```
# This is formatted as code
```

Chicago Recidivism

In the US, many offenders lack adequate rehabilitation, increasing recidivism risk. Chicago sees up to 89% yearly recidivism, meaning 89% of formerly incarcerated individuals commit another crime within three years of their dismissal. Understanding predictors of repeat crime is crucial to breaking this cycle. In this project, I implement a model to predict recidivism using demographic, geographic, and historical crime data in Chicago in order to inform interventions.

Imports

In [ ]:
```
import gdown
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, average_preci
```

In [ ]:
```
import os
from sklearn.neighbors import KNeighborsRegressor
from google.colab import drive
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
drive.mount('/content/drive/')
```

```
Mounted at /content/drive/
```

In [ ]:
```
os.chdir("/content/drive/My Drive/CIS 5450 Project/")
```

In [ ]:
```
sentencing_df = pd.read_csv("Sentence_Data.csv")
diversion_df = pd.read_csv("Diversion_Data.csv")
```

```
<ipython-input-4-59eaadd6b1d7>:1: DtypeWarning: Columns (10,11,14,25) have mixed types.
Specify dtype option on import or set low_memory=False.
  sentencing_df = pd.read_csv("Sentence_Data.csv")
```

Load Data

Chicago Sentencing Data: https://datacatalog.cookcountyil.gov/Courts/Sentencing/tg8v-tm6u \ Chicago Diversion Program Data: https://datacatalog.cookcountyil.gov/Courts/Diversion/gpu3-5dfh

In [ ]:
```
# Check the columns and their dtypes
sentencing_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 171542 entries, 0 to 171541
Data columns (total 41 columns):
 #   Column                              Non-Null Count   Dtype
---  ------                              --------------   -----
```

```
 0   case_id                           171542 non-null  int64
 1   case_participant_id               171542 non-null  int64
 2   received_date                     171542 non-null  object
 3   offense_category                  171542 non-null  object
 4   primary_charge_flag               171542 non-null  bool
 5   charge_id                         171542 non-null  int64
 6   charge_version_id                 171542 non-null  int64
 7   disposition_charged_offense_title 171542 non-null  object
 8   charge_count                      171542 non-null  int64
 9   disposition_date                  171542 non-null  object
 10  disposition_charged_chapter       171542 non-null  object
 11  disposition_charged_act           171542 non-null  object
 12  disposition_charged_section       171542 non-null  object
 13  disposition_charged_class         171542 non-null  object
 14  disposition_charged_aoic          171542 non-null  object
 15  charge_disposition                171542 non-null  object
 16  charge_disposition_reason         619 non-null     object
 17  sentence_judge                    171445 non-null  object
 18  sentence_court_name               171536 non-null  object
 19  sentence_court_facility           171062 non-null  object
 20  sentence_phase                    171542 non-null  object
 21  sentence_date                     171542 non-null  object
 22  sentence_type                     171542 non-null  object
 23  current_sentence_flag             171542 non-null  bool
 24  commitment_type                   170939 non-null  object
 25  commitment_term                   170939 non-null  object
 26  commitment_unit                   170939 non-null  object
 27  length_of_case_in_days            168307 non-null  float64
 28  age_at_incident                   170976 non-null  float64
 29  race                              171363 non-null  object
 30  gender                            171433 non-null  object
 31  incident_city                     171542 non-null  object
 32  incident_begin_date               171403 non-null  object
 33  incident_end_date                 11351 non-null   object
 34  law_enforcement_agency            171542 non-null  object
 35  law_enforcement_unit              76638 non-null   object
 36  arrest_date                       171542 non-null  object
 37  felony_review_date                116124 non-null  object
 38  felony_review_result              116124 non-null  object
 39  arraignment_date                  168307 non-null  object
 40  updated_offense_category          171542 non-null  object
dtypes: bool(2), float64(2), int64(5), object(32)
memory usage: 51.4+ MB
```

In [ ]:
```
# Check first 5 entries in sentencing_df
sentencing_df.head(5)
```

Out[ ]:

	case_id	case_participant_id	received_date	offense_category	primary_charge_flag	charge_id	ch
0	167083341487	670458920516	09/02/2009 12:00:00 AM	PROMIS Conversion	False	2409768744879	
1	167083341487	670458920516	09/02/2009 12:00:00 AM	PROMIS Conversion	False	2409776412625	
2	224609276363	386948574911	09/16/1994 12:00:00 AM	Attempt Homicide	False	2501088814098	
3	224609276363	386948574911	09/16/1994 12:00:00 AM	Attempt Homicide	False	2501089511166	
4	224609276363	386948574911	09/16/1994 12:00:00 AM	Attempt Homicide	True	2501092299437	

In [ ]:
```
# Check the columns and their dtypes
diversion_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16124 entries, 0 to 16123
Data columns (total 16 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   case_id                        16124 non-null  int64  
 1   case_participant_id            16124 non-null  int64  
 2   received_date                  16124 non-null  object 
 3   offense_category               16124 non-null  object 
 4   diversion_program              16124 non-null  object 
 5   referral_date                  16124 non-null  object 
 6   diversion_count                16124 non-null  int64  
 7   primary_charge_offense_title   16124 non-null  object 
 8   statute                        16124 non-null  object 
 9   race                           16124 non-null  object 
 10  gender                         16124 non-null  object 
 11  diversion_result               11769 non-null  object 
 12  diversion_closed_date          11769 non-null  object 
 13  incident_city                  16124 non-null  object 
 14  arrest_date                    16124 non-null  object 
 15  age_at_incident                16103 non-null  float64
dtypes: float64(1), int64(3), object(12)
memory usage: 2.0+ MB
```

In [ ]:
```
# Check first 5 entries in div_prog_df
diversion_df.head(5)
```

Out[ ]:

	case_id	case_participant_id	received_date	offense_category	diversion_program	referral_date	diversi
0	274959941057	2193361164603	01/01/2011 12:00:00 AM	Retail Theft	DS	06/17/2013 12:00:00 AM	
1	274959941057	2193361164603	01/01/2011 12:00:00 AM	Retail Theft	VC	08/11/2011 12:00:00 AM	
2	274962262468	2193390288678	01/02/2011 12:00:00 AM	Retail Theft	MHC	09/14/2012 12:00:00 AM	
3	274971231556	2193494552866	01/03/2011 12:00:00 AM	Narcotics	DS	01/19/2011 12:00:00 AM	
4	274983577241	2193661725056	01/04/2011 12:00:00 AM	Narcotics	DS	01/19/2011 12:00:00 AM	

Sentencing Dataset: Data Cleaning

Remove Unnecessary Columns

First, I want to remove any unnecessary columns that won't be used for implementing the model. \
Specifically, I will only keep the following columns in sentencing_df:

- **case_participant_id** (integer identifying each defendant - will be used to merge the dataframes)
- **offense_category** (string indicating offense category of crime)
- **arrest_date** (string indicating date of the arrest)
- **sentence_judge** (string indicating the judge presiding over the case)
- **sentence_type** (string indicating type of sentence issued)
- **age_at_incident** (integer indicating the defendant's age at the time of the incident)

- **race** (string indicating the defendant's race)
- **gender** (string indicating the defendant's gender)
- **incident_city** (string indicating the city the incident occured)

In [ ]:
```
# Keep the columns specified above in sentencing_df and save them in cleaned_sentencing_
cleaned_sentencing_df = sentencing_df.copy()
cleaned_sentencing_df = cleaned_sentencing_df[["case_participant_id", "offense_category"
                                               "sentence_type", "age_at_incident", "race
cleaned_sentencing_df.head()
```

Out[ ]:

	case_participant_id	offense_category	arrest_date	sentence_judge	sentence_type	age_at_incident	race
0	670458920516	PROMIS Conversion	2011-07-27 19:39:00	Mary Margaret Brosnahan	Prison	31.0	Black
1	670458920516	PROMIS Conversion	2011-07-27 19:39:00	Mary Margaret Brosnahan	Prison	31.0	Black
2	386948574911	Attempt Homicide	2012-08-07 09:00:00	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]
3	386948574911	Attempt Homicide	2012-08-07 09:00:00	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]
4	386948574911	Attempt Homicide	2012-08-07 09:00:00	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]

Here, I do the following in order:

- Remove NaN values
- Change type of 'arrest_date' to datetime

In [ ]:
```
# Remove NaN values in cleaned_sentencing_df
cleaned_sentencing_df.dropna(inplace=True)
cleaned_sentencing_df.isna().sum()
```

Out[ ]:
```
case_participant_id    0
offense_category       0
arrest_date            0
sentence_judge         0
sentence_type          0
age_at_incident        0
race                   0
gender                 0
incident_city          0
dtype: int64
```

In [ ]:
```
# Convert to 'arrest_date' datetime
cleaned_sentencing_df['arrest_date'] = pd.to_datetime(cleaned_sentencing_df['arrest_date
```

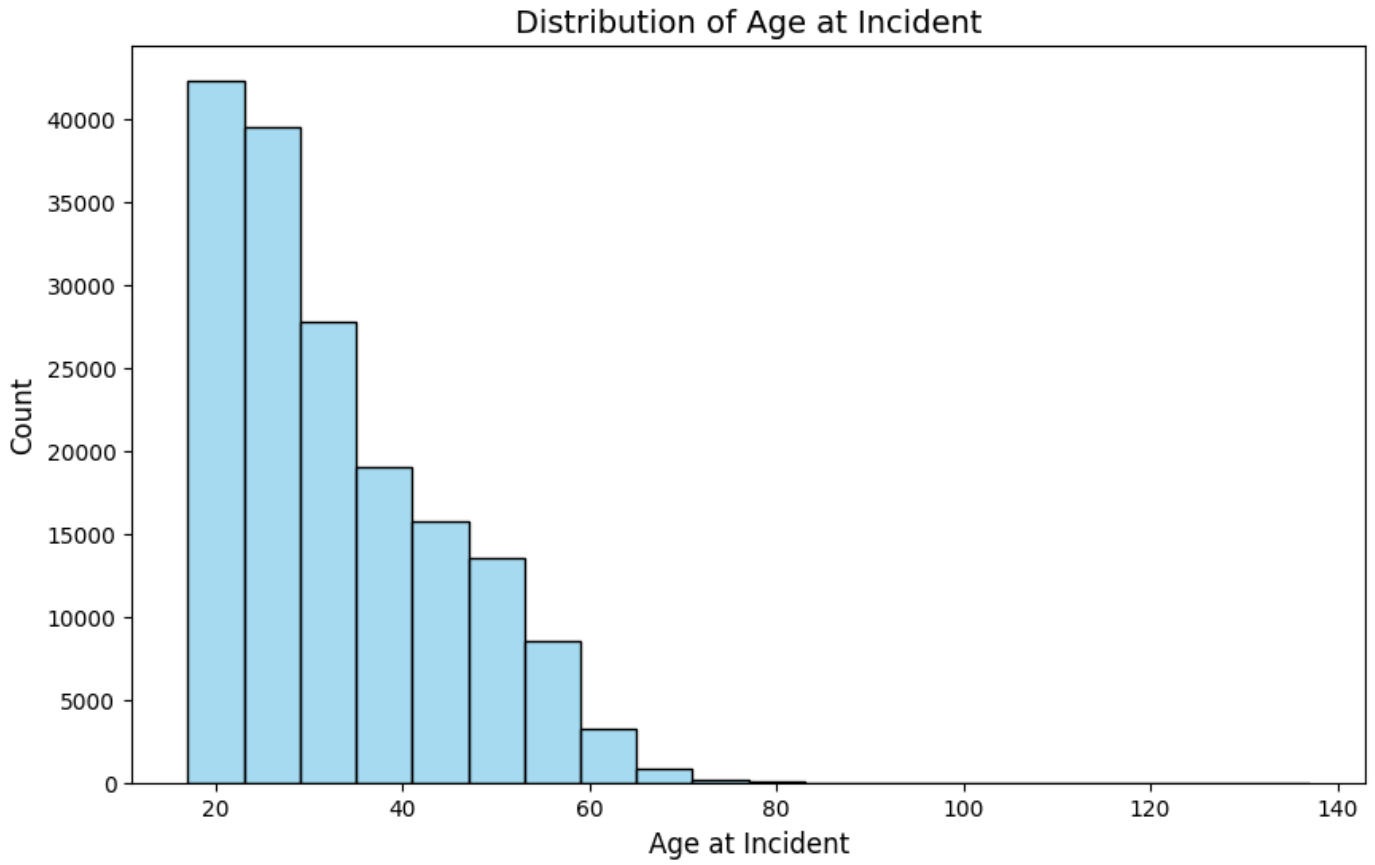
In [ ]:
```
# Reset index
cleaned_sentencing_df.reset_index(drop=True, inplace=True)
```

In [ ]:
```
# Group by 'case_participant_id' and count occurrences
counts = cleaned_sentencing_df.groupby('case_participant_id').size()

# Create a Series indicating whether each ID is repeated or not
repeated_ids = counts[cleaned_sentencing_df['case_participant_id']].apply(lambda x: x >
```

```
# Assign the result to the 'Repeated' column
cleaned_sentencing_df['repeated'] = repeated_ids.values
```

Sentencing Data: Initial EDA

In [ ]:
```
plt.figure(figsize=(10, 6))  # Set the figure size (width, height)

# Create a bar plot of the distribution of 'age_at_incident'
sns.histplot(data=cleaned_sentencing_df, x='age_at_incident', bins=20, kde=False, color=

# Set plot labels and title
plt.xlabel('Age at Incident', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Age at Incident', fontsize=14)

# Show the plot
plt.show()
```



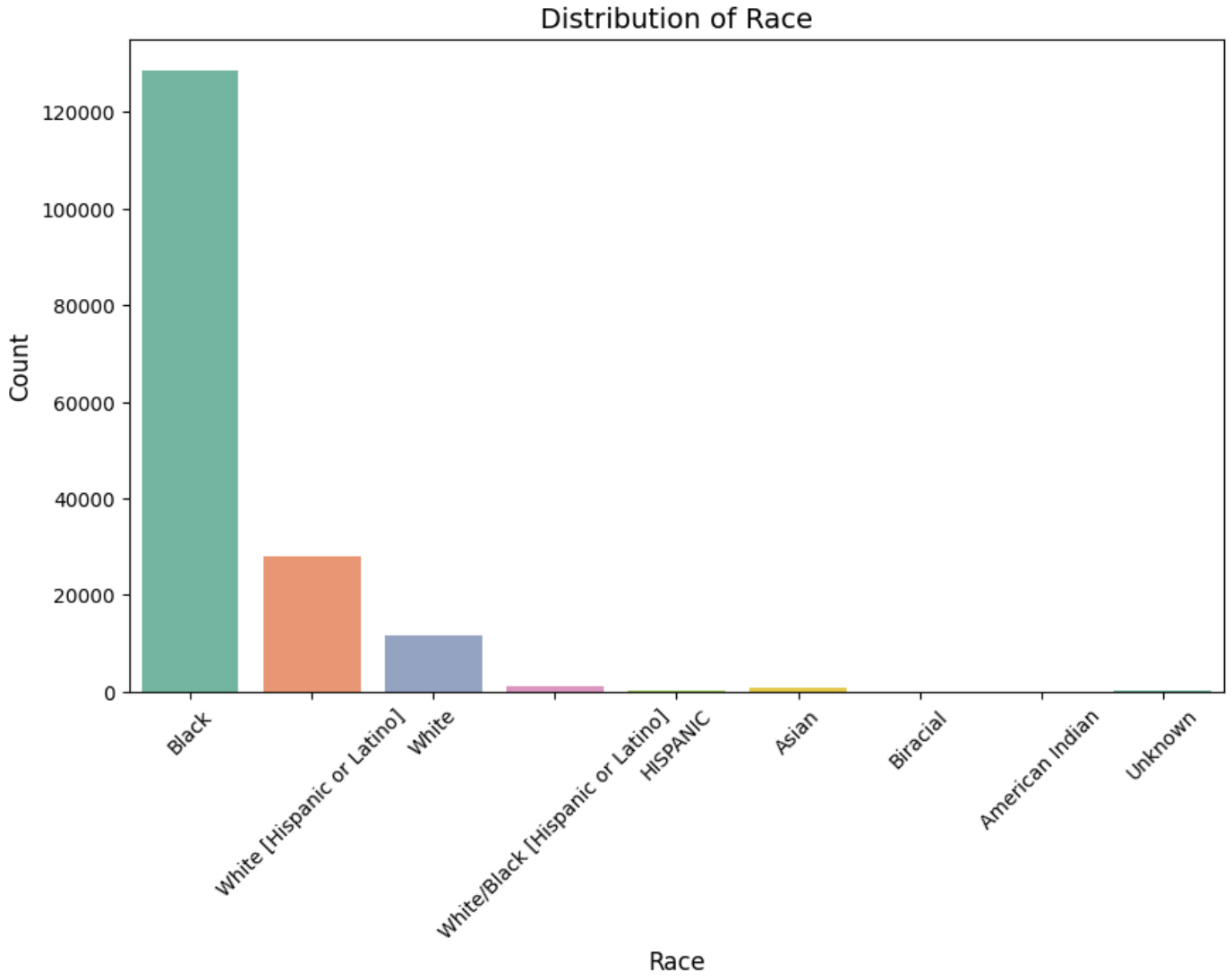
The graph above shows that the most frequent age at incident for offenders in Chicago is between 20 to 30 years old, with a long tail to the right due to a decreasing number of older offenders.

As the above chart shows,

In [ ]:
```
# Set figure size
plt.figure(figsize=(10, 6))

# Plot count plot of race
sns.countplot(data=cleaned_sentencing_df, x='race', palette='Set2')

# Set plot labels and title
plt.xlabel('Race', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Race', fontsize=14)
```

```
# Rotate x-axis labels for better readability (optional)
plt.xticks(rotation=45)

# Show the plot
plt.show()
```

```
<ipython-input-15-263069dc64c8>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=cleaned_sentencing_df, x='race', palette='Set2')
```



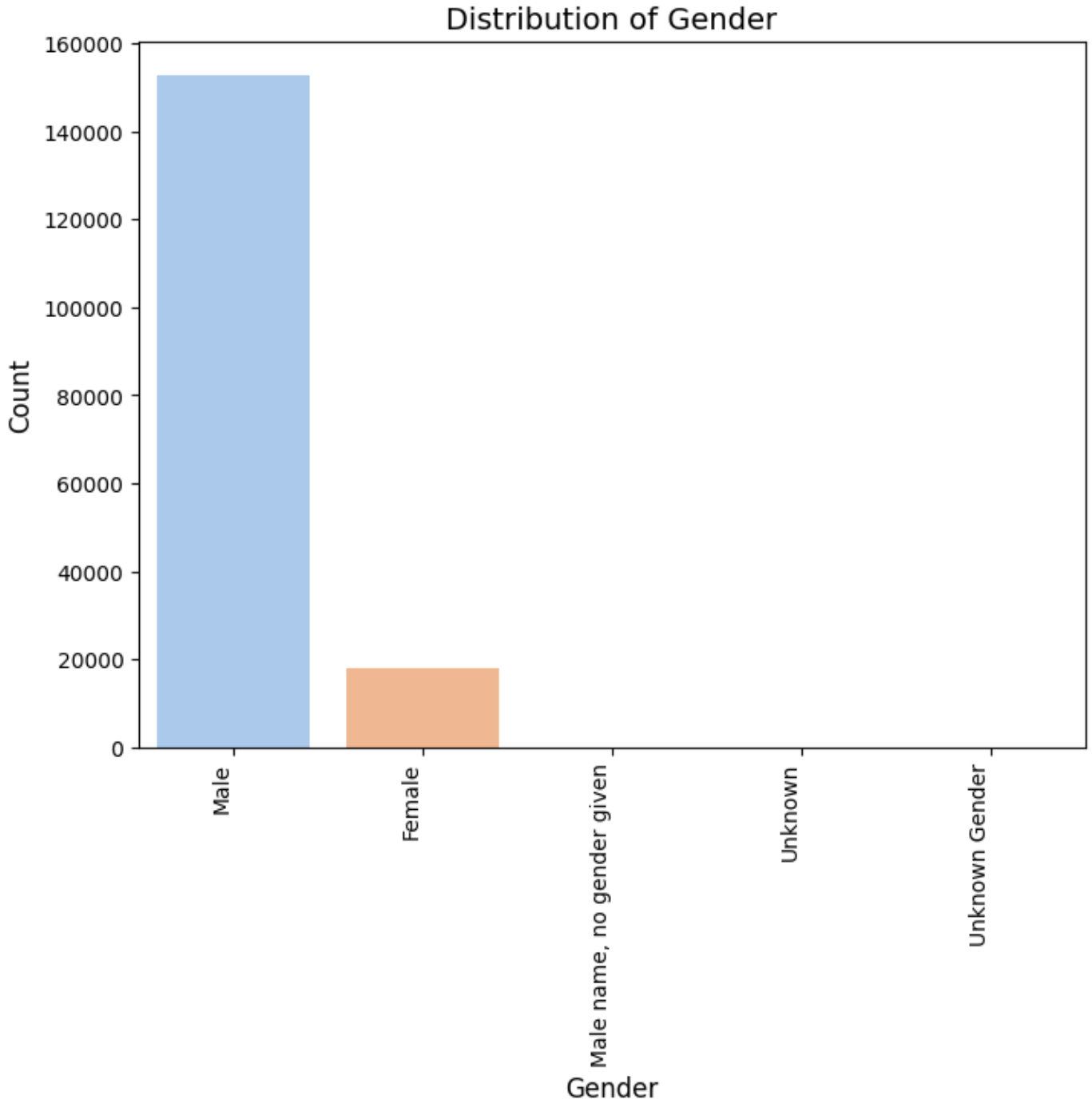
The graph above shows that the most common offenders are

In [ ]:

```
# Set figure size
plt.figure(figsize=(8, 6))

# Plot count plot of gender
sns.countplot(data=cleaned_sentencing_df, x='gender', palette='pastel')

# Set plot labels and title
plt.xlabel('Gender', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Gender', fontsize=14)

# Customize x-axis labels spacing and rotation
plt.xticks(rotation=90, ha='right')  # Adjust rotation and alignment of x-axis labels
```

```
# Show the plot
plt.show()
```

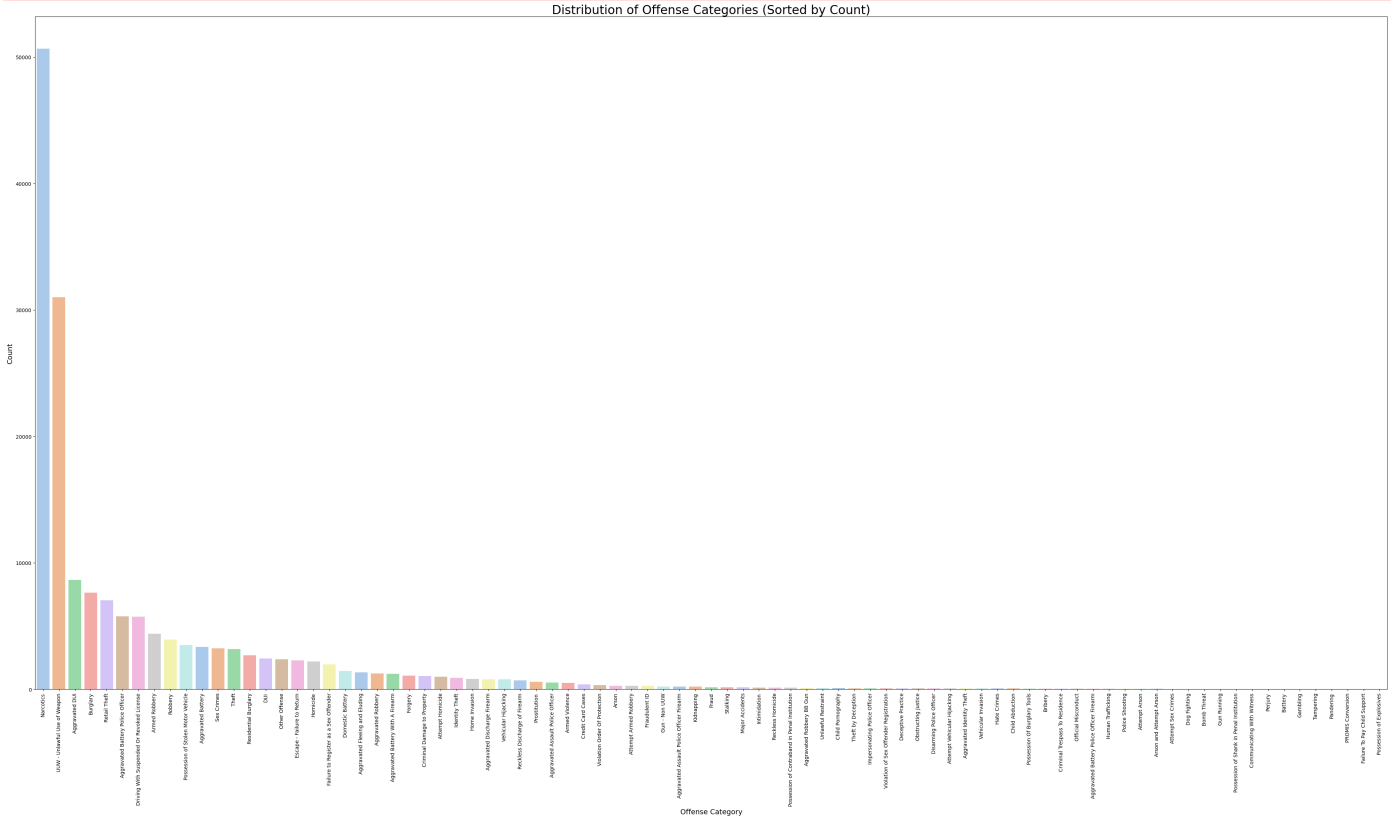
```
<ipython-input-16-090adc65d3ed>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=cleaned_sentencing_df, x='gender', palette='pastel')
```



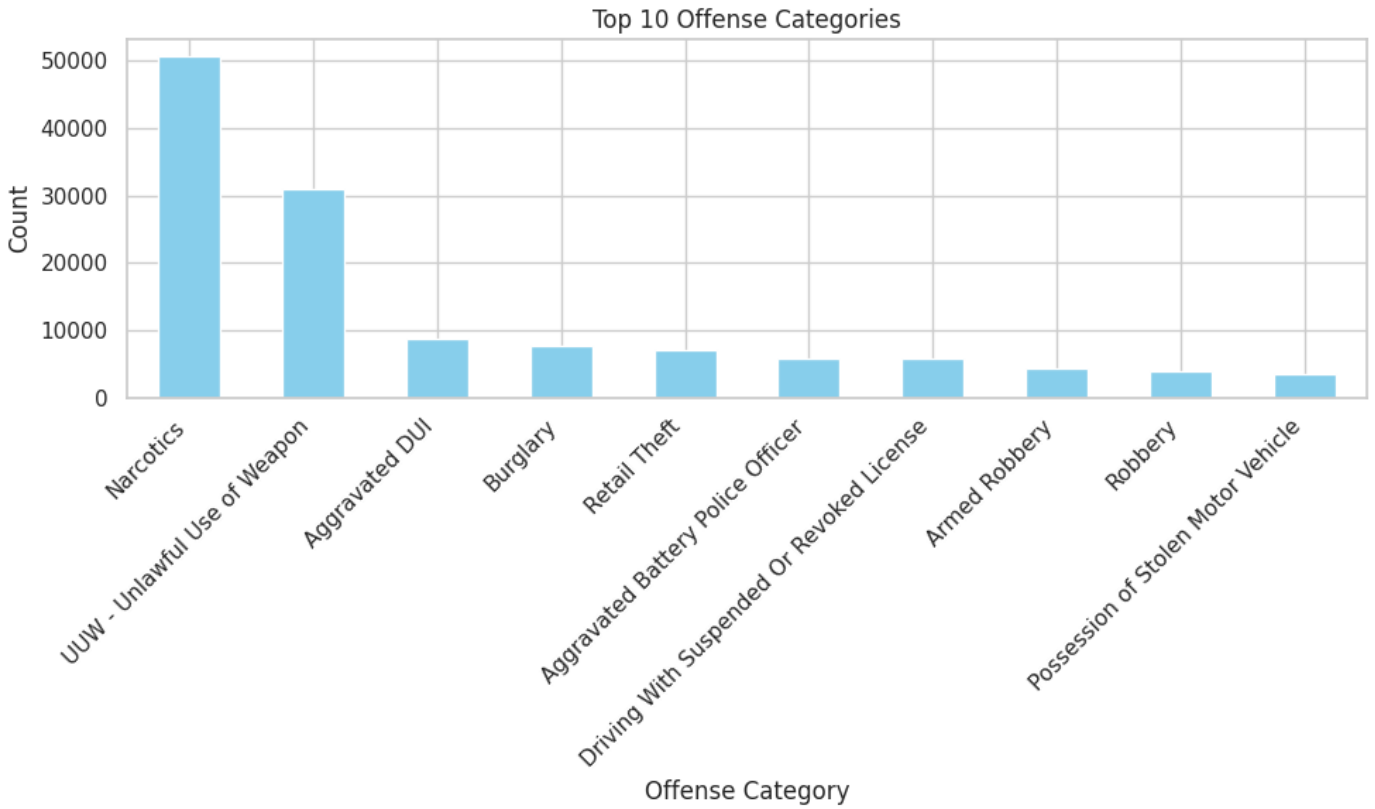
In [ ]:
```
# Calculate value counts of offense_category
offense_counts = cleaned_sentencing_df['offense_category'].value_counts()

# Sort offense categories by count in descending order
sorted_offense_categories = offense_counts.index.tolist()

# Set figure size
plt.figure(figsize=(48, 24))

# Plot count plot of offense_category (sorted)
sns.countplot(data=cleaned_sentencing_df, x='offense_category', order=sorted_offense_cat
```

```
plt.title('Distribution of Offense Categories (Sorted by Count)', fontsize=24)
plt.xlabel('Offense Category', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(rotation=90)  # Rotate x-axis labels for better readability

# Show the plot
plt.show()
```

```
<ipython-input-17-2b9e7dbb1b96>:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=cleaned_sentencing_df, x='offense_category', order=sorted_offense_categories, palette='pastel')
```

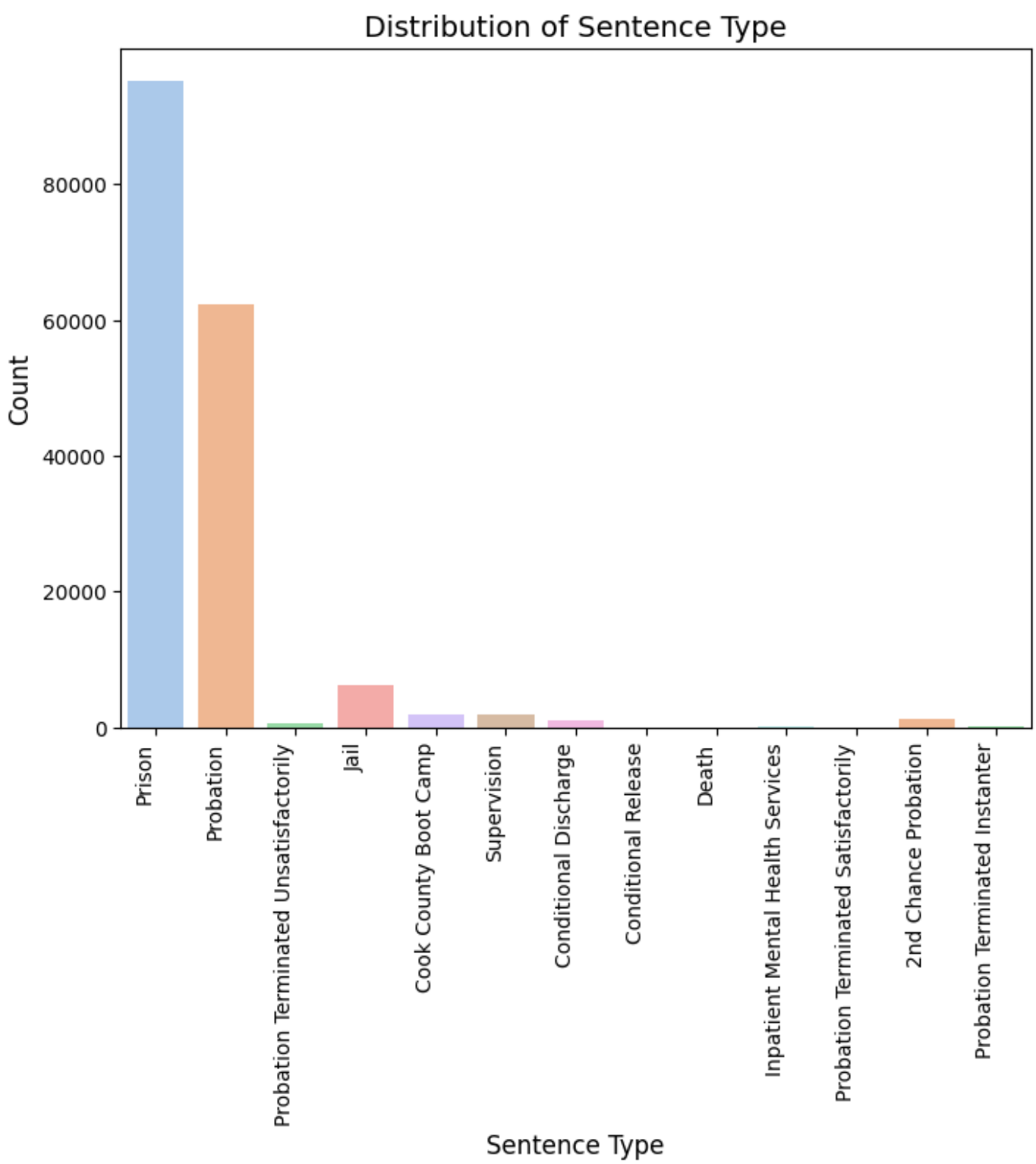


In [ ]:
```
top_10_offense_categories = cleaned_sentencing_df['offense_category'].value_counts().nla

# Plotting
plt.figure(figsize=(10, 6))
top_10_offense_categories.plot(kind='bar', color='skyblue')
plt.title('Top 10 Offense Categories')
plt.xlabel('Offense Category')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



In [ ]:
```python
# Set figure size
plt.figure(figsize=(8, 6))

# Plot count plot of gender
sns.countplot(data=cleaned_sentencing_df, x='sentence_type', palette='pastel')

# Set plot labels and title
plt.xlabel('Sentence Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Sentence Type', fontsize=14)

# Customize x-axis labels spacing and rotation
plt.xticks(rotation=90, ha='right')  # Adjust rotation and alignment of x-axis labels

# Show the plot
plt.show()
```

```
<ipython-input-18-a330a42a9da2>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=cleaned_sentencing_df, x='sentence_type', palette='pastel')
```



Sentencing Data: Data Preprocessing & Feature Engineering

In [ ]:
```
# Check dtypes of the columns in cleaned_sentencing_df
cleaned_sentencing_df.dtypes
```

Out[ ]:
```
case_participant_id             int64
offense_category               object
arrest_date            datetime64[ns]
sentence_judge                 object
sentence_type                  object
age_at_incident               float64
race                           object
gender                         object
incident_city                  object
```

```
repeated                        bool
dtype: object
```

In [ ]:
```
# Extract year, month, day from 'arrest_date' and store them in new columns in df
cleaned_sentencing_df['arrest_year'] = cleaned_sentencing_df['arrest_date'].dt.year.asty
cleaned_sentencing_df['arrest_month'] = cleaned_sentencing_df['arrest_date'].dt.month.as
cleaned_sentencing_df['arrest_day'] = cleaned_sentencing_df['arrest_date'].dt.day.astype

# Define a function for extracting and categorizing the arrest time
def categorize_time(hour):
    if 6 <= hour < 12:
        return 'Morning'
    elif 12 <= hour < 18:
        return 'Afternoon'
    elif 18 <= hour < 22:
        return 'Evening'
    else:
        return 'Night'

# Extract and categorize arrest_time into four catgories: Morning, Afternoon, Evening, o
cleaned_sentencing_df['arrest_time'] = cleaned_sentencing_df['arrest_date'].dt.hour.appl
cleaned_sentencing_df.head()
```

Out[ ]:

	case_participant_id	offense_category	arrest_date	sentence_judge	sentence_type	age_at_incident	race
0	670458920516	PROMIS Conversion	2011-07-27 19:39:00	Mary Margaret Brosnahan	Prison	31.0	Black
1	670458920516	PROMIS Conversion	2011-07-27 19:39:00	Mary Margaret Brosnahan	Prison	31.0	Black
2	386948574911	Attempt Homicide	2012-08-07 09:00:00	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]
3	386948574911	Attempt Homicide	2012-08-07 09:00:00	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]
4	386948574911	Attempt Homicide	2012-08-07 09:00:00	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]

In [ ]:
```
# Let's now remove 'arrest_date' column from the dataframe
cleaned_sentencing_df.drop('arrest_date', axis=1, inplace=True)
cleaned_sentencing_df.dtypes
```

Out[ ]:
```
case_participant_id      int64
offense_category        object
sentence_judge          object
sentence_type           object
age_at_incident        float64
race                    object
gender                  object
incident_city           object
repeated                  bool
arrest_year            float64
arrest_month           float64
arrest_day             float64
arrest_time             object
dtype: object
```

In [ ]:
```
# Identify numerical and categorical columns
numerical_features = sorted(cleaned_sentencing_df.select_dtypes(include="float64").colum
```

```
categorical_features = sorted(cleaned_sentencing_df.select_dtypes(include=["object", "bo

print(f'There are {len(categorical_features)} categorical variables')
print(f'There are {len(numerical_features)} numerical variables')
```

```
There are 8 categorical variables
There are 4 numerical variables
```

In [ ]:
```
categorical_features
```

Out[ ]:
```
['arrest_time',
 'gender',
 'incident_city',
 'offense_category',
 'race',
 'repeated',
 'sentence_judge',
 'sentence_type']
```

First, I preprocess categorical variables:

- Identify binary categorical variables and change them with 0 and 1
- Identify ordinal and nominal categorical variables

In [ ]:
```
# For every 'object' column in cleaned_sentencing_df, see if it has 2 unique values and
binary_cs_df = cleaned_sentencing_df.copy()
binary_columns = [col for col in binary_cs_df.columns if binary_cs_df[col].nunique() ==
binary_columns
```

Out[ ]:
```
['repeated']
```

In [ ]:
```
# Create encoder
encoder = OneHotEncoder(drop='first')

# Encode binary columns
encoded_columns = encoder.fit_transform(binary_cs_df[binary_columns])
```

In [ ]:
```
# Replace original binary columns with encoded values
binary_cs_df = binary_cs_df.drop(columns=binary_columns)

# Convert encoded values to 1.0/0.0
encoded_df = pd.DataFrame(encoded_columns.toarray(), columns=binary_columns)

# Concatenate the encoded DataFrame with the original DataFrame
binary_cs_df = pd.concat([binary_cs_df, encoded_df], axis=1)
binary_cs_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gender	inc
0	670458920516	PROMIS Conversion	Mary Margaret Brosnahan	Prison	31.0	Black	Male	
1	670458920516	PROMIS Conversion	Mary Margaret Brosnahan	Prison	31.0	Black	Male	
2	386948574911	Attempt Homicide	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]	Male	
3	386948574911	Attempt Homicide	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]	Male	
4	386948574911	Attempt Homicide	Nicholas R Ford	Prison	39.0	White [Hispanic	Male	

						or Latino]		

For 'incident_city' column, since there were 133 unique values, doing regular nominal category encoding would not be helpful as it would dramatically increase the number of features. Therefore, here, I categorize cities into cities with high crime (1.0) vs low crime (0.0) rate.

In [ ]:
```
# Calculate the frequency of each city
city_frequency = binary_cs_df['incident_city'].value_counts()

# Define the threshold based on the 75th percentile
threshold = np.percentile(city_frequency, 75)

# Create a boolean mask indicating whether each city's frequency is above (1.0) or below
high_crime_mask = city_frequency >= threshold

# Create a dictionary mapping each city to its crime frequency category
city_crime_category = {city: 1.0 if high_crime_mask[city] else 0.0 for city in city_freq

# Map the city to its crime category using the dictionary
binary_cs_df['incident_city'] = binary_cs_df['incident_city'].map(city_crime_category)
binary_cs_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gender	inc
0	670458920516	PROMIS Conversion	Mary Margaret Brosnahan	Prison	31.0	Black	Male	
1	670458920516	PROMIS Conversion	Mary Margaret Brosnahan	Prison	31.0	Black	Male	
2	386948574911	Attempt Homicide	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]	Male	
3	386948574911	Attempt Homicide	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]	Male	
4	386948574911	Attempt Homicide	Nicholas R Ford	Prison	39.0	White [Hispanic or Latino]	Male	

I do the same for 'sentence_judge' column as well. I categorize judges into judges with high case load (1.0) vs low case load (0.0).

In [ ]:
```
# Calculate the frequency of each judge
judge_frequency = binary_cs_df['sentence_judge'].value_counts()

# Define the threshold based on the 75th percentile
threshold_judge = np.percentile(judge_frequency, 75)

# Create a boolean mask indicating whether each judge's frequency is above or below the
high_case_load_mask = judge_frequency >= threshold_judge

# Create a dictionary mapping each judge to their case load category
judge_case_category = {judge: 1.0 if high_case_load_mask[judge] else 0.0 for judge in ju

# Map the judge to their case load category using the dictionary
binary_cs_df['sentence_judge'] = binary_cs_df['sentence_judge'].map(judge_case_category)
binary_cs_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gender	inc
0	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	Male	
1	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	Male	
2	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	Male	
3	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	Male	
4	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	Male	

In [ ]:
```
# Create copy of binary_cs_df and save in ordered_cs_df
ordered_cs_df = binary_cs_df.copy()

# Identify the columns that represent ordered categories and store them in ordered_featu
ordered_features = ['arrest_time']
```

In [ ]:
```
ordered_cs_df['arrest_time'].unique()
```

Out[ ]:
```
array(['Evening', 'Morning', 'Afternoon', 'Night'], dtype=object)
```

In [ ]:
```
# Extract the ordering of each ordered feature and place them in a list.
# Use a logical ordering of the categories in increasing order
ordered_categories = [
    ['Morning', 'Afternoon', 'Evening', 'Night']
]
```

In [ ]:
```
# Apply Ordinal Encoding to ordered columns in the dataset.
encoder = OrdinalEncoder(categories=ordered_categories)

# Fit and transform the ordered features
ordered_cs_df[ordered_features] = encoder.fit_transform(ordered_cs_df[ordered_features])
ordered_cs_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gender	inc
0	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	Male	
1	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	Male	
2	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	Male	
3	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	Male	
4	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	Male	

Binary Encoding for Gender

Since there are only 11 values that are not Male or Female, I can use binary encoding here.

In [ ]:
```
ordered_cs_df['gender'].value_counts()
```

Out[ ]:
```
gender
Male                          152871
Female                         17806
Unknown                            6
Unknown Gender                     4
Male name, no gender given         1
Name: count, dtype: int64
```

In [ ]:
```
replace_map = {
    'Male': 0,
    'Female': 1
}

# Replace values in the 'gender' column based on the specified mapping
ordered_cs_df['gender'] = ordered_cs_df['gender'].replace(replace_map)
ordered_cs_df['gender'] = ordered_cs_df['gender'].where(ordered_cs_df['gender'].isin([0,

# Set all other values (e.g., 'Other', 'Unknown') to 1, since "Male" is the mode for thi
ordered_cs_df['gender'] = ordered_cs_df['gender'].fillna(1)
```

In [ ]:
```
ordered_cs_df['gender'].value_counts()
```

Out[ ]:
```
gender
0    152871
1     17817
Name: count, dtype: int64
```

In [ ]:
```
ordered_cs_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gender	inc
0	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	0	
1	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	0	
2	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0	
3	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0	
4	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0	

Encoding Unordered Features

In [ ]:
```
# Identify the columns that represent unordered categories and store them in unordered_f
unordered_features = ['offense_category', 'race', 'sentence_type']
```

In [ ]:
```
# Create copy of ordered_cs_df and save in encoded_cs_df
```

```
encoded_cs_df = ordered_cs_df.copy()

# Apply One Hot Encoding to the unordered features
encoder = OneHotEncoder(drop='first')
encoded_features = encoder.fit_transform(encoded_cs_df[unordered_features])

# Replace the unordered features in encoded_cs_df
encoded_feature_names = encoder.get_feature_names_out(unordered_features)
encoded_df = pd.DataFrame(encoded_features.toarray(), columns=encoded_feature_names)

# Drop original unordered columns
encoded_cs_df = encoded_cs_df.drop(unordered_features, axis=1)

# Concatenate the encoded DataFrame with the original DataFrame
encoded_cs_df = pd.concat([encoded_cs_df, encoded_df], axis=1)
encoded_cs_df.rename(columns=str.lower, inplace=True)
encoded_cs_df.head()
```

Out[ ]:

	case_participant_id	sentence_judge	age_at_incident	gender	incident_city	arrest_year	arrest_month	arrest
0	670458920516	1.0	31.0	0	1.0	2011.0	7.0	
1	670458920516	1.0	31.0	0	1.0	2011.0	7.0	
2	386948574911	1.0	39.0	0	1.0	2012.0	8.0	
3	386948574911	1.0	39.0	0	1.0	2012.0	8.0	
4	386948574911	1.0	39.0	0	1.0	2012.0	8.0	

In [ ]:
```
encoded_cs_df.dtypes
```

Out[ ]:
```
case_participant_id                                          int64
sentence_judge                                             float64
age_at_incident                                            float64
gender                                                       int64
incident_city                                              float64
arrest_year                                                float64
arrest_month                                               float64
arrest_day                                                 float64
arrest_time                                                float64
repeated                                                   float64
offense_category_aggravated assault police officer firearm float64
offense_category_aggravated battery                        float64
offense_category_aggravated battery police officer         float64
offense_category_aggravated battery police officer firearm float64
offense_category_aggravated battery with a firearm         float64
offense_category_aggravated dui                            float64
offense_category_aggravated discharge firearm              float64
offense_category_aggravated fleeing and eluding            float64
offense_category_aggravated identity theft                 float64
offense_category_aggravated robbery                        float64
offense_category_aggravated robbery bb gun                 float64
offense_category_armed robbery                             float64
offense_category_armed violence                            float64
offense_category_arson                                     float64
offense_category_arson and attempt arson                   float64
offense_category_attempt armed robbery                     float64
offense_category_attempt arson                             float64
offense_category_attempt homicide                          float64
offense_category_attempt sex crimes                        float64
offense_category_attempt vehicular hijacking               float64
offense_category_battery                                   float64
offense_category_bomb threat                               float64
```

offense_category_bribery	float64
offense_category_burglary	float64
offense_category_child abduction	float64
offense_category_child pornography	float64
offense_category_communicating with witness	float64
offense_category_credit card cases	float64
offense_category_criminal damage to property	float64
offense_category_criminal trespass to residence	float64
offense_category_dui	float64
offense_category_deceptive practice	float64
offense_category_disarming police officer	float64
offense_category_dog fighting	float64
offense_category_domestic battery	float64
offense_category_driving with suspended or revoked license	float64
offense_category_escape - failure to return	float64
offense_category_failure to pay child support	float64
offense_category_failure to register as a sex offender	float64
offense_category_forgery	float64
offense_category_fraud	float64
offense_category_fraudulent id	float64
offense_category_gambling	float64
offense_category_gun - non uuw	float64
offense_category_gun running	float64
offense_category_hate crimes	float64
offense_category_home invasion	float64
offense_category_homicide	float64
offense_category_human trafficking	float64
offense_category_identity theft	float64
offense_category_impersonating police officer	float64
offense_category_intimidation	float64
offense_category_kidnapping	float64
offense_category_major accidents	float64
offense_category_narcotics	float64
offense_category_obstructing justice	float64
offense_category_official misconduct	float64
offense_category_other offense	float64
offense_category_promis conversion	float64
offense_category_pandering	float64
offense_category_perjury	float64
offense_category_police shooting	float64
offense_category_possession of burglary tools	float64
offense_category_possession of contraband in penal institution	float64
offense_category_possession of explosives	float64
offense_category_possession of shank in penal institution	float64
offense_category_possession of stolen motor vehicle	float64
offense_category_prostitution	float64
offense_category_reckless discharge of firearm	float64
offense_category_reckless homicide	float64
offense_category_residential burglary	float64
offense_category_retail theft	float64
offense_category_robbery	float64
offense_category_sex crimes	float64
offense_category_stalking	float64
offense_category_tampering	float64
offense_category_theft	float64
offense_category_theft by deception	float64
offense_category_uuw - unlawful use of weapon	float64
offense_category_unlawful restraint	float64
offense_category_vehicular hijacking	float64
offense_category_vehicular invasion	float64
offense_category_violation order of protection	float64
offense_category_violation of sex offender registration	float64
race_asian	float64
race_biracial	float64
race_black	float64
race_hispanic	float64

```
race_unknown                                                    float64
race_white                                                      float64
race_white [hispanic or latino]                                 float64
race_white/black [hispanic or latino]                           float64
sentence_type_conditional discharge                             float64
sentence_type_conditional release                               float64
sentence_type_cook county boot camp                             float64
sentence_type_death                                             float64
sentence_type_inpatient mental health services                  float64
sentence_type_jail                                              float64
sentence_type_prison                                            float64
sentence_type_probation                                         float64
sentence_type_probation terminated instanter                    float64
sentence_type_probation terminated satisfactorily               float64
sentence_type_probation terminated unsatisfactorily             float64
sentence_type_supervision                                       float64
dtype: object
```

Check for Outliers

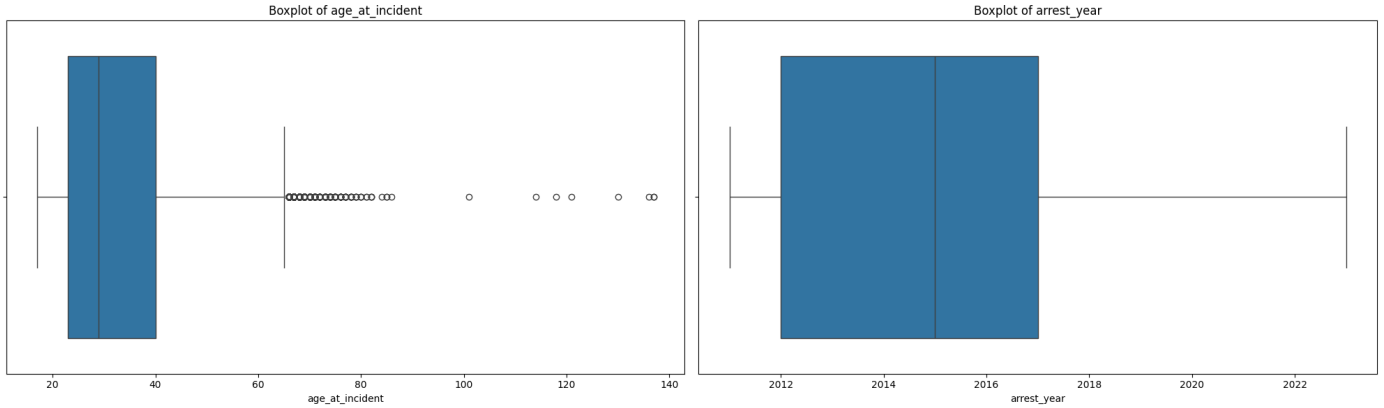
In [ ]:
```
encoded_cs_df.loc[encoded_cs_df['age_at_incident'].idxmax()]
```

Out[ ]:
```
case_participant_id                                             2.732413e+12
sentence_judge                                                  1.000000e+00
age_at_incident                                                 1.370000e+02
gender                                                          0.000000e+00
incident_city                                                   1.000000e+00
arrest_year                                                     2.019000e+03
arrest_month                                                    1.000000e+01
arrest_day                                                      1.400000e+01
arrest_time                                                     2.000000e+00
repeated                                                        0.000000e+00
offense_category_aggravated assault police officer firearm      0.000000e+00
offense_category_aggravated battery                             0.000000e+00
offense_category_aggravated battery police officer              0.000000e+00
offense_category_aggravated battery police officer firearm      0.000000e+00
offense_category_aggravated battery with a firearm              0.000000e+00
offense_category_aggravated dui                                 0.000000e+00
offense_category_aggravated discharge firearm                   0.000000e+00
offense_category_aggravated fleeing and eluding                 0.000000e+00
offense_category_aggravated identity theft                      0.000000e+00
offense_category_aggravated robbery                             0.000000e+00
offense_category_aggravated robbery bb gun                      0.000000e+00
offense_category_armed robbery                                  0.000000e+00
offense_category_armed violence                                 0.000000e+00
offense_category_arson                                          0.000000e+00
offense_category_arson and attempt arson                        0.000000e+00
offense_category_attempt armed robbery                          0.000000e+00
offense_category_attempt arson                                  0.000000e+00
offense_category_attempt homicide                               0.000000e+00
offense_category_attempt sex crimes                             0.000000e+00
offense_category_attempt vehicular hijacking                    0.000000e+00
offense_category_battery                                        0.000000e+00
offense_category_bomb threat                                    0.000000e+00
offense_category_bribery                                        0.000000e+00
offense_category_burglary                                       0.000000e+00
offense_category_child abduction                                0.000000e+00
offense_category_child pornography                              0.000000e+00
offense_category_communicating with witness                     0.000000e+00
offense_category_credit card cases                              0.000000e+00
offense_category_criminal damage to property                    0.000000e+00
offense_category_criminal trespass to residence                 0.000000e+00
offense_category_dui                                            0.000000e+00
offense_category_deceptive practice                             0.000000e+00
offense_category_disarming police officer                       0.000000e+00
```

offense_category_dog fighting	0.000000e+00
offense_category_domestic battery	0.000000e+00
offense_category_driving with suspended or revoked license	1.000000e+00
offense_category_escape - failure to return	0.000000e+00
offense_category_failure to pay child support	0.000000e+00
offense_category_failure to register as a sex offender	0.000000e+00
offense_category_forgery	0.000000e+00
offense_category_fraud	0.000000e+00
offense_category_fraudulent id	0.000000e+00
offense_category_gambling	0.000000e+00
offense_category_gun - non uuw	0.000000e+00
offense_category_gun running	0.000000e+00
offense_category_hate crimes	0.000000e+00
offense_category_home invasion	0.000000e+00
offense_category_homicide	0.000000e+00
offense_category_human trafficking	0.000000e+00
offense_category_identity theft	0.000000e+00
offense_category_impersonating police officer	0.000000e+00
offense_category_intimidation	0.000000e+00
offense_category_kidnapping	0.000000e+00
offense_category_major accidents	0.000000e+00
offense_category_narcotics	0.000000e+00
offense_category_obstructing justice	0.000000e+00
offense_category_official misconduct	0.000000e+00
offense_category_other offense	0.000000e+00
offense_category_promis conversion	0.000000e+00
offense_category_pandering	0.000000e+00
offense_category_perjury	0.000000e+00
offense_category_police shooting	0.000000e+00
offense_category_possession of burglary tools	0.000000e+00
offense_category_possession of contraband in penal institution	0.000000e+00
offense_category_possession of explosives	0.000000e+00
offense_category_possession of shank in penal institution	0.000000e+00
offense_category_possession of stolen motor vehicle	0.000000e+00
offense_category_prostitution	0.000000e+00
offense_category_reckless discharge of firearm	0.000000e+00
offense_category_reckless homicide	0.000000e+00
offense_category_residential burglary	0.000000e+00
offense_category_retail theft	0.000000e+00
offense_category_robbery	0.000000e+00
offense_category_sex crimes	0.000000e+00
offense_category_stalking	0.000000e+00
offense_category_tampering	0.000000e+00
offense_category_theft	0.000000e+00
offense_category_theft by deception	0.000000e+00
offense_category_uuw - unlawful use of weapon	0.000000e+00
offense_category_unlawful restraint	0.000000e+00
offense_category_vehicular hijacking	0.000000e+00
offense_category_vehicular invasion	0.000000e+00
offense_category_violation order of protection	0.000000e+00
offense_category_violation of sex offender registration	0.000000e+00
race_asian	0.000000e+00
race_biracial	0.000000e+00
race_black	1.000000e+00
race_hispanic	0.000000e+00
race_unknown	0.000000e+00
race_white	0.000000e+00
race_white [hispanic or latino]	0.000000e+00
race_white/black [hispanic or latino]	0.000000e+00
sentence_type_conditional discharge	0.000000e+00
sentence_type_conditional release	0.000000e+00
sentence_type_cook county boot camp	0.000000e+00
sentence_type_death	0.000000e+00
sentence_type_inpatient mental health services	0.000000e+00
sentence_type_jail	0.000000e+00
sentence_type_prison	0.000000e+00

```
sentence_type_probation                                  1.000000e+00
sentence_type_probation terminated instanter             0.000000e+00
sentence_type_probation terminated satisfactorily        0.000000e+00
sentence_type_probation terminated unsatisfactorily      0.000000e+00
sentence_type_supervision                                0.000000e+00
Name: 149595, dtype: float64
```

In [ ]:
```python
# Select numeric columns
numeric_columns = ['age_at_incident', 'arrest_year']

# Set up subplots
fig, axes = plt.subplots(nrows=1, ncols=len(numeric_columns), figsize=(10 * len(numeric_

# Visualize distributions and outliers for each numeric column
for i, column in enumerate(numeric_columns):
    sns.boxplot(x=encoded_cs_df[column], ax=axes[i])
    axes[i].set_title(f'Boxplot of {column}')
    axes[i].set_xlabel(column)

plt.tight_layout()
plt.show()
```



In [ ]:
```python
# Define a function to remove outliers from a encoded_cs_df
def remove_outliers(df, columns, threshold=1.5):
    """
    Remove outliers from a DataFrame based on the specified columns and threshold.

    Args:
        df (DataFrame): The input DataFrame.
        columns (list): A list of column names to consider for outlier removal.
        threshold (float): The threshold multiplier for defining outliers (default is 1.

    Returns:
        DataFrame: The DataFrame with outliers removed.
    """
    cleaned_df = df.copy()
    for col in columns:
        # Calculate Q1, Q3, and IQR
        Q1 = np.percentile(cleaned_df[col], 25)
        Q3 = np.percentile(cleaned_df[col], 75)
        IQR = Q3 - Q1

        # Define the outlier boundaries
        lower_bound = Q1 - threshold * IQR
        upper_bound = Q3 + threshold * IQR

        # Remove outliers
        cleaned_df = cleaned_df[(cleaned_df[col] >= lower_bound) & (cleaned_df[col] <= u

    return cleaned_df

# Define the columns to consider for outlier removal
```

```
numeric_columns = ['age_at_incident', 'arrest_year']

# Remove outliers from the DataFrame
cleaned_encoded_cs_df = remove_outliers(encoded_cs_df, numeric_columns)
cleaned_encoded_cs_df.head()
```

Out[ ]:

	case_participant_id	sentence_judge	age_at_incident	gender	incident_city	arrest_year	arrest_month	arrest
0	670458920516	1.0	31.0	0	1.0	2011.0	7.0	
1	670458920516	1.0	31.0	0	1.0	2011.0	7.0	
2	386948574911	1.0	39.0	0	1.0	2012.0	8.0	
3	386948574911	1.0	39.0	0	1.0	2012.0	8.0	
4	386948574911	1.0	39.0	0	1.0	2012.0	8.0	

In [ ]:
```
# Maximum age in dataframe - make sure outliers are removed
cleaned_encoded_cs_df.loc[cleaned_encoded_cs_df['age_at_incident'].idxmax()] # 65
```

Out[ ]:
```
case_participant_id                                                2.197467e+12
sentence_judge                                                     1.000000e+00
age_at_incident                                                    6.500000e+01
gender                                                             0.000000e+00
incident_city                                                      1.000000e+00
arrest_year                                                        2.011000e+03
arrest_month                                                       1.000000e+00
arrest_day                                                         2.300000e+01
arrest_time                                                        2.000000e+00
repeated                                                           0.000000e+00
offense_category_aggravated assault police officer firearm         0.000000e+00
offense_category_aggravated battery                                0.000000e+00
offense_category_aggravated battery police officer                 0.000000e+00
offense_category_aggravated battery police officer firearm         0.000000e+00
offense_category_aggravated battery with a firearm                 0.000000e+00
offense_category_aggravated dui                                    0.000000e+00
offense_category_aggravated discharge firearm                      0.000000e+00
offense_category_aggravated fleeing and eluding                    0.000000e+00
offense_category_aggravated identity theft                         0.000000e+00
offense_category_aggravated robbery                                0.000000e+00
offense_category_aggravated robbery bb gun                         0.000000e+00
offense_category_armed robbery                                     0.000000e+00
offense_category_armed violence                                    0.000000e+00
offense_category_arson                                             0.000000e+00
offense_category_arson and attempt arson                           0.000000e+00
offense_category_attempt armed robbery                             0.000000e+00
offense_category_attempt arson                                     0.000000e+00
offense_category_attempt homicide                                  0.000000e+00
offense_category_attempt sex crimes                                0.000000e+00
offense_category_attempt vehicular hijacking                       0.000000e+00
offense_category_battery                                           0.000000e+00
offense_category_bomb threat                                       0.000000e+00
offense_category_bribery                                           0.000000e+00
offense_category_burglary                                          0.000000e+00
offense_category_child abduction                                   0.000000e+00
offense_category_child pornography                                 0.000000e+00
offense_category_communicating with witness                        0.000000e+00
offense_category_credit card cases                                 0.000000e+00
offense_category_criminal damage to property                       0.000000e+00
offense_category_criminal trespass to residence                    0.000000e+00
offense_category_dui                                               0.000000e+00
offense_category_deceptive practice                                0.000000e+00
offense_category_disarming police officer                          0.000000e+00
```

offense_category_dog fighting	0.000000e+00
offense_category_domestic battery	0.000000e+00
offense_category_driving with suspended or revoked license	0.000000e+00
offense_category_escape - failure to return	0.000000e+00
offense_category_failure to pay child support	0.000000e+00
offense_category_failure to register as a sex offender	0.000000e+00
offense_category_forgery	0.000000e+00
offense_category_fraud	0.000000e+00
offense_category_fraudulent id	0.000000e+00
offense_category_gambling	0.000000e+00
offense_category_gun - non uuw	0.000000e+00
offense_category_gun running	0.000000e+00
offense_category_hate crimes	0.000000e+00
offense_category_home invasion	0.000000e+00
offense_category_homicide	0.000000e+00
offense_category_human trafficking	0.000000e+00
offense_category_identity theft	0.000000e+00
offense_category_impersonating police officer	0.000000e+00
offense_category_intimidation	0.000000e+00
offense_category_kidnapping	0.000000e+00
offense_category_major accidents	0.000000e+00
offense_category_narcotics	1.000000e+00
offense_category_obstructing justice	0.000000e+00
offense_category_official misconduct	0.000000e+00
offense_category_other offense	0.000000e+00
offense_category_promis conversion	0.000000e+00
offense_category_pandering	0.000000e+00
offense_category_perjury	0.000000e+00
offense_category_police shooting	0.000000e+00
offense_category_possession of burglary tools	0.000000e+00
offense_category_possession of contraband in penal institution	0.000000e+00
offense_category_possession of explosives	0.000000e+00
offense_category_possession of shank in penal institution	0.000000e+00
offense_category_possession of stolen motor vehicle	0.000000e+00
offense_category_prostitution	0.000000e+00
offense_category_reckless discharge of firearm	0.000000e+00
offense_category_reckless homicide	0.000000e+00
offense_category_residential burglary	0.000000e+00
offense_category_retail theft	0.000000e+00
offense_category_robbery	0.000000e+00
offense_category_sex crimes	0.000000e+00
offense_category_stalking	0.000000e+00
offense_category_tampering	0.000000e+00
offense_category_theft	0.000000e+00
offense_category_theft by deception	0.000000e+00
offense_category_uuw - unlawful use of weapon	0.000000e+00
offense_category_unlawful restraint	0.000000e+00
offense_category_vehicular hijacking	0.000000e+00
offense_category_vehicular invasion	0.000000e+00
offense_category_violation order of protection	0.000000e+00
offense_category_violation of sex offender registration	0.000000e+00
race_asian	0.000000e+00
race_biracial	0.000000e+00
race_black	1.000000e+00
race_hispanic	0.000000e+00
race_unknown	0.000000e+00
race_white	0.000000e+00
race_white [hispanic or latino]	0.000000e+00
race_white/black [hispanic or latino]	0.000000e+00
sentence_type_conditional discharge	0.000000e+00
sentence_type_conditional release	0.000000e+00
sentence_type_cook county boot camp	0.000000e+00
sentence_type_death	0.000000e+00
sentence_type_inpatient mental health services	0.000000e+00
sentence_type_jail	0.000000e+00
sentence_type_prison	0.000000e+00

```
sentence_type_probation                                  1.000000e+00
sentence_type_probation terminated instanter             0.000000e+00
sentence_type_probation terminated satisfactorily        0.000000e+00
sentence_type_probation terminated unsatisfactorily      0.000000e+00
sentence_type_supervision                                0.000000e+00
Name: 1212, dtype: float64
```

In [ ]:
```
# Minimum year in dataframe - make sure outliers are removed
cleaned_encoded_cs_df.loc[cleaned_encoded_cs_df['arrest_year'].idxmin()] # 2004
```

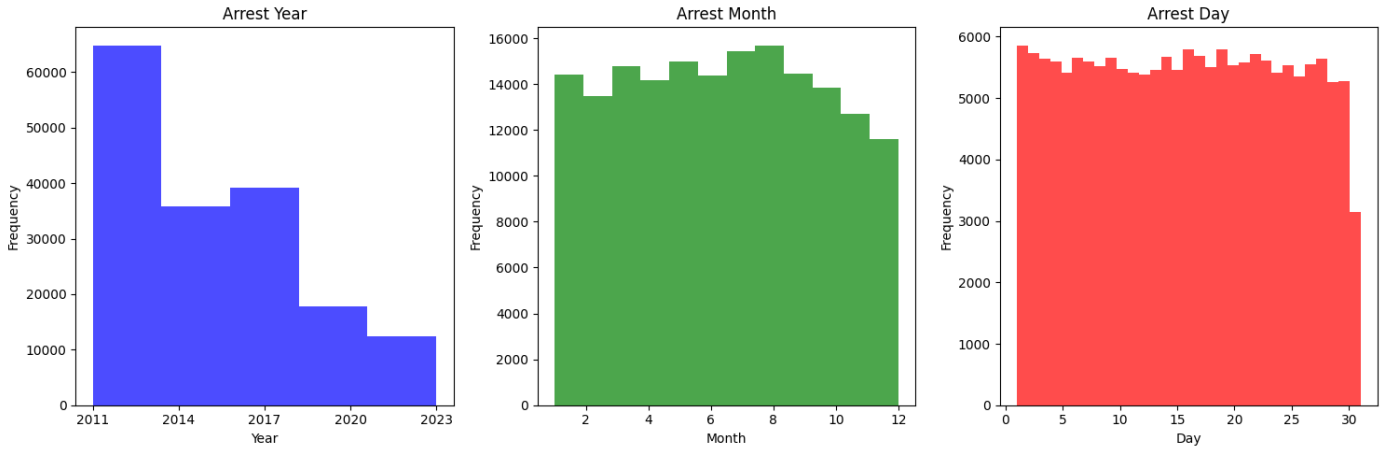
Out[ ]:
```
case_participant_id                                      6.704589e+11
sentence_judge                                           1.000000e+00
age_at_incident                                          3.100000e+01
gender                                                   0.000000e+00
incident_city                                            1.000000e+00
arrest_year                                              2.011000e+03
arrest_month                                             7.000000e+00
arrest_day                                               2.700000e+01
arrest_time                                              2.000000e+00
repeated                                                 1.000000e+00
offense_category_aggravated assault police officer firearm  0.000000e+00
offense_category_aggravated battery                      0.000000e+00
offense_category_aggravated battery police officer       0.000000e+00
offense_category_aggravated battery police officer firearm  0.000000e+00
offense_category_aggravated battery with a firearm       0.000000e+00
offense_category_aggravated dui                          0.000000e+00
offense_category_aggravated discharge firearm            0.000000e+00
offense_category_aggravated fleeing and eluding          0.000000e+00
offense_category_aggravated identity theft               0.000000e+00
offense_category_aggravated robbery                      0.000000e+00
offense_category_aggravated robbery bb gun               0.000000e+00
offense_category_armed robbery                           0.000000e+00
offense_category_armed violence                          0.000000e+00
offense_category_arson                                   0.000000e+00
offense_category_arson and attempt arson                 0.000000e+00
offense_category_attempt armed robbery                   0.000000e+00
offense_category_attempt arson                           0.000000e+00
offense_category_attempt homicide                        0.000000e+00
offense_category_attempt sex crimes                      0.000000e+00
offense_category_attempt vehicular hijacking             0.000000e+00
offense_category_battery                                 0.000000e+00
offense_category_bomb threat                             0.000000e+00
offense_category_bribery                                 0.000000e+00
offense_category_burglary                                0.000000e+00
offense_category_child abduction                         0.000000e+00
offense_category_child pornography                       0.000000e+00
offense_category_communicating with witness              0.000000e+00
offense_category_credit card cases                       0.000000e+00
offense_category_criminal damage to property             0.000000e+00
offense_category_criminal trespass to residence          0.000000e+00
offense_category_dui                                     0.000000e+00
offense_category_deceptive practice                      0.000000e+00
offense_category_disarming police officer                0.000000e+00
offense_category_dog fighting                            0.000000e+00
offense_category_domestic battery                        0.000000e+00
offense_category_driving with suspended or revoked license  0.000000e+00
offense_category_escape - failure to return              0.000000e+00
offense_category_failure to pay child support            0.000000e+00
offense_category_failure to register as a sex offender   0.000000e+00
offense_category_forgery                                 0.000000e+00
offense_category_fraud                                   0.000000e+00
offense_category_fraudulent id                           0.000000e+00
offense_category_gambling                                0.000000e+00
offense_category_gun - non uuw                           0.000000e+00
offense_category_gun running                             0.000000e+00
offense_category_hate crimes                             0.000000e+00
```

```
offense_category_home invasion                                    0.000000e+00
offense_category_homicide                                         0.000000e+00
offense_category_human trafficking                                0.000000e+00
offense_category_identity theft                                   0.000000e+00
offense_category_impersonating police officer                     0.000000e+00
offense_category_intimidation                                     0.000000e+00
offense_category_kidnapping                                       0.000000e+00
offense_category_major accidents                                  0.000000e+00
offense_category_narcotics                                        0.000000e+00
offense_category_obstructing justice                              0.000000e+00
offense_category_official misconduct                              0.000000e+00
offense_category_other offense                                    0.000000e+00
offense_category_promis conversion                                1.000000e+00
offense_category_pandering                                        0.000000e+00
offense_category_perjury                                          0.000000e+00
offense_category_police shooting                                  0.000000e+00
offense_category_possession of burglary tools                     0.000000e+00
offense_category_possession of contraband in penal institution    0.000000e+00
offense_category_possession of explosives                         0.000000e+00
offense_category_possession of shank in penal institution         0.000000e+00
offense_category_possession of stolen motor vehicle               0.000000e+00
offense_category_prostitution                                     0.000000e+00
offense_category_reckless discharge of firearm                    0.000000e+00
offense_category_reckless homicide                                0.000000e+00
offense_category_residential burglary                             0.000000e+00
offense_category_retail theft                                     0.000000e+00
offense_category_robbery                                          0.000000e+00
offense_category_sex crimes                                       0.000000e+00
offense_category_stalking                                         0.000000e+00
offense_category_tampering                                        0.000000e+00
offense_category_theft                                            0.000000e+00
offense_category_theft by deception                               0.000000e+00
offense_category_uuw - unlawful use of weapon                     0.000000e+00
offense_category_unlawful restraint                               0.000000e+00
offense_category_vehicular hijacking                              0.000000e+00
offense_category_vehicular invasion                               0.000000e+00
offense_category_violation order of protection                    0.000000e+00
offense_category_violation of sex offender registration           0.000000e+00
race_asian                                                        0.000000e+00
race_biracial                                                     0.000000e+00
race_black                                                        1.000000e+00
race_hispanic                                                     0.000000e+00
race_unknown                                                      0.000000e+00
race_white                                                        0.000000e+00
race_white [hispanic or latino]                                   0.000000e+00
race_white/black [hispanic or latino]                             0.000000e+00
sentence_type_conditional discharge                               0.000000e+00
sentence_type_conditional release                                 0.000000e+00
sentence_type_cook county boot camp                               0.000000e+00
sentence_type_death                                               0.000000e+00
sentence_type_inpatient mental health services                    0.000000e+00
sentence_type_jail                                                0.000000e+00
sentence_type_prison                                              1.000000e+00
sentence_type_probation                                           0.000000e+00
sentence_type_probation terminated instanter                      0.000000e+00
sentence_type_probation terminated satisfactorily                 0.000000e+00
sentence_type_probation terminated unsatisfactorily               0.000000e+00
sentence_type_supervision                                         0.000000e+00
Name: 0, dtype: float64
```

In [ ]:

```python
# Create subplots with 1 row and 3 columns
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15, 5))

# Plot histogram for arrest_year
axes[0].hist(cleaned_encoded_cs_df['arrest_year'], bins=5, color='blue', alpha=0.7)
```

```
axes[0].set_title('Arrest Year')
axes[0].set_xlabel('Year')
axes[0].set_ylabel('Frequency')

# Set xticks for arrest_year
xticks = np.arange(int(np.min(cleaned_encoded_cs_df['arrest_year'])), int(np.max(cleaned
axes[0].set_xticks(xticks)

# Plot histogram for arrest_month
axes[1].hist(cleaned_encoded_cs_df['arrest_month'], bins=12, color='green', alpha=0.7)
axes[1].set_title('Arrest Month')
axes[1].set_xlabel('Month')
axes[1].set_ylabel('Frequency')

# Plot histogram for arrest_day
axes[2].hist(cleaned_encoded_cs_df['arrest_day'], bins=31, color='red', alpha=0.7)
axes[2].set_title('Arrest Day')
axes[2].set_xlabel('Day')
axes[2].set_ylabel('Frequency')

# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



Diversion Dataset: EDA and Data Preprocessing

Remove Unnecessary Columns

In diversion_df, I will only keep the following columns:

- **case_participant_id** (integer identifying each defendant - will be used to merge the dataframes)
- **diversion_program** (string indicating the type of program)
- referral_date (string indicating when a defendant was referred to diversion program)
- **diversion_count** (integer indicating the number of diversion programs the defendant was referred to)
- **diversion_result** (string indicating whether the offender graduated from or failed the program)

In [ ]:
```
# Keep the columns specified above in diversion_df and save them in cleaned_diversion_df
cleaned_diversion_df = diversion_df.copy()
cleaned_diversion_df = cleaned_diversion_df[["case_participant_id", "diversion_program",
cleaned_diversion_df.head()

# Remove NaN values in cleaned_diversion_df
cleaned_diversion_df.dropna(inplace=True)
cleaned_diversion_df.isna().sum()
```

```
# Reset index
cleaned_diversion_df.reset_index(drop=True, inplace=True)

cleaned_diversion_df.head()
```

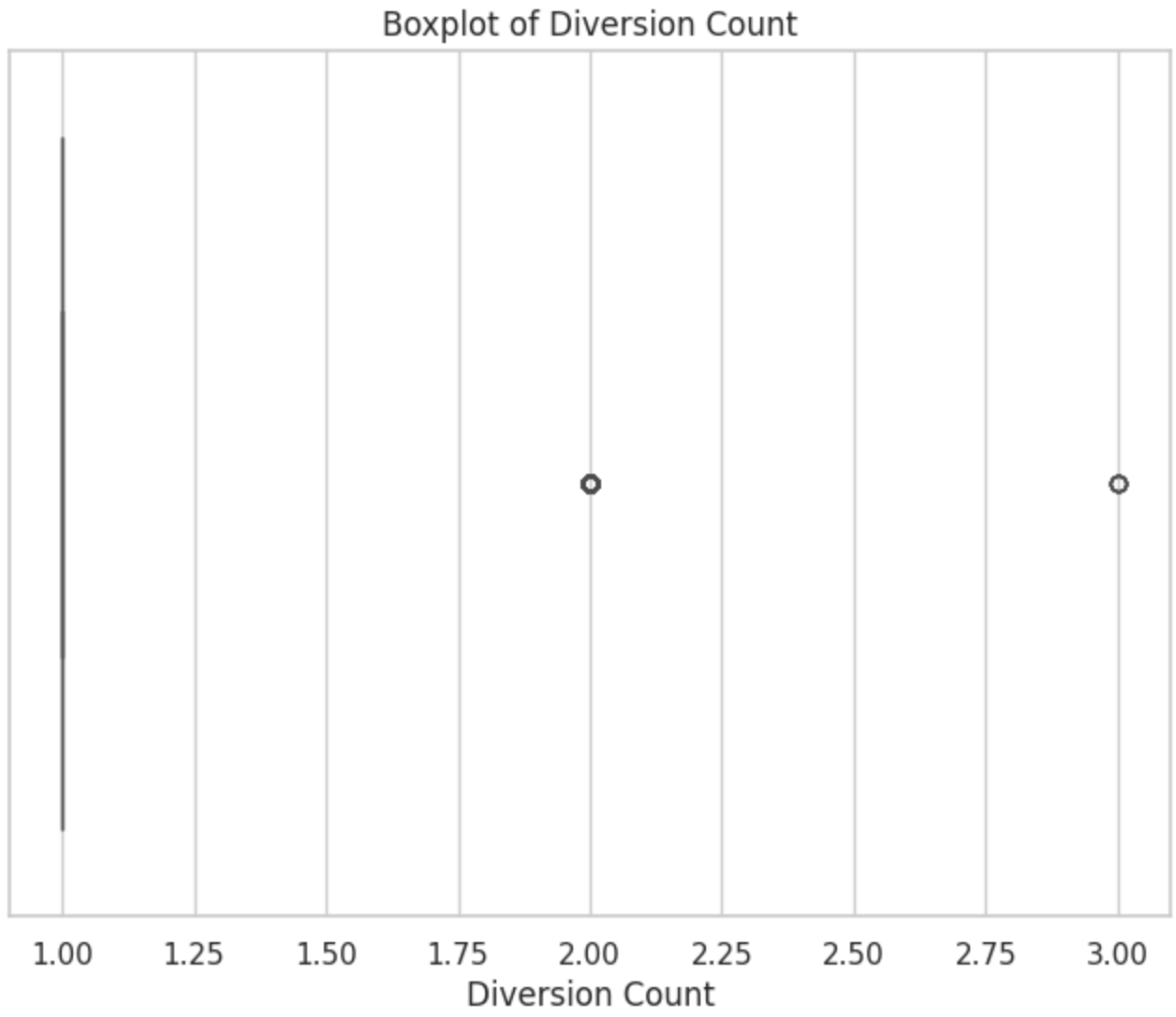
Out[ ]:

	case_participant_id	diversion_program	diversion_count	diversion_result
0	2193361164603	DS	2	Graduated
1	2193390288678	MHC	1	Failed
2	2193494552866	DS	1	Graduated
3	2193661725056	DS	1	Graduated
4	2193763950558	DS	1	Graduated

Check for Outliers

In [ ]:

```
sns.set(style="whitegrid")
plt.figure(figsize=(8, 6))
sns.boxplot(x=cleaned_diversion_df['diversion_count'])
plt.title('Boxplot of Diversion Count')
plt.xlabel('Diversion Count')
plt.show()
```

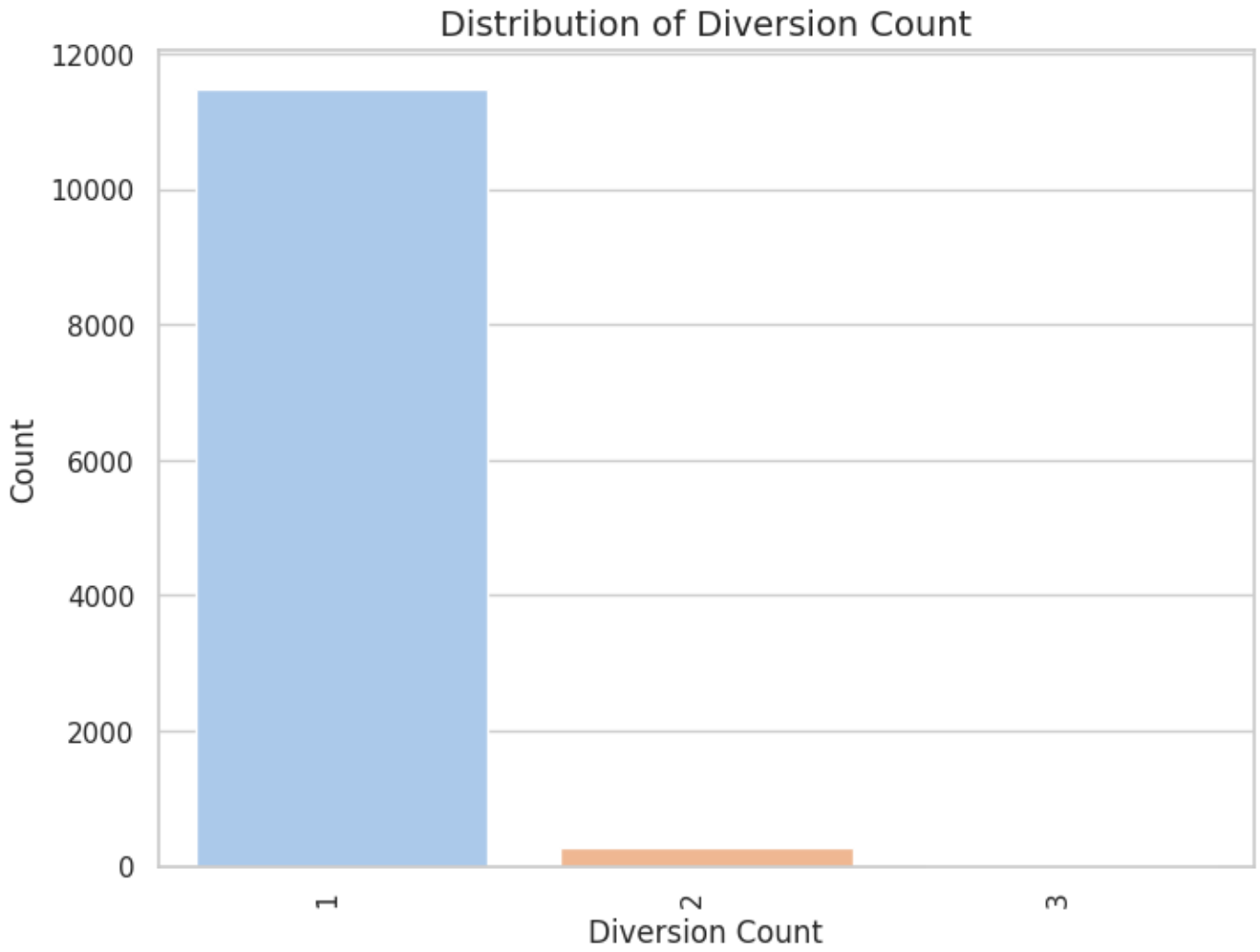


In [ ]:

```
# Set figure size
plt.figure(figsize=(8, 6))

# Plot count plot
```

```
sns.countplot(data=cleaned_diversion_df, x='diversion_count', palette='pastel')

# Set plot labels and title
plt.xlabel('Diversion Count', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Diversion Count', fontsize=14)

# Customize x-axis labels spacing and rotation
plt.xticks(rotation=90, ha='right')  # Adjust rotation and alignment of x-axis labels

# Show the plot
plt.show()
```

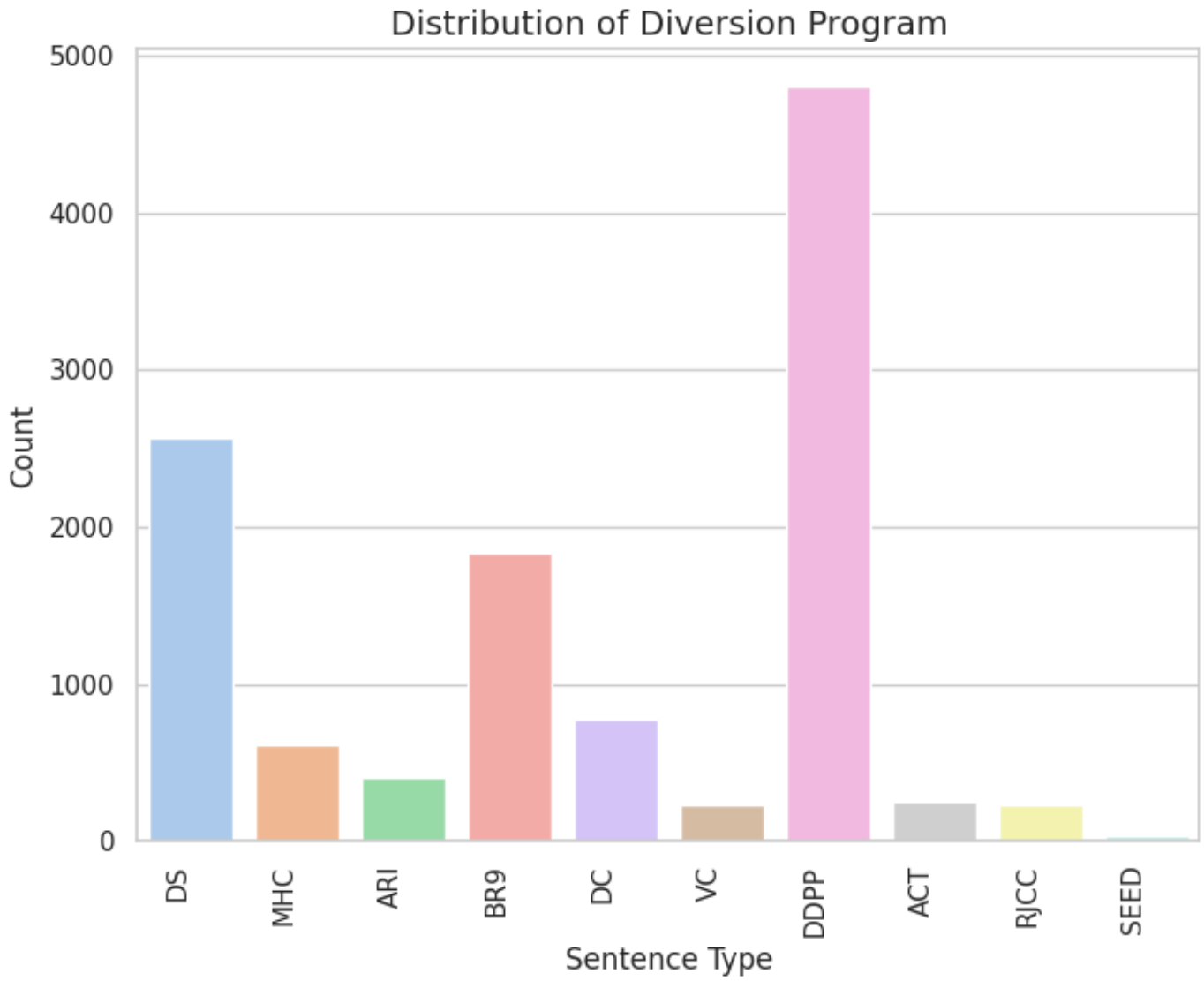
```
<ipython-input-48-4dd6cb722e05>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=cleaned_diversion_df, x='diversion_count', palette='pastel')
```



In [ ]:
```
# Set figure size
plt.figure(figsize=(8, 6))

# Plot count plot
sns.countplot(data=cleaned_diversion_df, x='diversion_program', palette='pastel')

# Set plot labels and title
plt.xlabel('Sentence Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Diversion Program', fontsize=14)

# Customize x-axis labels spacing and rotation
```

```
plt.xticks(rotation=90, ha='right')  # Adjust rotation and alignment of x-axis labels

# Show the plot
plt.show()
```

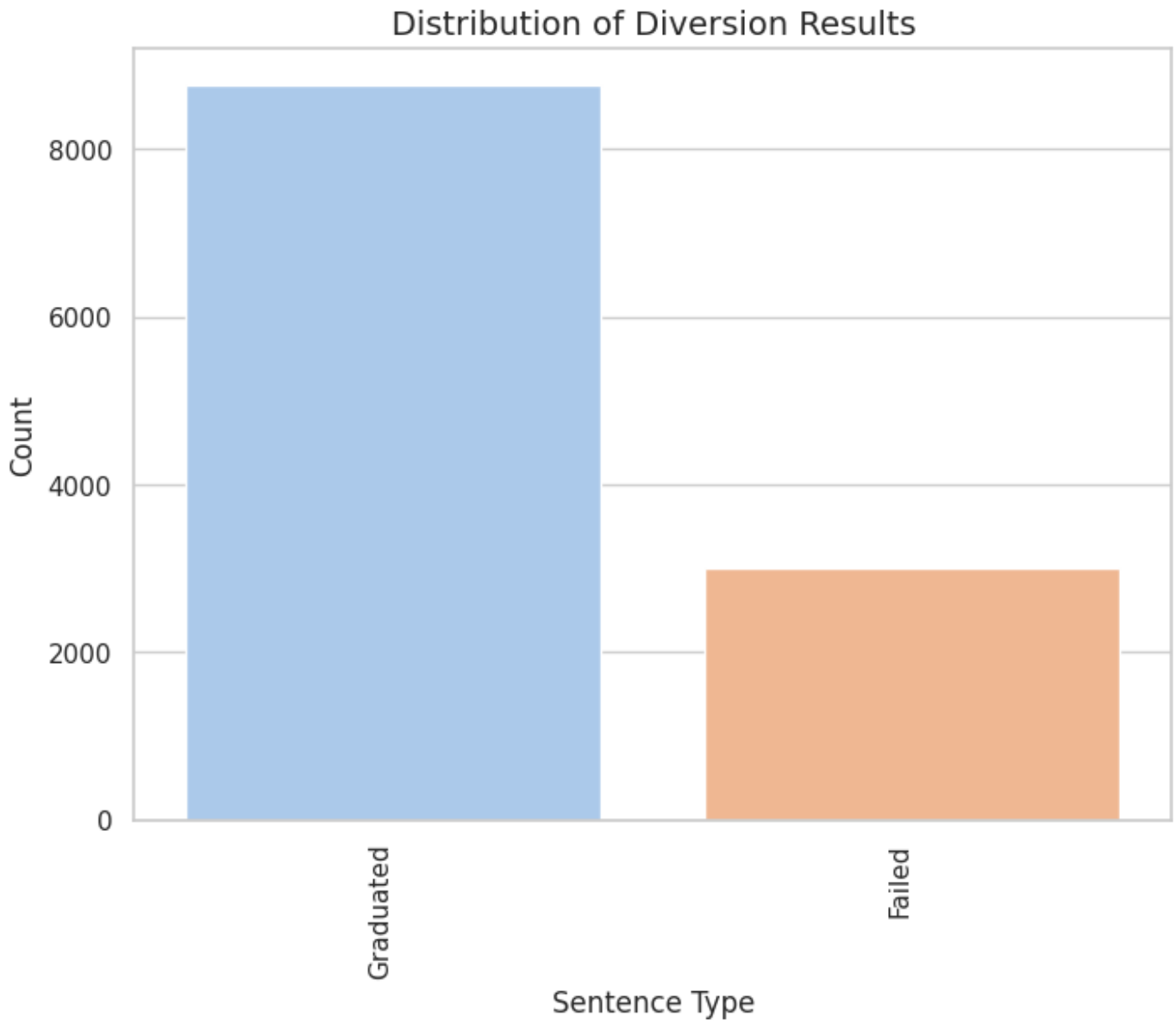
```
<ipython-input-49-0a3481e3539f>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=cleaned_diversion_df, x='diversion_program', palette='pastel')
```



In [ ]:
```
# Set figure size
plt.figure(figsize=(8, 6))

# Plot count plot
sns.countplot(data=cleaned_diversion_df, x='diversion_result', palette='pastel')

# Set plot labels and title
plt.xlabel('Sentence Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Diversion Results', fontsize=14)

# Customize x-axis labels spacing and rotation
plt.xticks(rotation=90, ha='right')  # Adjust rotation and alignment of x-axis labels

# Show the plot
plt.show()
```

```
<ipython-input-50-b4c2bff01c4b>:5: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=cleaned_diversion_df, x='diversion_result', palette='pastel')
```



In [ ]:
```
#use one-hot encoding for diversion program and diversion result
unordered_features = ["diversion_program", "diversion_result"]
numerical_features = ["case_participant_id", "diversion_count"]

# Apply One Hot Encoding to the unordered features
encoder = OneHotEncoder()
encoded_features = encoder.fit_transform(cleaned_diversion_df[unordered_features])

# Replace the unordered features in encoded_cs_df
encoded_feature_names = encoder.get_feature_names_out(unordered_features)
encoded_diversion_df = pd.DataFrame(encoded_features.toarray(), columns=encoded_feature_

# Concatenate the encoded DataFrame with the original DataFrame
encoded_diversion_df = pd.concat([cleaned_diversion_df[numerical_features], encoded_dive
encoded_diversion_df.head()
```

Out[ ]:

	case_participant_id	diversion_count	diversion_program_ACT	diversion_program_ARI	diversion_program_BR
0	2193361164603	2	0.0	0.0	0.0
1	2193390288678	1	0.0	0.0	0.0
2	2193494552866	1	0.0	0.0	0.0

3	2193661725056	1	0.0	0.0	0.0
4	2193763950558	1	0.0	0.0	0.0

Joining the Sentencing and Diversion Datasets

I will do a left outer join of the cleaned sentencing dataset with the cleaned diversion dataset. For entries in the sentencing dataset that are not in the diversion dataset, I assume the offender they never participated in diversion programs at all.

In [ ]:
```
# Merge dataframes
merged_df = pd.merge(cleaned_encoded_cs_df, encoded_diversion_df, on="case_participant_i
merged_df.head()
```

Out[ ]:

	case_participant_id	sentence_judge	age_at_incident	gender	incident_city	arrest_year	arrest_month	arrest
0	670458920516	1.0	31.0	0	1.0	2011.0	7.0	
1	670458920516	1.0	31.0	0	1.0	2011.0	7.0	
2	386948574911	1.0	39.0	0	1.0	2012.0	8.0	
3	386948574911	1.0	39.0	0	1.0	2012.0	8.0	
4	386948574911	1.0	39.0	0	1.0	2012.0	8.0	

In [ ]:
```
len(merged_df)
```

Out[ ]:
```
170126
```

In [ ]:
```
#diversion_count: NaN is imputed to 0
#diversion_program columns: NaN is imputed to 0
#diversion_result_failed and diversion_result_graduated: NaN is imputed to 0

from sklearn.impute import SimpleImputer

# Initialize SimpleImputer with strategy='constant' and fill_value=0
imputer = SimpleImputer(strategy='constant', fill_value=0)

# Fit and transform the df
imputed_df = pd.DataFrame(imputer.fit_transform(merged_df), columns=merged_df.columns)
```

In [ ]:
```
imputed_df.head()
```

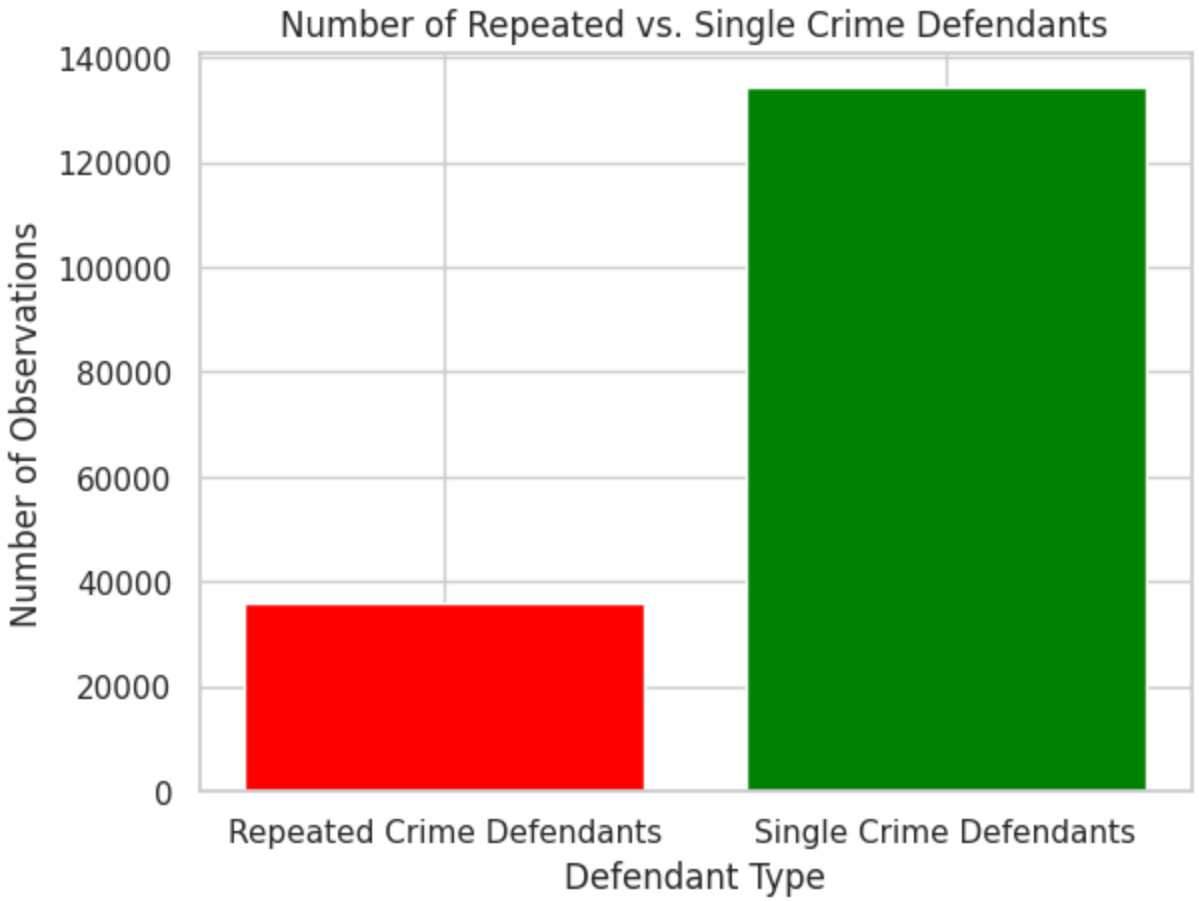
Out[ ]:

	case_participant_id	sentence_judge	age_at_incident	gender	incident_city	arrest_year	arrest_month	arrest
0	6.704589e+11	1.0	31.0	0.0	1.0	2011.0	7.0	
1	6.704589e+11	1.0	31.0	0.0	1.0	2011.0	7.0	
2	3.869486e+11	1.0	39.0	0.0	1.0	2012.0	8.0	
3	3.869486e+11	1.0	39.0	0.0	1.0	2012.0	8.0	
4	3.869486e+11	1.0	39.0	0.0	1.0	2012.0	8.0	

In [ ]:
```
# Remove NaN values
imputed_df.dropna(inplace=True)
```

Class Imbalance and Train Test Split

In [ ]:
```
# Calculate the counts of repeated and single crime defendants
counts = imputed_df['repeated'].value_counts()

# Create a bar graph
labels = ['Repeated Crime Defendants', 'Single Crime Defendants']
counts_values = [counts.get(1.0, 0), counts.get(0.0, 0)]  # Get counts for both categori

plt.bar(labels, counts_values, color=['red', 'green'])
plt.title('Number of Repeated vs. Single Crime Defendants')
plt.xlabel('Defendant Type')
plt.ylabel('Number of Observations')
plt.show()
```



In [ ]:
```
imputed_df['repeated'].value_counts()
```

Out[ ]:
```
repeated
0.0    134237
1.0     35889
Name: count, dtype: int64
```

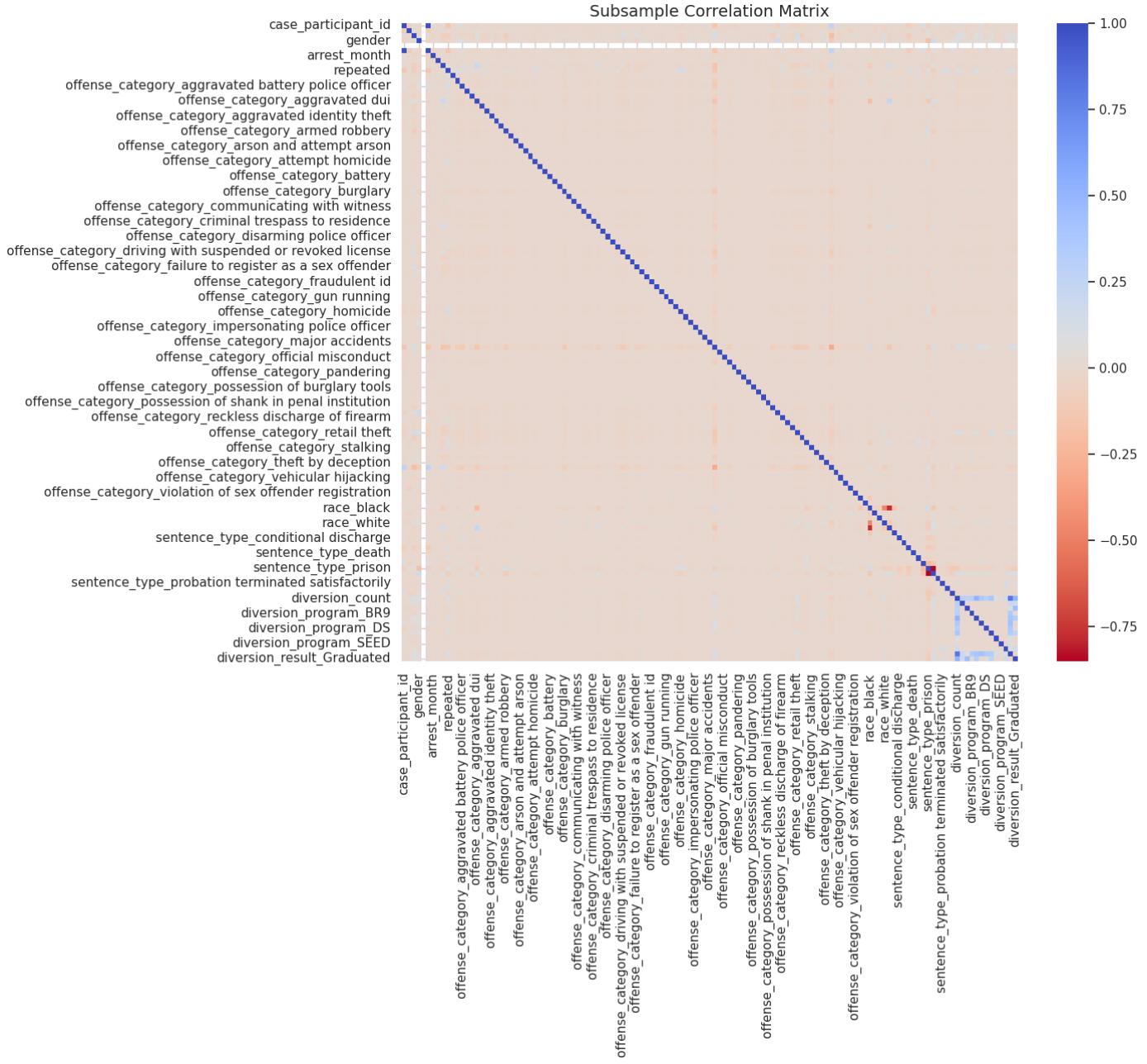
In [ ]:
```
# Find the ratio
class_ratio = counts[0] / counts[1]
print(f'Target variable has {class_ratio:.2f}x more observations in the negative (majori
```

```
Target variable has 3.74x more observations in the negative (majority) class than the po
sitive (minority) class.
```

Correlation Matrix

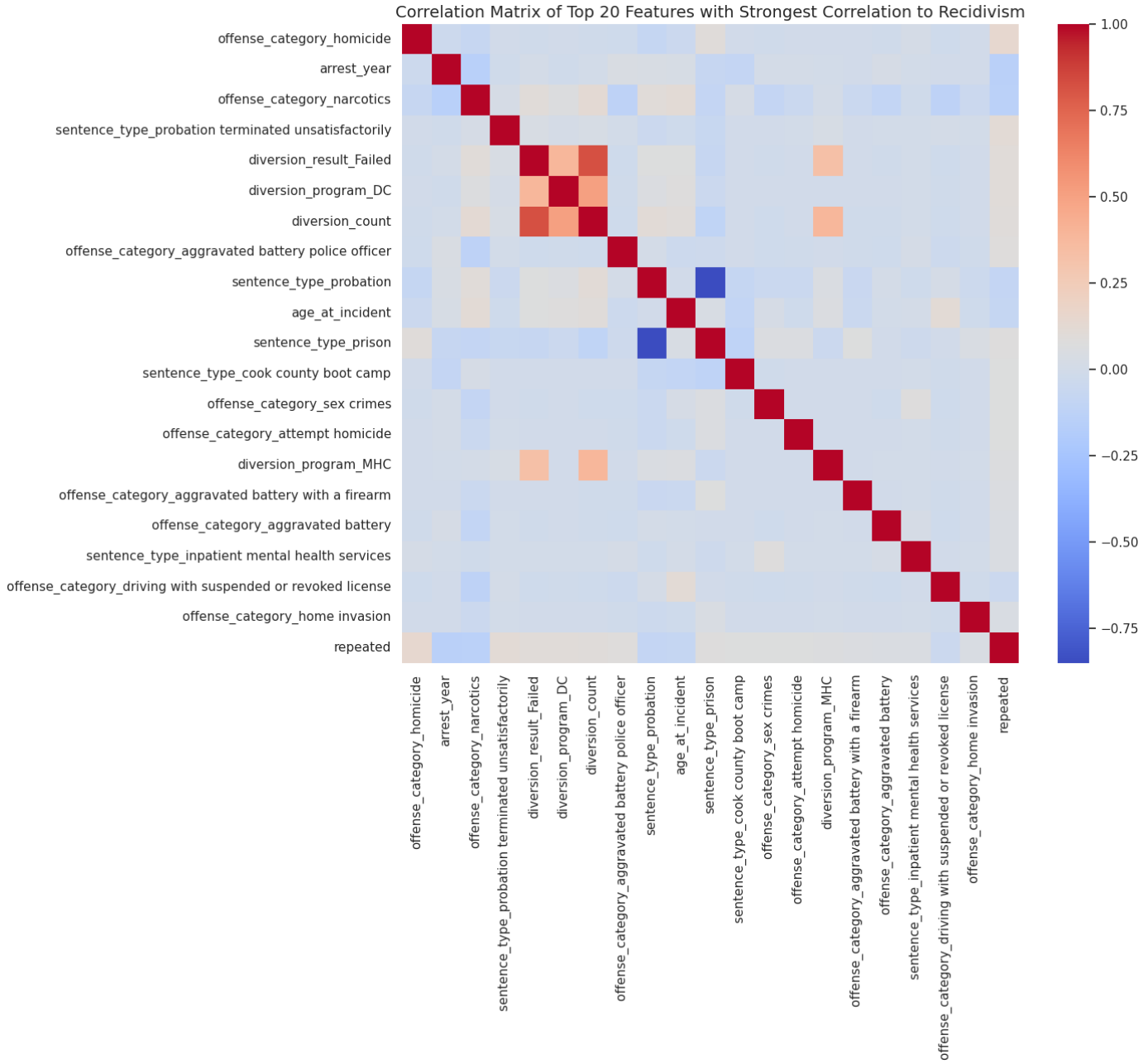
In [ ]:
```
imputed_df = imputed_df.drop('case_participant_id', axis=1)
fig, ax2 = plt.subplots(1, 1, figsize=(12, 10))
```

```
# Calculate the correlation matrix
corr = imputed_df.corr()

# Plot the correlation matrix using seaborn heatmap
sns.heatmap(corr, cmap='coolwarm_r', annot_kws={'size': 12}, ax=ax2)
ax2.set_title('Correlation Matrix', fontsize=14)
plt.show()
```



In [ ]:
```
correlations = imputed_df.corr()['repeated'].abs().sort_values(ascending=False)

# Select top 20 features
top_features = correlations[1:21].index.tolist()

# Create a subset DataFrame containing only the top 20 features and 'repeated'
subset_df = imputed_df[top_features + ['repeated']]

# Calculate the correlation matrix for the subset DataFrame
correlation_matrix = subset_df.corr()

# Plot the correlation matrix heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, cmap='coolwarm', fmt='.2f', annot_kws={'size': 10})
```

```
plt.title("Correlation Matrix of Top 20 Features with Strongest Correlation to Recidivis
plt.show()
```



In [ ]:
```
# Assign features to x and label to y
x = imputed_df.drop(columns=['repeated'])
y = imputed_df['repeated']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, stratify=y, shu

# DO NOT CHANGE ----------------------------------------------------------------
print(f'Training data set has size {X_train.shape} and {y_train.shape}')
print(f'Testing data set has size {X_test.shape} and {y_test.shape}')
```

```
Training data set has size (136100, 125) and (136100,)
Testing data set has size (34026, 125) and (34026,)
```

Undersampling

In [ ]:
```
from imblearn.under_sampling import RandomUnderSampler
rus = RandomUnderSampler(sampling_strategy=0.40)
X_train, y_train = rus.fit_resample(X_train, y_train)
```

In [ ]:
```
# Scale the numerical features
```

```
scaler = StandardScaler()

# Select numerical features, excluding 'repeated' column
numerical_columns = merged_df.select_dtypes(include=['float']).columns
features_scale = [col for col in numerical_columns if col != 'repeated']

# Fit and transform the training data
X_train[features_scale] = scaler.fit_transform(X_train[features_scale])

# Transform the testing data using the learned parameters from the training data
X_test[features_scale] = scaler.transform(X_test[features_scale])

# Convert X_train, y_train, X_test, y_test into numpy arrays
X_train = X_train.values
X_test = X_test.values
y_train = y_train.values
y_test = y_test.values
```

Baseline Model

I used random forest classifier for our baseline model.

In [ ]:
```
# Create an instance of RandomForestClassifier
rf_classifier = RandomForestClassifier()

# Train the classifier on the training data
rf_classifier.fit(X_train, y_train)

y_train_pred_baseline = rf_classifier.predict(X_train)

# Predict on the testing data
y_pred_baseline = rf_classifier.predict(X_test)
```

In [ ]:
```
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred_baseline)

# Calculate precision
precision = precision_score(y_test, y_pred_baseline)

# Calculate recall
recall = recall_score(y_test, y_pred_baseline)

# Compute the average precision score (AUPRC)
auprc = average_precision_score(y_test, y_pred_baseline)
```

Random Forest Classifier Performance

For this classification model, training scores are significantly higher than testing scores across the metrics I used of AUPRC, accuracy, recall, and precision. This suggests the model is overfitting, learning to fit the training data too closely, capturing noise that does not generalize to the test set.

In [ ]:
```
print('Baseline Random Forest Classifier Performance')
print(f'Training ROC AUC: {roc_auc_score(y_train, y_train_pred_baseline)*100:.2f}%')
print(f'Testing ROC AUC: {roc_auc_score(y_test, y_pred_baseline)*100:.2f}%')
print(f'Training AUPRC: {average_precision_score(y_train, y_train_pred_baseline)*100:.2f
print(f'Testing AUPRC: {auprc*100:.2f}%')
print(f'Training Accuracy: {accuracy_score(y_train, y_train_pred_baseline)*100:.2f}%')
print(f'Testing Accuracy: {accuracy*100:.2f}%')
print(f'Training Recall: {recall_score(y_train, y_train_pred_baseline)*100:.2f}%')
print(f'Testing Recall: {recall*100:.2f}%')
```

```
print(f'Training Precision: {precision_score(y_train, y_train_pred_baseline)*100:.2f}%')
print(f'Testing Precision: {precision*100:.2f}%')
```

```
Baseline Random Forest Classifier Performance
Training ROC AUC: 99.69%
Testing ROC AUC: 84.85%
Training AUPRC: 99.25%
Testing AUPRC: 64.61%
Training Accuracy: 99.75%
Testing Accuracy: 90.55%
Training Recall: 99.55%
Testing Recall: 74.99%
Training Precision: 99.56%
Testing Precision: 79.12%
```

Hyperparameter Tuning

In [ ]:
```
from sklearn.model_selection import RandomizedSearchCV
rf = RandomForestClassifier()

# Define the parameter grid for RandomSearchCV
param_grid = {
    'n_estimators': [100, 200, 300],  # Number of trees in the forest
    'max_depth': [None, 10, 20, 30],  # Maximum depth of the trees
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to split a no
    'min_samples_leaf': [1, 2, 4]     # Minimum number of samples required at each leaf
}

# Create RandomSearchCV object with optimized parameters
random_search = RandomizedSearchCV(estimator=rf, param_distributions=param_grid,
                                   scoring='average_precision', cv=3, verbose=1, random_

# Fit the RandomSearchCV object on the training data
random_search.fit(X_train, y_train)

# Get the best model and its hyperparameters
best_rf = random_search.best_estimator_
best_params = random_search.best_params_
print("Best Hyperparameters:", best_params)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
/usr/local/lib/python3.10/dist-packages/joblib/externals/loky/process_executor.py:752: U
serWarning: A worker stopped while some jobs were given to the executor. This can be cau
sed by a too short worker timeout or by a memory leak.
  warnings.warn(
Best Hyperparameters: {'n_estimators': 200, 'min_samples_split': 5, 'min_samples_leaf':
1, 'max_depth': None}
```

In [ ]:
```
y_pred_rf = best_rf.predict(X_test)
y_train_pred_rf = best_rf.predict(X_train)
```

In [ ]:
```
# Evaluate the best model on the test set

print('Tuned Random Forest Performance')

print('Training AUPRC: {0:0.4f}'.format(roc_auc_score(y_train, y_train_pred_rf)))
print('Testing AUPRC: {0:0.4f}'.format(roc_auc_score(y_test, y_pred_rf)))

print('Training AUPRC: {0:0.4f}'.format(average_precision_score(y_train, y_train_pred_rf
print('Testing AUPRC: {0:0.4f}'.format(average_precision_score(y_test, y_pred_rf)))

print('Training Accuracy: {0:0.4f}'.format(accuracy_score(y_train, y_train_pred_rf)))
print('Testing Accuracy: {0:0.4f}'.format(accuracy_score(y_test, y_pred_rf)))

print('Training Recall: {0:0.4f}'.format(recall_score(y_train, y_train_pred_rf)))
```

```
print('Testing Recall: {0:0.4f}'.format(recall_score(y_test, y_pred_rf)))

print('Training Precision: {0:0.4f}'.format(precision_score(y_train, y_train_pred_rf)))
print('Testing Precision: {0:0.4f}'.format(precision_score(y_test, y_pred_rf)))
```

```
Tuned Random Forest Performance
Training AUPRC: 0.9392
Testing AUPRC: 0.7940
Training AUPRC: 0.9074
Testing AUPRC: 0.5756
Training Accuracy: 0.9639
Testing Accuracy: 0.8864
Training Recall: 0.8818
Testing Recall: 0.6342
Training Precision: 0.9908
Testing Precision: 0.7859
```

Best Hyperparameters: {'n_estimators': 200, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_depth': None}

Feature Importance

In [ ]:
```
# Get feature importances
importances = rf_classifier.feature_importances_

# Sort feature importances in descending order
indices = np.argsort(importances)[::-1]

# Get column names from clean_encoded_cs_df excluding 'repeated' column
column_names = cleaned_encoded_cs_df.columns
column_names = [col for col in column_names if col != 'repeated']

# Plot
plt.figure(figsize=(10, 6))
plt.title("Top 10 Feature Importance")
plt.barh(range(10), importances[indices[:10]], align="center")  # Use barh for horizonta
plt.yticks(range(10), [column_names[i] for i in indices[:10]])  # Use yticks instead of
plt.xlabel("Importance")
plt.show()
```

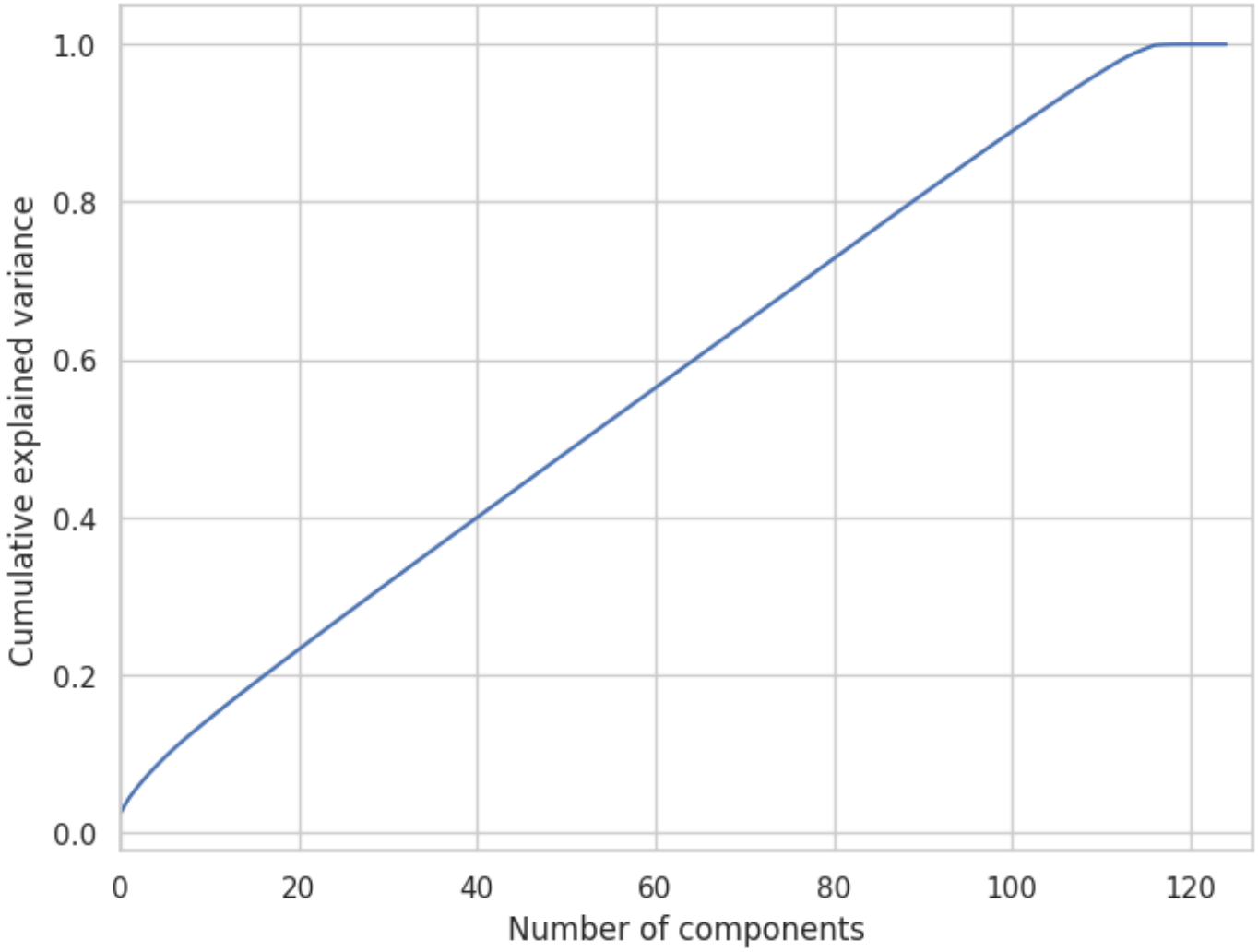
Model 2: Logistic Regression

In [ ]:
```
from sklearn.decomposition import PCA
pca= PCA()
pca.fit(X_train)
cumsum = np.cumsum(pca.explained_variance_ratio_)
dim = np.argmax(cumsum >= 0.90) + 1
print('The number of dimensions required to preserve 90% of variance is',dim)
```

```
The number of dimensions required to preserve 90% of variance is 103
```

In [ ]:
```
plt.figure(figsize=(8,6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlim(0,merged_df.shape[1],1)
plt.xlabel('Number of components')
plt.ylabel('Cumulative explained variance')
plt.show()
```

```
<ipython-input-84-77a13431fff7>:3: MatplotlibDeprecationWarning: Passing the emit parame
ter of set_xlim() positionally is deprecated since Matplotlib 3.6; the parameter will be
come keyword-only two minor releases later.
  plt.xlim(0,merged_df.shape[1],1)
```

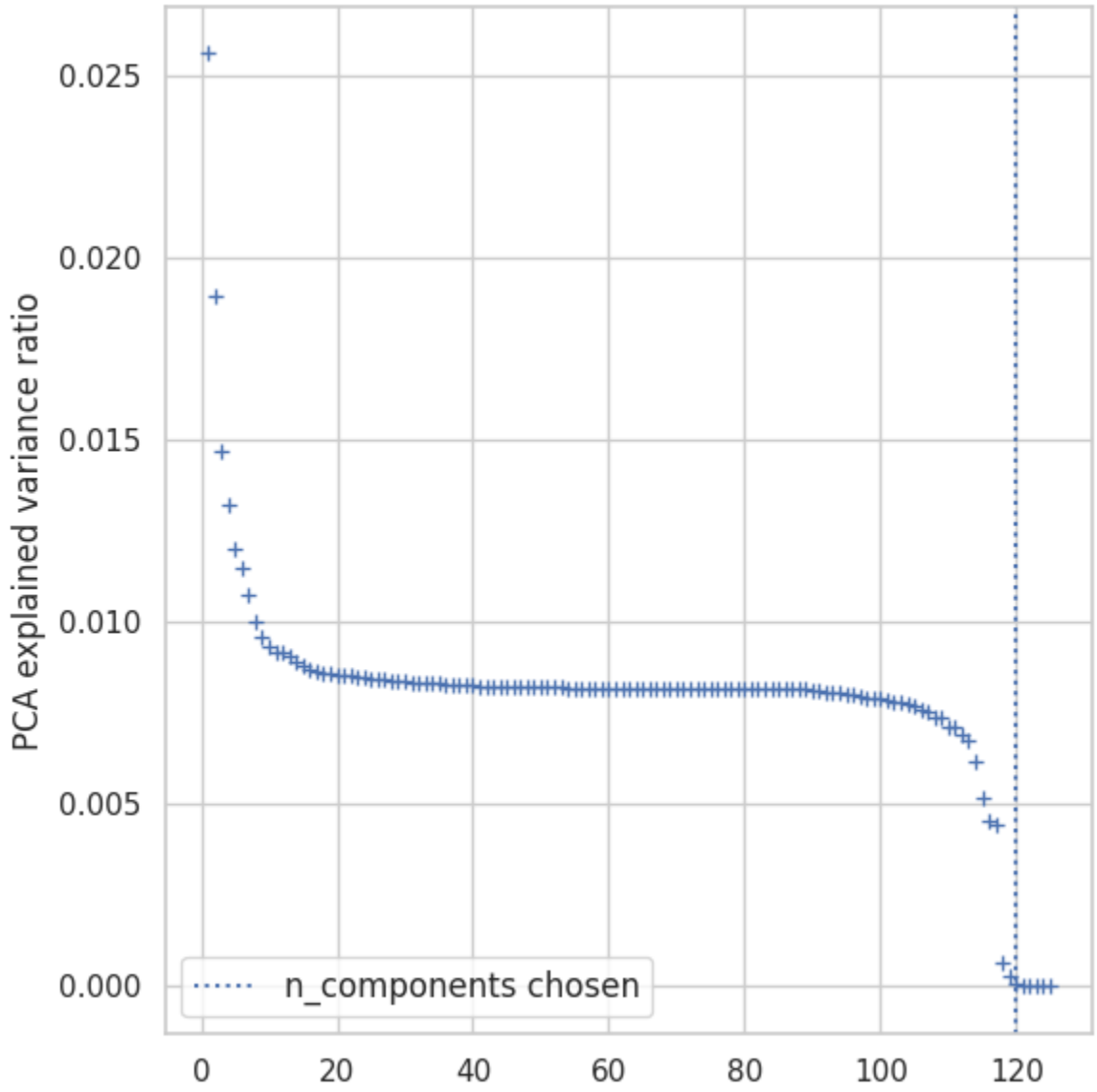


In [ ]:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

from sklearn import datasets
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

# Define a pipeline to search for the best combination of PCA truncation
# and classifier regularization.
pca = PCA()
# Define a Standard Scaler to normalize inputs
scaler = StandardScaler()

# set the tolerance to a large value to make the example faster
logistic = LogisticRegression(max_iter=10000, tol=0.1, penalty='l2')
pipe = Pipeline(steps=[("scaler", scaler), ("pca", pca), ("logistic", logistic)])

# Parameters of pipelines can be set using '__' separated parameter names:
param_grid = {
    "pca__n_components": [80, 100, 120],
    "logistic__C": np.logspace(-4, 4, 4),
    "logistic__class_weight": [None, 'balanced']
}
search = GridSearchCV(pipe, param_grid, n_jobs=2, scoring='roc_auc')
search.fit(X_train, y_train)
print("Best parameter (CV score=%0.3f):" % search.best_score_)
print(search.best_params_)
```

```
Best parameter (CV score=0.588):
{'logistic__C': 10000.0, 'logistic__class_weight': None, 'pca__n_components': 120}
```

In [ ]:
```
# Plot the PCA spectrum
pca.fit(X_train)

plt.figure(figsize=(6, 6))
plt.plot(
    np.arange(1, pca.n_components_ + 1), pca.explained_variance_ratio_, "+", linewidth=2
)
plt.ylabel("PCA explained variance ratio")

plt.axvline(
    search.best_estimator_.named_steps["pca"].n_components,
    linestyle=":",
    label="n_components chosen",
)
plt.legend(prop=dict(size=12))

plt.tight_layout()
plt.show()
```



In [ ]:
```
best_logreg = search.best_estimator_
y_train_pred_lg = best_logreg.predict(X_train)
y_pred_lg = best_logreg.predict(X_test)
```

In [ ]:
```
print('Logistic Regression Performance')
```

```
print('Training ROC AUC: {0:0.4f}'.format(roc_auc_score(y_train, y_train_pred_lg)))
print('Testing ROC AUC: {0:0.4f}'.format(roc_auc_score(y_test, y_pred_lg)))

print('Training AUPRC: {0:0.4f}'.format(average_precision_score(y_train, y_train_pred_lg
print('Testing AUPRC: {0:0.4f}'.format(average_precision_score(y_test, y_pred_lg)))

print('Training Accuracy: {0:0.4f}'.format(accuracy_score(y_train, y_train_pred_lg)))
print('Testing Accuracy: {0:0.4f}'.format(accuracy_score(y_test, y_pred_lg)))

print('Training Recall: {0:0.4f}'.format(recall_score(y_train, y_train_pred_lg)))
print('Testing Recall: {0:0.4f}'.format(recall_score(y_test, y_pred_lg)))

print('Training Precision: {0:0.4f}'.format(precision_score(y_train, y_train_pred_lg)))
print('Testing Precision: {0:0.4f}'.format(precision_score(y_test, y_pred_lg)))
```

```
Logistic Regression Performance
Training ROC AUC: 0.6268
Testing ROC AUC: 0.6183
Training AUPRC: 0.4032
Testing AUPRC: 0.3107
Training Accuracy: 0.7566
Testing Accuracy: 0.7974
Training Recall: 0.3240
Testing Recall: 0.3084
Training Precision: 0.6483
Testing Precision: 0.5343
```

For the logistic regression model with PCA performed, I see that training and testing scores are much more comparable. This suggests that the model is not overfitting to the training data.

Regularized Logistic Regression

In [ ]:
```
# Instantiate the Logistic Regression model with L2 regularization (Ridge)
ridge_logreg = LogisticRegression(penalty='l2', class_weight='balanced', solver='libline

# Fit the Ridge logistic regression model on the training data
ridge_logreg.fit(X_train, y_train)

# Predict the target values on the test set
y_pred_ridge = ridge_logreg.predict(X_test)
y_train_pred_ridge = ridge_logreg.predict(X_train)
```

In [ ]:
```
print('Logistic Regression with L2 Regularization Performance')

print('Training AUPRC: {0:0.4f}'.format(average_precision_score(y_train, y_train_pred_ri
print('Testing AUPRC: {0:0.4f}'.format(average_precision_score(y_test, y_pred_ridge)))

print('Training Accuracy: {0:0.4f}'.format(accuracy_score(y_train, y_train_pred_ridge)))
print('Testing Accuracy: {0:0.4f}'.format(accuracy_score(y_test, y_pred_ridge)))

print('Training Recall: {0:0.4f}'.format(recall_score(y_train, y_train_pred_ridge)))
print('Testing Recall: {0:0.4f}'.format(recall_score(y_test, y_pred_ridge)))

print('Training Precision: {0:0.4f}'.format(precision_score(y_train, y_train_pred_ridge)
print('Testing Precision: {0:0.4f}'.format(precision_score(y_test, y_pred_ridge)))
```

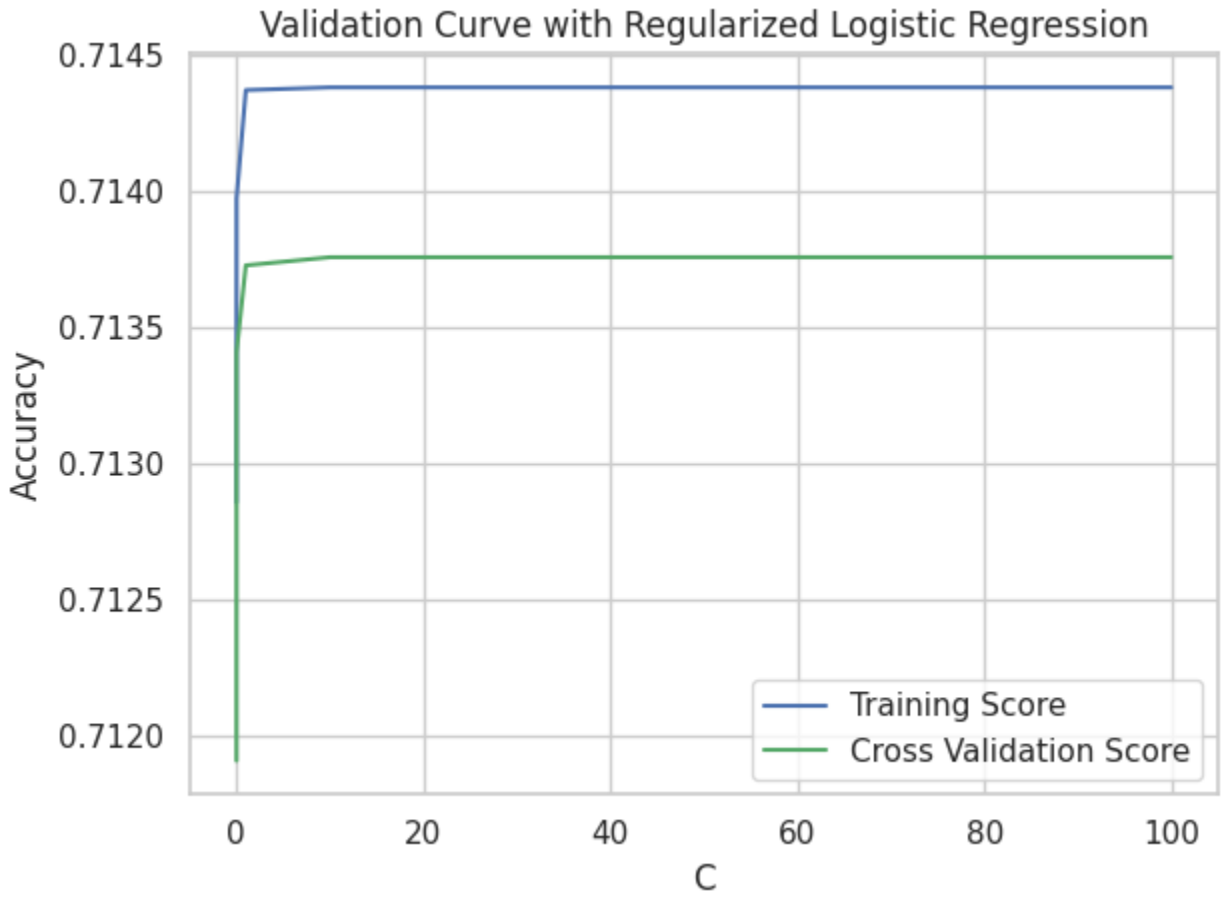
```
Logistic Regression with L2 Regularization Performance
Training AUPRC: 0.4280
Testing AUPRC: 0.3306
Training Accuracy: 0.7142
Testing Accuracy: 0.7144
Training Recall: 0.6641
Testing Recall: 0.6548
```

```
Training Precision: 0.4999
Testing Precision: 0.3936
```

Validation Curve

In [ ]:
```
from sklearn.model_selection import validation_curve

param_range = [0.001, 0.01, 0.01, 1.0, 10.0, 100.0]
train_scores, test_scores = validation_curve(ridge_logreg, X_train, y_train, param_name=
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)
```

In [ ]:
```
# Plot mean accuracy scores for training and testing scores
plt.plot(param_range, train_scores_mean,
         label="Training Score", color='b')
plt.plot(param_range, test_scores_mean,
         label="Cross Validation Score", color='g')

# Creating the plot
plt.title("Validation Curve with Regularized Logistic Regression")
plt.xlabel("C")
plt.ylabel("Accuracy")
plt.tight_layout()
plt.legend(loc='best')
plt.show()
```



In [ ]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_ridge))
```

```
              precision    recall  f1-score   support

         0.0       0.89      0.73      0.80     26848
         1.0       0.39      0.65      0.49      7178
```

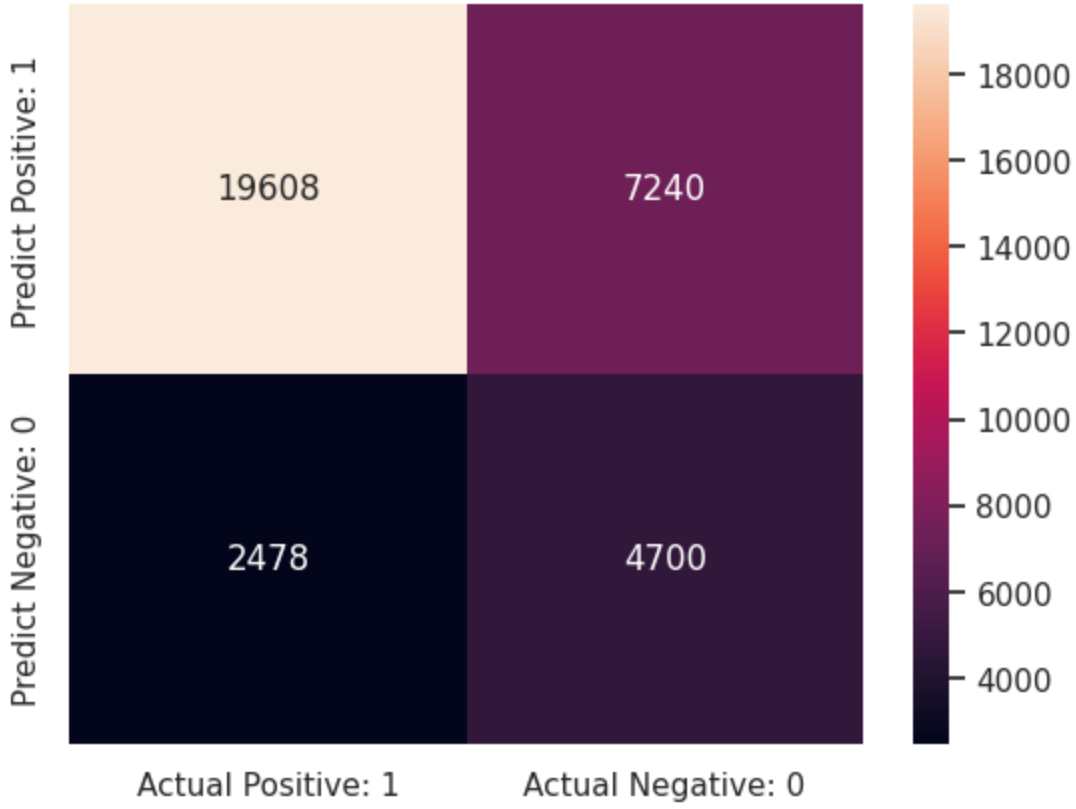
```
    accuracy                           0.71     34026
   macro avg       0.64      0.69      0.65     34026
weighted avg       0.78      0.71      0.74     34026
```

Confusion Matrix

In [ ]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_ridge)
print('Confusion matrix\n\n', cm)
print('\nTrue Positives(TP) = ', cm[0,0])
print('\nTrue Negatives(TN) = ', cm[1,1])
print('\nFalse Positives(FP) = ', cm[0,1])
print('\nFalse Negatives(FN) = ', cm[1,0])

cm_matrix = pd.DataFrame(data=cm, columns=['Actual Positive: 1', 'Actual Negative: 0'],
                                  index=['Predict Positive: 1', 'Predict Negative: 0'])
sns.heatmap(cm_matrix, annot=True, fmt='d')
```

```
Confusion matrix

 [[19608  7240]
 [ 2478  4700]]

True Positives(TP) =  19608

True Negatives(TN) =  4700

False Positives(FP) =  7240

False Negatives(FN) =  2478
```

Out[ ]:
```
<Axes: >
```



Model 3: CatBoost Using Categorical Features directly

https://www.kaggle.com/code/mitribunskiy/tutorial-catboost-overview/notebook

In [ ]:
```
!pip install catboost==1.2.5
```

```
Collecting catboost==1.2.5
  Downloading catboost-1.2.5-cp310-cp310-manylinux2014_x86_64.whl (98.2 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 98.2/98.2 MB 6.1 MB/s eta 0:00:00
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from
 catboost==1.2.5) (0.20.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (fr
om catboost==1.2.5) (3.7.1)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/dist-packages
 (from catboost==1.2.5) (1.25.2)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/dist-packages
 (from catboost==1.2.5) (2.0.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from ca
tboost==1.2.5) (1.11.4)
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (from c
atboost==1.2.5) (5.15.0)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from catb
oost==1.2.5) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.24->catboost==1.2.5) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages
 (from pandas>=0.24->catboost==1.2.5) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages
 (from pandas>=0.24->catboost==1.2.5) (2024.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packag
es (from matplotlib->catboost==1.2.5) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages
 (from matplotlib->catboost==1.2.5) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packa
ges (from matplotlib->catboost==1.2.5) (4.51.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packa
ges (from matplotlib->catboost==1.2.5) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-package
s (from matplotlib->catboost==1.2.5) (24.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages
 (from matplotlib->catboost==1.2.5) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packag
es (from matplotlib->catboost==1.2.5) (3.1.2)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-package
s (from plotly->catboost==1.2.5) (8.2.3)
Installing collected packages: catboost
Successfully installed catboost-1.2.5
```

In [ ]:
```
import catboost
from catboost import CatBoostClassifier
```

In [ ]:
```
# Merge dataframes
cat_merged_df = pd.merge(ordered_cs_df, cleaned_diversion_df, on="case_participant_id",
cat_merged_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gender	inc
0	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	0	
1	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	0	
2	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0	
3	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic	0	

						or Latino]	
4	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0

In [ ]:
```
cat_merged_df['diversion_count'].fillna(0, inplace=True)

# Fill missing values in 'diversion_program' with 'n/a'
cat_merged_df['diversion_program'].fillna('n/a', inplace=True)

# Fill missing values in 'diversion_result' with 'n/a'
cat_merged_df['diversion_result'].fillna('n/a', inplace=True)
cat_merged_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gender	inc
0	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	0	
1	670458920516	PROMIS Conversion	1.0	Prison	31.0	Black	0	
2	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0	
3	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0	
4	386948574911	Attempt Homicide	1.0	Prison	39.0	White [Hispanic or Latino]	0	

In [ ]:
```
cat_merged_df = cat_merged_df.sample(frac=1)

cat_repeat_df = cat_merged_df.loc[cat_merged_df['repeated'] == 1]
cat_one_time_df = cat_merged_df.loc[cat_merged_df['repeated'] == 0][:35889]

cat_df = pd.concat([cat_repeat_df, cat_one_time_df])

# Shuffle dataframe rows
cat_df = cat_df.sample(frac=1, random_state=42)

cat_df.head()
```

Out[ ]:

	case_participant_id	offense_category	sentence_judge	sentence_type	age_at_incident	race	gende
29318	2277999803575	UUW - Unlawful Use of Weapon	1.0	Prison	29.0	Black	
19345	2250704720597	UUW - Unlawful Use of Weapon	1.0	Prison	21.0	White [Hispanic or Latino]	
64135	2384354226499	Narcotics	1.0	Prison	22.0	Black	
55337	2355172194710	Narcotics	1.0	Prison	21.0	White	
157959	2785902700148	UUW - Unlawful Use of Weapon	0.0	Prison	30.0	Black	

In [ ]:
```
# Assign features to x and label to y
cat_x = cat_df.drop(columns=['repeated', 'case_participant_id'])
cat_y = cat_df['repeated']

# Split the data into training and testing sets
X_train_cat, X_test_cat, y_train_cat, y_test_cat = train_test_split(cat_x, cat_y, test_s
```

In [ ]:
```
# Scale the numerical features
scaler = StandardScaler()

# Select numerical features, excluding 'repeated' column
numerical_columns = cat_df.select_dtypes(include=['float']).columns
features_scale = [col for col in numerical_columns if col != 'repeated']

# Fit and transform the training data
X_train_cat[features_scale] = scaler.fit_transform(X_train_cat[features_scale])

# Transform the testing data using the learned parameters from the training data
X_test_cat[features_scale] = scaler.transform(X_test_cat[features_scale])

# Convert X_train, y_train, X_test, y_test into numpy arrays
X_train_cat = X_train_cat.values
X_test_cat = X_test_cat.values
y_train_cat = y_train_cat.values
y_test_cat = y_test_cat.values
```

In [ ]:
```
cat_features_names = ['offense_category', 'sentence_type', 'race', 'gender', 'diversion_
cat_features = [cat_x.columns.get_loc(col) for col in cat_features_names]
print(cat_features)
```

```
[0, 2, 4, 5, 11, 13]
```

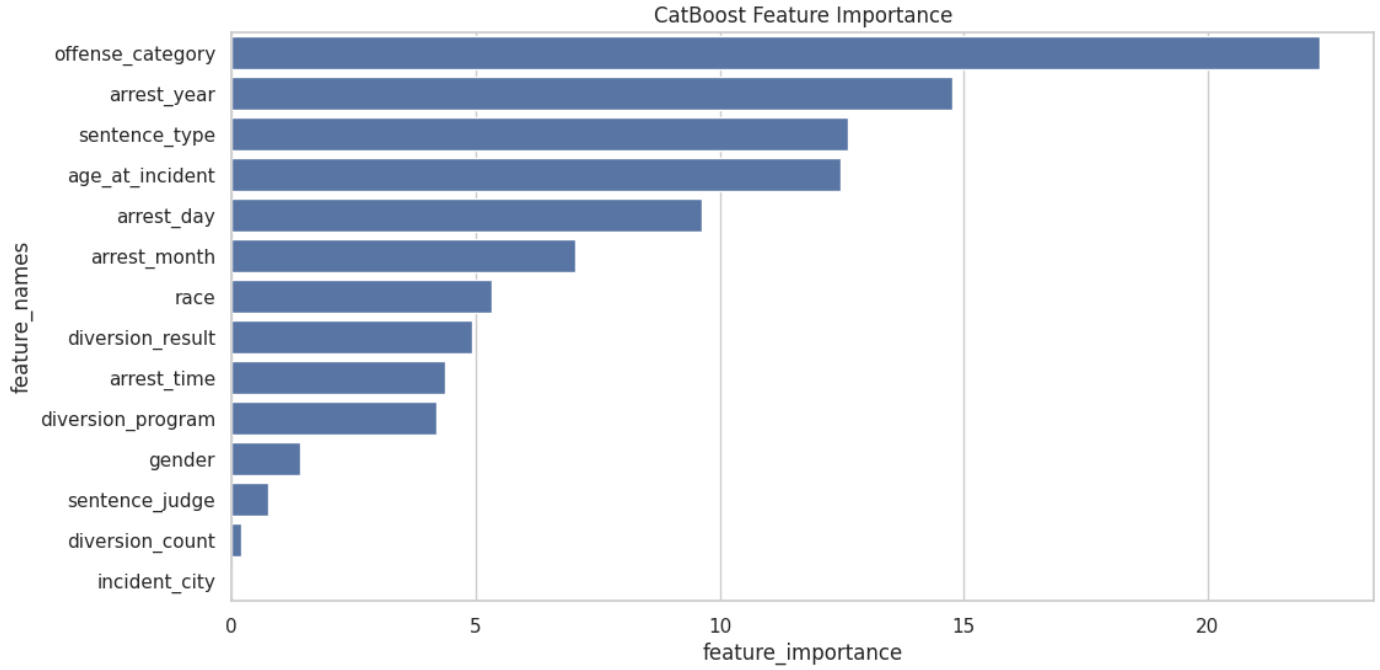
In [ ]:
```
params = {'loss_function':'Logloss',
          'eval_metric':'PRAUC',
          'early_stopping_rounds': 200,
          'cat_features': cat_features,
          'verbose': 200,
          'random_seed': 12345,
          'iterations': 2000
         }
cbc_2 = CatBoostClassifier(**params)
cbc_2.fit(X_train_cat, y_train_cat,
          eval_set=(X_test_cat, y_test_cat),
          use_best_model=True,
          plot=True
         );
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
Learning rate set to 0.063779
0:      learn: 0.7372834        test: 0.7439279 best: 0.7439279 (0)     total: 151ms
remaining: 5m 2s
200:    learn: 0.7861397        test: 0.7866447 best: 0.7866447 (200)   total: 40.8s
remaining: 6m 4s
400:    learn: 0.7993361        test: 0.7915150 best: 0.7915435 (396)   total: 1m 10s
remaining: 4m 40s
600:    learn: 0.8098150        test: 0.7948023 best: 0.7948023 (600)   total: 1m 33s
remaining: 3m 37s
800:    learn: 0.8181614        test: 0.7973224 best: 0.7973224 (800)   total: 2m 11s
remaining: 3m 16s
1000:   learn: 0.8246865        test: 0.7991210 best: 0.7991832 (988)   total: 2m 33s
remaining: 2m 33s
1200:   learn: 0.8306904        test: 0.8004144 best: 0.8004196 (1199)  total: 2m 57s
remaining: 1m 58s
1400:   learn: 0.8362526        test: 0.8017159 best: 0.8017159 (1400)  total: 3m 20s
```

```
remaining: 1m 25s
1600:   learn: 0.8415793        test: 0.8027756 best: 0.8027756 (1600)  total: 3m 44s
remaining: 56s
1800:   learn: 0.8462804        test: 0.8042884 best: 0.8042884 (1800)  total: 4m 10s
remaining: 27.7s
1999:   learn: 0.8514355        test: 0.8053103 best: 0.8053173 (1998)  total: 4m 39s
remaining: 0us

bestTest = 0.8053172782
bestIteration = 1998

Shrink model to first 1999 iterations.
```

In [ ]:
```
feature_importance_df = pd.DataFrame({'feature_importance': cbc_2.get_feature_importance
                'feature_names': cat_x.columns}).sort_values(by=['feature_importance'],
                                                             ascending=False)
```

In [ ]:
```
from matplotlib import pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 6));
sns.barplot(x="feature_importance", y="feature_names", data=feature_importance_df);
plt.title('CatBoost Feature Importance');
```



In [ ]:
```
# Predict the target values on the test set
y_pred_cat2 = cbc_2.predict(X_test_cat)
average_precision_score(y_test_cat, y_pred_cat2)
```

Out[ ]:
```
0.6665997929691467
```

In [ ]:
```
from catboost import CatBoostClassifier
from sklearn.model_selection import RandomizedSearchCV

#RandomSearchCV
cbc = CatBoostClassifier(**params)
from scipy.stats import uniform, randint

# Creating the hyperparameter grid
param_dist = { "learning_rate": np.linspace(0,0.2,5),
               "max_depth": randint(3, 10)
             }
```

```
param_grid = {
    'learning_rate': uniform(0.01, 0.3),  # Continuous uniform distribution
    'max_depth': randint(3, 10),              # Discrete uniform distribution
    'l2_leaf_reg': uniform(0, 5),          # Continuous uniform distribution
}


#Instantiate RandomSearchCV object
rscv = RandomizedSearchCV(cbc , param_dist, scoring='average_precision', cv=3)

# Perform RandomizedSearchCV
rscv.fit(X_train_cat, y_train_cat)


# Print the tuned parameters and score
print(rscv.best_params_)
print(rscv.best_score_)
print(rscv.best_estimator_)
best_cat_model = rscv.best_estimator_
```

```
0:      learn: 0.7225433        total: 138ms    remaining: 4m 34s
200:    learn: 0.7836693        total: 19.4s    remaining: 2m 53s
400:    learn: 0.7903396        total: 27.8s    remaining: 1m 50s
600:    learn: 0.7947468        total: 36.8s    remaining: 1m 25s
800:    learn: 0.7992733        total: 46.1s    remaining: 1m 8s
1000:   learn: 0.8031529        total: 53.4s    remaining: 53.3s
1200:   learn: 0.8058414        total: 1m 2s    remaining: 41.7s
1400:   learn: 0.8082141        total: 1m 11s   remaining: 30.5s
1600:   learn: 0.8111608        total: 1m 19s   remaining: 19.8s
1800:   learn: 0.8136803        total: 1m 29s   remaining: 9.89s
1999:   learn: 0.8160942        total: 1m 38s   remaining: 0us
0:      learn: 0.7186072        total: 67.2ms   remaining: 2m 14s
200:    learn: 0.7809185        total: 7.74s    remaining: 1m 9s
400:    learn: 0.7877166        total: 17.1s    remaining: 1m 8s
600:    learn: 0.7923488        total: 28.3s    remaining: 1m 5s
800:    learn: 0.7966827        total: 35.9s    remaining: 53.7s
1000:   learn: 0.8003341        total: 47.2s    remaining: 47.1s
1200:   learn: 0.8034957        total: 56.5s    remaining: 37.6s
1400:   learn: 0.8062464        total: 1m 3s    remaining: 27.4s
1600:   learn: 0.8092595        total: 1m 13s   remaining: 18.3s
1800:   learn: 0.8115795        total: 1m 21s   remaining: 9.02s
1999:   learn: 0.8135946        total: 1m 30s   remaining: 0us
0:      learn: 0.7133450        total: 34.5ms   remaining: 1m 9s
200:    learn: 0.7767875        total: 10.1s    remaining: 1m 30s
400:    learn: 0.7844065        total: 17.8s    remaining: 1m 11s
600:    learn: 0.7898523        total: 26.8s    remaining: 1m 2s
800:    learn: 0.7940668        total: 36.2s    remaining: 54.2s
1000:   learn: 0.7972788        total: 43.8s    remaining: 43.7s
1200:   learn: 0.8002864        total: 53.1s    remaining: 35.3s
1400:   learn: 0.8032916        total: 1m 2s    remaining: 26.6s
1600:   learn: 0.8057445        total: 1m 10s   remaining: 17.5s
1800:   learn: 0.8083478        total: 1m 19s   remaining: 8.79s
1999:   learn: 0.8107053        total: 1m 27s   remaining: 0us
0:      learn: 0.7286824        total: 108ms    remaining: 3m 35s
200:    learn: 0.7988205        total: 11.1s    remaining: 1m 39s
400:    learn: 0.8141198        total: 28.1s    remaining: 1m 52s
600:    learn: 0.8251825        total: 40.1s    remaining: 1m 33s
800:    learn: 0.8349466        total: 52.3s    remaining: 1m 18s
1000:   learn: 0.8426302        total: 1m 4s    remaining: 1m 4s
1200:   learn: 0.8509533        total: 1m 16s   remaining: 51.1s
1400:   learn: 0.8584758        total: 1m 29s   remaining: 38.2s
1600:   learn: 0.8648051        total: 1m 41s   remaining: 25.4s
1800:   learn: 0.8715274        total: 1m 53s   remaining: 12.5s
1999:   learn: 0.8773656        total: 2m 4s    remaining: 0us
0:      learn: 0.7256708        total: 83.9ms   remaining: 2m 47s
200:    learn: 0.7936435        total: 11.9s    remaining: 1m 46s
```

```
400:    learn: 0.8090081        total: 24s      remaining: 1m 35s
600:    learn: 0.8208686        total: 36.3s    remaining: 1m 24s
800:    learn: 0.8311811        total: 50.5s    remaining: 1m 15s
1000:   learn: 0.8402901        total: 1m 2s    remaining: 1m 2s
1200:   learn: 0.8484001        total: 1m 15s   remaining: 50s
1400:   learn: 0.8548272        total: 1m 29s   remaining: 38.4s
1600:   learn: 0.8619423        total: 1m 41s   remaining: 25.4s
1800:   learn: 0.8677035        total: 1m 53s   remaining: 12.5s
1999:   learn: 0.8729607        total: 2m 5s    remaining: 0us
0:      learn: 0.7205524        total: 51.1ms   remaining: 1m 42s
200:    learn: 0.7923570        total: 11.9s    remaining: 1m 46s
400:    learn: 0.8079857        total: 24.1s    remaining: 1m 36s
600:    learn: 0.8191698        total: 36.5s    remaining: 1m 24s
800:    learn: 0.8292867        total: 48.8s    remaining: 1m 13s
1000:   learn: 0.8376678        total: 1m 1s    remaining: 1m 1s
1200:   learn: 0.8470130        total: 1m 15s   remaining: 50.3s
1400:   learn: 0.8543949        total: 1m 28s   remaining: 37.6s
1600:   learn: 0.8612894        total: 1m 39s   remaining: 24.7s
1800:   learn: 0.8670789        total: 1m 51s   remaining: 12.3s
1999:   learn: 0.8730895        total: 2m 3s    remaining: 0us
0:      learn: 0.7471476        total: 77.5ms   remaining: 2m 35s
200:    learn: 0.8555427        total: 21.9s    remaining: 3m 15s
400:    learn: 0.8959173        total: 40.2s    remaining: 2m 40s
600:    learn: 0.9233436        total: 1m       remaining: 2m 20s
800:    learn: 0.9437859        total: 1m 20s   remaining: 2m 1s
1000:   learn: 0.9568059        total: 1m 45s   remaining: 1m 45s
1200:   learn: 0.9674195        total: 2m 5s    remaining: 1m 23s
1400:   learn: 0.9750320        total: 2m 24s   remaining: 1m 1s
1600:   learn: 0.9802429        total: 2m 45s   remaining: 41.3s
1800:   learn: 0.9846807        total: 3m 5s    remaining: 20.4s
1999:   learn: 0.9878019        total: 3m 27s   remaining: 0us
0:      learn: 0.7373076        total: 87.2ms   remaining: 2m 54s
200:    learn: 0.8468741        total: 17.7s    remaining: 2m 38s
400:    learn: 0.8900301        total: 38.1s    remaining: 2m 31s
600:    learn: 0.9193957        total: 58.9s    remaining: 2m 17s
800:    learn: 0.9376168        total: 1m 17s   remaining: 1m 56s
1000:   learn: 0.9512849        total: 1m 38s   remaining: 1m 38s
1200:   learn: 0.9616491        total: 1m 57s   remaining: 1m 18s
1400:   learn: 0.9699328        total: 2m 17s   remaining: 58.7s
1600:   learn: 0.9765917        total: 2m 39s   remaining: 39.8s
1800:   learn: 0.9815259        total: 3m 2s    remaining: 20.2s
1999:   learn: 0.9860806        total: 3m 22s   remaining: 0us
0:      learn: 0.7358305        total: 72.5ms   remaining: 2m 24s
200:    learn: 0.8532050        total: 18.2s    remaining: 2m 43s
400:    learn: 0.8952094        total: 39s      remaining: 2m 35s
600:    learn: 0.9228366        total: 57.6s    remaining: 2m 14s
800:    learn: 0.9401085        total: 1m 18s   remaining: 1m 57s
1000:   learn: 0.9531743        total: 1m 37s   remaining: 1m 37s
1200:   learn: 0.9646186        total: 1m 56s   remaining: 1m 17s
1400:   learn: 0.9731034        total: 2m 21s   remaining: 1m
1600:   learn: 0.9793223        total: 2m 42s   remaining: 40.5s
1800:   learn: 0.9842345        total: 3m 3s    remaining: 20.3s
1999:   learn: 0.9877835        total: 3m 22s   remaining: 0us
0:      learn: 0.7378656        total: 149ms    remaining: 4m 58s
200:    learn: 0.8096268        total: 25.8s    remaining: 3m 50s
400:    learn: 0.8333545        total: 39.8s    remaining: 2m 38s
600:    learn: 0.8502322        total: 53.8s    remaining: 2m 5s
800:    learn: 0.8652086        total: 1m 9s    remaining: 1m 44s
1000:   learn: 0.8773966        total: 1m 23s   remaining: 1m 23s
1200:   learn: 0.8880935        total: 1m 38s   remaining: 1m 5s
1400:   learn: 0.8983883        total: 1m 55s   remaining: 49.5s
1600:   learn: 0.9060490        total: 2m 10s   remaining: 32.4s
1800:   learn: 0.9133941        total: 2m 24s   remaining: 16s
1999:   learn: 0.9202966        total: 2m 38s   remaining: 0us
0:      learn: 0.7350119        total: 56.2ms   remaining: 1m 52s
200:    learn: 0.8072128        total: 13.3s    remaining: 1m 59s
```

```
400:    learn: 0.8288968        total: 27.1s    remaining: 1m 48s
600:    learn: 0.8464101        total: 41s      remaining: 1m 35s
800:    learn: 0.8597341        total: 56.9s    remaining: 1m 25s
1000:   learn: 0.8717471        total: 1m 10s   remaining: 1m 10s
1200:   learn: 0.8830802        total: 1m 25s   remaining: 56.6s
1400:   learn: 0.8923925        total: 1m 45s   remaining: 45s
1600:   learn: 0.9003957        total: 2m 9s    remaining: 32.2s
1800:   learn: 0.9074614        total: 2m 24s   remaining: 16s
1999:   learn: 0.9145523        total: 2m 46s   remaining: 0us
0:      learn: 0.7320575        total: 137ms    remaining: 4m 34s
200:    learn: 0.8056880        total: 18.8s    remaining: 2m 48s
400:    learn: 0.8287434        total: 34.9s    remaining: 2m 19s
600:    learn: 0.8461519        total: 49.6s    remaining: 1m 55s
800:    learn: 0.8614946        total: 1m 14s   remaining: 1m 51s
1000:   learn: 0.8733333        total: 1m 30s   remaining: 1m 30s
1200:   learn: 0.8844236        total: 1m 47s   remaining: 1m 11s
1400:   learn: 0.8942734        total: 2m 2s    remaining: 52.5s
1600:   learn: 0.9027405        total: 2m 24s   remaining: 35.9s
1800:   learn: 0.9103128        total: 2m 46s   remaining: 18.4s
1999:   learn: 0.9167628        total: 3m 22s   remaining: 0us
0:      learn: 0.7490411        total: 169ms    remaining: 5m 38s
200:    learn: 0.9023347        total: 51.2s    remaining: 7m 38s
400:    learn: 0.9495975        total: 1m 41s   remaining: 6m 44s
600:    learn: 0.9722496        total: 2m 35s   remaining: 6m 2s
800:    learn: 0.9843406        total: 3m 23s   remaining: 5m 5s
1000:   learn: 0.9913643        total: 3m 54s   remaining: 3m 53s
1200:   learn: 0.9952086        total: 4m 42s   remaining: 3m 7s
1400:   learn: 0.9974204        total: 5m 40s   remaining: 2m 25s
1600:   learn: 0.9986507        total: 6m 44s   remaining: 1m 40s
1800:   learn: 0.9993707        total: 7m 42s   remaining: 51.1s
1999:   learn: 0.9997081        total: 8m 20s   remaining: 0us
0:      learn: 0.7432897        total: 179ms    remaining: 5m 56s
200:    learn: 0.9032636        total: 57.3s    remaining: 8m 32s
400:    learn: 0.9489270        total: 1m 39s   remaining: 6m 36s
600:    learn: 0.9727050        total: 2m 8s    remaining: 4m 58s
800:    learn: 0.9849953        total: 2m 40s   remaining: 4m
1000:   learn: 0.9919055        total: 3m 9s    remaining: 3m 8s
1200:   learn: 0.9952753        total: 3m 38s   remaining: 2m 25s
1400:   learn: 0.9973493        total: 4m 8s    remaining: 1m 46s
1600:   learn: 0.9985573        total: 4m 39s   remaining: 1m 9s
1800:   learn: 0.9992582        total: 5m 14s   remaining: 34.7s
1999:   learn: 0.9995733        total: 5m 44s   remaining: 0us
0:      learn: 0.7421203        total: 121ms    remaining: 4m 2s
200:    learn: 0.9018648        total: 26.8s    remaining: 4m
400:    learn: 0.9498110        total: 53.4s    remaining: 3m 32s
600:    learn: 0.9732549        total: 1m 24s   remaining: 3m 16s
800:    learn: 0.9861322        total: 2m 8s    remaining: 3m 11s
1000:   learn: 0.9921109        total: 2m 37s   remaining: 2m 37s
1200:   learn: 0.9960558        total: 3m 5s    remaining: 2m 3s
1400:   learn: 0.9978766        total: 3m 34s   remaining: 1m 31s
1600:   learn: 0.9988627        total: 4m 3s    remaining: 1m
1800:   learn: 0.9994252        total: 4m 30s   remaining: 29.9s
1999:   learn: 0.9997260        total: 4m 57s   remaining: 0us
0:      learn: 0.7397398        total: 65.1ms   remaining: 2m 10s
200:    learn: 0.8279633        total: 17.5s    remaining: 2m 36s
400:    learn: 0.8623146        total: 33.3s    remaining: 2m 12s
600:    learn: 0.8861710        total: 49.8s    remaining: 1m 55s
800:    learn: 0.9024018        total: 1m 9s    remaining: 1m 44s
1000:   learn: 0.9174740        total: 1m 26s   remaining: 1m 25s
1200:   learn: 0.9296056        total: 1m 42s   remaining: 1m 8s
1400:   learn: 0.9401296        total: 1m 58s   remaining: 50.8s
1600:   learn: 0.9480900        total: 2m 16s   remaining: 34.1s
1800:   learn: 0.9549793        total: 2m 33s   remaining: 17s
1999:   learn: 0.9611992        total: 2m 50s   remaining: 0us
0:      learn: 0.7372910        total: 63.9ms   remaining: 2m 7s
200:    learn: 0.8243708        total: 17.4s    remaining: 2m 35s
```

```
400:    learn: 0.8562994        total: 34.9s    remaining: 2m 19s
600:    learn: 0.8781026        total: 51.7s    remaining: 2m
800:    learn: 0.8965887        total: 1m 9s    remaining: 1m 43s
1000:   learn: 0.9107462        total: 1m 25s   remaining: 1m 25s
1200:   learn: 0.9228378        total: 1m 41s   remaining: 1m 7s
1400:   learn: 0.9331354        total: 1m 58s   remaining: 50.6s
1600:   learn: 0.9422158        total: 2m 15s   remaining: 33.8s
1800:   learn: 0.9497453        total: 2m 33s   remaining: 16.9s
1999:   learn: 0.9561586        total: 2m 51s   remaining: 0us
0:      learn: 0.7357866        total: 107ms    remaining: 3m 34s
200:    learn: 0.8223736        total: 16.9s    remaining: 2m 31s
400:    learn: 0.8545139        total: 32.7s    remaining: 2m 10s
600:    learn: 0.8783093        total: 48.7s    remaining: 1m 53s
800:    learn: 0.8969129        total: 1m 6s    remaining: 1m 39s
1000:   learn: 0.9131451        total: 1m 25s   remaining: 1m 25s
1200:   learn: 0.9251148        total: 1m 42s   remaining: 1m 8s
1400:   learn: 0.9358396        total: 1m 58s   remaining: 50.6s
1600:   learn: 0.9449211        total: 2m 18s   remaining: 34.5s
1800:   learn: 0.9528467        total: 2m 34s   remaining: 17.1s
1999:   learn: 0.9590328        total: 2m 52s   remaining: 0us
0:      learn: 0.7397398        total: 80.6ms   remaining: 2m 41s
200:    learn: 0.7947371        total: 14.5s    remaining: 2m 9s
400:    learn: 0.8152552        total: 30.8s    remaining: 2m 3s
600:    learn: 0.8307238        total: 47.2s    remaining: 1m 49s
800:    learn: 0.8422788        total: 1m 2s    remaining: 1m 33s
1000:   learn: 0.8522573        total: 1m 18s   remaining: 1m 18s
1200:   learn: 0.8608557        total: 1m 34s   remaining: 1m 2s
1400:   learn: 0.8692577        total: 1m 51s   remaining: 47.5s
1600:   learn: 0.8777002        total: 2m 7s    remaining: 31.8s
1800:   learn: 0.8849513        total: 2m 24s   remaining: 16s
1999:   learn: 0.8913997        total: 2m 40s   remaining: 0us
0:      learn: 0.7372910        total: 71.5ms   remaining: 2m 22s
200:    learn: 0.7918150        total: 16.8s    remaining: 2m 30s
400:    learn: 0.8131606        total: 32.3s    remaining: 2m 8s
600:    learn: 0.8266414        total: 47.5s    remaining: 1m 50s
800:    learn: 0.8388525        total: 1m 3s    remaining: 1m 35s
1000:   learn: 0.8485449        total: 1m 22s   remaining: 1m 22s
1200:   learn: 0.8578564        total: 1m 38s   remaining: 1m 5s
1400:   learn: 0.8663786        total: 1m 53s   remaining: 48.7s
1600:   learn: 0.8733349        total: 2m 9s    remaining: 32.3s
1800:   learn: 0.8802020        total: 2m 25s   remaining: 16.1s
1999:   learn: 0.8859858        total: 2m 43s   remaining: 0us
0:      learn: 0.7357866        total: 61.2ms   remaining: 2m 2s
200:    learn: 0.7854087        total: 16.5s    remaining: 2m 27s
400:    learn: 0.8081852        total: 32s      remaining: 2m 7s
600:    learn: 0.8242799        total: 49.5s    remaining: 1m 55s
800:    learn: 0.8375500        total: 1m 5s    remaining: 1m 37s
1000:   learn: 0.8482372        total: 1m 22s   remaining: 1m 22s
1200:   learn: 0.8571705        total: 1m 39s   remaining: 1m 5s
1400:   learn: 0.8659556        total: 1m 54s   remaining: 49.1s
1600:   learn: 0.8728931        total: 2m 10s   remaining: 32.6s
1800:   learn: 0.8804109        total: 2m 27s   remaining: 16.3s
1999:   learn: 0.8869226        total: 2m 43s   remaining: 0us
0:      learn: 0.7471476        total: 147ms    remaining: 4m 54s
200:    learn: 0.8678881        total: 23.5s    remaining: 3m 30s
400:    learn: 0.9155698        total: 42.3s    remaining: 2m 48s
600:    learn: 0.9438559        total: 1m 1s    remaining: 2m 23s
800:    learn: 0.9613259        total: 1m 21s   remaining: 2m 1s
1000:   learn: 0.9727895        total: 1m 40s   remaining: 1m 40s
1200:   learn: 0.9805728        total: 2m 1s    remaining: 1m 20s
1400:   learn: 0.9861102        total: 2m 20s   remaining: 1m
1600:   learn: 0.9901158        total: 2m 43s   remaining: 40.6s
1800:   learn: 0.9931957        total: 3m 4s    remaining: 20.4s
1999:   learn: 0.9952916        total: 3m 25s   remaining: 0us
0:      learn: 0.7373076        total: 77.7ms   remaining: 2m 35s
200:    learn: 0.8691182        total: 17.9s    remaining: 2m 39s
```

```
400:    learn: 0.9120929        total: 36.9s    remaining: 2m 27s
600:    learn: 0.9367360        total: 56.8s    remaining: 2m 12s
800:    learn: 0.9539496        total: 1m 15s   remaining: 1m 53s
1000:   learn: 0.9667187        total: 1m 38s   remaining: 1m 37s
1200:   learn: 0.9778953        total: 1m 57s   remaining: 1m 18s
1400:   learn: 0.9836665        total: 2m 20s   remaining: 59.9s
1600:   learn: 0.9882870        total: 2m 39s   remaining: 39.6s
1800:   learn: 0.9913821        total: 2m 59s   remaining: 19.9s
1999:   learn: 0.9937675        total: 3m 19s   remaining: 0us
0:      learn: 0.7358305        total: 73.2ms   remaining: 2m 26s
200:    learn: 0.8662207        total: 19.4s    remaining: 2m 53s
400:    learn: 0.9097616        total: 40.4s    remaining: 2m 41s
600:    learn: 0.9364496        total: 58.7s    remaining: 2m 16s
800:    learn: 0.9555709        total: 1m 19s   remaining: 1m 58s
1000:   learn: 0.9695522        total: 1m 40s   remaining: 1m 40s
1200:   learn: 0.9786062        total: 1m 59s   remaining: 1m 19s
1400:   learn: 0.9844765        total: 2m 20s   remaining: 60s
1600:   learn: 0.9889203        total: 2m 42s   remaining: 40.4s
1800:   learn: 0.9921808        total: 3m 2s    remaining: 20.2s
1999:   learn: 0.9945460        total: 3m 21s   remaining: 0us
0:      learn: 0.7170245        total: 70.4ms   remaining: 2m 20s
200:    learn: 0.7844107        total: 10.2s    remaining: 1m 31s
400:    learn: 0.7926259        total: 20.7s    remaining: 1m 22s
600:    learn: 0.7984757        total: 31.5s    remaining: 1m 13s
800:    learn: 0.8035730        total: 40.4s    remaining: 1m
1000:   learn: 0.8082294        total: 51.7s    remaining: 51.6s
1200:   learn: 0.8121778        total: 1m 3s    remaining: 42.5s
1400:   learn: 0.8154870        total: 1m 14s   remaining: 31.9s
1600:   learn: 0.8186884        total: 1m 25s   remaining: 21.2s
1800:   learn: 0.8220743        total: 1m 36s   remaining: 10.6s
1999:   learn: 0.8248289        total: 1m 46s   remaining: 0us
0:      learn: 0.7119778        total: 44ms     remaining: 1m 27s
200:    learn: 0.7814997        total: 10.5s    remaining: 1m 33s
400:    learn: 0.7891779        total: 19.1s    remaining: 1m 16s
600:    learn: 0.7951421        total: 29.8s    remaining: 1m 9s
800:    learn: 0.8003195        total: 40.4s    remaining: 1m
1000:   learn: 0.8043070        total: 50.6s    remaining: 50.5s
1200:   learn: 0.8084965        total: 59.9s    remaining: 39.8s
1400:   learn: 0.8122875        total: 1m 10s   remaining: 30.2s
1600:   learn: 0.8153775        total: 1m 21s   remaining: 20.3s
1800:   learn: 0.8187356        total: 1m 31s   remaining: 10.1s
1999:   learn: 0.8213401        total: 1m 41s   remaining: 0us
0:      learn: 0.7021416        total: 46.8ms   remaining: 1m 33s
200:    learn: 0.7772773        total: 14.4s    remaining: 2m 8s
400:    learn: 0.7856943        total: 24.9s    remaining: 1m 39s
600:    learn: 0.7924111        total: 35.6s    remaining: 1m 22s
800:    learn: 0.7976221        total: 45s      remaining: 1m 7s
1000:   learn: 0.8022696        total: 55.4s    remaining: 55.3s
1200:   learn: 0.8063554        total: 1m 6s    remaining: 44s
1400:   learn: 0.8100160        total: 1m 17s   remaining: 32.9s
1600:   learn: 0.8134529        total: 1m 26s   remaining: 21.5s
1800:   learn: 0.8166184        total: 1m 36s   remaining: 10.7s
1999:   learn: 0.8190748        total: 1m 47s   remaining: 0us
0:      learn: 0.7170245        total: 44.4ms   remaining: 1m 28s
200:    learn: 0.7776452        total: 10.8s    remaining: 1m 36s
400:    learn: 0.7840745        total: 19.6s    remaining: 1m 18s
600:    learn: 0.7889218        total: 30s      remaining: 1m 9s
800:    learn: 0.7927896        total: 42.8s    remaining: 1m 4s
1000:   learn: 0.7961519        total: 53s      remaining: 52.9s
1200:   learn: 0.7989305        total: 1m 4s    remaining: 43.1s
1400:   learn: 0.8016671        total: 1m 15s   remaining: 32.1s
1600:   learn: 0.8040586        total: 1m 26s   remaining: 21.4s
1800:   learn: 0.8062713        total: 1m 36s   remaining: 10.7s
1999:   learn: 0.8085089        total: 1m 45s   remaining: 0us
0:      learn: 0.7119778        total: 62.5ms   remaining: 2m 4s
200:    learn: 0.7748409        total: 9.86s    remaining: 1m 28s
```

```
400:    learn: 0.7815936        total: 20.5s    remaining: 1m 21s
600:    learn: 0.7862340        total: 30.7s    remaining: 1m 11s
800:    learn: 0.7896311        total: 39.5s    remaining: 59.2s
1000:   learn: 0.7925617        total: 50.1s    remaining: 50s
1200:   learn: 0.7955587        total: 1m 2s    remaining: 41.8s
1400:   learn: 0.7979494        total: 1m 13s   remaining: 31.4s
1600:   learn: 0.8003783        total: 1m 22s   remaining: 20.5s
1800:   learn: 0.8023876        total: 1m 33s   remaining: 10.3s
1999:   learn: 0.8045759        total: 1m 43s   remaining: 0us
0:      learn: 0.7021416        total: 43.9ms   remaining: 1m 27s
200:    learn: 0.7706110        total: 11.5s    remaining: 1m 42s
400:    learn: 0.7777692        total: 20.9s    remaining: 1m 23s
600:    learn: 0.7831430        total: 31.5s    remaining: 1m 13s
800:    learn: 0.7868402        total: 42.1s    remaining: 1m 3s
1000:   learn: 0.7904147        total: 51.1s    remaining: 51s
1200:   learn: 0.7935469        total: 1m 1s    remaining: 41.1s
1400:   learn: 0.7963046        total: 1m 12s   remaining: 31s
1600:   learn: 0.7987198        total: 1m 23s   remaining: 20.8s
1800:   learn: 0.8011384        total: 1m 36s   remaining: 10.6s
1999:   learn: 0.8031308        total: 1m 45s   remaining: 0us
0:      learn: 0.7372834        total: 86.5ms   remaining: 2m 53s
200:    learn: 0.8830068        total: 33.3s    remaining: 4m 58s
400:    learn: 0.9286821        total: 1m 8s    remaining: 4m 31s
600:    learn: 0.9551908        total: 1m 43s   remaining: 3m 59s
800:    learn: 0.9718474        total: 2m 18s   remaining: 3m 27s
1000:   learn: 0.9818393        total: 2m 54s   remaining: 2m 53s
1200:   learn: 0.9884536        total: 3m 29s   remaining: 2m 19s
1400:   learn: 0.9927204        total: 4m 8s    remaining: 1m 46s
1600:   learn: 0.9953963        total: 4m 43s   remaining: 1m 10s
1800:   learn: 0.9969850        total: 5m 20s   remaining: 35.4s
1999:   learn: 0.9980937        total: 5m 54s   remaining: 0us
{'learning_rate': 0.2, 'max_depth': 9}
0.8290391633631794
<catboost.core.CatBoostClassifier object at 0x794fe82d70d0>
```

In [ ]:
```python
# Evaluate the best model on the test data
y_pred_cat = best_cat_model.predict(X_test_cat)

# Compare with training data
y_train_pred_cat = best_cat_model.predict(X_train_cat)
```

In [ ]:
```python
print('Catboost Performance')

print('Training AUPRC: {0:0.4f}'.format(average_precision_score(y_train_cat, y_train_pre
print('Testing AUPRC: {0:0.4f}'.format(average_precision_score(y_test_cat, y_pred_cat)))

print('Training Accuracy: {0:0.4f}'.format(accuracy_score(y_train_cat, y_train_pred_cat)
print('Testing Accuracy: {0:0.4f}'.format(accuracy_score(y_test_cat, y_pred_cat)))

print('Training Recall: {0:0.4f}'.format(recall_score(y_train_cat, y_train_pred_cat)))
print('Testing Recall: {0:0.4f}'.format(recall_score(y_test_cat, y_pred_cat)))

print('Training Precision: {0:0.4f}'.format(precision_score(y_train_cat, y_train_pred_ca
print('Testing Precision: {0:0.4f}'.format(precision_score(y_test_cat, y_pred_cat)))
```

```
Catboost Performance
Training AUPRC: 0.9079
Testing AUPRC: 0.7195
Training Accuracy: 0.9352
Testing Accuracy: 0.7831
Training Recall: 0.9339
Testing Recall: 0.8024
Training Precision: 0.9367
Testing Precision: 0.7733
```

In [ ]:

```
import streamlit as st

def main():
    # Set background image
    page_bg_img = f"""
    <style>
    [data-testid="stAppViewContainer"] > .main {{
    background-image: url("https://wallpapers.com/images/high/gradient-background-7xsdz9
    background-size: cover;
    background-position: center center;
    background-repeat: repeat;
    background-attachment: local;
    }}
    [data-testid="stHeader"] {{
    background: rgba(249, 55, 55, 0);
    }}
    </style>
    """
    st.markdown(page_bg_img, unsafe_allow_html=True)

    # Add a sidebar
    st.sidebar.title("Navigation")
    page = st.sidebar.radio("Go to", ["Introduction"])

    if page == "Introduction":
        show_introduction()

def show_introduction():
    st.title("Predicting Recidivism in Chicago: Overview")
    st.markdown("""

    ### Data Sources:
    - [Chicago Sentencing Data](https://datacatalog.cookcountyil.gov/Courts/Sentencing/t
    - [Chicago Diversion Program Data](https://datacatalog.cookcountyil.gov/Courts/Diver

    ### Objective and Value Proposition:
    In the US, many individuals are dismissed from prison without having had the proper

    Our model aims to predict recidivism among individuals found in prior criminal recor
    """)

if __name__ == "__main__":
    main()
```