

PROJECT: LA CRIME ANALYTICS

INTRODUCTION

In the era of increasing urbanization and social complexity, understanding crime patterns through data has become crucial for improving public safety and supporting informed decision-making. This Python-based project, titled “Crime Analytics Dashboard”, aims to provide meaningful insights into crime trends using real-world crime data.

By leveraging libraries such as Pandas, Matplotlib, Seaborn, and NumPy, the project processes and visualizes data extracted from crime records, with the objective of uncovering significant patterns in criminal activities, victim demographics, and geographical distribution.

Key components of the analysis include:

- Identification of top crime types and premises where these crimes occur most frequently.
- Study of victim demographics, including age, gender, and descent distribution.
- Analysis of weapon usage, offering a deeper understanding of crime severity and risk levels.
- Visualization of crime locations using latitude and longitude data to identify hotspots across regions.
- Use of correlation heatmaps to discover interrelationships between numerical variables such as victim age and crime frequency.
- Advanced statistical breakdowns to highlight the most dangerous locations, top crimes by victim descent, and a cross-tab view of crime types vs. weapons.

The project offers multiple visual representations such as bar charts, pie charts, histograms, box plots, violin plots, scatter plots, and heatmaps—making the insights not only informative but also visually engaging and easy to interpret.

This interactive analytical framework serves as a foundational tool for law enforcement agencies, data scientists, and policy makers to evaluate trends, enhance safety strategies, and support data-driven crime prevention measures.

ANALYSIS ON DATASET

EDA PROCESS:

Exploratory Data Analysis (EDA) is a critical phase in any data science workflow. It helps uncover initial insights, detect anomalies, identify patterns, and prepare data for deeper analysis.

1. Data Loading:

Using `pandas.read_csv()`, the dataset was read from the local path into a DataFrame for manipulation.

2. Data Cleaning:

- Removed duplicate records using `drop_duplicates()` to maintain unique entries.
- Stripped column name whitespaces with `df.columns.str.strip()` for consistency in referencing.
- Checked and printed null values per column using `df.isna().sum()` to identify missing data.
- Retained only rows with valid coordinates for location-based plotting (LAT, LON).

3. Visualization Setup:

- Set Seaborn's theme to `whitegrid` for clean, consistent visuals.
- Used diverse plot types:
 - **Bar and Pie Charts:** Top crime types and premises.
 - **Histogram:** Victim age distribution.
 - **Box & Violin Plots:** Age variation by victim sex.
 - **Heatmap:** Correlation among numeric columns.
 - **Scatter Plot:** Crime hotspots via latitude and longitude.

4. Analysis Readiness:

- Ensured all essential columns (e.g., Crm Cd Desc, Vict Age, Vict Sex, LAT, LON) were free from critical missing values.
- Transformed data into appropriate formats for grouped aggregations and cross-tab analysis.
- Ready for insights generation on crime frequency, demographic impact, and spatial distribution.

Objective 1: Identifying the most common Crime Types

i. General Description

This objective focuses on identifying and analyzing the most frequently occurring crimes in Los Angeles. By understanding which crimes are most common, authorities can allocate resources efficiently, and the public can stay informed about prevalent threats.

ii. Specific Requirements

- Detailed crime type data (Crm Cd Desc column)
- Aggregation of occurrences by crime type
- Visualization to compare frequencies among the top reported crimes

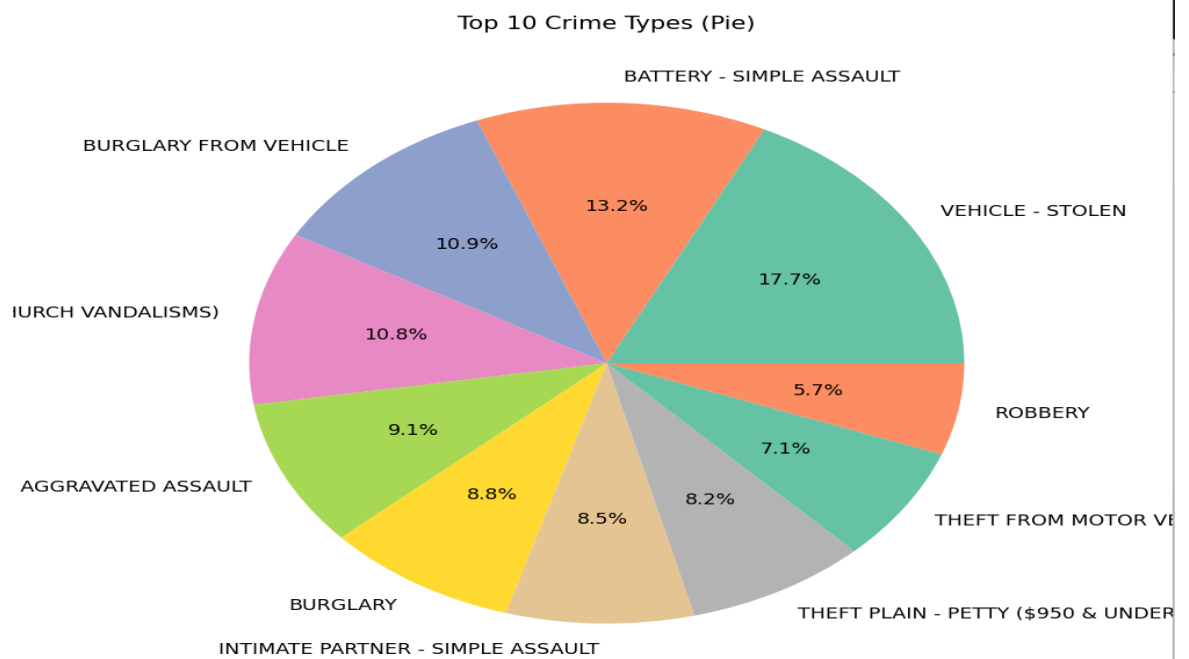
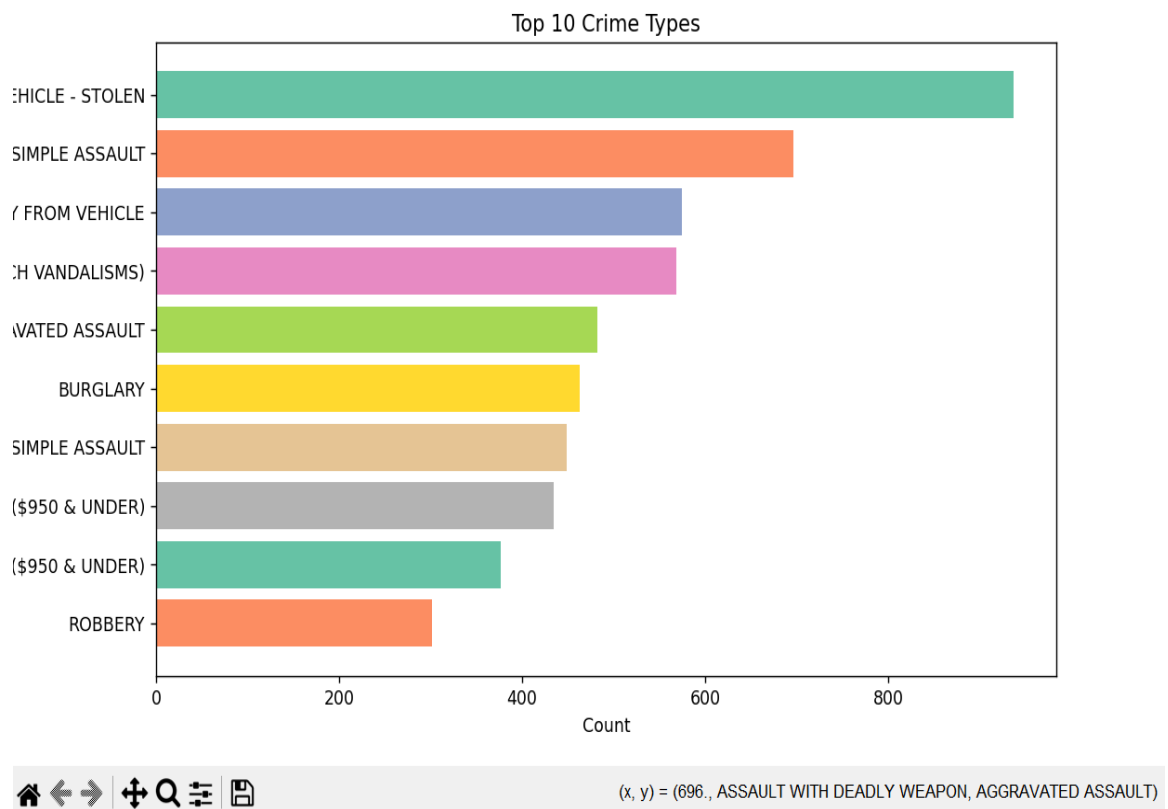
iii. Analysis Results

The analysis revealed that crimes like *Battery - Simple Assault*, *Vehicle Theft*, and *Burglary* are among the most common in Los Angeles. This frequency insight provides a basis for developing crime-prevention strategies and raising public awareness in affected areas.

iv. Visualization

Bar and pie charts were used to represent the **top 10 crime types** by frequency.

- **Bar Chart** allowed for direct comparison of absolute numbers of crimes.
- **Pie Chart** offered a proportional view to understand how each crime contributes to the overall distribution.



Objective 2: Understanding Age Distribution of Victims

i. General Description

This objective aims to analyze the age distribution of crime victims in Los Angeles. By identifying which age groups are most frequently targeted, this analysis supports the development of focused safety campaigns and community outreach initiatives.

ii. Specific Requirements

- Cleaned and validated data from the Vict Age column
- Removal of missing or unrealistic age values
- Aggregated age data using appropriate binning techniques

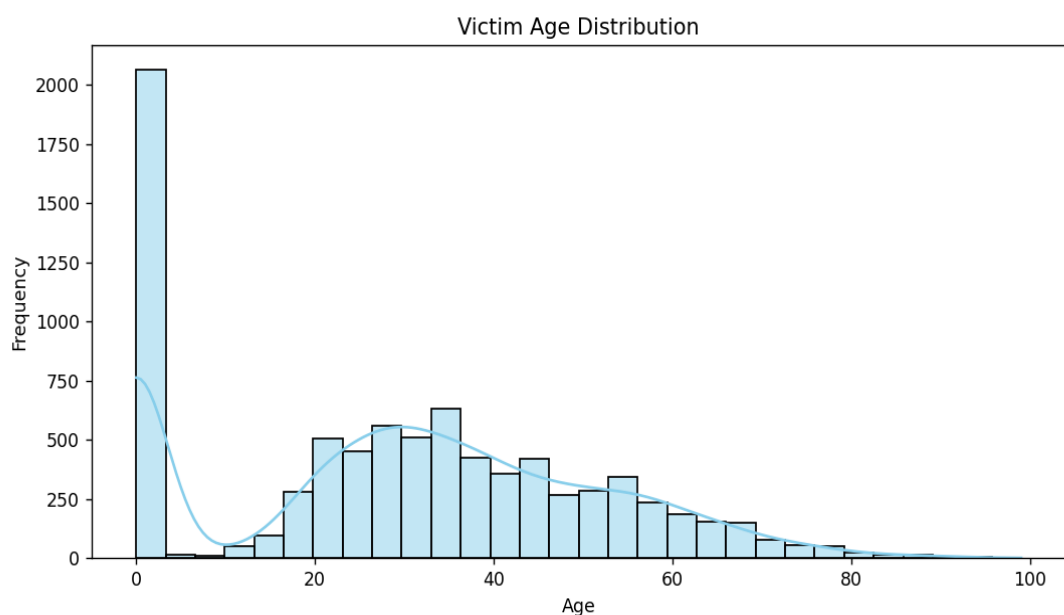
iii. Analysis Results

The results indicated that individuals aged between **20 and 40 years** are most commonly victimized, followed by teenagers and middle-aged adults. This insight emphasizes the need for protective measures tailored to these vulnerable groups.

iv. Visualization

A **Histogram with KDE (Kernel Density Estimation) plot** was used to visualize the distribution:

- The **Histogram** shows the frequency of victims in various age brackets.
- The **KDE Plot** overlays a smoothed curve, helping to identify age peaks and overall trends in the data.



Objective 3: Analyzing Victim Age Based on Gender

i. General Description

This objective aims to explore how victim age distribution varies across different genders. Understanding this pattern can help authorities design gender-sensitive crime prevention strategies and support systems.

ii. Specific Requirements

- Clean and complete data in Vict Sex and Vict Age columns
- Grouping data based on gender
- Removing invalid or missing age entries for accurate distribution analysis

iii. Analysis Results

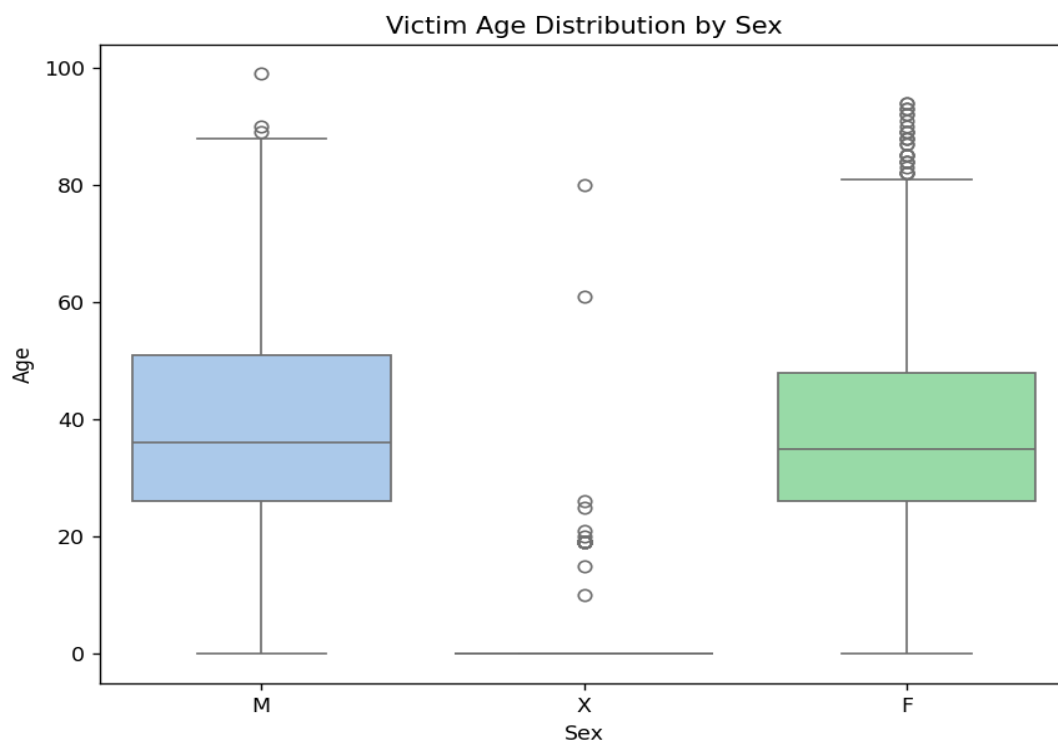
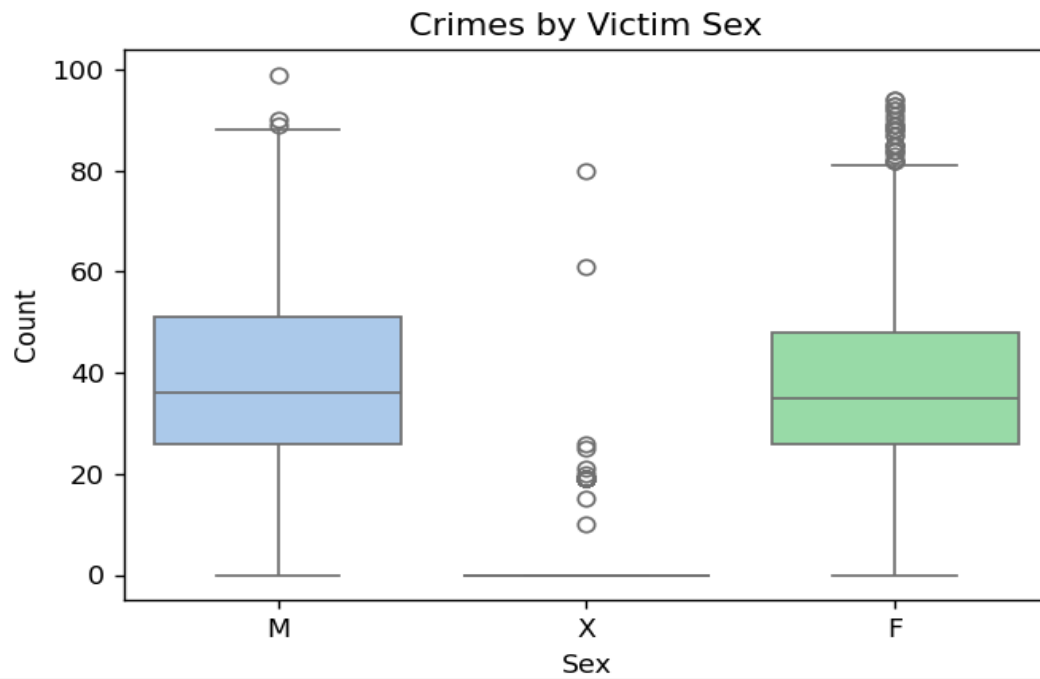
The box plot highlighted that male and female victims show different age distribution patterns. Males had a wider range of ages affected by crimes, whereas females had more concentration in certain age groups. Outliers were also visible, indicating occasional crimes affecting extreme age ranges.

iv. Visualization

A Box Plot and Violin Plot was used to compare victim age across genders:

- It shows the median, interquartile range, and outliers for each gender.
- Helps quickly identify which age groups are most affected and how spread out the data is.

It provides a clear view of crime concentration and aids in comparative risk assessment across locations





Objective 4: Exploring Correlations in Crime Data

i. General Description

This objective seeks to uncover potential relationships between numerical features in the dataset, such as victim age, time of occurrence, and crime-related variables. These correlations may reveal underlying behavioural or situational patterns.

ii. Specific Requirements

- Selection of only numeric columns from the dataset
- Removal of missing or non-numeric values
- Application of correlation matrix techniques to measure linear relationships

iii. Analysis Results

The correlation heatmap identified weak to moderate correlations among numeric fields. While most variables showed low correlation, certain fields like victim age and crime resolution time showed interesting trends that can be investigated further.

iv. Visualization

A **Correlation Heatmap** was used:

- Displays Pearson correlation values between numeric features
- Annotated and color-coded for easier interpretation
- Helps in feature selection for predictive modelling or further statistical analysis

Objective 5: Mapping Geographical Distribution of Crimes

i. General Description

This objective focuses on identifying where crimes occur most frequently within Los Angeles. By analyzing spatial patterns, law enforcement can allocate resources more effectively and proactively monitor high-risk areas.

ii. Specific Requirements

- Latitude (LAT) and Longitude (LON) data points without missing values
- Removal of invalid or zeroed coordinates
- Visualization with spatial scatter plots to display crime density

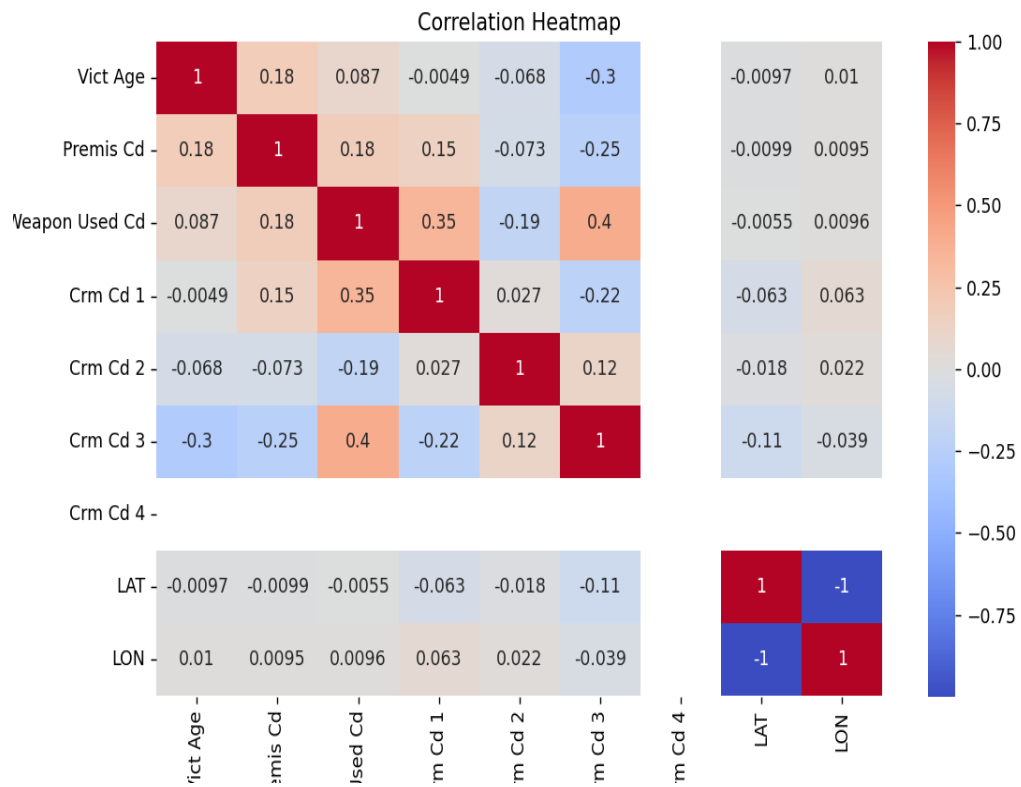
iii. Analysis Results

The scatter plot revealed crime hotspots, particularly in central and downtown Los Angeles. Densely clustered points indicate areas with high crime volume, suggesting a need for increased surveillance and community outreach in those regions.

iv. Visualization

A **Scatter Plot using Latitude and Longitude** was implemented:

- Plots crime locations as points on a coordinate plane
- Makes spatial clusters of crime immediately visible
- Supports geographic targeting for patrol planning and community safety initiatives



Data Shape: (8249, 19)

Data Info:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 8249 entries, 0 to 8248

Data columns (total 19 columns):

#	Column	Non-Null Count	Dtype
0	Crm Cd Desc	8249 non-null	object
1	Mocodes	7097 non-null	object
2	Vict Age	8249 non-null	int64
3	Vict Sex	7133 non-null	object
4	Vict Descent	7132 non-null	object
5	Premis Cd	8249 non-null	int64
6	Premis Desc	8244 non-null	object
7	Weapon Used Cd	3136 non-null	float64
8	Weapon Desc	3136 non-null	object
9	Status	8249 non-null	object
10	Status Desc	8249 non-null	object
11	Crm Cd 1	8248 non-null	float64
12	Crm Cd 2	704 non-null	float64
13	Crm Cd 3	17 non-null	float64
14	Crm Cd 4	1 non-null	float64
15	LOCATION	8249 non-null	object
16	Cross Street	1564 non-null	object
17	LAT	8249 non-null	float64
18	LON	8249 non-null	float64

dtypes: float64(7), int64(2), object(10)

memory usage: 1.2+ MB

Summary Statistics:

	Crm Cd Desc	Mocodes	...	LAT	LON
count	8249	7097	...	8249.000000	8249.000000
unique	96	4900	...	NaN	NaN
top	VEHICLE - STOLEN	344	...	NaN	NaN
freq	948	276	...	NaN	NaN
mean	NaN	NaN	...	33.942420	-117.965834
std	NaN	NaN	...	1.874142	6.505045
min	NaN	NaN	...	0.000000	-118.565100
25%	NaN	NaN	...	34.017300	-118.361900
50%	NaN	NaN	...	34.050900	-118.300300
75%	NaN	NaN	...	34.096000	-118.264300
max	NaN	NaN	...	34.221200	0.000000

[11 rows x 19 columns]

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unique	96	4900	...	NaN	NaN
top	VEHICLE - STOLEN	344	...	NaN	NaN
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75%	NaN	NaN	...	34.096000	-118.264300
max	NaN	NaN	...	34.221200	0.000000

[11 rows x 19 columns]

NaN Count per Column:

Crm Cd Desc	0
Mocodes	1141
Vict Age	0
Vict Sex	1105
Vict Descent	1106
Premis Cd	0
Premis Desc	5
Weapon Used Cd	5097
Weapon Desc	5097
Status	0
Status Desc	0
Crm Cd 1	1
Crm Cd 2	7529
Crm Cd 3	8216
Crm Cd 4	8232
LOCATION	0
Cross Street	6670
LAT	0
LON	0

dtype: int64

Top 10 Crime Types:

Crm Cd Desc	
VEHICLE - STOLEN	937
BATTERY - SIMPLE ASSAULT	696
BURGLARY FROM VEHICLE	575
VANDALISM - FELONY (\$400 & OVER, ALL CHURCH VANDALISMS)	568
ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT	482
BURGLARY	463
INTIMATE PARTNER - SIMPLE ASSAULT	449
THEFT PLAIN - PETTY (\$950 & UNDER)	434
THEFT FROM MOTOR VEHICLE - PETTY (\$950 & UNDER)	377
ROBBERY	301

Name: count, dtype: int64

```

UNKNOWN FIREARM                                60
OTHER KNIFE                                    52
BOTTLE                                          35
ROCK/THROWN OBJECT                            34
Name: count, dtype: int64
Crime Status Summary:
Status Desc
Invest Cont      6230
Adult Other      1108
Adult Arrest      854
Juv Arrest        34
Juv Other         7
Name: count, dtype: int64

```

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===== RESTART: C:\Users\hp\OneDrive\Desktop\project\r.py ==
```

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Data Info:
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	Crm Cd Desc	Mocodes	...	LAT	LON
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unique	96	4900	...	NaN	NaN

DRIVEWAY	145
PARKING UNDERGROUND/BUILDING	131

Name: count, dtype: int64

Victim Sex Distribution:

Vict Sex

M	3422
F	2983
X	723

Name: count, dtype: int64

Victim Descent Distribution:

Vict Descent

H	2445
W	1767
B	1286
X	764
O	597
A	188
K	20
C	19
F	18
V	9
I	8
J	3
P	2
Z	1

Name: count, dtype: int64

Victim Age Stats:

count	8233.00000
mean	29.36876
std	21.67559
min	0.00000
25%	2.00000
50%	30.00000
75%	45.00000
max	99.00000

Name: Vict Age, dtype: float64

Top Weapon Types:

Weapon Desc

STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)	1699
UNKNOWN WEAPON/OTHER WEAPON	347
VERBAL THREAT	198
HAND GUN	179
KNIFE WITH BLADE 6INCHES OR LESS	76
SEMI-AUTOMATIC PISTOL	63
UNKNOWN FIREARM	60
OTHER KNIFE	52

[11 rows x 19 columns]

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ROBBERY	301

Name: count, dtype: int64

Top 10 Crime Premises:

Premis Desc	
STREET	2200
SINGLE FAMILY DWELLING	1234
MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)	1059
PARKING LOT	557
SIDEWALK	449
OTHER BUSINESS	362
VEHICLE, PASSENGER/TRUCK	276
GARAGE/CARPORT	161
DRIVEWAY	145

```

ROBBERY
Name: count, dtype: int64
Top 10 Crime Premises:
Premis Desc
STREET 2200
SINGLE FAMILY DWELLING 1234
MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC) 1059
PARKING LOT 557
SIDEWALK 449
OTHER BUSINESS 362
VEHICLE, PASSENGER/TRUCK 276
GARAGE/CARPORT 161
DRIVEWAY 145
PARKING UNDERGROUND/BUILDING 131
Name: count, dtype: int64
Victim Sex Distribution:
Vict Sex
M 3422
F 2983
X 723
Name: count, dtype: int64
Victim Descent Distribution:
Vict Descent
H 2445
W 1767
B 1286
X 764
O 597
A 188
K 20
C 19
F 18
V 9
I 8
J 3
P 2
Z 1
Name: count, dtype: int64
Victim Age Stats:
count 8233.00000
mean 29.36876
std 21.67559
min 0.00000
25% 2.00000
50% 30.00000
75% 45.00000

```



```

75%      45.00000
max       99.00000
Name: Vict Age, dtype: float64
Top Weapon Types:
Weapon Desc
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UNKNOWN WEAPON/OTHER WEAPON                      347
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HAND GUN                                           179
KNIFE WITH BLADE 6INCHES OR LESS                 76
SEMI-AUTOMATIC PISTOL                           63
UNKNOWN FIREARM                                  60
OTHER KNIFE                                       52
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ROCK/THROWN OBJECT                              34
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9   Status                8249 non-null  object
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```

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Top 10 Crime Premises:
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mean 29.36876
std 21.67559
min 0.00000
25% 2.00000
50% 30.00000
75% 45.00000
max 99.00000

```

Name: count, dtype: int64

Most Dangerous Locations:

LOCATION

6TH	ST	27
6TH		20
5TH		18
3RD	ST	16
7TH		16
WESTERN	AV	15
800 N ALAMEDA	ST	15
7TH	ST	15
SLAUSON	AV	14
VERMONT		12

Name: count, dtype: int64

Top Crime Type per Victim Descent:

Vict Descent

A	BURGLARY FROM VEHICLE
B	ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT
C	THEFT OF IDENTITY
F	THEFT FROM MOTOR VEHICLE - GRAND (\$950.01 AND ...
H	BATTERY - SIMPLE ASSAULT
I	BIKE - STOLEN
J	THEFT PLAIN - PETTY (\$950 & UNDER)
K	BURGLARY FROM VEHICLE
O	BURGLARY FROM VEHICLE
P	BIKE - STOLEN
V	THEFT FROM MOTOR VEHICLE - GRAND (\$950.01 AND ...
W	BURGLARY FROM VEHICLE
X	VANDALISM - FELONY (\$400 & OVER, ALL CHURCH VA...
Z	BURGLARY FROM VEHICLE

Name: Crm Cd Desc, dtype: object

Cross-tab: Crime Type vs Weapon

Weapon Desc	AIR PISTOL/REVOLVER/RIFLE/BB GUN	...	VERBAL THREAT
Crm Cd Desc		...	
ARSON	0	...	1
ASSAULT WITH DEADLY WEAPON ON POLICE OFFICER	0	...	0
ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT	9	...	1
ATTEMPTED ROBBERY	0	...	4
BATTERY - SIMPLE ASSAULT	0	...	0
BATTERY POLICE (SIMPLE)	0	...	1
BATTERY WITH SEXUAL CONTACT	0	...	0
BOMB SCARE	0	...	1
BRANDISH WEAPON	2	...	8
BUNCO, GRAND THEFT	0	...	0

[10 rows x 58 columns]

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