Predicting type of crimes in LA on given Time and location

Dataset Description

We will be using this data set:

https://data.lacity.org/Public-Safety/Crime-Data-from-2020-to-Present/2nrs-mtv8

Columns

- DR_NO: Division of Records Number, which is an official file number.
- Date Rptd: Date when the crime was reported, in the format MM/DD/YYYY.
- DATE OCC: Date when the crime occurred, in the format MM/DD/YYYY.
- TIME OCC: Time when the crime occurred, in 24-hour military time format.
- AREA: A code representing the community police station responsible for the area where the crime occurred.
- AREA NAME: Name of the geographic area or patrol division that is responsible for the area where the crime occurred.
- Rpt Dist No: A four-digit code that represents a sub-area within a geographic area.
- Part 1-2: A number indicating the type of crime committed.
- Crm Cd: A code indicating the crime committed.
- Crm Cd Desc: A description of the crime code provided.
- Mocodes: Modus Operandi, which are activities associated with the suspect in commission of the crime.
- Vict Age: The age of the victim, represented as a two-digit number.
- Vict Sex: The sex of the victim, represented as F (female), M (male), or X (unknown).
- Vict Descent: Descent code of the victim, indicating the racial or ethnic group they belong to.
- Premis Cd: A code indicating the type of structure, vehicle, or location where the crime took place.
- Premis Desc: A description of the premise code provided.
- Weapon Used Cd: A code indicating the type of weapon used in the crime.
- Weapon Desc: A description of the weapon used code provided.
- Status: A code indicating the status of the case.
- Status Desc: A description of the status code provided.
- Crm Cd 1: A code indicating the primary and most serious crime committed.
- Crm Cd 2-4: Additional codes indicating less serious offenses.
- LOCATION: Street address of crime incident rounded to the nearest hundred block to maintain anonymity.
- Cross Street: Cross street of the rounded address.

- LAT: Latitude of the location where the crime occurred.
- LON: Longitude of the location where the crime occurred.

```
import pandas as pd
import io
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score,f1_score,classification_report,confusion_ma
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

```
from google.colab import drive
drive.mount('/content/drive')
```

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

```
file_path = '/content/drive/MyDrive/Crime_Data_from_2020_to_Present.csv'
df = pd.read_csv(file_path)
```

```
# #Load data
# from google.colab import files
# uploaded = files.upload()
# df = pd.read_csv(io.BytesIO(uploaded['Crime_Data_from_2020_to_Present.csv']))
# #print(df)
df.head()
```

	DR_NO	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd I
0	10304468	01/08/2020 12:00:00 AM	01/08/2020 12:00:00 AM	2230	3	Southwest	377	2	624	BATTE SIM ASS/
1	190101086	01/02/2020 12:00:00	01/01/2020 12:00:00	330	1	Central	163	2	624	BATTE SIN
		04/14/2020	02/13/2020							REGISTE

Data Preprocessing

```
#checking for data info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 739687 entries, 0 to 739686
Data columns (total 28 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   DR_NO           739687 non-null  int64  
 1   Date Rptd       739687 non-null  object 
 2   DATE OCC        739687 non-null  object 
 3   TIME OCC        739687 non-null  int64  
 4   AREA            739687 non-null  int64  
 5   AREA NAME       739687 non-null  object 
 6   Rpt Dist No     739687 non-null  int64  
 7   Part 1-2        739687 non-null  int64  
 8   Crm Cd          739687 non-null  int64  
 9   Crm Cd Desc     739687 non-null  object 
 10  Mocodes         638226 non-null  object 
 11  Vict Age        739687 non-null  int64  
 12  Vict Sex        643115 non-null  object 
 13  Vict Descent    643109 non-null  object 
 14  Premis Cd       739677 non-null  float64
 15  Premis Desc     739266 non-null  object 
 16  Weapon Used Cd  256726 non-null  float64
 17  Weapon Desc     256726 non-null  object 
 18  Status          739687 non-null  object 
 19  Status Desc     739687 non-null  object 
 20  Crm Cd 1        739679 non-null  float64
 21  Crm Cd 2        54830 non-null   float64
 22  Crm Cd 3        1833 non-null    float64
 23  Crm Cd 4        54 non-null      float64
 24  LOCATION        739687 non-null  object 
 25  Cross Street    119144 non-null  object 
 26  LAT             739687 non-null  float64
 27  LON             739687 non-null  float64
dtypes: float64(8), int64(7), object(13)
memory usage: 158.0+ MB
```

```
# Removing irrelevant/not meaningful attributes from description of columns data. the
col = ['Date Rptd','DR_NO','AREA', 'Mocodes', 'Premis Desc', 'Weapon Desc', 'Status De
       'Crm Cd 2', 'Crm Cd 3', 'Crm Cd 4', 'Cross Street','Weapon Used Cd']
df = df.drop(col,axis=1)


# Handling null values
df.isna().sum()/df.shape[0]
# filling victim sex empty rows with "X" unknown symbol
df["Vict Sex"].fillna("X",inplace=True)

# filling victim descent empty rows with "X" unknown symbol
df["Vict Descent"].fillna("X",inplace=True)

#dropping any empty rows existing after this
df.dropna(inplace=True)


df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Desc	Vict Age	Vic Se
0	01/08/2020 12:00:00 AM	2230	Southwest	377	2	624	BATTERY - SIMPLE ASSAULT	36	
1	01/01/2020 12:00:00 AM	330	Central	163	2	624	BATTERY - SIMPLE ASSAULT	25	
2	02/13/2020 12:00:00 AM	1200	Central	155	2	845	SEX OFFENDER REGISTRANT OUT OF COMPLIANCE	0	
3	01/01/2020 12:00:00 AM	1730	N Hollywood	1543	2	745	VANDALISM - MISDEAMEANOR ($399 OR UNDER)	76	

```
# Converting the date column to datetime
df['DATE OCC'] = pd.to_datetime(df['DATE OCC'], format='%m/%d/%Y %I:%M:%S %p')


# Extracting year, month, day into separate columns
df['year'] = df['DATE OCC'].dt.year
df['month'] = df['DATE OCC'].dt.month
df['day'] = df['DATE OCC'].dt.day
df['day_of_week'] = df['DATE OCC'].dt.day_name()


# Converting time to string
df['TIME OCC'] = df['TIME OCC'].astype('str')

# converting the column with 4 digits
```

```
df['TIME OCC'] = df['TIME OCC'].apply(lambda x: x.zfill(4))

# extracting hour and minute
df['hour'] = df['TIME OCC'].str[:2]
df['minute'] = df['TIME OCC'].str[2:]
```

```
#Checking no of Targets
print(len(df["Crm Cd"].unique()))
```

```
138
```

```
df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Desc	Vict Age	Vict Sex	Vict Descent	...
0	2020-01-08	2230	Southwest	377	2	624	BATTERY - SIMPLE ASSAULT	36	F	B	...
1	2020-01-01	0330	Central	163	2	624	BATTERY - SIMPLE ASSAULT	25	M	H	...
2	2020-02-13	1200	Central	155	2	845	SEX OFFENDER REGISTRANT OUT OF COMPLIANCE	0	X	X	...
3	2020-01-01	1730	N Hollywood	1543	2	745	VANDALISM - MISDEAMEANOR ($399 OR UNDER)	76	F	W	...
	2020-						VANDALISM - FELONY ($400 &				

```
df.columns
```

```
Index(['DATE OCC', 'TIME OCC', 'AREA NAME', 'Rpt Dist No', 'Part 1-2',
       'Crm Cd', 'Crm Cd Desc', 'Vict Age', 'Vict Sex', 'Vict Descent',
       'Premis Cd', 'Status', 'LOCATION', 'LAT', 'LON', 'year', 'month', 'day',
       'day_of_week', 'hour', 'minute'],
      dtype='object')
```

```
df['Crm Cd Desc']
```

```
0                                  BATTERY - SIMPLE ASSAULT
1                                  BATTERY - SIMPLE ASSAULT
2                 SEX OFFENDER REGISTRANT OUT OF COMPLIANCE
3                  VANDALISM - MISDEAMEANOR ($399 OR UNDER)
4          VANDALISM - FELONY ($400 & OVER, ALL CHURCH VA...
```

```
                                    ...
739682                                   BUNCO, GRAND THEFT
739683    VANDALISM - FELONY ($400 & OVER, ALL CHURCH VA...
739684       ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT
739685       ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT
739686             VANDALISM - MISDEAMEANOR ($399 OR UNDER)
Name: Crm Cd Desc, Length: 739677, dtype: object
```

```
df.shape
```

```
(739677, 21)
```

```
df['Crm Cd Desc'].unique()
```

```
       'SHOTS FIRED AT INHABITED DWELLING', 'BURGLARY, ATTEMPTED',
       'INDECENT EXPOSURE', 'ORAL COPULATION',
       'EMBEZZLEMENT, GRAND THEFT ($950.01 & OVER)',
       'VIOLATION OF TEMPORARY RESTRAINING ORDER', 'BUNCO, PETTY THEFT',
       'KIDNAPPING - GRAND ATTEMPT',
       'SHOPLIFTING-GRAND THEFT ($950.01 & OVER)', 'RESISTING ARREST',
       'DISCHARGE FIREARMS/SHOTS FIRED',
       'THREATENING PHONE CALLS/LETTERS', 'KIDNAPPING',
       'LEWD/LASCIVIOUS ACTS WITH CHILD', 'LEWD CONDUCT',
       'UNAUTHORIZED COMPUTER ACCESS', 'PURSE SNATCHING',
       'SODOMY/SEXUAL CONTACT B/W PENIS OF ONE PERS TO ANUS OTH',
```

```
       'RECKLESS DRIVING', 'PURSE SNATCHING - ATTEMPT',
       'BIKE - ATTEMPTED STOLEN', 'CONSPIRACY', 'CONTRIBUTING',
       'WEAPONS POSSESSION/BOMBING', 'BRIBERY', 'BOAT - STOLEN',
       'THEFT, COIN MACHINE - GRAND ($950.01 & OVER)',
       'GRAND THEFT / INSURANCE FRAUD', 'LYNCHING', 'DISRUPT SCHOOL',
       'DISHONEST EMPLOYEE - PETTY THEFT',
       'THEFT, COIN MACHINE - ATTEMPT',
       'THEFT, COIN MACHINE - PETTY ($950 & UNDER)',
       'REPLICA FIREARMS(SALE,DISPLAY,MANUFACTURE OR DISTRIBUTE)',
       'DRUGS, TO A MINOR', 'GRAND THEFT / AUTO REPAIR',
       'PICKPOCKET, ATTEMPT', 'DRUNK ROLL', 'CHILD ABANDONMENT',
       'TELEPHONE PROPERTY - DAMAGE',
       'BEASTIALITY, CRIME AGAINST NATURE SEXUAL ASSLT WITH ANIM',
       'BIGAMY', 'FAILURE TO DISPERSE',
       'FIREARMS EMERGENCY PROTECTIVE ORDER (FIREARMS EPO)',
       'INCEST (SEXUAL ACTS BETWEEN BLOOD RELATIVES)',
       'DISHONEST EMPLOYEE ATTEMPTED THEFT',
       'BLOCKING DOOR INDUCTION CENTER', 'INCITING A RIOT'], dtype=object)
```

```
# due to the huge number of Labels we should map them to reduce its numbers
def Crime_type(crime):

    types = ["STOLEN",'BATTERY','THEFT', 'BURGLARY', 'VANDALISM', 'ASSAULT', 'CRIMINAI
             'TRESPASSING','VIOLATION',"CRIMINAL HOMICIDE", 'CHILD ABUSE', 'RAPE','ROI

    types_name = ["MOTOR VEHICLE THEFT",'BATTERY','THEFT', 'BURGLARY', 'VANDALISM', 'I
              'TRESPASSING','VIOLATION',"CRIMINAL HOMICIDE", 'CHILD ABUSE', 'RAPE','R(

    for name,t in zip(types_name,types) :
        if t in crime:
            return name

    return "OTHERS"


# apply function on each row
df["Crime"] = df["Crm Cd Desc"].apply(Crime_type)


df["Crime"].value_counts()
```

```
    THEFT                  199071
    ASSAULT                 97413
    BURGLARY                94335
    MOTOR VEHICLE THEFT     91767
    VANDALISM               65798
    BATTERY                 64073
    OTHERS                  52670
    ROBBERY                 29164
    CRIMINAL THREATS        15410
    VIOLATION               15241
    TRESPASSING             10299
    RAPE                     3177
    CRIMINAL HOMICIDE        1259
    Name: Crime, dtype: int64
```

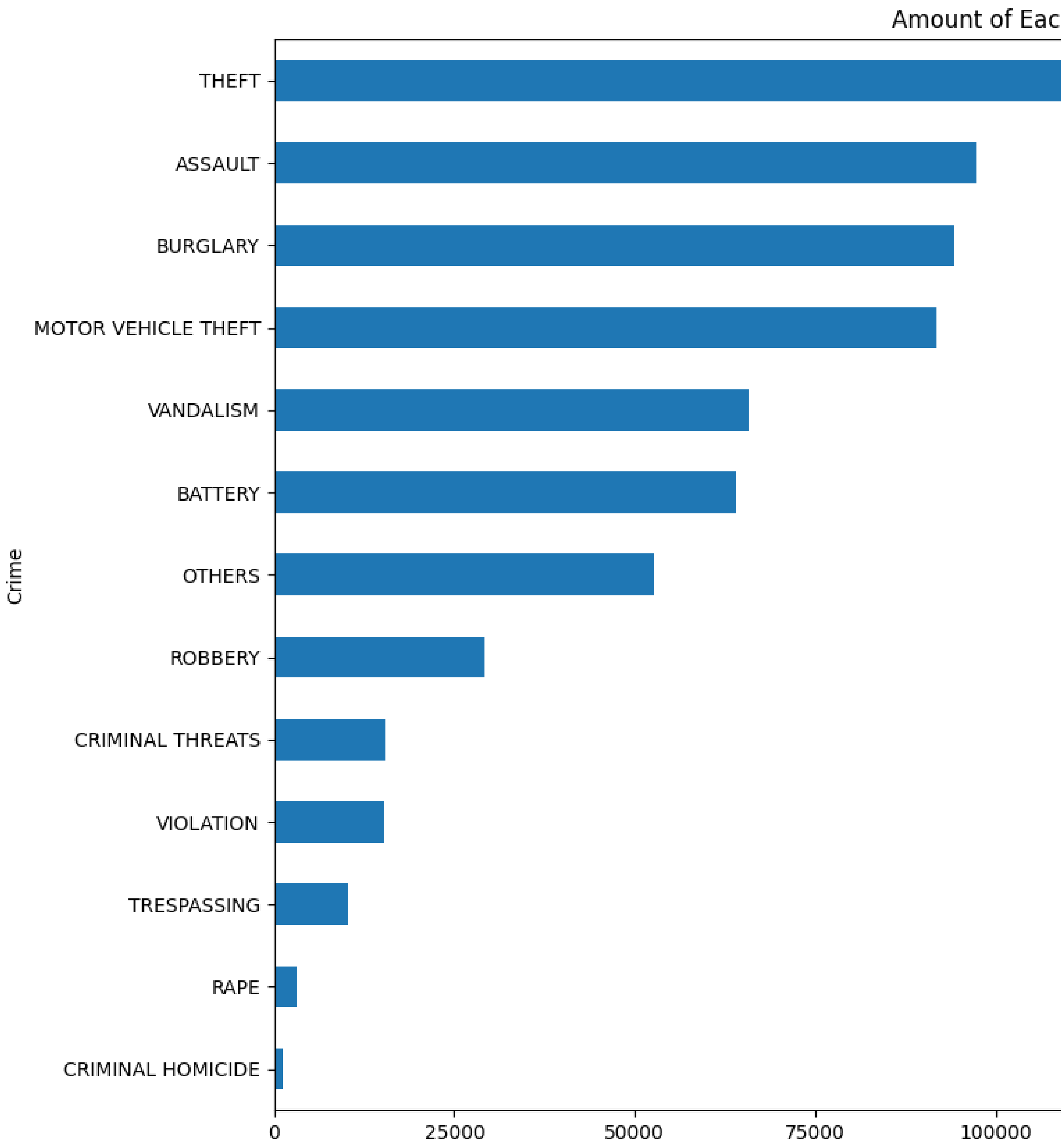
```
#drop "Crm Cd Desc" and "Crm Cd"
df = df.drop(['Crm Cd','Crm Cd Desc'],axis = 1)
df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Vict Age	Vict Sex	Vict Descent	Premis Cd	Status	LOCATION
0	2020-01-08	2230	Southwest	377	2	36	F	B	501.0	AO	1100 W 39TH PL
1	2020-01-01	0330	Central	163	2	25	M	H	102.0	IC	700 S HILL ST
2	2020-02-13	1200	Central	155	2	0	X	X	726.0	AA	200 E 6TH ST
3	2020-01-01	1730	N Hollywood	1543	2	76	F	W	502.0	IC	5400 CORTEEN PL
4	2020-	0415	Mission	1998	2	31	X	X	409.0	IC	14400

```
df.Crime.value_counts()
```

```
THEFT                  199071
ASSAULT                 97413
BURGLARY                94335
MOTOR VEHICLE THEFT     91767
VANDALISM               65798
BATTERY                 64073
OTHERS                  52670
ROBBERY                 29164
CRIMINAL THREATS        15410
VIOLATION               15241
TRESPASSING             10299
RAPE                     3177
CRIMINAL HOMICIDE        1259
Name: Crime, dtype: int64
```

```
# Plot Bar Chart visualization for Crime Types
plt.figure(figsize=(14,10))
plt.title('Amount of Each Crimes')
plt.ylabel('Crime Type')
plt.xlabel('Amount of Crimes')

df.groupby([df['Crime']]).size().sort_values(ascending=True).plot(kind='barh')

plt.show()
```




```
df['Crime'].value_counts()
```

```
THEFT                  199071
ASSAULT                 97413
BURGLARY                94335
MOTOR VEHICLE THEFT     91767
VANDALISM               65798
BATTERY                 64073
OTHERS                  52670
```

```
ROBBERY                 29164
CRIMINAL THREATS        15410
VIOLATION               15241
TRESPASSING             10299
RAPE                     3177
CRIMINAL HOMICIDE        1259
Name: Crime, dtype: int64
```

```
crime_types_to_update = ['OTHERS','CRIMINAL THREATS', 'VIOLATION', 'TRESPASSING', 'RAI

# Updating specified crime types to 'OTHERS' based on the total count
df.loc[df['Crime'].isin(crime_types_to_update), 'Crime'] = 'OTHERS'
```

```
df['Crime'].value_counts()
```

```
THEFT                  199071
OTHERS                  98056
ASSAULT                 97413
BURGLARY                94335
MOTOR VEHICLE THEFT     91767
VANDALISM               65798
BATTERY                 64073
ROBBERY                 29164
Name: Crime, dtype: int64
```

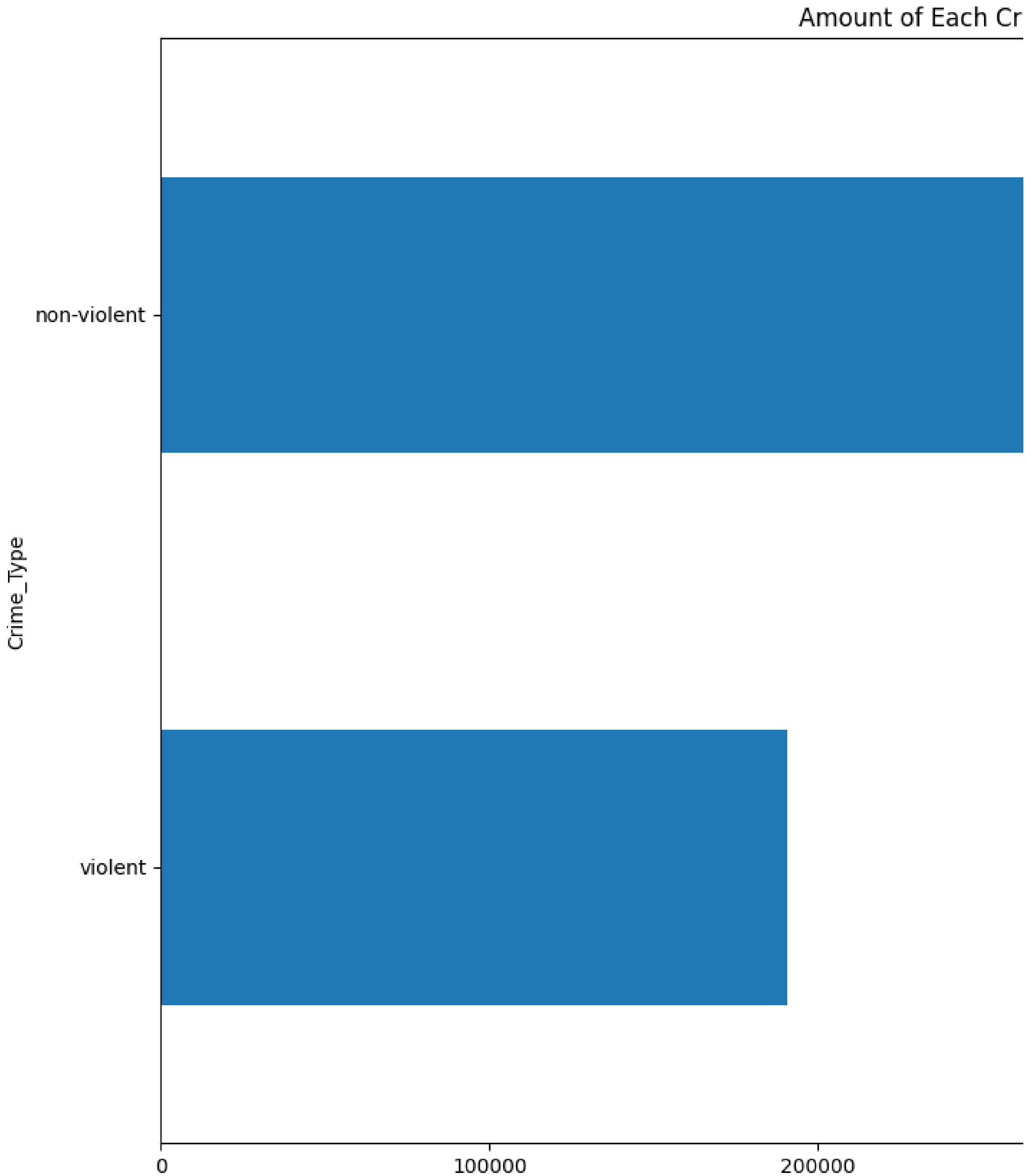
```
# Dropping all the rows with type 'OTHERS'
df = df[df['Crime']!='OTHERS']
```

```
# Converting the following into binary clasification by dividing the crime type into v

def categorize_crime(crime_type):
    if crime_type in ['ASSAULT','BATTERY', 'ROBBERY', 'RAPE', 'CRIMINAL HOMICIDE']:
        return 'violent'
    else:
        return 'non-violent'

df['Crime_Type'] = df['Crime'].apply(categorize_crime)

print(df['Crime_Type'].value_counts())
```

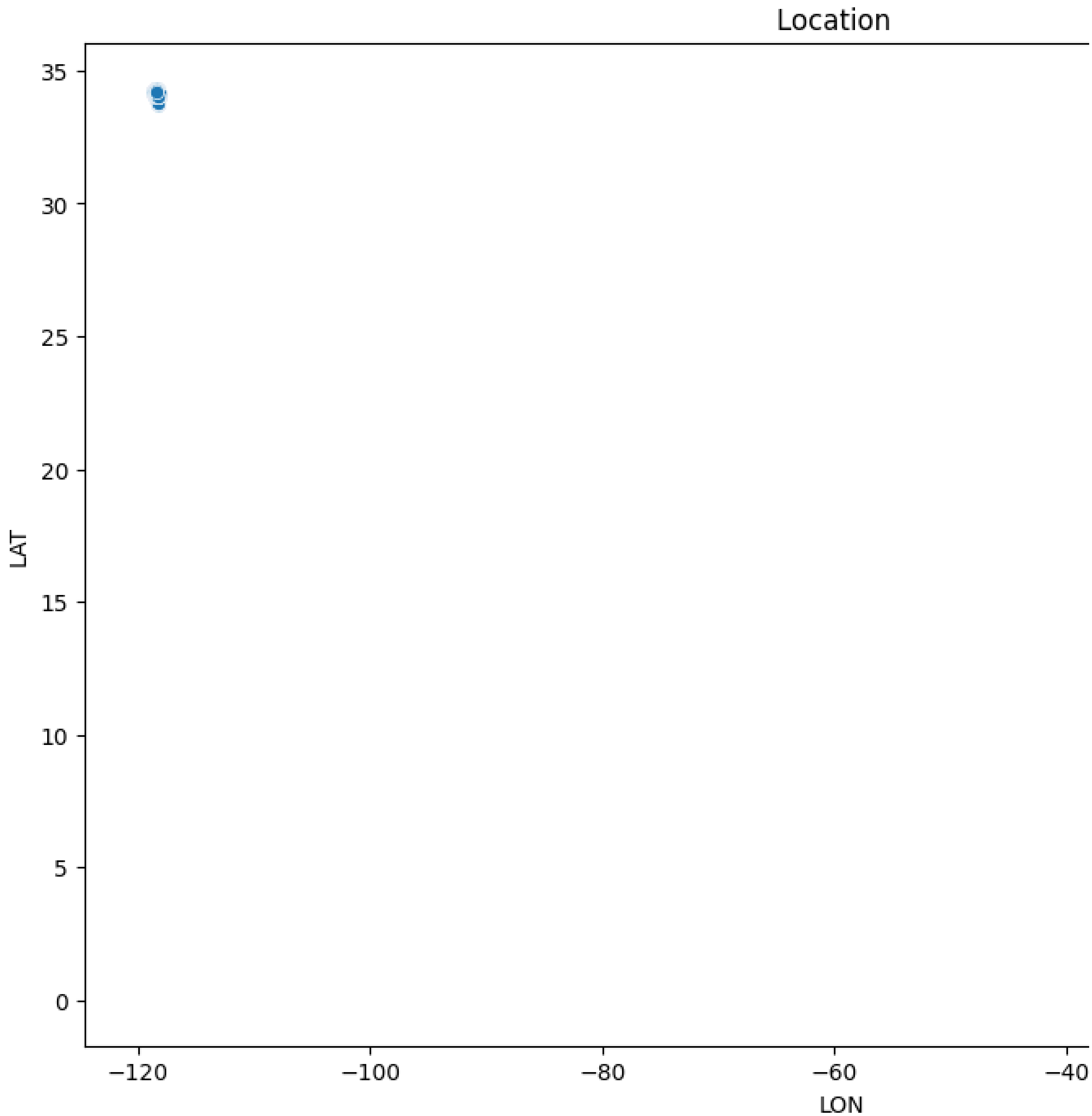
```
non-violent    450971
violent        190650
Name: Crime_Type, dtype: int64
```

```
# Plot Bar Chart visualize for Crime Types
plt.figure(figsize=(14,10))
plt.title('Amount of Each Crimes')
plt.ylabel('Crime Type')
plt.xlabel('Amount of Crimes')
```

```
df.groupby([df['Crime_Type']]).size().sort_values(ascending=True).plot(kind='barh')

plt.show()
```

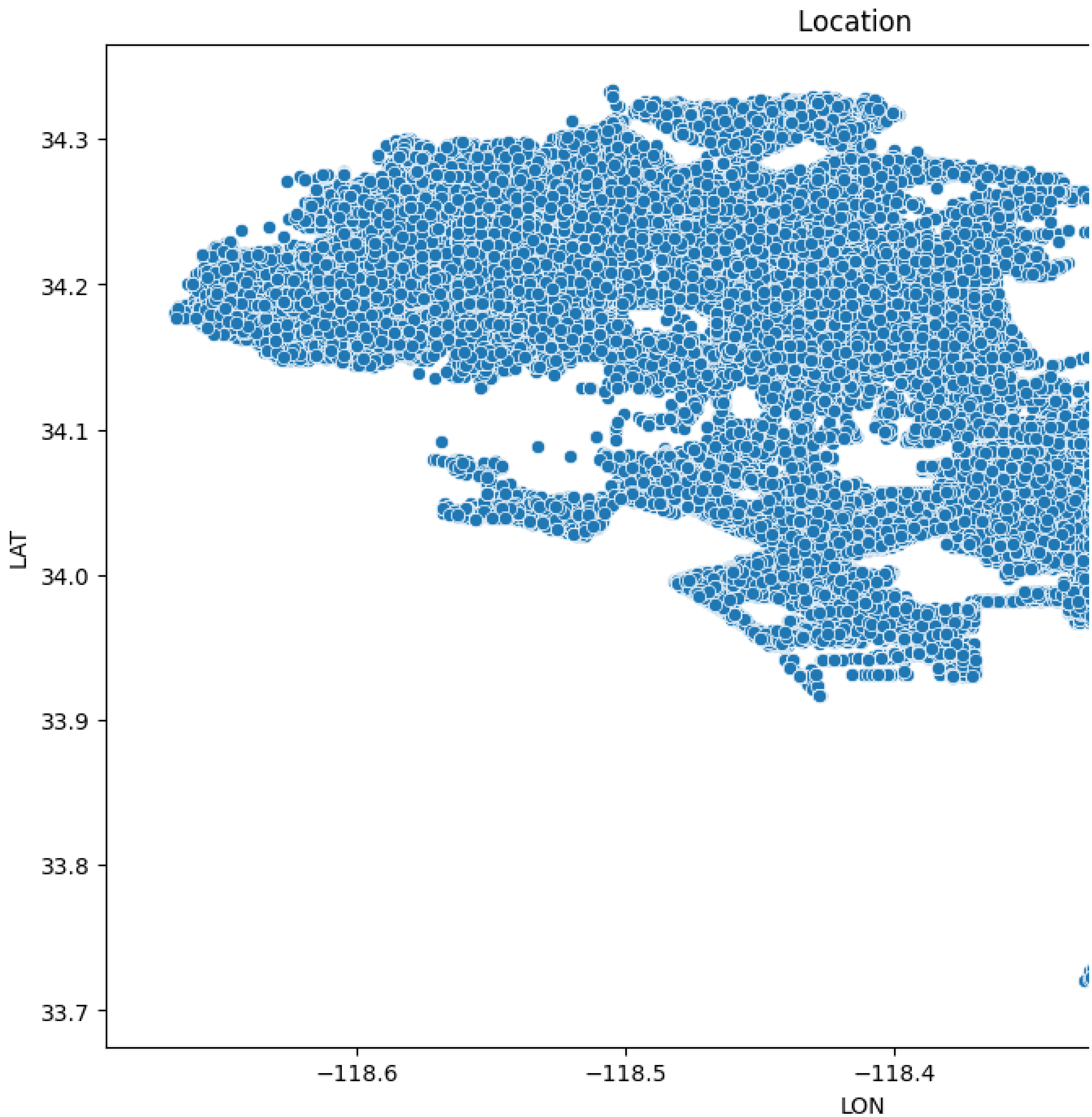


```
# Checking Location of Crimes

plt.figure(figsize=(12,8))
plt.title("Location  ");
sns.scatterplot(x="LON",y="LAT",data=df);
```




```
# There are some lat and lon with value of 0 which need to be neglected
#dropping rows where Lat or Lon is 0
df = df.drop(index = df[( df["LAT"] == 0 ) | ( df["LON"] == 0) ].index)


plt.figure(figsize=(12,8))
plt.title("Location  ");
```

```
sns.scatterplot(x="LON",y="LAT",data=df);
```




```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 640254 entries, 0 to 739686
Data columns (total 21 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   DATE OCC        640254 non-null  datetime64[ns]
 1   TIME OCC        640254 non-null  object
 2   AREA NAME       640254 non-null  object
 3   Rpt Dist No     640254 non-null  int64
 4   Part 1-2        640254 non-null  int64
```

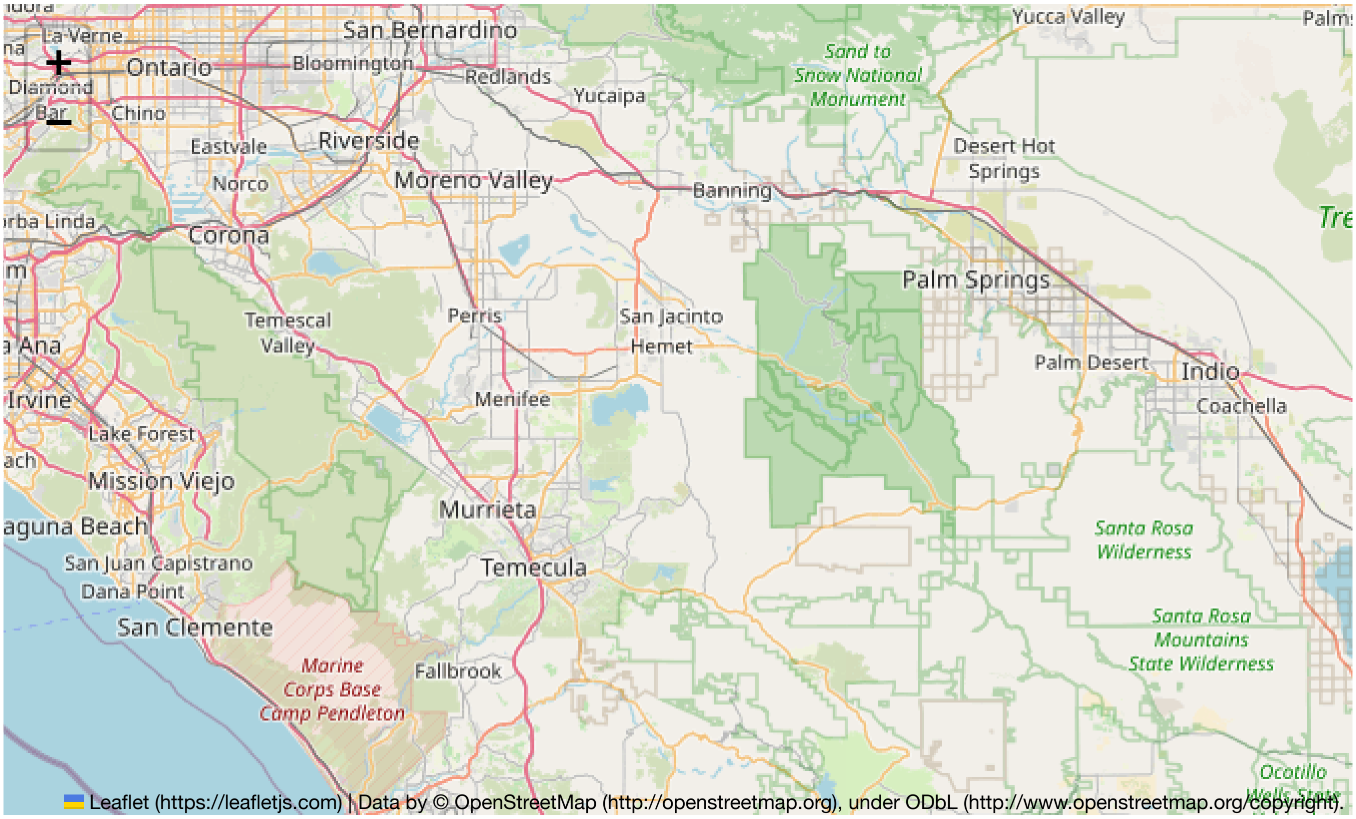
```
 5   Vict Age      640254 non-null  int64
 6   Vict Sex      640254 non-null  object
 7   Vict Descent  640254 non-null  object
 8   Premis Cd     640254 non-null  float64
 9   Status        640254 non-null  object
 10  LOCATION      640254 non-null  object
 11  LAT           640254 non-null  float64
 12  LON           640254 non-null  float64
 13  year          640254 non-null  int64
 14  month         640254 non-null  int64
 15  day           640254 non-null  int64
 16  day_of_week   640254 non-null  object
 17  hour          640254 non-null  object
 18  minute        640254 non-null  object
 19  Crime         640254 non-null  object
 20  Crime_Type    640254 non-null  object
dtypes: datetime64[ns](1), float64(3), int64(6), object(11)
memory usage: 107.5+ MB
```

```
df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Vict Age	Vict Sex	Vict Descent	Premis Cd	Status	...	LA
0	2020-01-08	2230	Southwest	377	2	36	F	B	501.0	AO	...	34.01
1	2020-01-01	0330	Central	163	2	25	M	H	102.0	IC	...	34.04
3	2020-01-01	1730	N Hollywood	1543	2	76	F	W	502.0	IC	...	34.16
4	2020-01-01	0415	Mission	1998	2	31	X	X	409.0	IC	...	34.21
6	2020-01-02	1315	Central	161	1	23	M	H	404.0	IC	...	34.04

5 rows × 21 columns

```
import folium
from folium.plugins import HeatMap
# create map centered at LA
la_map = folium.Map(location=[34.0522, -118.2437], zoom_start=10)

# create heatmap layer with reduced intensity
heat_data = [[row['LAT'], row['LON']] for index, row in df.iterrows()]
HeatMap(heat_data, min_opacity=0.2, max_val=10).add_to(la_map)

# display map
la_map
```



Unsupported Cell Type. Double-Click to inspect/edit the content.

```
df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Vict Age	Vict Sex	Vict Descent	Premis Cd	Status	...	LA
0	2020-01-08	2230	Southwest	377	2	36	F	B	501.0	AO	...	34.01
1	2020-01-01	0330	Central	163	2	25	M	H	102.0	IC	...	34.04
3	2020-01-01	1730	N Hollywood	1543	2	76	F	W	502.0	IC	...	34.16
4	2020-01-01	0415	Mission	1998	2	31	X	X	409.0	IC	...	34.21
6	2020-01-02	1315	Central	161	1	23	M	H	404.0	IC	...	34.04

5 rows × 21 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 640254 entries, 0 to 739686
Data columns (total 21 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   DATE OCC       640254 non-null  datetime64[ns]
 1   TIME OCC       640254 non-null  object
 2   AREA NAME      640254 non-null  object
 3   Rpt Dist No    640254 non-null  int64
 4   Part 1-2       640254 non-null  int64
 5   Vict Age       640254 non-null  int64
 6   Vict Sex       640254 non-null  object
 7   Vict Descent   640254 non-null  object
 8   Premis Cd      640254 non-null  float64
 9   Status         640254 non-null  object
 10  LOCATION       640254 non-null  object
 11  LAT            640254 non-null  float64
 12  LON            640254 non-null  float64
 13  year           640254 non-null  int64
 14  month          640254 non-null  int64
 15  day            640254 non-null  int64
 16  day_of_week    640254 non-null  object
 17  hour           640254 non-null  object
 18  minute         640254 non-null  object
 19  Crime          640254 non-null  object
 20  Crime_Type     640254 non-null  object
```

```
dtypes: datetime64[ns](1), float64(3), int64(6), object(11)
memory usage: 107.5+ MB
```

```
df['AREA NAME'] = df['AREA NAME'].astype('category')
df['Rpt Dist No'] = df['Rpt Dist No'].astype('category')
df['Premis Cd'] = df['Premis Cd'].astype('int')
df['Premis Cd'] = df['Premis Cd'].astype('category')
df['hour'] = df['hour'].astype('category')
df['minute'] = df['minute'].astype('category')
df['day'] = df['day'].astype('category')
df['month'] = df['month'].astype('category')
df['Status'] = df['Status'].astype('category')
df['Part 1-2'] = df['Part 1-2'].astype('category')
df['day_of_week'] = df['day_of_week'].astype('category')
```

```
df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Vict Age	Vict Sex	Vict Descent	Premis Cd	Status	...	LA
0	2020-01-08	2230	Southwest	377	2	36	F	B	501	AO	...	34.01
1	2020-01-01	0330	Central	163	2	25	M	H	102	IC	...	34.04
3	2020-01-01	1730	N Hollywood	1543	2	76	F	W	502	IC	...	34.16
4	2020-01-01	0415	Mission	1998	2	31	X	X	409	IC	...	34.21
6	2020-01-02	1315	Central	161	1	23	M	H	404	IC	...	34.04

5 rows × 21 columns

```
df['LOCATION']
```

```
0          1100 W  39TH                         PL
1           700 S  HILL                         ST
3          5400    CORTEEN                      PL
4         14400    TITUS                        ST
6           700 S  FIGUEROA                     ST
                            ...
739682     5300    DENNY                        AV
739683    12500    BRANFORD                     ST
739684    12800    FILMORE                      ST
```

```
739685     6100 S  VERMONT                      AV
739686    14500    HARTLAND                     ST
Name: LOCATION, Length: 640254, dtype: object
```

```
df.columns
```

```
Index(['DATE OCC', 'TIME OCC', 'AREA NAME', 'Rpt Dist No', 'Part 1-2',
       'Vict Age', 'Vict Sex', 'Vict Descent', 'Premis Cd', 'Status',
       'LOCATION', 'LAT', 'LON', 'year', 'month', 'day', 'day_of_week', 'hour',
       'minute', 'Crime', 'Crime_Type'],
      dtype='object')
```

```
df['LOCATION'][0]
```

```
'1100 W  39TH                         PL'
```

```
# Extract block and street name from the 'Address' column while removing extra spaces
df[['Block', 'Street']] = df['LOCATION'].str.extract(r'(\d+)\s+(.+)')
df['Street'] = df['Street'].str.replace(r'\s+', ' ').str.strip()
```

```
df['Block'].unique()
```

```
array(['1100', '700', '5400', '14400', '11900', nan, '800', '100',
       '14200', '3200', '14700', '13600', '5700', '600', '18600', '2700',
       '8500', '500', '8400', '14100', '12100', '200', '2600', '300',
       '2100', '400', '8900', '3000', '1800', '1200', '900', '10300',
       '1300', '23400', '13100', '1600', '6000', '19700', '2200', '1400',
       '11400', '1000', '2500', '2000', '6100', '13500', '00', '5200',
       '10500', '6800', '3900', '6500', '7000', '8700', '11700', '6600',
       '3100', '1700', '5300', '14600', '4400', '3400', '2400', '5800',
       '16700', '10200', '3800', '3500', '4900', '9200', '9800', '7800',
       '4300', '3300', '15600', '7200', '7700', '4600', '9000', '19000',
       '1500', '6200', '1900', '16800', '16400', '13300', '7900', '4000',
       '8200', '2800', '26300', '11800', '2900', '3600', '10700', '4100',
       '19200', '24900', '7100', '7500', '12200', '4800', '18500',
       '18900', '9100', '14800', '14500', '17300', '17000', '10900',
       '11000', '5600', '2300', '21500', '8800', '4700', '5900', '3700',
       '20400', '4500', '18400', '8600', '19600', '17100', '5000', '6700',
       '19800', '4200', '19900', '6400', '10800', '19400', '10600',
       '17900', '5500', '11200', '15100', '20300', '22700', '5100',
       '15200', '12500', '9300', '17800', '15300', '11500', '13800',
       '24100', '12700', '7300', '16100', '13400', '19100', '8000',
       '12400', '8300', '17400', '6900', '11100', '9900', '6300', '7400',
       '14300', '20100', '19300', '16500', '7600', '14900', '24700',
       '20500', '9600', '21700', '25400', '12800', '18300', '12600',
       '17200', '22800', '21100', '15000', '24400', '19500', '28000',
       '25800', '20600', '25600', '25300', '25500', '14000', '15900',
       '13700', '22500', '17600', '28100', '25200', '22900', '18700',
       '22400', '12900', '23200', '21000', '24600', '18800', '20700',
       '20900', '13000', '10100', '8100', '21200', '22000', '15500',
       '10400', '13900', '11300', '11600', '17500', '9700', '21600',
       '21300', '16900', '18200', '15700', '24800', '21900', '9400',
```

```
       '12300', '22200', '25700', '16300', '23500', '13200', '17700',
       '22100', '20800', '15400', '9500', '12000', '18000', '18100',
       '23600', '16200', '23900', '10000', '22600', '20000', '25900',
       '21400', '26100', '16000', '16600', '21800', '20200', '25000',
       '15800', '26400', '24000', '06300', '26200', '23700', '23100',
       '24500', '22300', '24200', '26600', '23000', '110', '24300',
       '23300', '28900', '26000', '01100', '25100', '101', '23800',
       '26500', '57', '08600', '0700', '56', '09000', '05200', '05900',
       '118', '405', '54000', '09300', '39000', '06100', '90', '04900',
       '09100', '247', '00000', '07400', '09200', '08100', '01900',
       '08400', '27900', '30100', '5', '52', '07300', '27800', '00500',
       '05100', '06200', '04300', '80700', '03900', '51000', '105',
       '06900', '05300', '29000', '04700', '04800', '55', '01200',
       '28200', '00900', '07800', '09900', '11', '27700', '0800', '0600',
       '28300', '09500', '00700', '0900', '27600', '07000', '60100',
       '07100', '69400', '01400', '38100', '97200', '10', '06600',
       '05600', '36100', '60'], dtype=object)
```

```
# Dropping all the block with 00
df = df[df['Block'] != '00']
```

```
df.shape
```

```
(638809, 23)
```

```
#Dropping all rows with NaN
df = df.dropna()
```

```
#Counting all missing or NaN vaalues
df.isna().sum().sum()
```

```
0
```

```
df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Vict Age	Vict Sex	Vict Descent	Premis Cd	Status	...	year
0	2020-01-08	2230	Southwest	377	2	36	F	B	501	AO	...	2020
1	2020-01-01	0330	Central	163	2	25	M	H	102	IC	...	2020

```
len(df['Street'].unique())
```

```
9663
```

4	2020-	0415	Mission	1998	2	31	X	X	409	IC		2020

```
df.shape
```

```
(534818, 23)
```

```
df.describe()
```

	Vict Age	LAT	LON	year
count	534818.000000	534818.000000	534818.000000	534818.000000
mean	29.570155	34.077066	-118.359011	2021.332253
std	22.184458	0.111832	0.105565	1.009669
min	-2.000000	33.706400	-118.667600	2020.000000
25%	0.000000	34.017900	-118.435600	2020.000000
50%	31.000000	34.061800	-118.331000	2021.000000
75%	45.000000	34.168300	-118.276700	2022.000000
max	120.000000	34.334300	-118.156000	2023.000000

```
# Selecting features for model
```

```
df.columns
```

```
Index(['DATE OCC', 'TIME OCC', 'AREA NAME', 'Rpt Dist No', 'Part 1-2',
       'Vict Age', 'Vict Sex', 'Vict Descent', 'Premis Cd', 'Status',
       'LOCATION', 'LAT', 'LON', 'year', 'month', 'day', 'day_of_week', 'hour',
       'minute', 'Crime', 'Crime_Type', 'Block', 'Street'],
      dtype='object')
```

```
df.head()
```

	DATE OCC	TIME OCC	AREA NAME	Rpt Dist No	Part 1-2	Vict Age	Vict Sex	Vict Descent	Premis Cd	Status	...	year
0	2020-01-08	2230	Southwest	377	2	36	F	B	501	AO	...	2020
1	2020-01-01	0330	Central	163	2	25	M	H	102	IC	...	2020
3	2020-01-01	1730	N Hollywood	1543	2	76	F	W	502	IC	...	2020
4	2020-01-01	0415	Mission	1998	2	31	X	X	409	IC	...	2020
6	2020-01-02	1315	Central	161	1	23	M	H	404	IC	...	2020

```
features = ['AREA NAME','Rpt Dist No','Premis Cd','Block','Street','LAT','LON','hour',

df = df[features]
df.head()
```

	AREA NAME	Rpt Dist No	Premis Cd	Block	Street	LAT	LON	hour
0	Southwest	377	501	1100	W 39TH PL	34.0141	-118.2978	22
1	Central	163	102	700	S HILL ST	34.0459	-118.2545	03
3	N Hollywood	1543	502	5400	CORTEEN PL	34.1685	-118.4019	17
4	Mission	1998	409	14400	TITUS ST	34.2198	-118.4468	04
6	Central	161	404	700	S FIGUEROA ST	34.0483	-118.2631	13

```
# Refined data
df.to_csv('crime_data.csv')
#files.download('crime_data.csv')
```

```
# copy of data
df_1 = df.copy()
```

```
# To reduce the traning time we take random sample and them do undersampling to balanc
```

```
df.shape
```

```
(534818, 11)
```

```
# sample size
sample_size = 50000  # Adjust the sample size as desired

# Randomly sample the data
sampled_df = df.sample(n=sample_size, random_state=42)
sampled_df.reset_index(drop=True, inplace=True)

# shape of sampled dataframe
sampled_df.shape
```

```
(50000, 11)
```

```
X = sampled_df.drop(columns=['Crime','Crime_Type'])
y = sampled_df['Crime']
```

```
y.value_counts()
```

```
THEFT                  16949
BURGLARY                7806
MOTOR VEHICLE THEFT     6815
ASSAULT                 6795
VANDALISM               5296
BATTERY                 4676
ROBBERY                 1663
Name: Crime, dtype: int64
```

```
from imblearn.under_sampling import RandomUnderSampler

# Create an instance of RandomUnderSampler
rus = RandomUnderSampler(random_state=42)

# Resample the data using RandomUnderSampler
X_resampled, y_resampled = rus.fit_resample(X, y)
```

```
y_resampled.value_counts()
```

```
ASSAULT                1663
BATTERY                1663
BURGLARY               1663
```

```
MOTOR VEHICLE THEFT    1663
ROBBERY                1663
THEFT                  1663
VANDALISM              1663
Name: Crime, dtype: int64
```

```
df = X_resampled.join(y_resampled)
df.head()
```

	AREA NAME	Rpt Dist No	Premis Cd	Block	Street	LAT	LON	hour
0	Mission	1994	108	14700	TITUS ST	34.2197	-118.4536	15
1	Southeast	1863	501	400	E 118TH PL	33.9256	-118.2674	00
2	N Hollywood	1506	502	7400	VINELAND AV	34.2027	-118.3745	09
3	West LA	842	502	11700	WILSHIRE BL	34.0491	-118.4614	23
4	Southwest	334	242	3000	CRENSHAW BL	34.0276	-118.3351	20

```
df.Crime.value_counts()
```

```
ASSAULT                1663
BATTERY                1663
BURGLARY               1663
MOTOR VEHICLE THEFT    1663
ROBBERY                1663
THEFT                  1663
VANDALISM              1663
Name: Crime, dtype: int64
```

```
from sklearn.preprocessing import LabelEncoder

# Initialize LabelEncoder
label_encoder = LabelEncoder()

df['Crime'] = label_encoder.fit_transform(df['Crime'])
```

```
df.Crime.value_counts()
```

```
0    1663
1    1663
2    1663
3    1663
4    1663
```

```
5    1663
6    1663
Name: Crime, dtype: int64
```

```
# One-hot encoding all columns except for LAT, LON, and Crime
df_encoded = pd.get_dummies(df[['AREA NAME','Rpt Dist No','Block','Street','Premis Cd'
```

```
# Concatenate the one-hot encoded columns with the original dataframe
new_df = pd.concat([df[['LAT', 'LON', 'Crime']], df_encoded], axis=1)
```

```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11641 entries, 0 to 11640
Columns: 4380 entries, LAT to day_of_week_Wednesday
dtypes: float64(2), int64(1), uint8(4377)
memory usage: 48.9 MB
```

```
new_df.head()
```

	LAT	LON	Crime	AREA NAME_Central	AREA NAME_Devonshire	AREA NAME_Foothill	AI NAME_Harl
0	34.2197	-118.4536	0	0	0	0	
1	33.9256	-118.2674	0	0	0	0	
2	34.2027	-118.3745	0	0	0	0	
3	34.0491	-118.4614	0	0	0	0	
4	34.0276	-118.3351	0	0	0	0	

5 rows × 4380 columns

```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11641 entries, 0 to 11640
Columns: 4380 entries, LAT to day_of_week_Wednesday
dtypes: float64(2), int64(1), uint8(4377)
memory usage: 48.9 MB
```

```
X = new_df.drop(columns=['Crime'])
y = new_df["Crime"]
```

```
X.head()
```

	LAT	LON	AREA NAME_Central	AREA NAME_Devonshire	AREA NAME_Foothill	AREA NAME_Harbor	NAI
0	34.2197	-118.4536	0	0	0	0	
1	33.9256	-118.2674	0	0	0	0	
2	34.2027	-118.3745	0	0	0	0	
3	34.0491	-118.4614	0	0	0	0	
4	34.0276	-118.3351	0	0	0	0	

5 rows × 4379 columns

```
#Split dataset to Training Set & Test Set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

```
#define a function for train ML model
def train_model(clf, X_train, y_train):
    clf.fit(X_train, y_train)

#define a function for predict ML model
def predict_data(clf, features, target):
    y_pred = clf.predict(features)

    acc = accuracy_score(target,y_pred)
    f1 = f1_score(target, y_pred, average='micro')
    con_matrix = confusion_matrix(target,y_pred)
    class_report = classification_report(target,y_pred)
    return f1, acc, con_matrix, class_report

#define a function for create ML model
def model(clf, X_train, y_train, X_test, y_test):
    train_model(clf, X_train, y_train)

    f1, acc, con_matrix, class_report = predict_data(clf, X_test, y_test)
    print("Test Data:")
    print("-" * 20)
    print("F1 Score:{}".format(f1))
    print("Accuracy:{}".format(acc))
    print("Confusion Matrix")
    print(con_matrix)
    print("Classfication Report")
```

```
    print(class_report)
    print("-" * 20)
```

```
# Multinomial Classification
```

```
pip install catboost
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Collecting catboost
  Downloading catboost-1.2-cp310-cp310-manylinux2014_x86_64.whl (98.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 98.6/98.6 MB 9.9 MB/s eta 0:00:00
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dis
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/di
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/di
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dis
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist
Installing collected packages: catboost
Successfully installed catboost-1.2
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import AdaBoostClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from catboost import CatBoostClassifier
from lightgbm import LGBMClassifier
```

```
# Instantiate the additional classification models
lrc = LogisticRegression(multi_class='multinomial')
dtc = DecisionTreeClassifier()
knn = KNeighborsClassifier(n_neighbors=1)
```

```
rfc = RandomForestClassifier(n_estimators=100)
gnb = GaussianNB()
adaboost = AdaBoostClassifier()
mlp = MLPClassifier()
qda = QuadraticDiscriminantAnalysis()
gbm = GradientBoostingClassifier()
xgb = XGBClassifier()
catboost = CatBoostClassifier()
lgbm = LGBMClassifier()


#print("\nXGBoost Classifier")
#print("-" * 20)
#model(xgb, X_train, y_train, X_test, y_test)

#print("\nCatBoost Classifier")
#print("-" * 20)
#model(catboost, X_train, y_train, X_test, y_test)

#print("\nLightGBM Classifier")
#print("-" * 20)
#model(lgbm, X_train, y_train, X_test, y_test)



# print("Logistic Regression")
# print("-" * 20)
# model(lrc, X_train, y_train, X_test, y_test)

# print("\nDecision Tree")
# print("-" * 20)
# model(dtc, X_train, y_train, X_test, y_test)

# print("\nRandom Forest Classifier")
# print("-" * 20)
# model(rfc, X_train, y_train, X_test, y_test)

# print("\nXGBoost Classifier")
# print("-" * 20)
# model(xgb, X_train, y_train, X_test, y_test)

# print("\nCatBoost Classifier")
# print("-" * 20)
# model(catboost, X_train, y_train, X_test, y_test)

# print("\nLightGBM Classifier")
# print("-" * 20)
# model(lgbm, X_train, y_train, X_test, y_test)

# print("\nGradient Boosting Classifier")
# print("-" * 20)
# model(gbm, X_train, y_train, X_test, y_test)
```

```
# print("\nAdaBoost Classifier")
# print("-" * 20)
# model(adaboost, X_train, y_train, X_test, y_test)

# print("\nK Nearest Neighbors (KNN)")
# print("-" * 20)
# model(knn, X_train, y_train, X_test, y_test)

# print("\nGaussian Naive Bayes")
# print("-" * 20)
# model(gnb, X_train, y_train, X_test, y_test)

# print("\nMultilayer Perceptron (MLP) Classifier")
# print("-" * 20)
# model(mlp, X_train, y_train, X_test, y_test)

# print("\nQuadratic Discriminant Analysis (QDA)")
# print("-" * 20)
# model(qda, X_train, y_train, X_test, y_test)
```

```
Logistic Regression
--------------------
Test Data:
--------------------
F1 Score:0.3374838986689566
Accuracy:0.3374838986689566
Confusion Matrix
[[128  71  23  50  28  37  12]
 [ 72  68  30  42  46  44  20]
 [ 31  24  89 102  20  45  24]
 [  4  17  32 214  30  32   4]
 [ 25  42  20  71 118  37  13]
 [ 57  31  33  97  45  72  22]
 [ 36  39  33  61  14  27  97]]
Classfication Report
              precision    recall  f1-score   support

           0       0.36      0.37      0.36       349
           1       0.23      0.21      0.22       322
           2       0.34      0.27      0.30       335
           3       0.34      0.64      0.44       333
           4       0.39      0.36      0.38       326
           5       0.24      0.20      0.22       357
           6       0.51      0.32      0.39       307

    accuracy                           0.34      2329
   macro avg       0.35      0.34      0.33      2329
weighted avg       0.34      0.34      0.33      2329

--------------------

Decision Tree
--------------------
```

```
Test Data:
--------------------
F1 Score:0.2803778445684843
Accuracy:0.2803778445684843
Confusion Matrix
[[ 89  56  31  36  47  37  53]
 [ 58  59  33  30  59  44  39]
 [ 26  28  91  72  36  42  40]
 [ 27  26  49 141  29  38  23]
 [ 33  52  25  47 108  35  26]
 [ 50  42  42  55  63  69  36]
 [ 41  38  32  35  30  35  96]]
Classfication Report
              precision    recall  f1-score   support

           0       0.27      0.26      0.26       349
           1       0.20      0.18      0.19       322
           2       0.30      0.27      0.29       335
           3       0.34      0.42      0.38       333
           4       0.29      0.33      0.31       326
           5       0.23      0.19      0.21       357
           6       0.31      0.31      0.31       307

    accuracy                           0.28      2329
   macro avg       0.28      0.28      0.28      2329
```

```
# --------------------------------------------------------
```

```
# Binomial Classification
```

```
df_1.head()
```

	AREA NAME	Rpt Dist No	Premis Cd	Block	Street	LAT	LON	hour
0	Southwest	377	501	1100	W 39TH PL	34.0141	-118.2978	22
1	Central	163	102	700	S HILL ST	34.0459	-118.2545	03
3	N Hollywood	1543	502	5400	CORTEEN PL	34.1685	-118.4019	17
4	Mission	1998	409	14400	TITUS ST	34.2198	-118.4468	04
6	Central	161	404	700	S FIGUEROA ST	34.0483	-118.2631	13

```
df_1.shape
```

```
(534818, 11)
```

```
# sample size
sample_size = 50000  # Adjust the sample size as desired

# Randomly sample the data
sampled_df = df_1.sample(n=sample_size, random_state=42)
sampled_df.reset_index(drop=True, inplace=True)

# shape of sampled dataframe
sampled_df.shape
```

```
(50000, 11)
```

```
X = df_1.drop(columns=['Crime_Type','Crime'])
y = df_1["Crime_Type"]
```

```
df = X.join(y)
```

```
y.value_counts()
```

```
non-violent    393673
violent        141145
Name: Crime_Type, dtype: int64
```

```
# Resampling
from imblearn.under_sampling import RandomUnderSampler

# Creating an instance of RandomUnderSampler
rus = RandomUnderSampler(random_state=42)

# Resampling the data using RandomUnderSampler
X_resampled, y_resampled = rus.fit_resample(X, y)

df = X_resampled.join(y_resampled)
df.head()
```

	AREA NAME	Rpt Dist No	Premis Cd	Block	Street	LAT	LON
0	Foothill	1653	501	9700	PINE ORCHARD ST	34.2461	-118.4105
1	Newton	1365	750	4700	COMPTON AV	33.9994	-118.2499
2	Harbor	563	101	1000	S GAFFEY ST	33.7350	-118.2924
3	Topanga	2156	404	6700	TOPANGA CANYON BL	34.1923	-118.6059

```
from sklearn.preprocessing import LabelEncoder

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Encode the column
df['Block'] = label_encoder.fit_transform(df['Block'])
df['Street'] = label_encoder.fit_transform(df['Street'])
df['Crime_Type'] = label_encoder.fit_transform(df['Crime_Type'])
```

```
df['Crime_Type'].value_counts()
```

```
0    141145
1    141145
Name: Crime_Type, dtype: int64
```

```
# One-hot encoding all columns except for LAT, LON, and Crime
df_encoded = pd.get_dummies(df[['AREA NAME','Premis Cd','Rpt Dist No','hour','day_of_w
```

```
data = pd.concat([df[['LAT', 'LON', 'Crime_Type']], df_encoded], axis=1)
data.head()
```

	LAT	LON	Crime_Type	AREA NAME_Central	AREA NAME_Devonshire	AREA NAME_Foothill	NAMI
0	34.2461	-118.4105	0	0	0	1	
1	33.9994	-118.2499	0	0	0	0	
2	33.7350	-118.2924	0	0	0	0	
3	34.1923	-118.6059	0	0	0	0	
4	34.1079	-118.2972	0	0	0	0	

5 rows × 1545 columns

```
data.shape
```

```
(282290, 1545)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 282290 entries, 0 to 282289
Columns: 1545 entries, LAT to day_of_week_Wednesday
dtypes: float64(2), int64(1), uint8(1542)
memory usage: 421.6 MB
```

```
X = data.drop(columns=['Crime_Type'])
y = data["Crime_Type"]
```

```
y.value_counts()
```

```
0    141145
1    141145
Name: Crime_Type, dtype: int64
```

```
#Split dataset to Training Set & Test Set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

```
#import lightgbm as lgb
#num_classes = 2  # Replace with the actual number of classes in your dataset

#lgbm = lgb.LGBMClassifier(num_class=num_classes)
```

```
#print("\nXGBoost Classifier")
#print("-" * 20)
#model(xgb, X_train, y_train, X_test, y_test)

# print("\nCatBoost Classifier")
# print("-" * 20)
# model(catboost, X_train, y_train, X_test, y_test)

#print("\nLightGBM Classifier")
#print("-" * 20)
#model(lgbm, X_train, y_train, X_test, y_test)

# print("\nAdaBoost Classifier")
# print("-" * 20)
# model(adaboost, X_train, y_train, X_test, y_test)

# print("\nGradient Boosting Classifier")
# print("-" * 20)
# model(gbm, X_train, y_train, X_test, y_test)

# print("\nQuadratic Discriminant Analysis (QDA)")
```

```
# print("-" * 20)
# model(qda, X_train, y_train, X_test, y_test)

# print("\nGaussian Naive Bayes")
# print("-" * 20)
# model(gnb, X_train, y_train, X_test, y_test)

# print("\nMultilayer Perceptron (MLP) Classifier")
# print("-" * 20)
# model(mlp, X_train, y_train, X_test, y_test)

# print("\nK Nearest Neighbors (KNN)")
# print("-" * 20)
# model(knn, X_train, y_train, X_test, y_test)

# print("Logistic Regression")
# print("-" * 20)
# model(lrc, X_train, y_train, X_test, y_test)

# print("\nDecision Tree")
# print("-" * 20)
# model(dtc, X_train, y_train, X_test, y_test)

# print("\nRandom Forest Classifier")
# print("-" * 20)
# model(rfc, X_train, y_train, X_test, y_test)
```

```
XGBoost Classifier
--------------------

CatBoost Classifier
--------------------
Learning rate set to 0.104232
0:	learn: 0.6803918	total: 118ms	remaining: 1m 57s
1:	learn: 0.6708233	total: 227ms	remaining: 1m 53s
2:	learn: 0.6631095	total: 305ms	remaining: 1m 41s
3:	learn: 0.6567852	total: 417ms	remaining: 1m 43s
4:	learn: 0.6519575	total: 482ms	remaining: 1m 36s
5:	learn: 0.6475213	total: 581ms	remaining: 1m 36s
6:	learn: 0.6443142	total: 651ms	remaining: 1m 32s
7:	learn: 0.6416041	total: 704ms	remaining: 1m 27s
8:	learn: 0.6386102	total: 752ms	remaining: 1m 22s
9:	learn: 0.6362210	total: 852ms	remaining: 1m 24s
10:	learn: 0.6344116	total: 937ms	remaining: 1m 24s
11:	learn: 0.6326695	total: 1.02s	remaining: 1m 23s
12:	learn: 0.6311544	total: 1.09s	remaining: 1m 22s
13:	learn: 0.6298831	total: 1.17s	remaining: 1m 22s
14:	learn: 0.6286843	total: 1.24s	remaining: 1m 21s
15:	learn: 0.6272631	total: 1.31s	remaining: 1m 20s
16:	learn: 0.6262006	total: 1.4s	remaining: 1m 20s
17:	learn: 0.6250664	total: 1.43s	remaining: 1m 18s
18:	learn: 0.6242701	total: 1.5s	remaining: 1m 17s
19:	learn: 0.6233201	total: 1.54s	remaining: 1m 15s
```

```
20:	learn: 0.6223452	total: 1.57s	remaining: 1m 13s
21:	learn: 0.6217173	total: 1.6s	remaining: 1m 10s
22:	learn: 0.6209490	total: 1.63s	remaining: 1m 9s
23:	learn: 0.6201942	total: 1.66s	remaining: 1m 7s
24:	learn: 0.6193029	total: 1.69s	remaining: 1m 5s
25:	learn: 0.6185627	total: 1.72s	remaining: 1m 4s
26:	learn: 0.6179876	total: 1.75s	remaining: 1m 3s
27:	learn: 0.6173284	total: 1.78s	remaining: 1m 1s
28:	learn: 0.6166312	total: 1.81s	remaining: 1m
29:	learn: 0.6160414	total: 1.84s	remaining: 59.7s
30:	learn: 0.6153634	total: 1.88s	remaining: 58.7s
31:	learn: 0.6148592	total: 1.91s	remaining: 57.8s
32:	learn: 0.6142480	total: 1.94s	remaining: 56.8s
33:	learn: 0.6134249	total: 1.97s	remaining: 56.1s
34:	learn: 0.6126606	total: 2s	remaining: 55.3s
35:	learn: 0.6121424	total: 2.04s	remaining: 54.5s
36:	learn: 0.6116181	total: 2.07s	remaining: 53.8s
37:	learn: 0.6112530	total: 2.1s	remaining: 53.2s
38:	learn: 0.6107940	total: 2.13s	remaining: 52.6s
39:	learn: 0.6102086	total: 2.17s	remaining: 52s
40:	learn: 0.6096856	total: 2.2s	remaining: 51.4s
41:	learn: 0.6092255	total: 2.23s	remaining: 50.9s
42:	learn: 0.6087715	total: 2.26s	remaining: 50.3s
43:	learn: 0.6083895	total: 2.29s	remaining: 49.8s
44:	learn: 0.6080422	total: 2.32s	remaining: 49.3s
45:	learn: 0.6077082	total: 2.35s	remaining: 48.8s
46:	learn: 0.6073165	total: 2.38s	remaining: 48.4s
47:	learn: 0.6070075	total: 2.42s	remaining: 48s
48:	learn: 0.6066209	total: 2.45s	remaining: 47.6s
49:	learn: 0.6060113	total: 2.49s	remaining: 47.3s
50:	learn: 0.6056947	total: 2.52s	remaining: 46.9s
```

```
# Violent Crime
```

```
df = df_1[df_1['Crime_Type']=='violent']
```

```
df.shape
```

```
(141145, 11)
```

```
df.Crime.value_counts()
```

```
ASSAULT    73042
BATTERY    50449
ROBBERY    17654
Name: Crime, dtype: int64
```

```
from sklearn.preprocessing import LabelEncoder

# Initialize LabelEncoder
label_encoder = LabelEncoder()
```

```
# Encode the column
df['Block'] = label_encoder.fit_transform(df['Block'])
df['Street'] = label_encoder.fit_transform(df['Street'])
df['Crime'] = label_encoder.fit_transform(df['Crime'])
```

```
df.Crime.value_counts()
```

```
0    73042
1    50449
2    17654
Name: Crime, dtype: int64
```

```
# One-hot encoding all columns except for LAT, LON, and Crime
df_encoded = pd.get_dummies(df[['AREA NAME','Premis Cd','Rpt Dist No','hour','day_of_w
```

```
data = pd.concat([df[['LAT', 'LON', 'Crime']], df_encoded], axis=1)
data.head()
```

	LAT	LON	Crime	AREA NAME_Central	AREA NAME_Devonshire	AREA NAME_Foothill	A NAME_Ha
0	34.0141	-118.2978	1	0	0	0	
1	34.0459	-118.2545	1	1	0	0	
15	34.3055	-118.4439	0	0	0	0	
16	34.1186	-118.2450	0	0	0	0	
24	34.0428	-118.2461	0	1	0	0	

5 rows × 1545 columns

```
X = data.drop(columns=['Crime'])
y = data["Crime"]
```

```
#Split dataset to Training Set & Test Set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

```
print("\nXGBoost Classifier")
print("-" * 20)
model(xgb, X_train, y_train, X_test, y_test)
```

```
XGBoost Classifier
```

```
--------------------
Test Data:
--------------------
F1 Score:0.592227850791739
Accuracy:0.592227850791739
Confusion Matrix
[[12455  1868   227]
 [ 6266  3429   429]
 [ 1714  1007   834]]
Classfication Report
              precision    recall  f1-score   support

           0       0.61      0.86      0.71     14550
           1       0.54      0.34      0.42     10124
           2       0.56      0.23      0.33      3555

    accuracy                           0.59     28229
   macro avg       0.57      0.48      0.49     28229
weighted avg       0.58      0.59      0.56     28229

--------------------
```

```
print("\nCatBoost Classifier")
print("-" * 20)
model(catboost, X_train, y_train, X_test, y_test)
```

```
CatBoost Classifier
--------------------
Learning rate set to 0.100696
0:	learn: 1.0673258	total: 101ms	remaining: 1m 41s
1:	learn: 1.0414981	total: 133ms	remaining: 1m 6s
2:	learn: 1.0206431	total: 165ms	remaining: 54.7s
3:	learn: 1.0033390	total: 199ms	remaining: 49.5s
4:	learn: 0.9885313	total: 229ms	remaining: 45.5s
5:	learn: 0.9750663	total: 263ms	remaining: 43.6s
6:	learn: 0.9647275	total: 291ms	remaining: 41.3s
7:	learn: 0.9552116	total: 326ms	remaining: 40.5s
8:	learn: 0.9467975	total: 356ms	remaining: 39.2s
9:	learn: 0.9395802	total: 383ms	remaining: 38s
10:	learn: 0.9332917	total: 414ms	remaining: 37.2s
11:	learn: 0.9277149	total: 446ms	remaining: 36.7s
12:	learn: 0.9228893	total: 477ms	remaining: 36.2s
13:	learn: 0.9192688	total: 505ms	remaining: 35.5s
14:	learn: 0.9150599	total: 538ms	remaining: 35.4s
15:	learn: 0.9112700	total: 568ms	remaining: 34.9s
16:	learn: 0.9084734	total: 595ms	remaining: 34.4s
17:	learn: 0.9062024	total: 624ms	remaining: 34s
18:	learn: 0.9041730	total: 653ms	remaining: 33.7s
19:	learn: 0.9024076	total: 685ms	remaining: 33.6s
20:	learn: 0.9008262	total: 713ms	remaining: 33.2s
21:	learn: 0.8992271	total: 743ms	remaining: 33s
22:	learn: 0.8971059	total: 774ms	remaining: 32.9s
23:	learn: 0.8958589	total: 801ms	remaining: 32.6s
24:	learn: 0.8946032	total: 829ms	remaining: 32.3s
```

```
25:     learn: 0.8934820        total: 861ms    remaining: 32.2s
26:     learn: 0.8917705        total: 895ms    remaining: 32.3s
27:     learn: 0.8907429        total: 923ms    remaining: 32.1s
28:     learn: 0.8899195        total: 954ms    remaining: 32s
29:     learn: 0.8890989        total: 985ms    remaining: 31.8s
30:     learn: 0.8882386        total: 1.01s    remaining: 31.6s
31:     learn: 0.8876072        total: 1.04s    remaining: 31.4s
32:     learn: 0.8869340        total: 1.07s    remaining: 31.3s
33:     learn: 0.8862046        total: 1.1s     remaining: 31.4s
34:     learn: 0.8852503        total: 1.13s    remaining: 31.3s
35:     learn: 0.8848246        total: 1.17s    remaining: 31.3s
36:     learn: 0.8843947        total: 1.2s     remaining: 31.2s
37:     learn: 0.8833710        total: 1.23s    remaining: 31.1s
38:     learn: 0.8829299        total: 1.25s    remaining: 30.9s
39:     learn: 0.8823681        total: 1.28s    remaining: 30.7s
40:     learn: 0.8819298        total: 1.32s    remaining: 30.9s
41:     learn: 0.8815476        total: 1.35s    remaining: 30.7s
42:     learn: 0.8809442        total: 1.38s    remaining: 30.7s
43:     learn: 0.8805429        total: 1.41s    remaining: 30.6s
44:     learn: 0.8801547        total: 1.44s    remaining: 30.5s
45:     learn: 0.8796245        total: 1.46s    remaining: 30.3s
46:     learn: 0.8786321        total: 1.49s    remaining: 30.3s
47:     learn: 0.8782009        total: 1.52s    remaining: 30.3s
48:     learn: 0.8778483        total: 1.55s    remaining: 30.2s
49:     learn: 0.8775571        total: 1.59s    remaining: 30.2s
50:     learn: 0.8771883        total: 1.62s    remaining: 30.1s
51:     learn: 0.8767915        total: 1.64s    remaining: 30s
52:     learn: 0.8765221        total: 1.67s    remaining: 29.9s
53:     learn: 0.8760972        total: 1.7s     remaining: 29.8s
```

```
print("\nLightGBM Classifier")
print("-" * 20)
model(lgbm, X_train, y_train, X_test, y_test)
```

```
LightGBM Classifier
--------------------
Test Data:
--------------------
F1 Score:0.5929717666229763
Accuracy:0.5929717666229763
Confusion Matrix
[[12314  1981   255]
 [ 6109  3521   494]
 [ 1626  1025   904]]
Classfication Report
              precision    recall  f1-score   support

           0       0.61      0.85      0.71     14550
           1       0.54      0.35      0.42     10124
           2       0.55      0.25      0.35      3555

    accuracy                           0.59     28229
   macro avg       0.57      0.48      0.49     28229
weighted avg       0.58      0.59      0.56     28229
```

```
    --------------------

print("\nAdaBoost Classifier")
print("-" * 20)
model(adaboost, X_train, y_train, X_test, y_test)


    AdaBoost Classifier
    --------------------
    Test Data:
    --------------------
    F1 Score:0.5802897729285487
    Accuracy:0.5802897729285487
    Confusion Matrix
    [[13391   915   244]
     [ 7505  2153   466]
     [ 2118   600   837]]
    Classfication Report
                  precision    recall  f1-score   support

               0       0.58      0.92      0.71     14550
               1       0.59      0.21      0.31     10124
               2       0.54      0.24      0.33      3555

        accuracy                           0.58     28229
       macro avg       0.57      0.46      0.45     28229
    weighted avg       0.58      0.58      0.52     28229

    --------------------

print("\nGradient Boosting Classifier")
print("-" * 20)
model(gbm, X_train, y_train, X_test, y_test)


    Gradient Boosting Classifier
    --------------------
    Test Data:
    --------------------
    F1 Score:0.5839030783945588
    Accuracy:0.5839030783945588
    Confusion Matrix
    [[12783  1577   190]
     [ 6783  2986   355]
     [ 1888   953   714]]
    Classfication Report
                  precision    recall  f1-score   support

               0       0.60      0.88      0.71     14550
               1       0.54      0.29      0.38     10124
               2       0.57      0.20      0.30      3555

        accuracy                           0.58     28229
```

```
   macro avg       0.57      0.46      0.46     28229
weighted avg       0.57      0.58      0.54     28229

--------------------
```

```
print("\nQuadratic Discriminant Analysis (QDA)")
print("-" * 20)
model(qda, X_train, y_train, X_test, y_test)
```

```
Quadratic Discriminant Analysis (QDA)
--------------------
Test Data:
--------------------
F1 Score:0.15778100534910908
Accuracy:0.15778100534910908
Confusion Matrix
[[  524   250 13776]
 [  398   493  9233]
 [   71    47  3437]]
Classfication Report
              precision    recall  f1-score   support

           0       0.53      0.04      0.07     14550
           1       0.62      0.05      0.09     10124
           2       0.13      0.97      0.23      3555

    accuracy                           0.16     28229
   macro avg       0.43      0.35      0.13     28229
weighted avg       0.51      0.16      0.10     28229

--------------------
```

```
print("\nGaussian Naive Bayes")
print("-" * 20)
model(gnb, X_train, y_train, X_test, y_test)
```

```
Gaussian Naive Bayes
--------------------
Test Data:
--------------------
F1 Score:0.21424775939636545
Accuracy:0.21424775939636545
Confusion Matrix
[[ 1614   699 12237]
 [  973  1189  7962]
 [  181   129  3245]]
Classfication Report
              precision    recall  f1-score   support

           0       0.58      0.11      0.19     14550
           1       0.59      0.12      0.20     10124
           2       0.14      0.91      0.24      3555
```

```
    accuracy                           0.21     28229
   macro avg       0.44      0.38      0.21     28229
weighted avg       0.53      0.21      0.20     28229

--------------------
```

```
print("\nMultilayer Perceptron (MLP) Classifier")
print("-" * 20)
model(mlp, X_train, y_train, X_test, y_test)
```

```
Multilayer Perceptron (MLP) Classifier
--------------------
Test Data:
--------------------
F1 Score:0.5730277374331362
Accuracy:0.5730277374331362
Confusion Matrix
[[11071  2918   561]
 [ 5361  4130   633]
 [ 1464  1116   975]]
Classfication Report
              precision    recall  f1-score   support

           0       0.62      0.76      0.68     14550
           1       0.51      0.41      0.45     10124
           2       0.45      0.27      0.34      3555

    accuracy                           0.57     28229
   macro avg       0.52      0.48      0.49     28229
weighted avg       0.56      0.57      0.56     28229

--------------------
```

```
print("\nK Nearest Neighbors (KNN)")
print("-" * 20)
model(knn, X_train, y_train, X_test, y_test)
```

```
K Nearest Neighbors (KNN)
--------------------
Test Data:
--------------------
F1 Score:0.5227248574161324
Accuracy:0.5227248574161324
Confusion Matrix
[[9178 4143 1229]
 [4461 4657 1006]
 [1554 1080  921]]
Classfication Report
              precision    recall  f1-score   support

           0       0.60      0.63      0.62     14550
```

```
           1       0.47      0.46      0.47     10124
           2       0.29      0.26      0.27      3555

    accuracy                           0.52     28229
   macro avg       0.46      0.45      0.45     28229
weighted avg       0.52      0.52      0.52     28229

--------------------
```

```
print("Logistic Regression")
print("-" * 20)
model(lrc, X_train, y_train, X_test, y_test)
```

```
Logistic Regression
--------------------
Test Data:
--------------------
F1 Score:0.5800418009848028
Accuracy:0.5800418009848028
Confusion Matrix
[[11983  2318   249]
 [ 6020  3653   451]
 [ 1613  1204   738]]
Classfication Report
              precision    recall  f1-score   support

           0       0.61      0.82      0.70     14550
           1       0.51      0.36      0.42     10124
           2       0.51      0.21      0.30      3555

    accuracy                           0.58     28229
   macro avg       0.54      0.46      0.47     28229
weighted avg       0.56      0.58      0.55     28229

--------------------
```

```
print("\nDecision Tree")
print("-" * 20)
model(dtc, X_train, y_train, X_test, y_test)
```

```
Decision Tree
--------------------
Test Data:
--------------------
F1 Score:0.5335293492507704
Accuracy:0.5335293492507704
Confusion Matrix
[[9202 4201 1147]
 [4333 4740 1051]
 [1317 1119 1119]]
Classfication Report
              precision    recall  f1-score   support
```

```
               0       0.62      0.63      0.63     14550
               1       0.47      0.47      0.47     10124
               2       0.34      0.31      0.33      3555

        accuracy                           0.53     28229
       macro avg       0.48      0.47      0.47     28229
    weighted avg       0.53      0.53      0.53     28229

    --------------------
```

```
print("\nRandom Forest Classifier")
print("-" * 20)
model(rfc, X_train, y_train, X_test, y_test)
```

```
    Random Forest Classifier
    --------------------
    Test Data:
    --------------------
    F1 Score:0.5954514860604343
    Accuracy:0.5954514860604343
    Confusion Matrix
    [[11197  2885   468]
     [ 4877  4632   615]
     [ 1598   977   980]]
    Classfication Report
                  precision    recall  f1-score   support

               0       0.63      0.77      0.69     14550
               1       0.55      0.46      0.50     10124
               2       0.48      0.28      0.35      3555

        accuracy                           0.60     28229
       macro avg       0.55      0.50      0.51     28229
    weighted avg       0.58      0.60      0.58     28229

    --------------------
```

```
#print("\nXGBoost Classifier")
#print("-" * 20)
#model(xgb, X_train, y_train, X_test, y_test)

# print("\nCatBoost Classifier")
# print("-" * 20)
# model(catboost, X_train, y_train, X_test, y_test)

#print("\nLightGBM Classifier")
#print("-" * 20)
#model(lgbm, X_train, y_train, X_test, y_test)

# print("\nAdaBoost Classifier")
# print("-" * 20)
# model(adaboost, X_train, y_train, X_test, y_test)
```

```
# print("\nGradient Boosting Classifier")
# print("-" * 20)
# model(gbm, X_train, y_train, X_test, y_test)

# print("\nQuadratic Discriminant Analysis (QDA)")
# print("-" * 20)
# model(qda, X_train, y_train, X_test, y_test)

# print("\nGaussian Naive Bayes")
# print("-" * 20)
# model(gnb, X_train, y_train, X_test, y_test)

# print("\nMultilayer Perceptron (MLP) Classifier")
# print("-" * 20)
# model(mlp, X_train, y_train, X_test, y_test)

# print("\nK Nearest Neighbors (KNN)")
# print("-" * 20)
# model(knn, X_train, y_train, X_test, y_test)

# print("Logistic Regression")
# print("-" * 20)
# model(lrc, X_train, y_train, X_test, y_test)

# print("\nDecision Tree")
# print("-" * 20)
# model(dtc, X_train, y_train, X_test, y_test)

# print("\nRandom Forest Classifier")
# print("-" * 20)
# model(rfc, X_train, y_train, X_test, y_test)
```