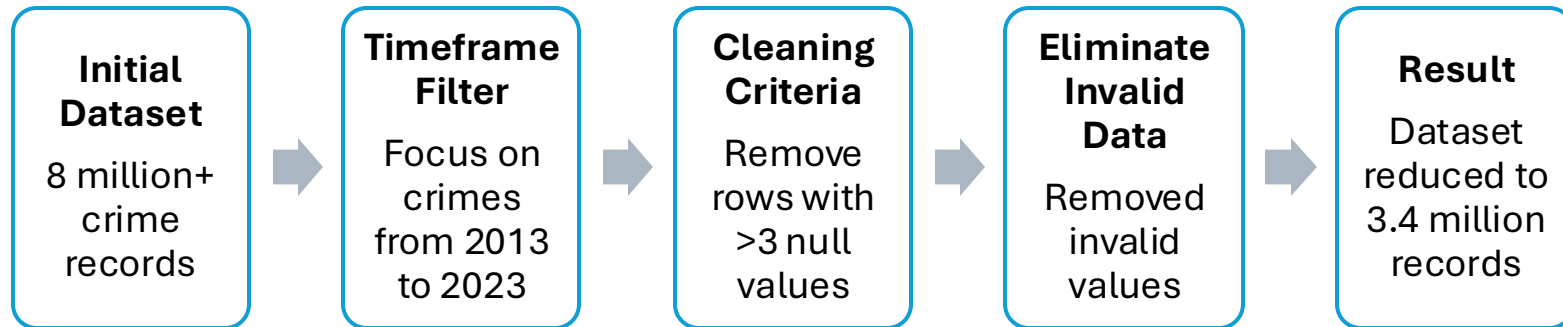




NYPD Crime Overview

Ali Adnan, Ayushman Shrestha, Hongyan, Shreya Karki

Data Cleaning Process



SUSP_AGE_GROUP	
UNKNOWN	1262252
25-44	1220372
45-64	438550
18-24	424517
<18	129064
...	...
967	1
964	1
-976	1
-5	1
-928	1

Imputing and Standardizing Values

Standardized gender categories

VIC_SEX

count

F 1476652

M 1149744

D 468929

E 315043

L 5885



VIC_SEX

F 1476652

M 1149744

UNKNOWN 783972

L 5885

Filled missing values with the mode

```
#find unique combination of borough and crime category
for boro in filtered_df['BORO_NM'].dropna().unique(): # Skip missing borough names
    for crime in filtered_df['CRIME_CTORY'].dropna().unique(): # Skip missing crime types

        # condition for current borough and crime
        condition = (filtered_df['BORO_NM'] == boro) & (filtered_df['CRIME_CTORY'] == crime)

        # Find the most common value
        most_common_age_group = filtered_df.loc[condition, 'SUSP_AGE_GROUP'].mode()

        # If there's at least one common value, fill missing values
        if not most_common_age_group.empty:
            filtered_df.loc[condition & filtered_df['SUSP_AGE_GROUP'].isna(), 'SUSP_AGE_GROUP'] = most_common_age_group.iloc[0]
        else:
            # fill with Unknown if no mode is found
            filtered_df.loc[condition & df.copy['SUSP_AGE_GROUP'].isna(), 'SUSP_AGE_GROUP'] = 'UNKNOWN'
```


Statistical Analysis- Descriptive

CRIME_STATUS	COMPLETED	ATTEMPTED	Total	Completed %	Attempted %
YEAR					
2013	111471	1745	113216	98.46	1.54
2014	120995	1898	122893	98.46	1.54
2015	202804	3892	206696	98.12	1.88
2016	337596	6380	343976	98.15	1.85
2017	338567	6277	344844	98.18	1.82
2018	338627	6005	344632	98.26	1.74
2019	344674	6075	350749	98.27	1.73
2020	313499	5346	318845	98.32	1.68
2021	355376	5718	361094	98.42	1.58
2022	428724	6719	435443	98.46	1.54
2023	466851	7013	473864	98.52	1.48

Status of Crime

	count
CRIME_CTGORY	
MISDEMEANOR	1714135
FELONY	1020612
VIOLATION	681506

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
CRIME_CTGORY											
FELONY	26279	29232	59171	98939	96701	96854	101920	99516	114640	141849	155511
MISDEMEANOR	49539	52890	101725	181902	184839	181037	180574	155758	174624	213785	237462
VIOLATION	37398	40772	45800	63135	63304	66741	68255	63571	71830	79809	80891

Crime Trend (2013-2023)

Hourly Crime Distribution Statistics:										
	count	mean	std	min	25%	50%	75%	max	range	IQR
HOURLY	3416253.0	13.171977	6.506642	0.0	9.0	14.0	18.0	23.0	23.0	9.0

Hourly Distribution

Statistical Analysis- Counts

	count
SUSP_SEX	
M	2085630
UNKNOWN	712516
F	618107

dtype: int64

Suspect and Victim

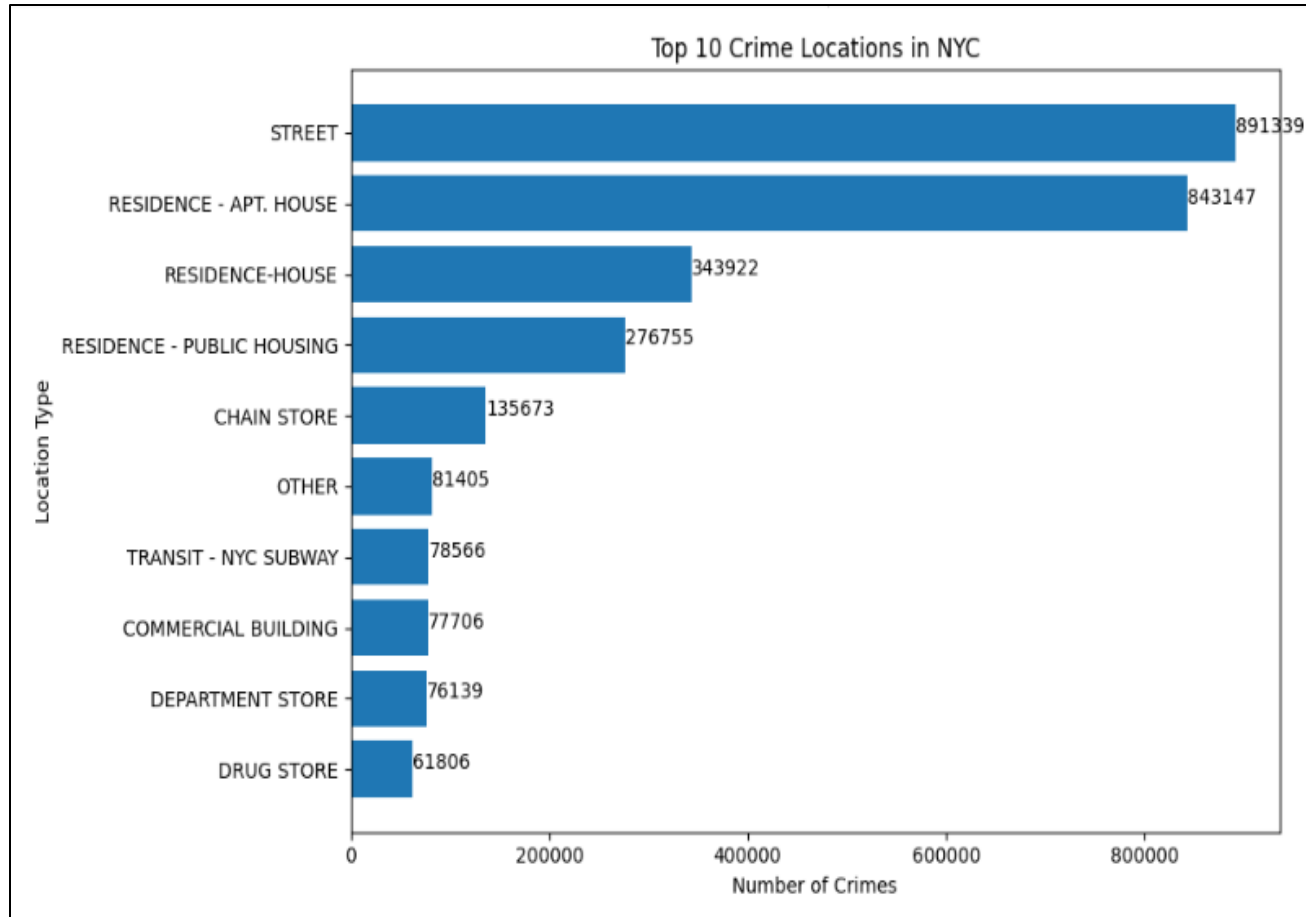
SUSP_AGE_GROUP	
UNKNOWN	1262178
25-44	1172612
45-64	419571
18-24	399576
<18	122392
65+	39924
Name: count, dtype: int64	
1262178	

Suspect Age

VIC_AGE_GROUP	
25-44	1260985
UNKNOWN	851045
45-64	644048
18-24	357328
<18	164558
65+	138289
Name: count, dtype: int64	
1260985	

Victim Age

Bar Chart & Box Plot



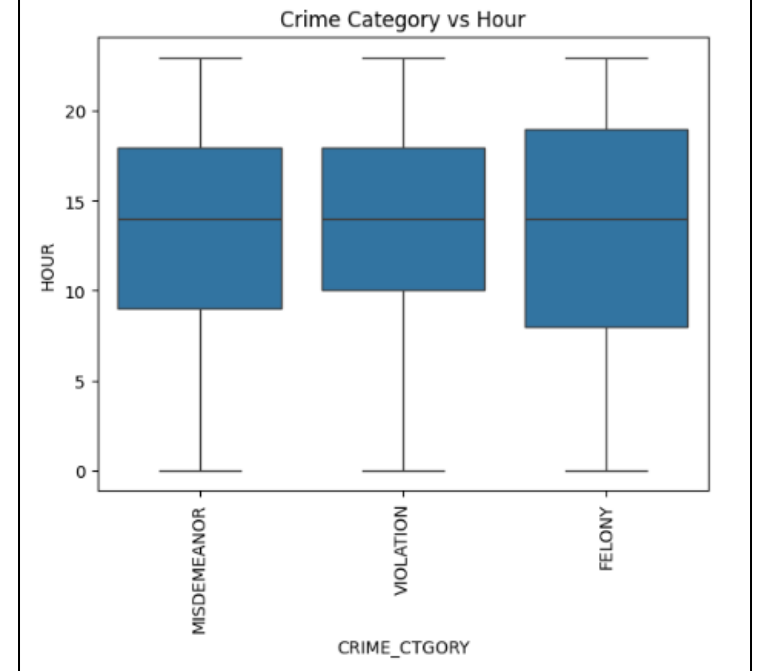
```
import seaborn as sns

# Gender pairing
gender_pair = pd.crosstab(filtered_df['SUSP_SEX'], filtered_df['VIC_SEX'])
print("Suspect-Victim Gender Crosstab:")
print(gender_pair)

# Crime category by hour
sns.boxplot(x='CRIME_CTORY', y='HOUR', data=filtered_df)
plt.xticks(rotation=90)
plt.title('Crime Category vs Hour')
plt.show()
```

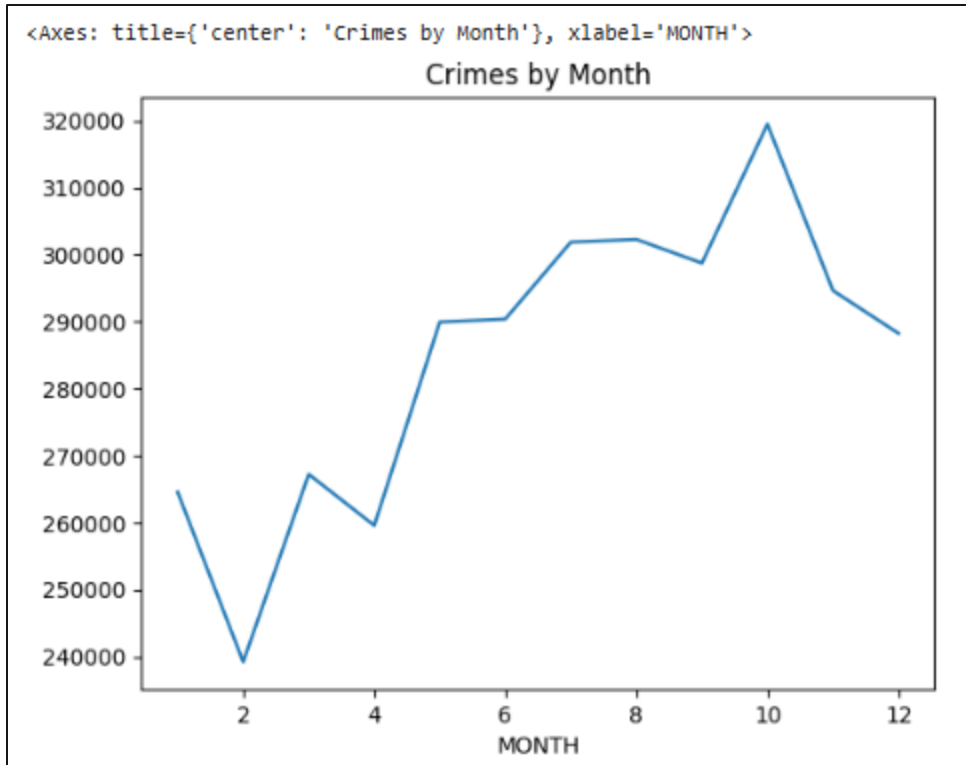
Suspect-Victim Gender Crosstab:

VIC_SEX	F	L	M	UNKNOWN
SUSP_SEX				
F	324432	868	193549	99258
M	889165	4573	623995	567897
UNKNOWN	263055	444	332200	116817

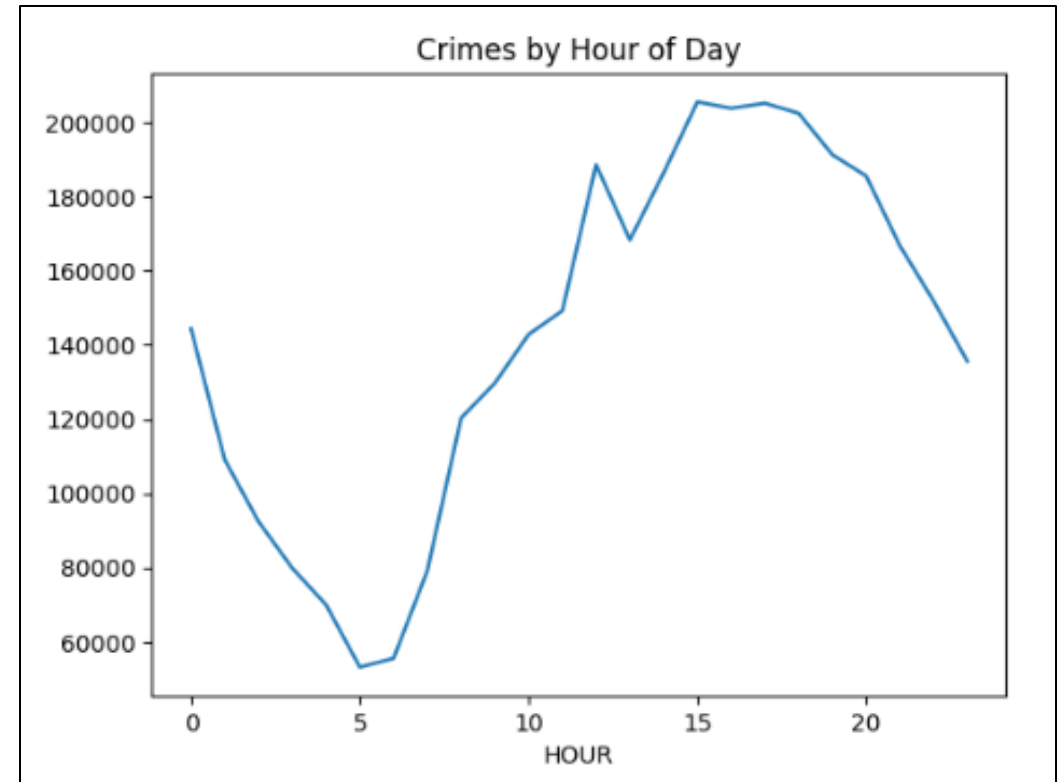


Crime Timing and Gender Patterns

Line Plot



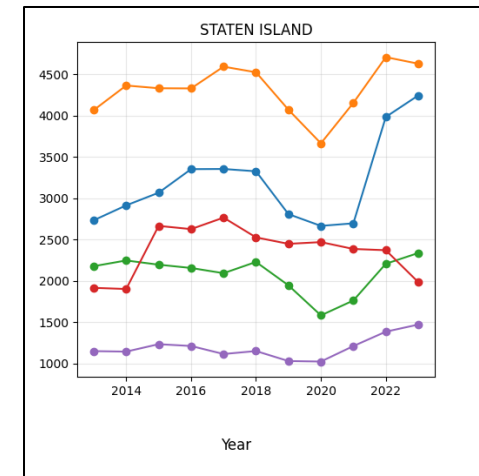
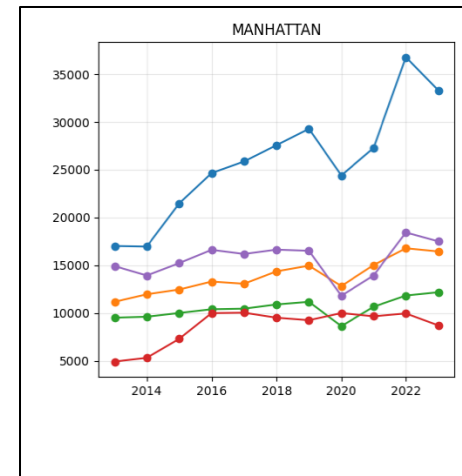
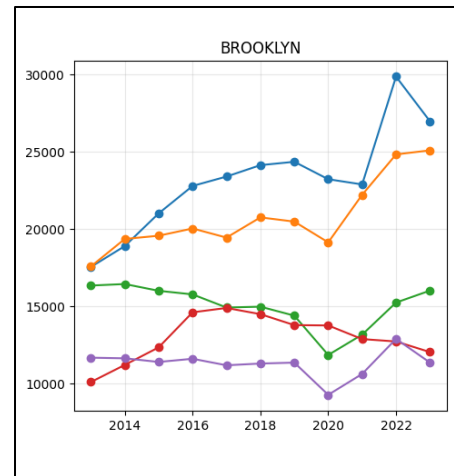
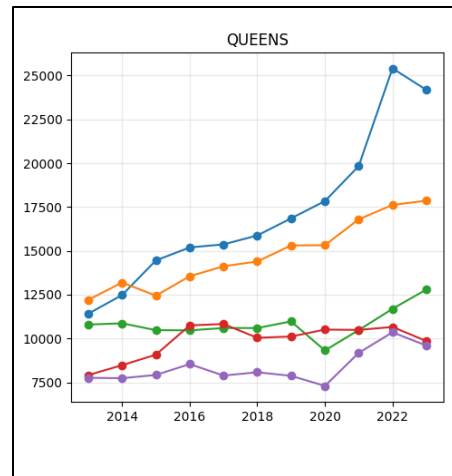
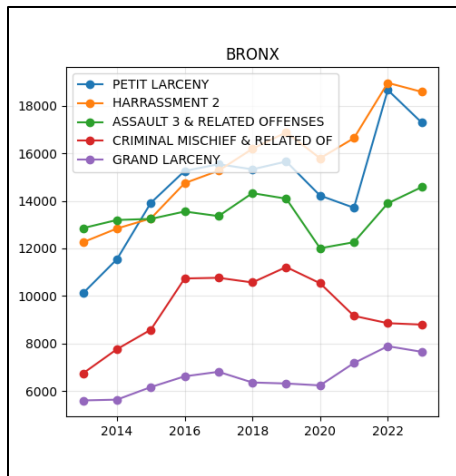
Crimes per month



Crimes by hour

Line Charts Representing Boroughs

Top 5 crimes from 2013 to 2023



NYC Heatmap

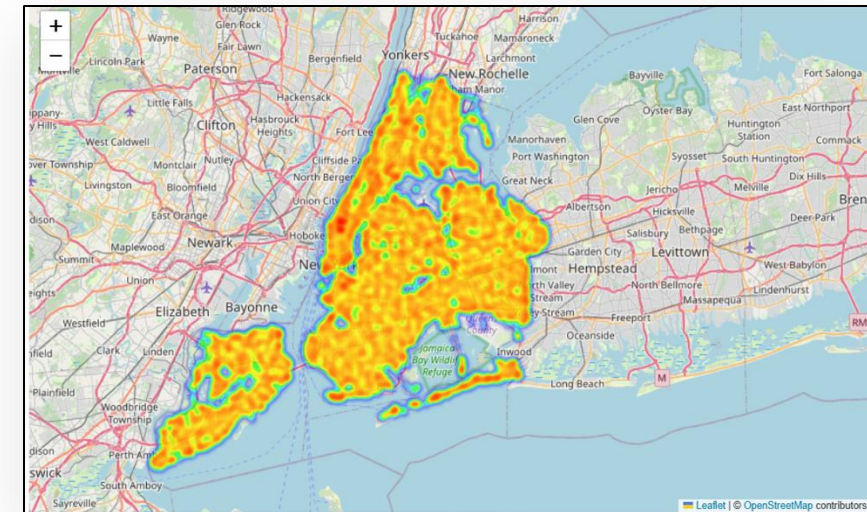
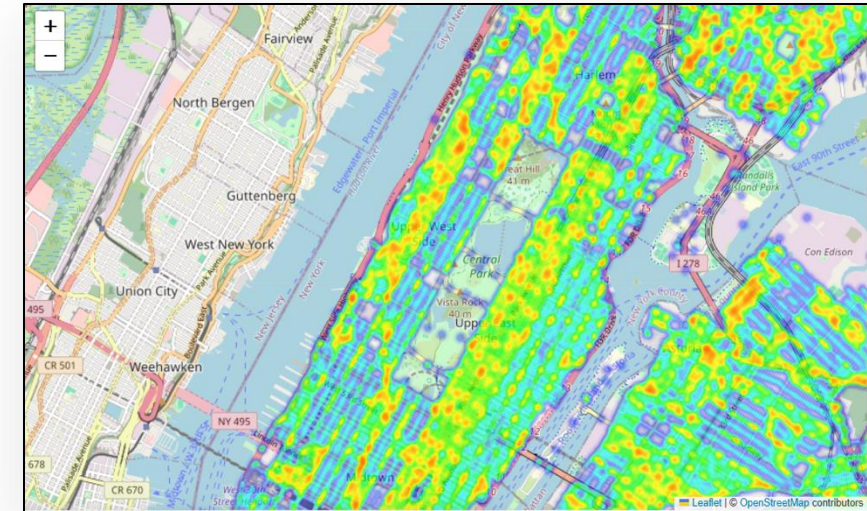
```
import folium
from folium.plugins import HeatMap

df_map = filtered_df.dropna(subset=['LAT', 'LONG'])
nyc_map = folium.Map(location=[40.7128, -74.0060], zoom_start=11)

heatmap_data = df_map[['LAT', 'LONG']].values.tolist()

# Adjust Heatmap parameters
HeatMap(
    heatmap_data,
    radius=5, # Decreased radius for more concentrated heat
    blur=4,   # Decreased blur for sharper heat spots
    max_zoom=18 # Increased max_zoom for better visibility at higher zoom level
).add_to(nyc_map)

nyc_map
```



Prediction Model

	precision	recall	f1-score	support
ADMINISTRATIVE CODE	0.76	0.13	0.23	1841
ASSAULT 3 & RELATED OFFENSES	0.57	0.88	0.69	94462
BURGLARY	0.55	0.42	0.48	15266
CRIMINAL MISCHIEF & RELATED OF	0.53	0.18	0.26	47906
CRIMINAL TRESPASS	0.40	0.10	0.16	4156
DANGEROUS DRUGS	0.48	0.75	0.59	18889
DANGEROUS WEAPONS	0.41	0.22	0.29	8924
FELONY ASSAULT	0.48	0.61	0.54	39203
FORGERY	0.47	0.54	0.50	6416
FRAUDS	0.48	0.05	0.10	2309
GRAND LARCENY	0.58	0.71	0.64	46690
GRAND LARCENY OF MOTOR VEHICLE	0.37	0.29	0.32	7740
HARRASSMENT 2	1.00	1.00	1.00	135053
INTOXICATED & IMPAIRED DRIVING	0.59	0.68	0.63	5401
MISCELLANEOUS PENAL LAW	0.46	0.46	0.46	24821
NYS LAWS-UNCLASSIFIED FELONY	0.78	0.34	0.47	970
OFF. AGNST PUB ORD SENSBLTY &	0.46	0.24	0.32	36442
OFFENSES AGAINST PUBLIC ADMINI	0.48	0.08	0.13	12815
OFFENSES AGAINST THE PERSON	0.51	0.08	0.14	1913
OFFENSES INVOLVING FRAUD	0.46	0.16	0.23	2379
OTHER	0.59	0.23	0.33	3864
OTHER OFFENSES RELATED TO THEF	0.47	0.28	0.35	2048
PETIT LARCENY	0.74	0.82	0.78	104239
POSSESSION OF STOLEN PROPERTY	0.40	0.02	0.03	2259
RAPE	0.67	0.70	0.68	2710
ROBBERY	0.52	0.51	0.51	27751
SEX CRIMES	0.87	0.81	0.84	10412
THEFT-FRAUD	0.44	0.02	0.03	3096
UNAUTHORIZED USE OF A VEHICLE	0.69	0.13	0.21	2512
UNKNOWN	0.43	0.02	0.03	178
VEHICLE AND TRAFFIC LAWS	0.44	0.23	0.30	10586
accuracy			0.66	683251
macro avg	0.55	0.38	0.40	683251
weighted avg	0.65	0.66	0.63	683251

