0.0	0	2399030	object
1	Subject ID	0.0	0	2399030	int64
10	Subject Perceived Race	0.0	0	2399030	object
9	Officer Race	0.0	0	2399030	object
8	Officer Gender	0.0	0	2399030	object
7	Officer YOB	0.0	0	2399030	int64

	Column	Missing Percentage	Missing Values	Length	Data type
6	Officer ID	0.0	0	2399030	object
5	Weapon Type	0.0	0	2399030	object
4	Stop Resolution	0.0	0	2399030	object
3	Terry Stop ID	0.0	0	2399030	int64
2	GO / SC Num	0.0	0	2399030	int64
22	Beat	0.0	0	2399030	object

- `Officer Squad` has about 38.8 percent of missing data which translates to 930838 rows. From the total number of rows available and what the data in this squad signifies, I'll drop just the missing rows since the remaining data is sufficient.

In [5]:
```
# dropping null values
df.dropna(inplace=True)
```

In [6]:
```
# investigating the Beat column
df.Beat.value_counts()
```

Out[6]:
```
-      383904
N3      50482
E2      45107
K3      40807
M2      36593
M3      33927
N2      30358
E1      30014
R2      28810
B1      27606
U2      27262
M1      26918
F2      26574
K2      25843
B2      25069
D1      24725
L1      24467
L3      23005
L2      23005
S2      22747
D2      22747
E3      21414
O1      21070
S3      20812
K1      19135
Q3      19135
J1      19049
B3      18490
F3      17888
U1      17587
G2      17544
R1      17458
D3      17329
W2      16426
R3      16297
J3      16168
G3      16125
C3      15394
C1      15351
O2      14663
S1      14190
F1      14147
O3      14104
W1      14018
```

```
Q2      13416
N1      13244
J2      12857
C2      11739
G1      11180
U3      11094
W3       9804
Q1       8729
99       2279
S          86
Name: Beat, dtype: int64
```

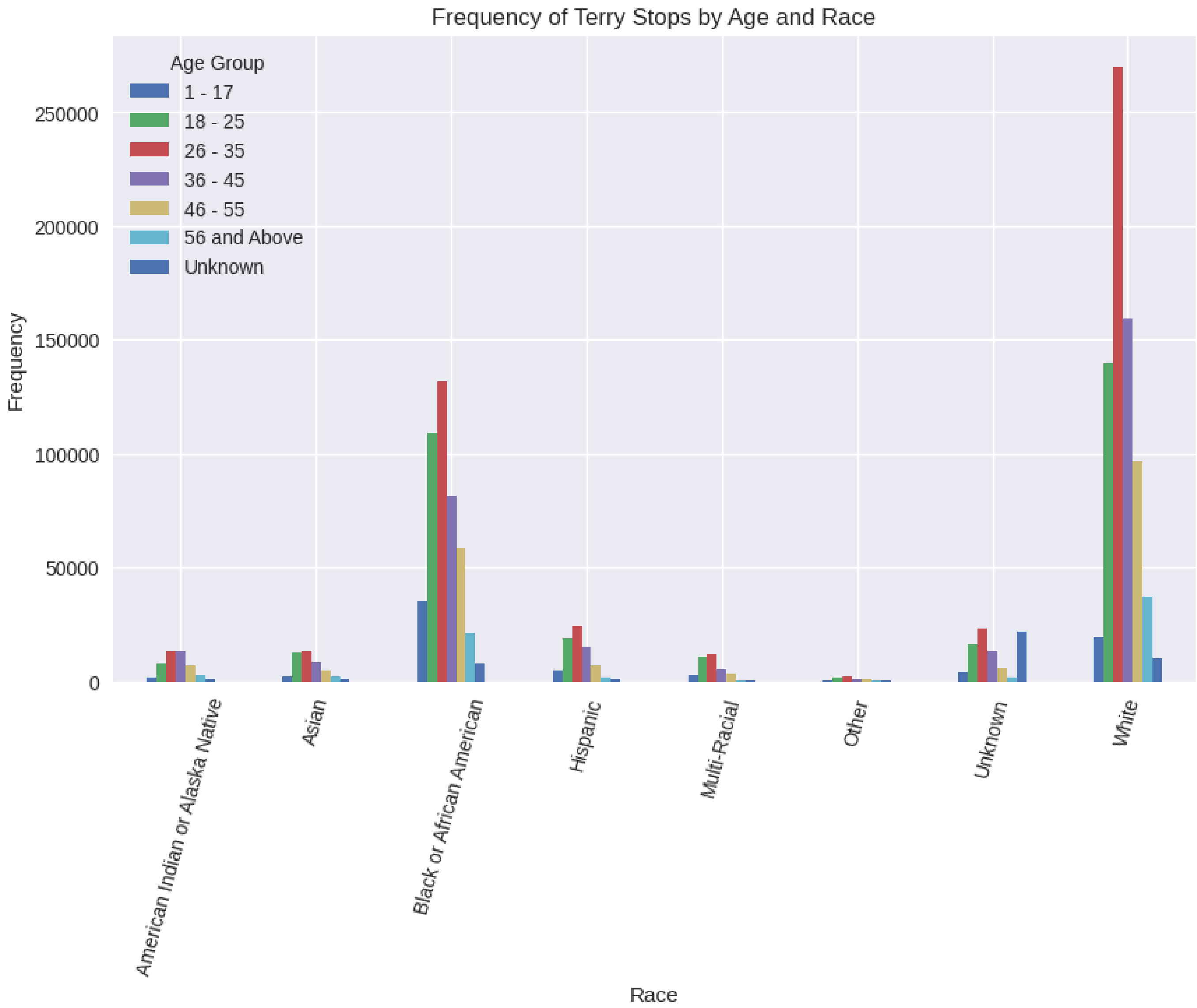
It has `-` as the most occuring value, I'll change that to `unknown`

In [9]:
```
# replacing values
df.replace({'Frisk Flag': '-', 'Subject Perceived Gender': '-', 'Subject Perceived Rac
            'Subject Age Group': '-', 'Call Type': '-', 'Precinct': '-', 'Weapon Type'
            'Beat':'-', 'Final Call Type':'-'}, 'Unknown', inplace=True)
```

In [10]:
```
# the column for officer year of birth will be dropped and instead will use age
# I'll use the reporting date to calculate the age at the time of reporting
# Convert strings to datetime objects

df['Reported Date'] = pd.to_datetime(df['Reported Date'])
df['Officer YOB'] = pd.to_numeric(df['Officer YOB'], errors='coerce')

df['age'] = df['Reported Date'].dt.year - df['Officer YOB']
```

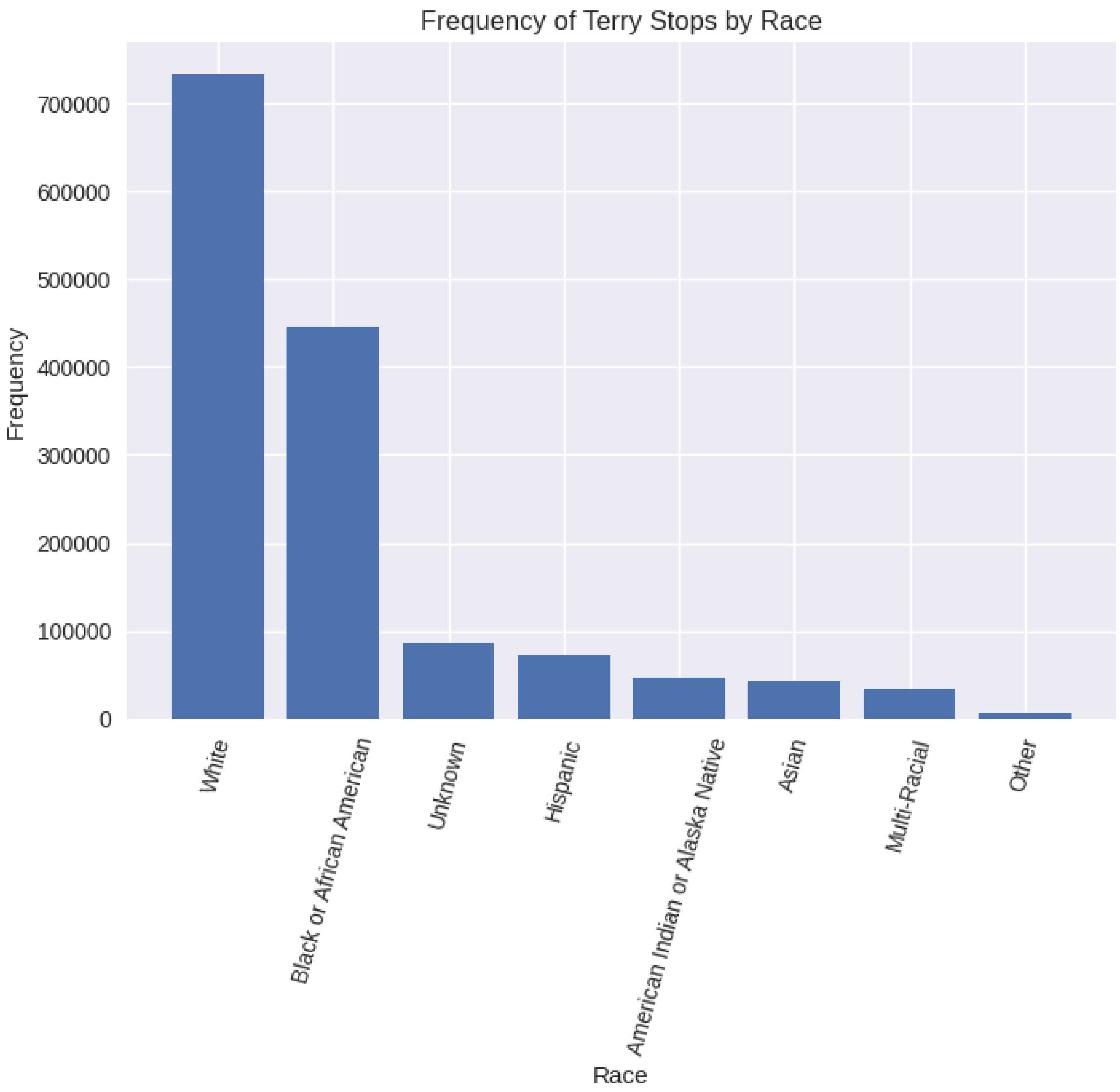
EDA

In [11]:
```
# subset the data
new_df = df[['Subject Perceived Race','Subject Age Group']]

# group the DataFrame
grouped_df = df.groupby(['Subject Perceived Race', 'Subject Age Group']).size().unstac

# plotting the bar chart
grouped_df.plot(kind='bar', figsize=(10, 6))

plt.title('Frequency of Terry Stops by Age and Race')
plt.xlabel('Race')
plt.ylabel('Frequency')
plt.xticks(rotation=75)
plt.legend(title='Age Group')
plt.show()
```



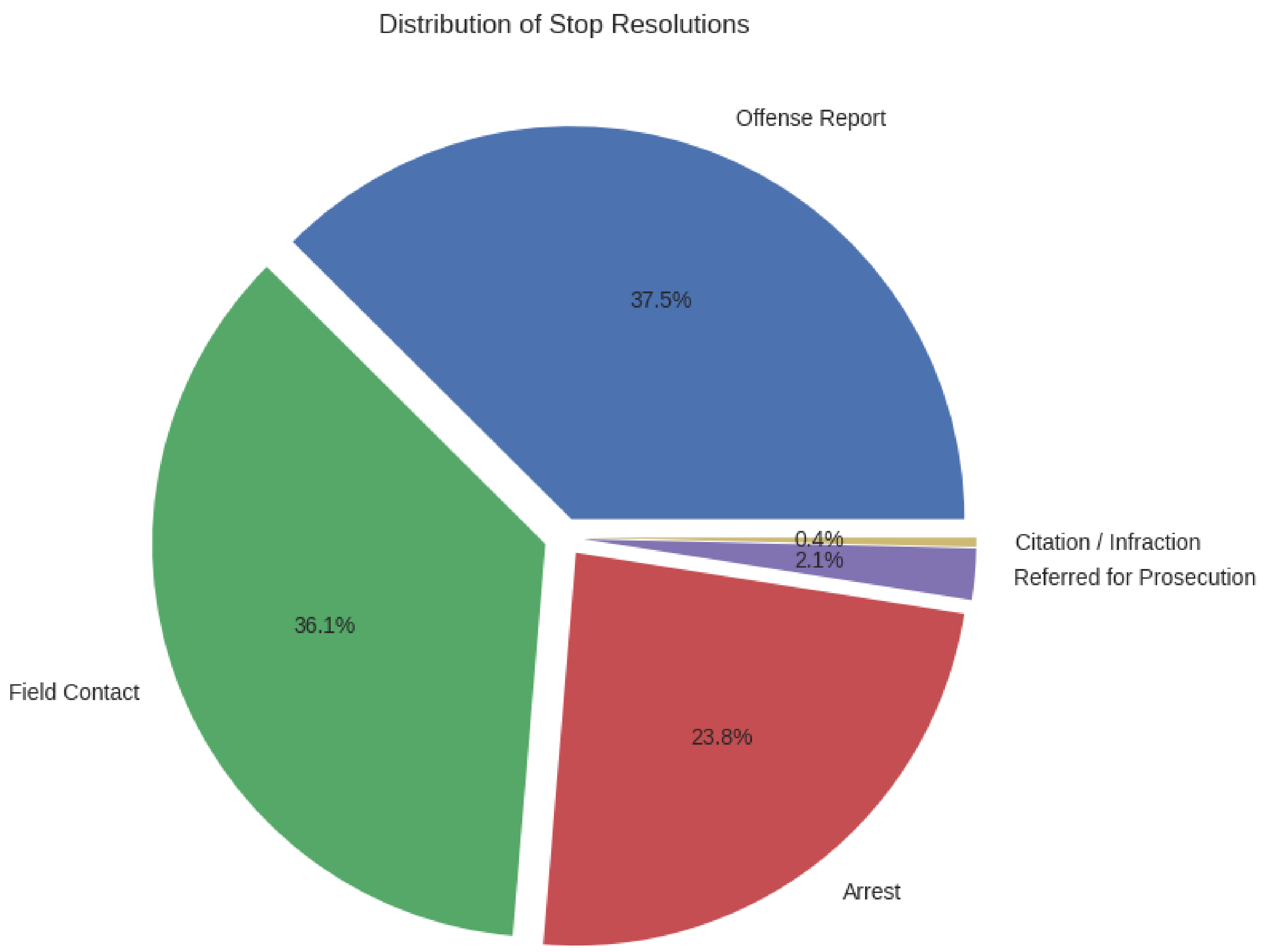
In [13]:

```
# calculate the count of each race in the 'Subject Perceived Race' column
race_counts = df['Subject Perceived Race'].value_counts()

# plot a bar chart using the race counts
plt.bar(race_counts.index, race_counts.values)

# set the title, x-label, and y-label for the chart
plt.title('Frequency of Terry Stops by Race')
plt.xlabel('Race')
plt.ylabel('Frequency')

# rotate the x-axis tick labels for better readability
plt.xticks(rotation=75)

# display the chart
plt.show()
```



In [14]:

```
# calculate the count of each stop resolution in the 'Stop Resolution' column
stop_resolution_counts = df['Stop Resolution'].value_counts()

# define the extent to which each pie slice is separated from the center
explode = [0.05, 0.05, 0.05, 0.05, 0.05]

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

# generate a pie chart using the stop resolution counts
plt.pie(stop_resolution_counts, labels=stop_resolution_counts.index, autopct='%1.1f%%'

# set the title of the pie chart
plt.title('Distribution of Stop Resolutions')

# display the chart
plt.show()
```



Feature Engineering

Some of the columns contain data that is not useful as it is. I'll use various techniques to create new features and drop the original columns.

In [15]:
```
# investigating age column
print(f"Youngest: {df['age'].min()}")
print(f"Oldest: {df['age'].max()}")
```

```
Youngest: 21
Oldest: 119
```

Given that in Seattle the minimum age to enroll at the time of this project is 20.5 years and the retirement age is 65, we will drop any above 65 by the time of the stop.

In [16]:
```
# dropping officers who were above 65 or below 21 by the time of the stop
df = df[(df['age'] <= 65) & (df['age'] >= 21)]
```

In [17]:
```
# investigating age column
print(f"Youngest: {df['age'].min()}")
print(f"Oldest: {df['age'].max()}")
```

```
Youngest: 21
Oldest: 65
```

In the `weapon type` column, there are different types that can be grouped together.

In [18]:
```
# getting count of weapons
df['Weapon Type'].value_counts()
```

Out[18]:
```
None                              1383611
Lethal Cutting Instrument           62952
Handgun                              9804
Firearm Other                        4257
Unknown                              2623
Club, Blackjack, Brass Knuckles      2107
Firearm (unk type)                    645
Club                                  387
Rifle                                 172
Shotgun                               129
Automatic Handgun                      86
Blackjack                              43
Brass Knuckles                         43
Name: Weapon Type, dtype: int64
```

In [19]:
```
# replace some values in the 'Weapon Type' column with 'Firearm'
df.replace({'Weapon Type': ['Handgun', 'Firearm Other', 'Firearm (unk type)', 'Other F
                            'Rifle', 'Shotgun', 'Automatic Handgun']}, 'Firearm', inpl

# replace some values in the 'Weapon Type' column with 'Striking Object'
df.replace({'Weapon Type': ['Club, Blackjack, Brass Knuckles', 'Blackjack', 'Brass Knu
                            'Club', 'Personal Weapons (hands, feet, etc.)']}, 'Strikin
```

In [20]:
```
# cols to drop
cols = ['Subject ID', 'GO / SC Num', 'Terry Stop ID', 'Officer YOB', 'Initial Call Typ
        'Arrest Flag', 'Reported Date', 'Sector', 'Officer ID', 'Beat']

# drop the specified columns from the DataFrame
drop(df, cols)
```

```
Number of columns before dropping: 24
Number of columns after dropping: 14
```

In [21]:
```
# change data type
df['Reported Time'] = df['Reported Time'].astype('str')

# extract the first 5 characters
df['Reported Time'] = df['Reported Time'].str[:5]
```

In [22]:
```
df.head()
```

Out[22]:

	Subject Age Group	Stop Resolution	Weapon Type	Officer Gender	Officer Race	Subject Perceived Race	Subject Perceived Gender	Reported Time	Final Call Type	
2	26 - 35	Field Contact	None	M	Nat Hawaiian/Oth Pac Islander	White	Male	16:14	Unknown	Unk
6	26 - 35	Field Contact	None	M	White	White	Male	16:56	Unknown	Unk
7	56 and Above	Offense Report	None	M	White	White	Male	17:38	--DV - ASSIST VICTIM BY COURT ORDER	
9	26 - 35	Offense Report	None	M	Hispanic or Latino	White	Male	00:52	--ASSAULTS, OTHER	ON

	Subject Age Group	Stop Resolution	Weapon Type	Officer Gender	Officer Race	Subject Perceived Race	Subject Perceived Gender	Reported Time	Final Call Type
10	18 - 25	Offense Report	Lethal Cutting Instrument	M	Hispanic or Latino	White	Male	02:34	-- DISTURBANCE - OTHER

In [23]:
```
df['Stop Resolution'].unique()
```

Out[23]:
```
array(['Field Contact', 'Offense Report', 'Arrest',
       'Citation / Infraction', 'Referred for Prosecution'], dtype=object)
```

The target column can then be engineered to contain binary according to the outcome of the stop. From the above cell, there are 5 different outcomes, I'll combine them according to the severity of the outcome

- `1` means `Arrest` while `0` means `No Arrest`.

In [40]:
```
# Replace some values in the 'Stop Resolution' column with 0
df.replace({'Stop Resolution': ['Field Contact', 'Citation / Infraction', 'Offense Repo

# Replace some values in the 'Stop Resolution' column with 1
df.replace({'Stop Resolution': ['Arrest', 'Referred for Prosecution']}, 1, inplace=Tru
```

In [25]:
```
# removing minutes in time by rounding to the next hour
df['Reported Time'] = df['Reported Time'].apply(round_time)
```

In [26]:
```
df['Subject Age Group'].unique()
```

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

Using the age groups in subjects, I will create similar groups for the police.

In [27]:
```
# Create a new column 'Officer Age Group' by applying the function 'map_age' to the 'ag
df['Officer Age Group'] = df['age'].apply(map_age)

# Drop the 'age' column from the DataFrame
df.drop('age', axis=1, inplace=True)

# Apply the function 'map_time' to the 'Reported Time' column
df['Reported Time'] = df['Reported Time'].apply(map_time)

# Apply the function 'call_group' to the 'Final Call Type' column
df['Final Call Type'] = df['Final Call Type'].apply(call_group)

# Apply the function 'squad_groups' to the 'Officer Squad' column
df['Officer Squad'] = df['Officer Squad'].apply(squad_groups)
```

In [28]:
```
info(df)
```

Out[28]:

	Column	Missing Percentage	Missing Values	Length	Data type
0	Subject Age Group	0.0	0	1466859	object
1	Stop Resolution	0.0	0	1466859	object
2	Weapon Type	0.0	0	1466859	object
3	Officer Gender	0.0	0	1466859	object
4	Officer Race	0.0	0	1466859	object

	Column	Missing Percentage	Missing Values	Length	Data type
5	Subject Perceived Race	0.0	0	1466859	object
6	Subject Perceived Gender	0.0	0	1466859	object
7	Reported Time	0.0	0	1466859	object
8	Final Call Type	0.0	0	1466859	object
9	Call Type	0.0	0	1466859	object
10	Officer Squad	0.0	0	1466859	object
11	Frisk Flag	0.0	0	1466859	object
12	Precinct	0.0	0	1466859	object
13	Officer Age Group	0.0	0	1466859	object

In [41]:
```
df.head()
```

Out[41]:

	Subject Age Group	Stop Resolution	Weapon Type	Officer Gender	Officer Race	Subject Perceived Race	Subject Perceived Gender	Reported Time	Final Call Type
2	26 - 35	0	None	M	Nat Hawaiian/Oth Pac Islander	White	Male	Afternoon	Unknown
6	26 - 35	0	None	M	White	White	Male	Afternoon	Unknown
7	56 and Above	0	None	M	White	White	Male	Afternoon	Domestic_Violence
9	26 - 35	0	None	M	Hispanic or Latino	White	Male	After Midnight	Assault
10	18 - 25	0	Lethal Cutting Instrument	M	Hispanic or Latino	White	Male	After Midnight	Disturbances

Modelling

In [42]:
```
# separate data into features and target
X = df.drop('Stop Resolution', axis=1)
y = df['Stop Resolution']
```

The target variable and the features are separated.

`Precision` will be used as the classification metric for the models. In this project, precision will represent the ratio of correctly predicted arrests after a stop to the instances predicted as arrests by the model. High precision will indicate that the model might be highly reliable and accurate. A good precision score for the models will indicate a high level of accuracy in predicting actual arrests.

Splitting the data

Split into train and test data.

- `X_train_second` and `y_train_second` will be used for training.
- `X_test_second` and `y_test_second` will be used for validation.
- `X_test_first` and `y_test_first` will be for the final evaluation of the model on unseen data.

In [43]:
```
df.shape
```
Out[43]:
```
(1466859, 14)
```
In [44]:
```
# first split
X_train_first, X_test_first, y_train_first, y_test_first = train_test_split(X, y, test_
```
In [46]:
```
print(f'Shape of X_train: {X_train_first.shape}')
print('=========================================')
print(f'Shape of y_train: {y_train_first.shape}')
```
```
Shape of X_train: (1173487, 13)
=========================================
Shape of y_train: (1173487,)
```
In [47]:
```
# second split
X_train_second, X_test_second, y_train_second, y_test_second = train_test_split(X_trai
```
In [48]:
```
print(f'Shape of X_train: {X_train_second.shape}')
print('=========================================')
print(f'Shape of y_train: {y_train_second.shape}')
```
```
Shape of X_train: (938789, 13)
=========================================
Shape of y_train: (938789,)
```

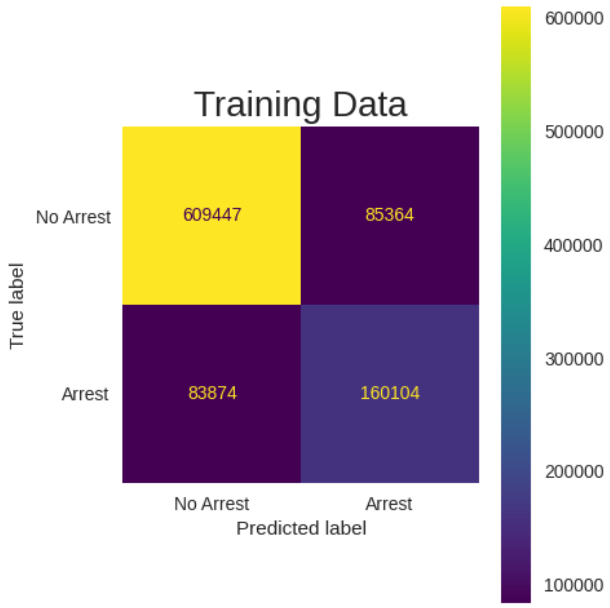
Feature Encoding

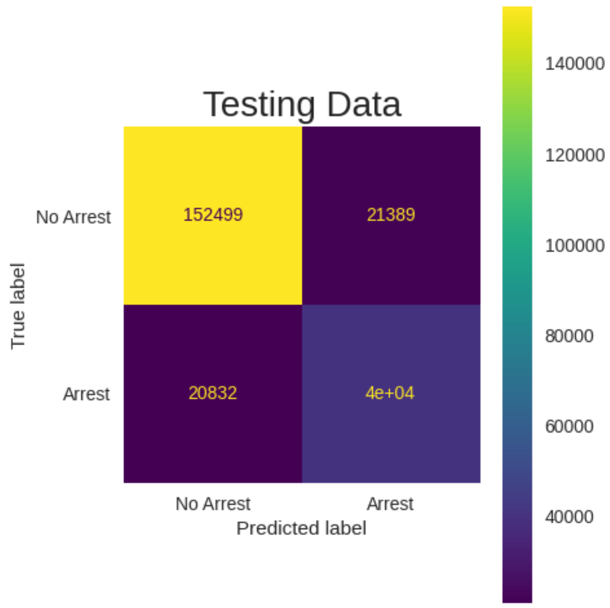
In [49]:
```
# using OneHotEncoder to transform the columns
ohe = OneHotEncoder(handle_unknown='ignore', sparse=False)
X_train_ohe = ohe.fit_transform(X_train_second)
X_test_ohe = ohe.transform(X_test_second)
```

First Model - Logistic Regression

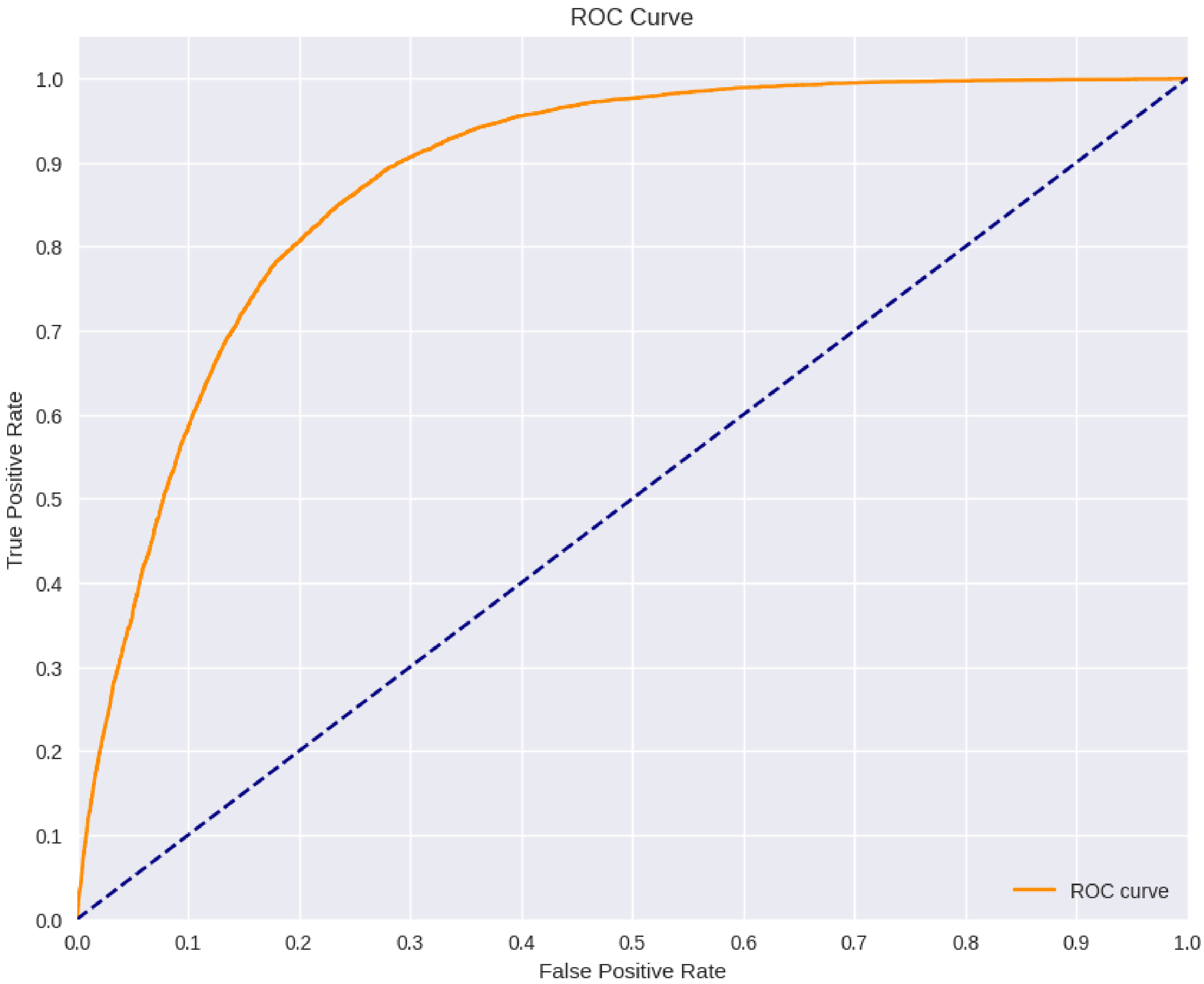
- This will be a baseline model.

In [50]:
```
# instantiating and fitting
logreg = LogisticRegression(random_state=42)

first_model = logreg.fit(X_train_ohe, y_train_second)
```
In [51]:
```
# generating predictions
y_hat_train1 = logreg.predict(X_train_ohe)
y_hat_test1 = logreg.predict(X_test_ohe)
```
In [52]:
```
# checking scores
calc_scores(y_train_second, y_hat_train1, y_test_second, y_hat_test1)
```
```
F1 score for training data: 0.6542253895220311
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
F1 score for testing data: 0.6544275927547738
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for training data: 0.6562231020829747
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for testing data: 0.6574247656635421
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for training data: 0.652239803151531
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for testing data: 0.6514576238043248
```
In [53]:
```
plot_cm(y_train_second, y_hat_train1, y_test_second, y_hat_test1)
```





In [54]:
```
# plotting a ROC curve
plot_roc(X_train_ohe, y_train_second, X_test_ohe, y_test_second, logreg)
```




```
AUC: 0.8794
```

Review

Given that we are using `Precision` as the metric to analyse the models, this model is not good as it only attains `0.65` precision. Our target is a serious issue thus a high precision is needed

- The `F1 Score` of `0.65` shows the average between recall and precision.
- We can further see the `recall score` and `precision score` are `0.65` .

- The confusion matrix shows that the model correctly predicts about `40000` as `Arrest` and `152499` as `Not arrest` using the test data.

- Although there is still a big number that it predicts wrong

Second Model - Decision Tree

Given the scores the first model produced, the second model should hopefully improve on that

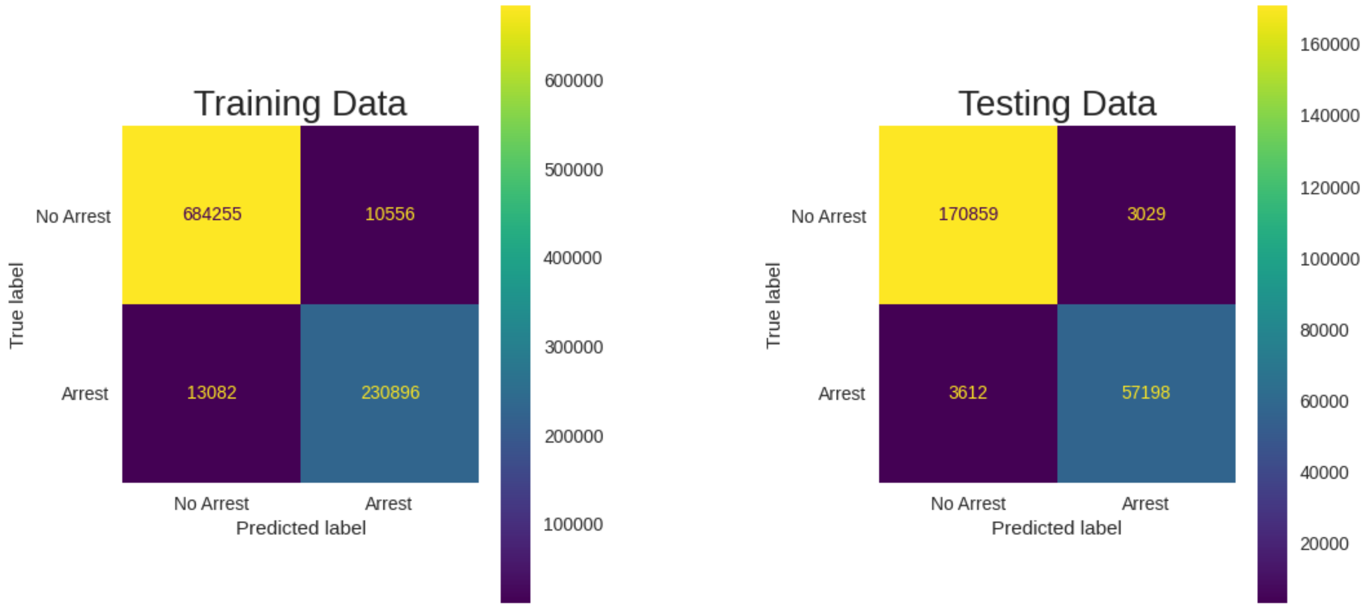
In [61]:
```
# create an instance
dt = DecisionTreeClassifier()

# fit the model
second_model = dt.fit(X_train_ohe, y_train_second)
```

In [56]:
```
# predict the target variable for the training data
y_hat_train2 = dt.predict(X_train_ohe)

# predict the target variable for the testing data
y_hat_test2 = dt.predict(X_test_ohe)
```

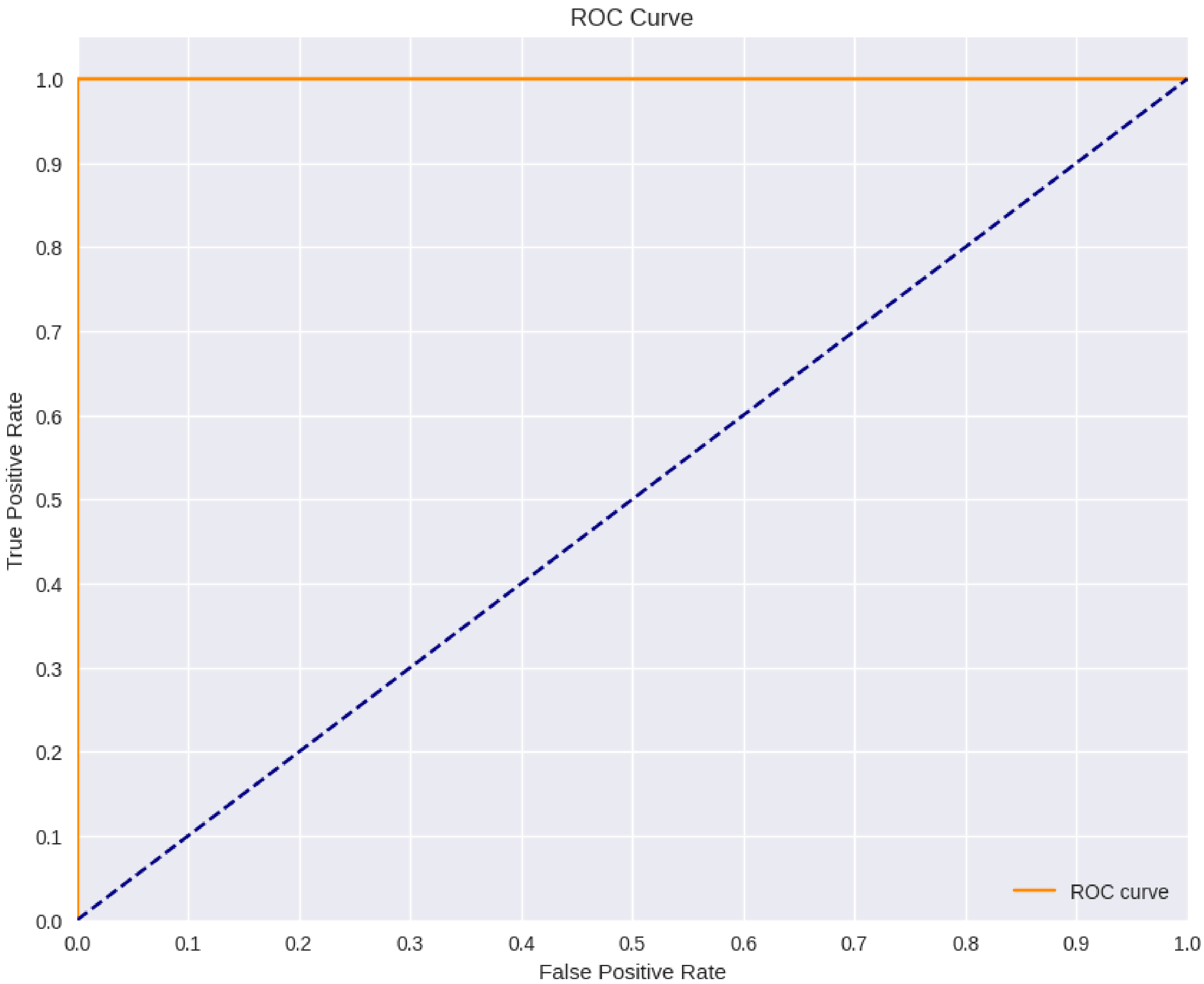
In [57]:
```
calc_scores(y_train_second, y_hat_train2, y_test_second, y_hat_test2)
```

```
F1 score for training data: 0.9513050285314051
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
F1 score for testing data: 0.9451324801506976
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for training data: 0.9463804113485642
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for testing data: 0.9406018746916626
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for training data: 0.9562811656146978
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for testing data: 0.9497069420691716
```

In [58]:
```
plot_cm(y_train_second, y_hat_train2, y_test_second, y_hat_test2)
```



In [59]:
```
plot_roc(X_train_ohe, y_hat_train2, X_test_ohe, y_hat_test2, dt)
```




```
AUC: 1.0000
```

Review

The metrics from the second model suggest an even better performance.

The `Precision` score has improved massively reaching `0.95`. This is a good number considering the target though we can try to improve it further.

Other models will be developed to test whether the `Precision` will improve.

Third Model - Random Forest

In [62]:

```
# Create a new instance of the RandomForestClassifier
rfc = RandomForestClassifier(random_state=42)

# Fit the model
third_model = rfc.fit(X_train_ohe, y_train_second)
```

In [63]:

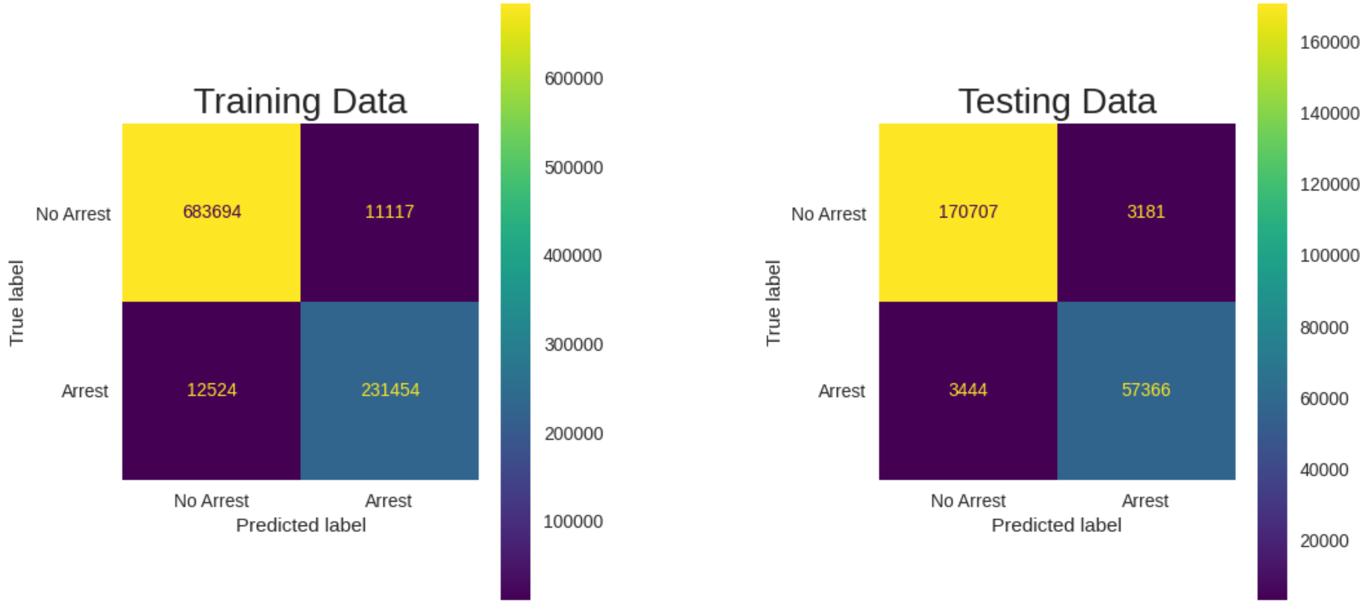
```
# Predict the target variable for the training data
y_hat_train3 = rfc.predict(X_train_ohe)

# Predict the target variable for the testing data
y_hat_test3 = rfc.predict(X_test_ohe)
```

In [64]:

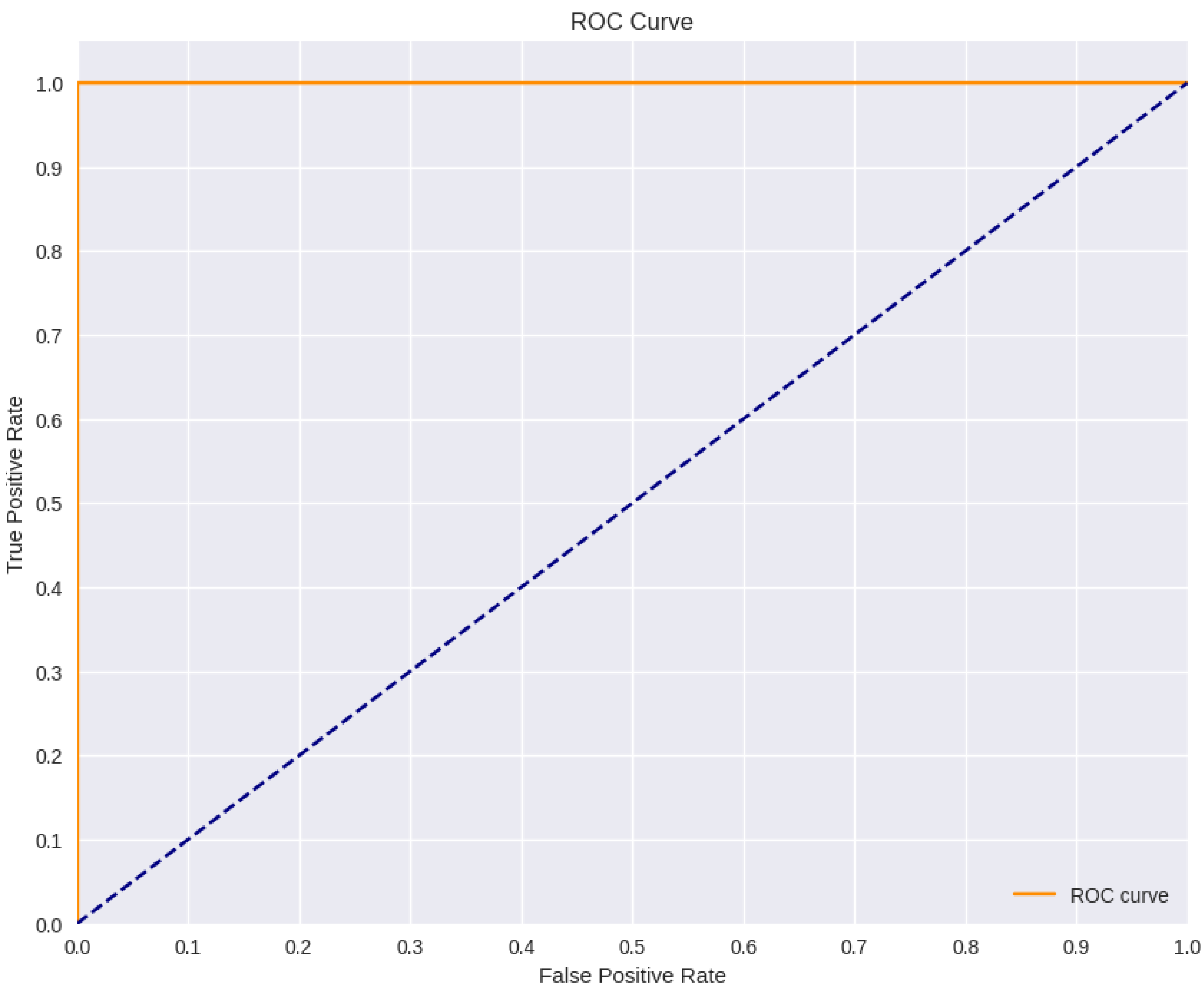
```
# calculate evaluation scores
calc_scores(y_train_second, y_hat_train3, y_test_second, y_hat_test3)
```

```
F1 score for training data: 0.9514108548162672
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
F1 score for testing data: 0.9454089998928781
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for training data: 0.9486675028076302
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for testing data: 0.9433645781943759
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for training data: 0.9541701192640505
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for testing data: 0.9474623020133119
```

In [65]:
```python
# plot confusion matrix
plot_cm(y_train_second, y_hat_train3, y_test_second, y_hat_test3)
```



In [66]:
```python
# plot roc curve
plot_roc(X_train_ohe, y_hat_train3, X_test_ohe, y_hat_test3, rfc)
```




```
AUC: 1.0000
```

Review

The `Precision` score for this model drops which is not acceptable. This model is therefore not suitable even though some of the other metrics improved.

Fourth Model - Using SMOTE

SMOTE will be applied to the features to generate balanced classes.

In [68]:
```
# applying smote to features
smote = SMOTE()
X_train_smote, y_train_smote = smote.fit_resample(X_train_ohe, y_train_second)
```

In [69]:
```
# checking smote results
print(pd.Series(y_train_smote).value_counts())
print('==================')
print(X_train_smote.shape)
```

```
0    694811
1    694811
Name: Stop Resolution, dtype: int64
==================
(1389622, 83)
```

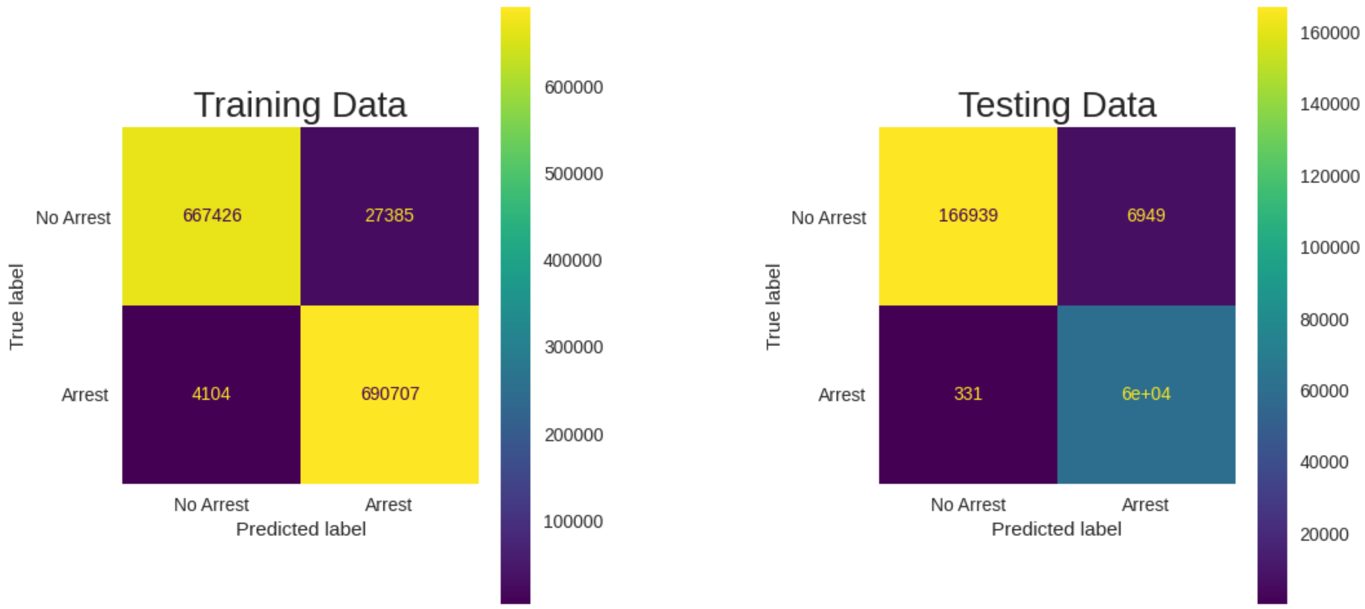
In [70]:
```
# decision tree after smote
fourth_model = dt.fit(X_train_smote, y_train_smote)
```

In [71]:
```
# predictions
y_hat_train22 = dt.predict(X_train_smote)
y_hat_test22 = dt.predict(X_test_ohe)
```

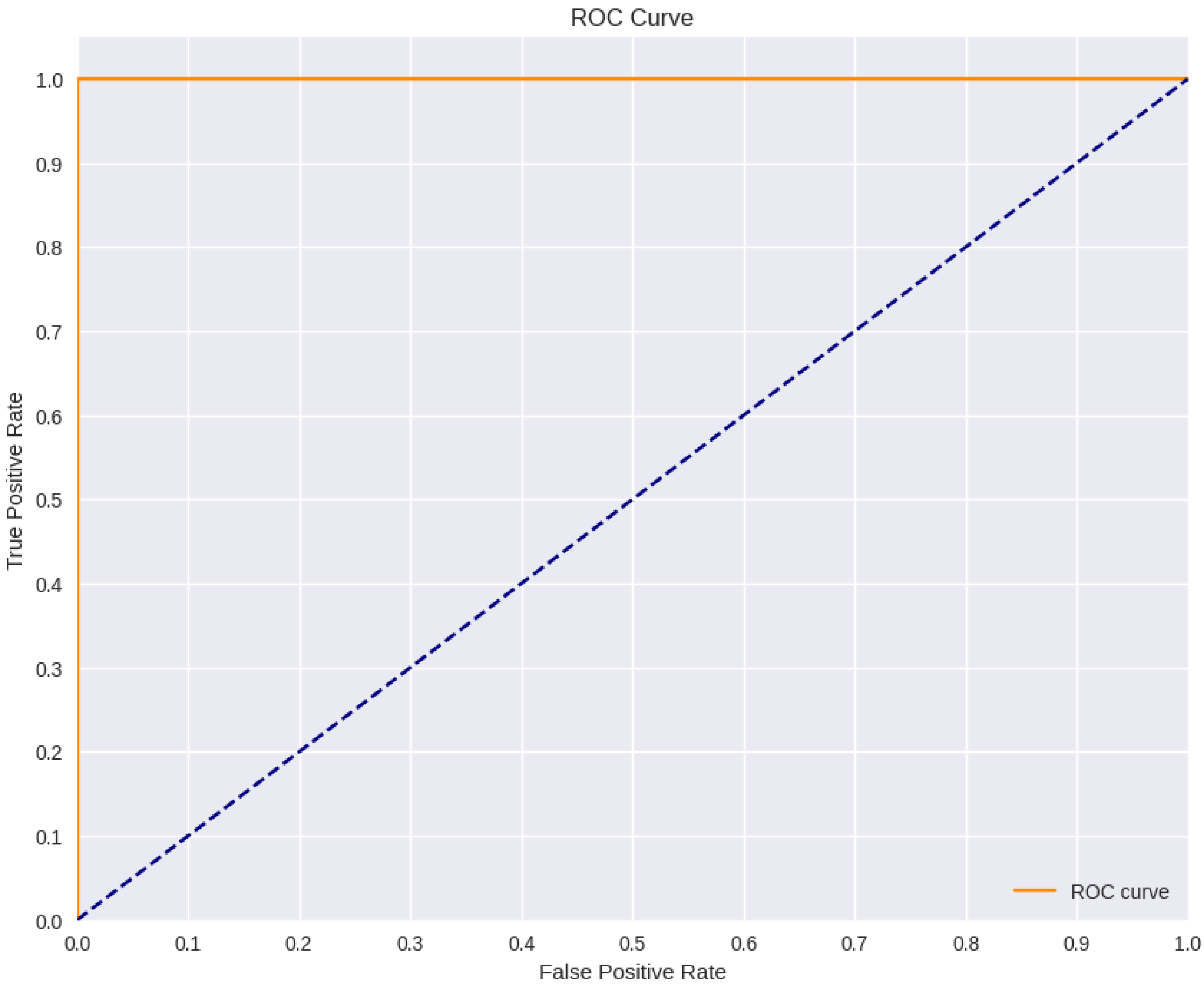
In [72]:
```
# checking scores
calc_scores(y_train_smote, y_hat_train22, y_test_second, y_hat_test22)
```

```
F1 score for training data: 0.9777132612783751
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
F1 score for testing data: 0.9432305556855222
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for training data: 0.9940933577620389
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for testing data: 0.9945568163131064
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for training data: 0.9618642179553595
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for testing data: 0.8969419232366376
```

In [73]:
```
# plotting confusion matrix
plot_cm(y_train_smote, y_hat_train22, y_test_second, y_hat_test22)
```



In [74]:
```
# plotting roc curve
plot_roc(X_train_smote, y_hat_train22, X_test_ohe, y_hat_test22, dt)
```




```
AUC: 1.0000
```

Review

The `Precision` score is worse than that of the `Decision Tree` without smote. The model is not good for predicting our target.

Fifth Model - XGBoost

In [79]:
```
# Create a new instance of the XGBClassifier
xgb = XGBClassifier()

# Fit the XGBClassifier model
fifth_model = xgb.fit(X_train_ohe, y_train_second)
```

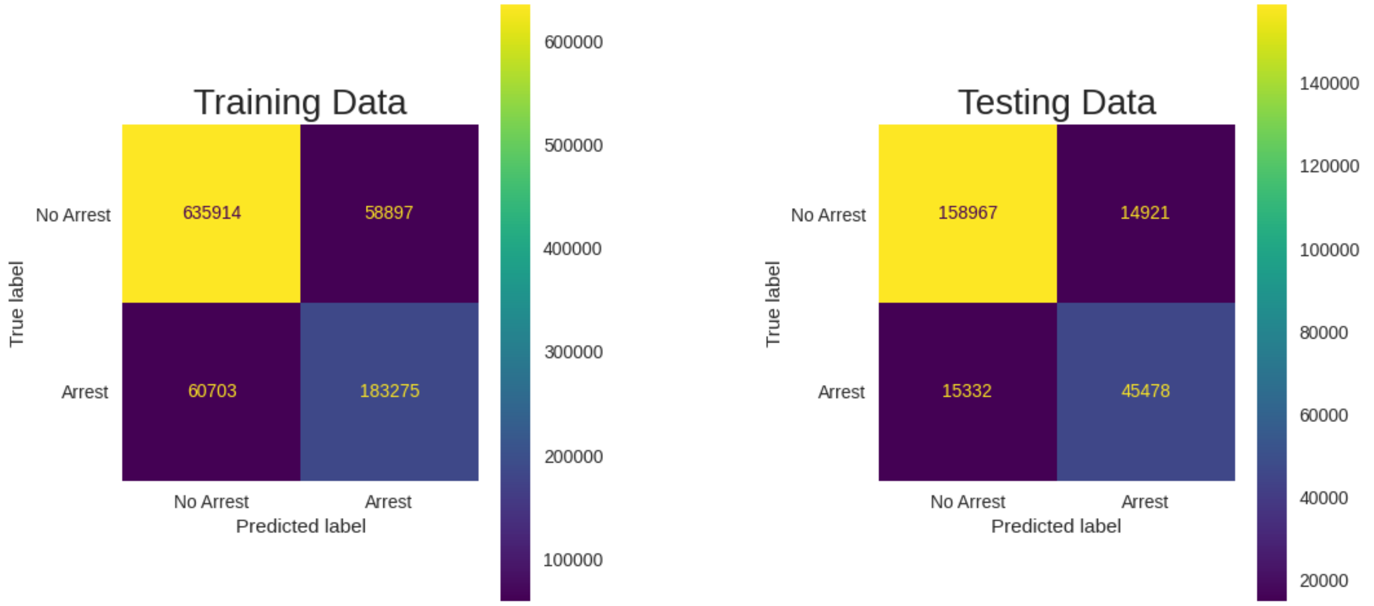
In [80]:
```
#Train Scores
train_preds = xgb.predict(X_train_ohe)

#Test Scores
test_preds = xgb.predict(X_test_ohe)
```

In [85]:
```
# checking scores
calc_scores(y_train_second, train_preds, y_test_second, test_preds)
```

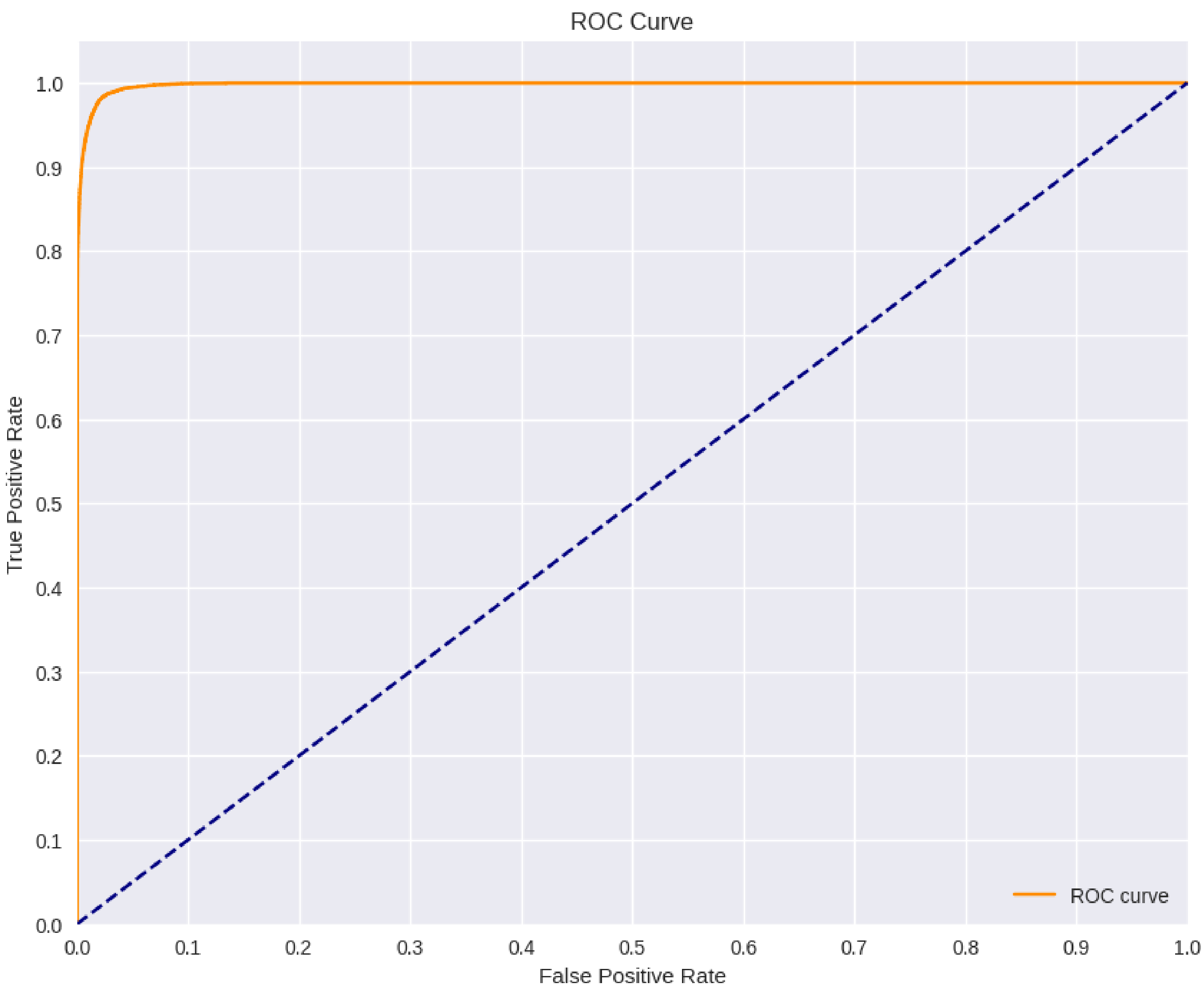
```
F1 score for training data: 0.753985395454078
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
F1 score for testing data: 0.7504063229628164
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for training data: 0.7511947798572003
```

```
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for testing data: 0.7478704160499918
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for training data: 0.7567968220933882
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for testing data: 0.7529594860842067
```

In [82]:
```python
# plotting confusion matrix
plot_cm(y_train_second, train_preds, y_test_second, test_preds)
```



In [83]:
```python
# plotting roc curve
plot_roc(X_train_ohe, train_preds, X_test_ohe, test_preds, xgb)
```




```
AUC: 0.9981
```

Review

This model performs better than the `Logistic Regression` but its `Precision` is too low to be considered for predicting the target.

Checking Cross_Val_Score

In [87]:

```python
# List of classifiers
classifiers = [first_model, second_model, third_model, fourth_model, fifth_model]

# Perform cross-validation for each classifier
for clf in classifiers:
    scores = cross_val_score(clf, X_train_ohe, y_train_second, cv=3)
    mean_score = scores.mean()
    print(f"{clf.__class__.__name__} Mean Score: {mean_score}")
```

```
LogisticRegression Mean Score: 0.8194940499581982
DecisionTreeClassifier Mean Score: 0.9728575852399622
RandomForestClassifier Mean Score: 0.9728117815718736
DecisionTreeClassifier Mean Score: 0.9728575852399622
XGBClassifier Mean Score: 0.8720266206168147
```

The three model, `decision tree` , `random forest` and `decision tree with smote` perform very similarly.

`Decision tree` will be considered for the final due to its less computation power and runtime.

Final Model - Decision Tree

The model will use all the data from the train test split

In [88]:
```
# Create a pipeline consisting of two steps: OneHotEncoder and DecisionTreeClassifier
pipe = Pipeline([('ohe', OneHotEncoder(handle_unknown='ignore', sparse=False)),
                 ('tree', DecisionTreeClassifier())])
```

In [90]:
```
# Fit the pipeline (final_model) on the training data
final_model = pipe.fit(X_train_second, y_train_second)

# Print the final_model
final_model
```

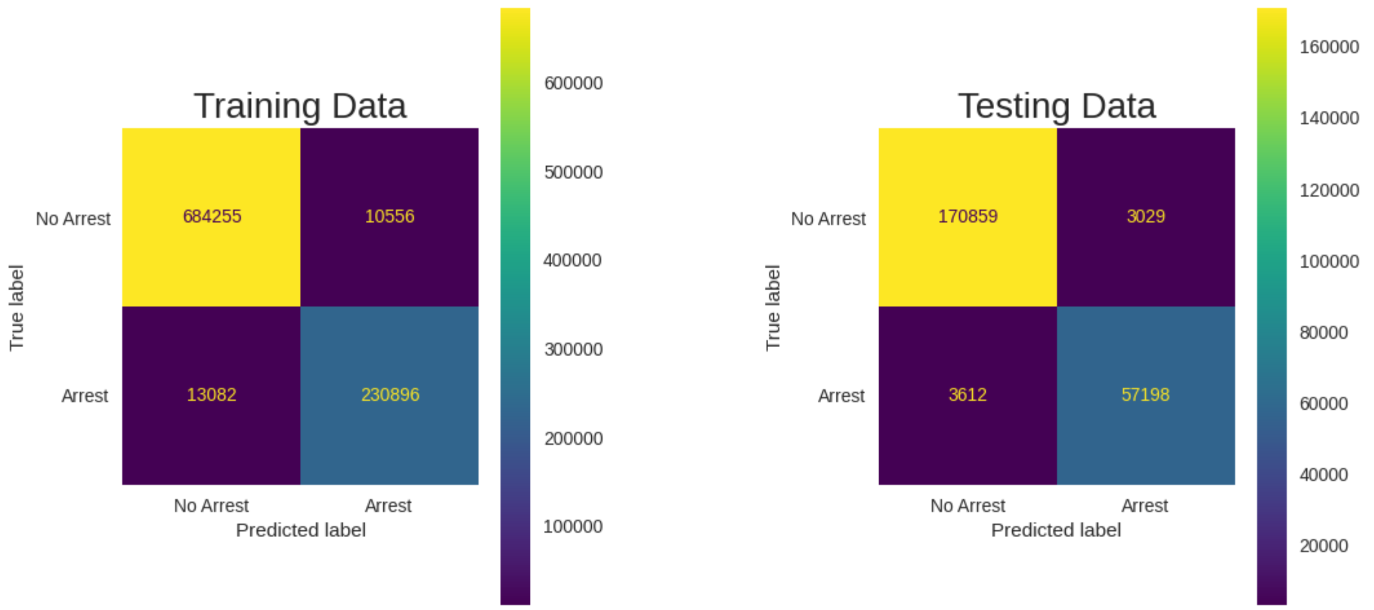
Out[90]:
```
▸ Pipeline
  ▸ OneHotEncoder
  ▸ DecisionTreeClassifier
```

In [91]:
```
# validation on the training data
final_preds_train = pipe.predict(X_train_second)
final_preds_test = pipe.predict(X_test_second)
```

In [93]:
```
# checking scores on training data
calc_scores(y_train_second, final_preds_train, y_test_second, final_preds_test)
```

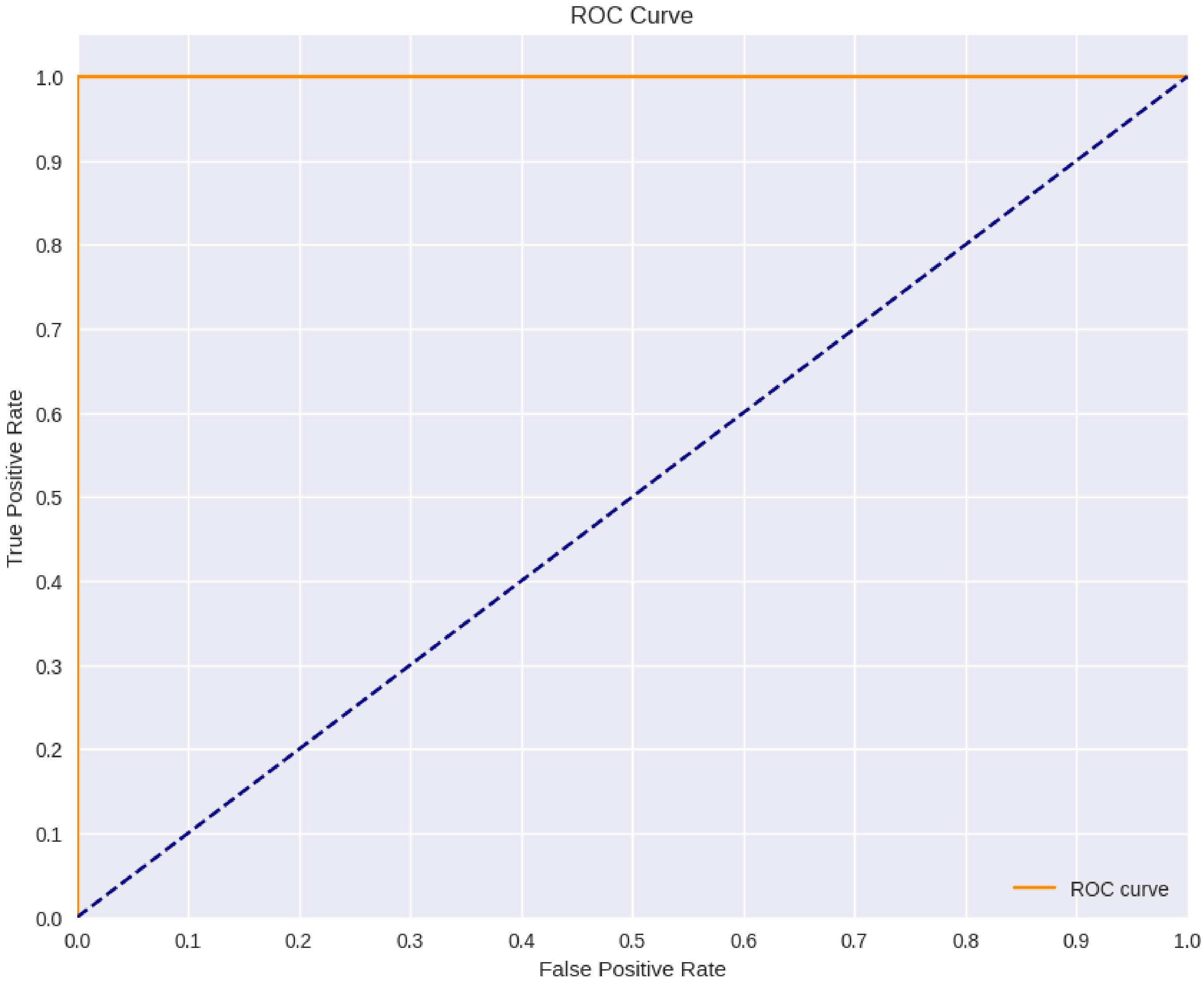
```
F1 score for training data: 0.9513050285314051
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
F1 score for testing data: 0.9451324801506976
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for training data: 0.9463804113485642
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for testing data: 0.9406018746916626
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for training data: 0.9562811656146978
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for testing data: 0.9497069420691716
```

In [120…
```
# plotting confusion matrix for training data
plot_cm(y_train_second, final_preds_train, y_test_second, final_preds_test)
```



In [123…

```
# plotting roc curve on training data
plot_roc(X_train_second, final_preds_train, X_test_second, final_preds_test, pipe)
```




```
AUC: 1.0000
```

Using the training data, the model produces great metrics indicating a good performance across all thresholds.

In [94]:

```
# validation on unseen data
unseen_preds_train = pipe.predict(X_train_first)
unseen_preds_test = pipe.predict(X_test_first)
```

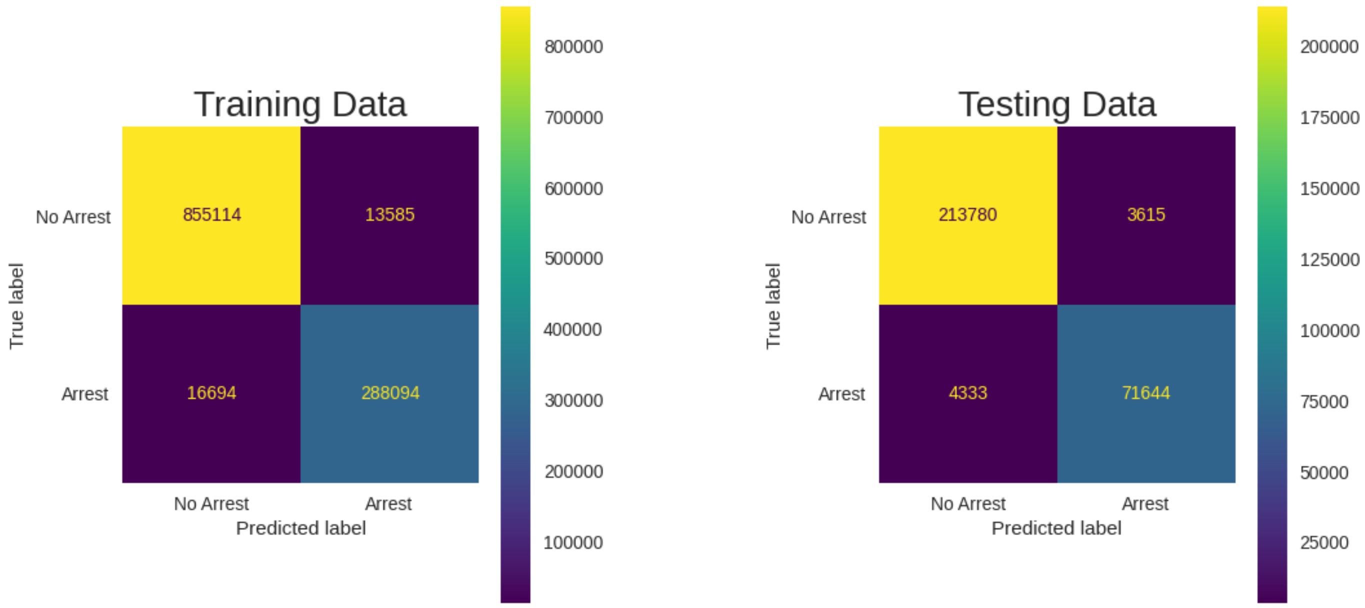
In [99]:

```
# checking scores on validation set
calc_scores(y_train_first, unseen_preds_train, y_test_first, unseen_preds_test)
```

```
F1 score for training data: 0.9500731284637086
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
F1 score for testing data: 0.9474463752016714
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for training data: 0.9452275023951074
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Recall score for testing data: 0.9429695829000881
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for training data: 0.9549686918877349
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
Precision score for testing data: 0.951965877835209
```

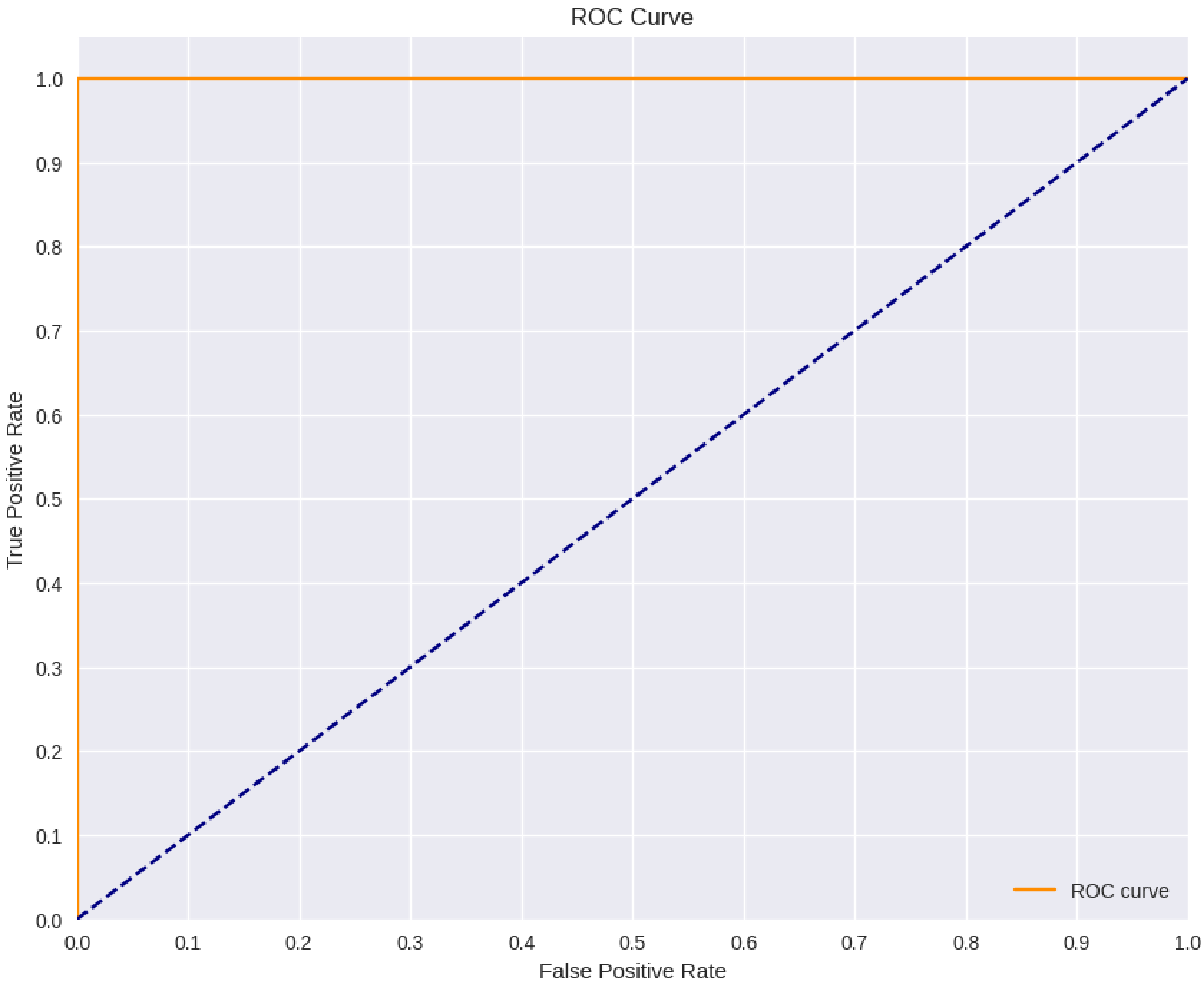
In [121…

```
# plotting confusion matrix on validation data
plot_cm(y_train_first, unseen_preds_train, y_test_first, unseen_preds_test)
```



In [124…

```
# plotting roc curve on validation data
plot_roc(X_train_first, unseen_preds_train, X_test_first, unseen_preds_test, pipe)
```

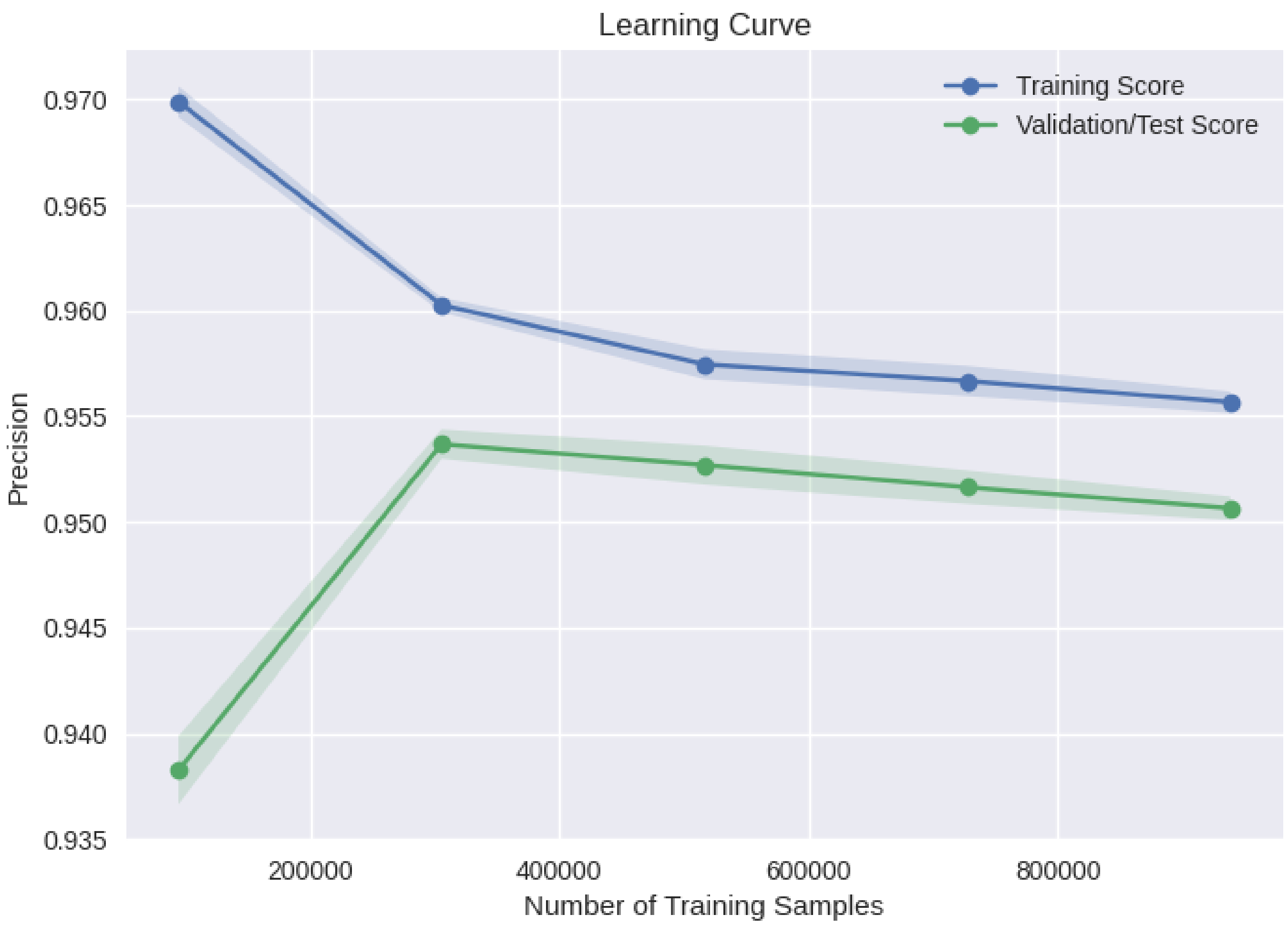



```
AUC: 1.0000
```

In [125…

```
# Define the number of training samples to use for the learning curve
train_sizes = np.linspace(0.1, 1.0, 5)

# Calculate learning curve scores
train_sizes_abs, train_scores, test_scores = learning_curve(
    estimator=pipe,
```

```
    X=X_train_first,
    y=y_train_first,
    train_sizes=train_sizes,
    cv=5,
    scoring='precision',
    n_jobs=-1
)

# Calculate mean and standard deviation of the scores
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)

# Plot the learning curve
plt.plot(train_sizes_abs, train_scores_mean, 'o-', label='Training Score')
plt.plot(train_sizes_abs, test_scores_mean, 'o-', label='Validation/Test Score')
plt.fill_between(train_sizes_abs, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.2)
plt.fill_between(train_sizes_abs, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.2)
plt.xlabel('Number of Training Samples')
plt.ylabel('Precision')
plt.title('Learning Curve')
plt.legend(loc='best')
plt.show()
```



The learning curve indicates the model's score on both the training and validation sets across various sample sizes.

Validation Curve:

The curve has an increase in the score upto around 300000 samples when it drops a bit as more data is added. It however remains stable and does not fall of completely.

Training Curve:

The curve starts on a very high score for about 120000 samples but then drops to around 0.96 for 300000 samples. This may suggest that the model may have experienced overfitting. The score then drops gradually until around 0.95.

Overall:

The curve shows that upto some point, increasing the number of samples stops having any effect on improvement of the model's performance. This may be because the model has already captured the most relevant patterns in the data.
This also shows that the model is able to generalize to unseen data.

Review of Final Model

The model has a high `Precision` score of `0.95`. This indicates that the model is able to correctly predict `arrests` after a stop. It has a low false positive rate and it performs well in classifying instances of `arrests`.

One of the main reasons this model may have performed this well is because of the feature engineering. Some features like `Officer Squad` had over `100` unique entries which were grouped together to `6` entries. Another example is `Final Call Type` which had about `160` unique entries and `Weapon Type` had over `10` unique entries. This grouping and simplification of all these features might be contributing to the high metrics in the models.

In [ ]:

```
```