AAI_510_Project_Grp_8

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0.1 Crime Patterns Recognition in LA region project

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0.2 Business Goal

The primary business objective of recognizing crime patterns in the Los Angeles region is to assist law enforcement in identifying crime severity, geographic hotspots, and demographic trends based on age and gender. This enables more effective resource allocation and policy development. A secondary goal is to support public safety initiatives by highlighting high-crime areas and time periods for better community awareness and prevention strategies.

0.3 Loading the data

[214]:
```
#@title Loading the required libraries

import numpy as np # Pandas for array manipulation
import pandas as pd # Pandas for data manipulation
import seaborn as sns # Seaborn for visualizing. Note: we will also use one of␣
 ↪the data sets
import matplotlib.pyplot as plt # Matplotlib for subplots
%matplotlib inline

from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler # Import for feature␣
 ↪standardization
from sklearn.metrics import silhouette_samples, silhouette_score # For kmeans␣
 ↪evaluation
from sklearn.datasets import load_wine # Used to pull in wine data

pd.options.display.float_format = '{:.2f}'.format
pd.set_option('display.max_columns', 500)
```

[215]:
```
## Importing the required  libraries
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt #to allow subplot creation
```

```python
# Apply the seaborn theme
sns.set_theme() #overwrite default Matplotlib styling parameters

#List the example datasets available in seaborn
names = sns.get_dataset_names()
##print("\r\nDatasets in Seaborn: \r\n",names,"\r\n")


# Load train dataset
df = pd.read_csv("Crime_Data_from_2020_to_Present.csv")
shap = df.shape
print("Shape of the dataframe (row, col):",shap,"\r\n")

# Show the dataframe
df.head()
```

```
Shape of the dataframe (row, col): (1005101, 28)
```

[215]:

```
       DR_NO              Date Rptd               DATE OCC  TIME OCC  AREA  \
0  190326475  03/01/2020 12:00:00 AM  03/01/2020 12:00:00 AM      2130     7
1  200106753  02/09/2020 12:00:00 AM  02/08/2020 12:00:00 AM      1800     1
2  200320258  11/11/2020 12:00:00 AM  11/04/2020 12:00:00 AM      1700     3
3  200907217  05/10/2023 12:00:00 AM  03/10/2020 12:00:00 AM      2037     9
4  200412582  09/09/2020 12:00:00 AM  09/09/2020 12:00:00 AM       630     4

    AREA NAME  Rpt Dist No  Part 1-2  Crm Cd  \
0    Wilshire          784         1     510
1     Central          182         1     330
2   Southwest          356         1     480
3    Van Nuys          964         1     343
4  Hollenbeck          413         1     510

                                 Crm Cd Desc        Mocodes  Vict Age  \
0                           VEHICLE - STOLEN            NaN         0
1                      BURGLARY FROM VEHICLE  1822 1402 0344        47
2                              BIKE - STOLEN      0344 1251        19
3  SHOPLIFTING-GRAND THEFT ($950.01 & OVER)      0325 1501        19
4                           VEHICLE - STOLEN            NaN         0

  Vict Sex Vict Descent  Premis Cd  \
0        M            O     101.00
1        M            O     128.00
2        X            X     502.00
3        M            O     405.00
4      NaN          NaN     101.00
```

```
                                  Premis Desc  Weapon Used Cd Weapon Desc  \
0                                      STREET             NaN         NaN
1              BUS STOP/LAYOVER (ALSO QUERY 124)          NaN         NaN
2  MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)           NaN         NaN
3                               CLOTHING STORE            NaN         NaN
4                                      STREET             NaN         NaN

  Status   Status Desc  Crm Cd 1  Crm Cd 2  Crm Cd 3  Crm Cd 4  \
0     AA  Adult Arrest    510.00    998.00       NaN       NaN
1     IC   Invest Cont    330.00    998.00       NaN       NaN
2     IC   Invest Cont    480.00       NaN       NaN       NaN
3     IC   Invest Cont    343.00       NaN       NaN       NaN
4     IC   Invest Cont    510.00       NaN       NaN       NaN

                                  LOCATION Cross Street   LAT     LON
0   1900 S  LONGWOOD                    AV          NaN 34.04 -118.35
1   1000 S  FLOWER                      ST          NaN 34.04 -118.26
2   1400 W  37TH                        ST          NaN 34.02 -118.30
3  14000    RIVERSIDE                   DR          NaN 34.16 -118.44
4                        200 E  AVENUE 28           NaN 34.08 -118.21
```

0.4 1. Initial Data Exploration and Summary Statistics

[216]:
```python
def generate_summary_statistics(df):
    """
    Generate comprehensive summary statistics for the dataset.

    Parameters:
    df (pandas.DataFrame): Input DataFrame

    Returns:
    dict: Dictionary containing various summary statistics
    """
    summary = {
        'basic_info': {
            'rows': df.shape[0],
            'columns': df.shape[1],
            'dtypes': df.dtypes.to_dict()
        },
        'numerical_summary': df.describe(),
        'categorical_summary': df.select_dtypes(include=['object']).describe(),
        'memory_usage': df.memory_usage(deep=True).sum() / 1024**2  # in MB
    }

    return summary

# Example usage with Iris dataset
```

```
summary_stats = generate_summary_statistics(df)
print("Dataset Overview:")
print(f"Number of samples: {summary_stats['basic_info']['rows']}")
print(f"Number of features: {summary_stats['basic_info']['columns']}")
print("\nNumerical Summary:")
print(summary_stats['numerical_summary'])
```

```
Dataset Overview:
Number of samples: 1005101
Number of features: 28

Numerical Summary:
               DR_NO    TIME OCC       AREA  Rpt Dist No   Part 1-2     Crm Cd  \
count   1005101.00  1005101.00 1005101.00   1005101.00 1005101.00 1005101.00
mean  220224858.64     1339.91      10.69      1115.58       1.40     500.16
std    13200269.98      651.05       6.11       611.17       0.49     205.26
min         817.00        1.00       1.00       101.00       1.00     110.00
25%   210616891.00      900.00       5.00       587.00       1.00     331.00
50%   220915983.00     1420.00      11.00      1139.00       1.00     442.00
75%   231110413.00     1900.00      16.00      1613.00       2.00     626.00
max   252104146.00     2359.00      21.00      2199.00       2.00     956.00

        Vict Age  Premis Cd  Weapon Used Cd   Crm Cd 1  Crm Cd 2  Crm Cd 3  \
count 1005101.00 1005085.00       327256.00 1005090.00  69156.00   2314.00
mean       28.91     305.62          363.96     499.92    958.10    984.02
std        21.99     219.31          123.73     205.06    110.36     52.35
min        -4.00     101.00          101.00     110.00    210.00    310.00
25%         0.00     101.00          311.00     331.00    998.00    998.00
50%        30.00     203.00          400.00     442.00    998.00    998.00
75%        44.00     501.00          400.00     626.00    998.00    998.00
max       120.00     976.00          516.00     956.00    999.00    999.00

       Crm Cd 4        LAT        LON
count     64.00 1005101.00 1005101.00
mean     991.22      34.00    -118.09
std       27.07       1.61       5.58
min      821.00       0.00    -118.67
25%      998.00      34.01    -118.43
50%      998.00      34.06    -118.32
75%      998.00      34.16    -118.27
max      999.00      34.33       0.00
```

The dataset being used has about a million records with 28 features. Key information that will be used in Clustering are Time based attriutes like Time of crime occurence, Location based feature like Latitude(LAT) and Longitude (LONGITUDE), gender based features like Victim's sex, age based features like Victime age and severity of a crime (Part 1-2), Crime code desc, Premise description. Upon missing data evaluation we will proceed to see which stratigeis (imputation or dropping) can be applied.

0.5 2. Missing values

[217]:
```python
def analyze_missing_values(df):
    """
    Perform comprehensive missing value analysis.

    Parameters:
    df (pandas.DataFrame): Input DataFrame

    Returns:
    dict: Dictionary containing various missing value analyses
    """
    # Basic missing value statistics
    missing_info = pd.DataFrame({
        'missing_count': df.isnull().sum(),
        'missing_percentage': (df.isnull().sum() / len(df) * 100).round(2),
        'data_type': df.dtypes
    })

    # Missing value patterns by location
    missing_by_location = pd.DataFrame({
        col: df.groupby('LOCATION')[col].apply(lambda x: x.isnull().mean() *␣
↪100).round(2)
        for col in df.select_dtypes(include=['float64']).columns
    })

    # Analyze missing value relationships
    missing_correlations = df.isnull().corr()

    # Create visualization of missing values using seaborn
    plt.figure(figsize=(10, 6))
    sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis')
    plt.title('Missing Value Patterns')
    plt.tight_layout()

    return {
        'missing_summary': missing_info,
        'missing_by_location': missing_by_location,
        'missing_correlations': missing_correlations
    }

# Example usage
missing_analysis = analyze_missing_values(df)
print("\nMissing Value Summary:")
print(missing_analysis['missing_summary'])
print("\nMissing Values by Location (%):")
print(missing_analysis['missing_by_location'])
```

Missing Value Summary:

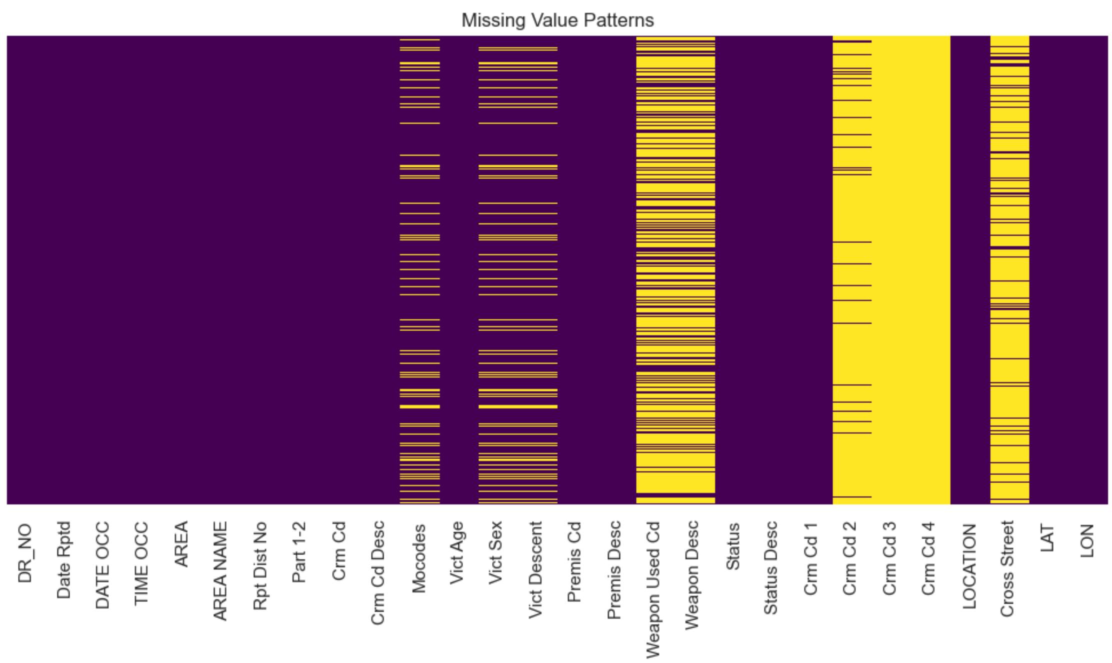
	missing_count	missing_percentage	data_type
DR_NO	0	0.00	int64
Date Rptd	0	0.00	object
DATE OCC	0	0.00	object
TIME OCC	0	0.00	int64
AREA	0	0.00	int64
AREA NAME	0	0.00	object
Rpt Dist No	0	0.00	int64
Part 1-2	0	0.00	int64
Crm Cd	0	0.00	int64
Crm Cd Desc	0	0.00	object
Mocodes	151706	15.09	object
Vict Age	0	0.00	int64
Vict Sex	144730	14.40	object
Vict Descent	144742	14.40	object
Premis Cd	16	0.00	float64
Premis Desc	588	0.06	object
Weapon Used Cd	677845	67.44	float64
Weapon Desc	677845	67.44	object
Status	1	0.00	object
Status Desc	0	0.00	object
Crm Cd 1	11	0.00	float64
Crm Cd 2	935945	93.12	float64
Crm Cd 3	1002787	99.77	float64
Crm Cd 4	1005037	99.99	float64
LOCATION	0	0.00	object
Cross Street	850864	84.65	object
LAT	0	0.00	float64
LON	0	0.00	float64

Missing Values by Location (%):

LOCATION	Premis Cd	Weapon Used Cd	Crm Cd 1 \
00 17TH	0.00	100.00	0.00
00 17TH AV	0.00	100.00	0.00
00 17TH PL	0.00	100.00	0.00
00 18TH AV	0.00	63.64	0.00
00 18TH PL	0.00	100.00	0.00
…	…	…	…
ZONAL	0.00	60.00	0.00
ZONAL AV	0.00	50.00	0.00
ZONAL ST	0.00	100.00	0.00
ZOO	0.00	66.67	0.00
ZOO DR	0.00	83.33	0.00

Crm Cd 2 Crm Cd 3 Crm Cd 4 LAT LON

```
LOCATION
00    17TH                                   100.00    100.00    100.00 0.00 0.00
00    17TH                             AV    100.00    100.00    100.00 0.00 0.00
00    17TH                             PL    100.00    100.00    100.00 0.00 0.00
00    18TH                             AV    100.00    100.00    100.00 0.00 0.00
00    18TH                             PL    100.00    100.00    100.00 0.00 0.00
…                                              …        …       …   …   …
ZONAL                                         80.00    100.00    100.00 0.00 0.00
ZONAL                            AV          100.00    100.00    100.00 0.00 0.00
ZONAL                            ST          100.00    100.00    100.00 0.00 0.00
ZOO                                          100.00    100.00    100.00 0.00 0.00
ZOO                              DR           91.67    100.00    100.00 0.00 0.00

[66566 rows x 8 columns]
```

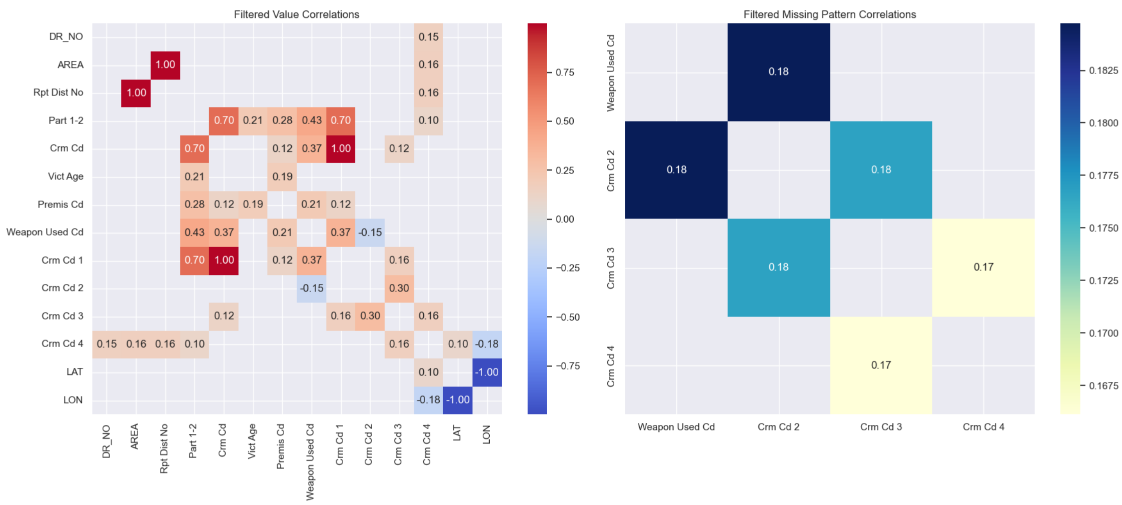


From the missing data pattern above we see that attributes Weapon Used Cd, Weapon Desc, Crime Cd2, 3,4 have have higher percentage of missing data along with few others. Missing Weapon Cd/Desc is acceptable as not every crime involves a weapon. Crimes like Vehicle theft, vandalism, shop lifting dont involve a weapon. We would still need this field but we cant use any imputation tecnhique to fill in the weapon information but instead will use a default 'No Weapon'. Since we have Crime cd 1 present for all records, the rest of the Crime codes fields can be ignored for the analyis

0.6 3. Correlation overview

[218]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

def analyze_correlations(df, method='pearson'):
    """
    Analyze correlations between numerical variables, handling missing values.
    """
    numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns

    # Correlation of actual values
    correlation_matrix = df[numerical_cols].corr(method=method)
    missing_correlation = df[numerical_cols].isnull().corr()

    # Filtered matrices
    threshold = 0.1
    corr_filtered = correlation_matrix[(abs(correlation_matrix) > threshold) &␣
↪(correlation_matrix != 1.0)].dropna(how='all').dropna(axis=1, how='all')

    missing_corr_filtered = missing_correlation[(abs(missing_correlation) >␣
↪threshold) & (missing_correlation != 1.0)].dropna(how='all').dropna(axis=1,␣
↪how='all')

    # Creating subplots
    fig, axes = plt.subplots(1, 2, figsize=(18, 8))

    if not corr_filtered.empty:
        sns.heatmap(corr_filtered, cmap='coolwarm', annot=True, fmt='.2f',␣
↪ax=axes[0])
        axes[0].set_title('Filtered Value Correlations')
    else:
        axes[0].set_visible(False)

    if not missing_corr_filtered.empty:
        sns.heatmap(missing_corr_filtered, cmap='YlGnBu', annot=True, fmt='.
↪2f', ax=axes[1])
        axes[1].set_title('Filtered Missing Pattern Correlations')
    else:
        axes[1].set_visible(False)

    plt.tight_layout()
    plt.show()

    return {
```

```python
        'value_correlations': correlation_matrix,
        'missing_correlations': missing_correlation
    }

# Example usage
correlations = analyze_correlations(df)
print("\nValue Correlations:")
print(correlations['value_correlations'])
```




```
Value Correlations:
                DR_NO  TIME OCC  AREA  Rpt Dist No  Part 1-2  Crm Cd  \
DR_NO            1.00     -0.00  0.03         0.03     -0.04   -0.02
TIME OCC        -0.00      1.00  0.00         0.00     -0.06    0.01
AREA             0.03      0.00  1.00         1.00      0.01   -0.01
Rpt Dist No      0.03      0.00  1.00         1.00      0.01   -0.01
Part 1-2        -0.04     -0.06  0.01         0.01      1.00    0.70
Crm Cd          -0.02      0.01 -0.01        -0.01      0.70    1.00
Vict Age        -0.07     -0.04  0.02         0.02      0.21   -0.02
Premis Cd        0.03     -0.06 -0.01        -0.01      0.28    0.12
Weapon Used Cd   0.02     -0.01 -0.02        -0.02      0.43    0.37
Crm Cd 1        -0.02      0.01 -0.01        -0.01      0.70    1.00
Crm Cd 2         0.03      0.01 -0.04        -0.04      0.08    0.00
Crm Cd 3         0.03     -0.01  0.04         0.04      0.01    0.12
Crm Cd 4         0.15     -0.03  0.16         0.16      0.10    0.04
LAT              0.05      0.00  0.03         0.03     -0.03   -0.04
LON             -0.05     -0.00 -0.01        -0.01      0.03    0.04

                Vict Age  Premis Cd  Weapon Used Cd  Crm Cd 1  Crm Cd 2  \
DR_NO              -0.07       0.03            0.02     -0.02      0.03
```

TIME OCC	-0.04	-0.06	-0.01	0.01	0.01
AREA	0.02	-0.01	-0.02	-0.01	-0.04
Rpt Dist No	0.02	-0.01	-0.02	-0.01	-0.04
Part 1-2	0.21	0.28	0.43	0.70	0.08
Crm Cd	-0.02	0.12	0.37	1.00	0.00
Vict Age	1.00	0.19	0.08	-0.02	-0.02
Premis Cd	0.19	1.00	0.21	0.12	-0.06
Weapon Used Cd	0.08	0.21	1.00	0.37	-0.15
Crm Cd 1	-0.02	0.12	0.37	1.00	0.02
Crm Cd 2	-0.02	-0.06	-0.15	0.02	1.00
Crm Cd 3	-0.01	-0.01	-0.06	0.16	0.30
Crm Cd 4	-0.00	-0.00	0.03	-0.03	0.02
LAT	-0.00	-0.01	-0.01	-0.04	-0.02
LON	0.00	0.01	0.01	0.04	0.02

	Crm Cd 3	Crm Cd 4	LAT	LON
DR_NO	0.03	0.15	0.05	-0.05
TIME OCC	-0.01	-0.03	0.00	-0.00
AREA	0.04	0.16	0.03	-0.01
Rpt Dist No	0.04	0.16	0.03	-0.01
Part 1-2	0.01	0.10	-0.03	0.03
Crm Cd	0.12	0.04	-0.04	0.04
Vict Age	-0.01	-0.00	-0.00	0.00
Premis Cd	-0.01	-0.00	-0.01	0.01
Weapon Used Cd	-0.06	0.03	-0.01	0.01
Crm Cd 1	0.16	-0.03	-0.04	0.04
Crm Cd 2	0.30	0.02	-0.02	0.02
Crm Cd 3	1.00	0.16	0.02	-0.03
Crm Cd 4	0.16	1.00	0.10	-0.18
LAT	0.02	0.10	1.00	-1.00
LON	-0.03	-0.18	-1.00	1.00

There is a strong correlation between following attribute and hence one of the attribute can be removed

Crm Cd 2 and AREA (1.00) -> redundant feature

Rpt Dist No and AREA (1.00) -> as both represent region this seems to be redundant

From the missing data correlation we can see that there is a weak correlation between weapon use and crime code 2, indicating that when crime is less severe weapon cd and crime code 2,3 are not recorded or likely not used. Crime cd 2,3,4 can be treated as supplementary data."-

0.7 4. Feature Engineering

The project focus on Crime patters for male or female gender for past 3 years. Dropping remaining gender records and date of crime occurence.

Features like Crime cd 1 and Part1-2 has strong correlation hence dropping Crime cd 1 column

Features like AREA, Premise Cd, Premise description, Cross Street are reduncat as we have LAT, LON

Features like Moode, Crm D 2 ,Crm Cd3, Crm Cd 4, Rept Dist No, Weapon used, Weapon Desc , Victim Descent, Status cd, status description are irrelavant to our project focus, date reported. Hence will be dropped

We Will be binning Victim Age to get more age group perspective of crime patterns and Victim Age will then be dropped.

Latitude and Longitude will be validated and invalid records will be filterd out

[219]:
```
df['Vict Age'].value_counts()
```

[219]:
```
Vict Age
 0      269316
 30      22290
 35      21836
 31      21420
 29      21345
         …
 98         71
-2          28
-3           6
-4           3
 120         1
Name: count, Length: 104, dtype: int64
```

[220]:
```
df.drop(df[df['Vict Age'] == 0].index, inplace=True)
```

[221]:
```
df['Vict Sex'].value_counts()
```

[221]:
```
Vict Sex
M    370329
F    354706
X     10606
H       112
Name: count, dtype: int64
```

[222]:
```
# Keep only rows where 'Vict Sex' is either 'M' or 'F'
df = df[df['Vict Sex'].isin(['M', 'F'])]
```

[223]:
```
print(len(df))  # Total number of rows
```

```
725035
```

[224]:
```
#Chcecking for invalid LAT LONG values

invalid_lat = df['LAT'].isnull() | (df['LAT'] == 0) | (df['LAT'] < -90) |␣
↪(df['LAT'] > 90)
invalid_lon = df['LON'].isnull() | (df['LON'] == 0) | (df['LON'] < -180) |␣
↪(df['LON'] > 180)

count_invalid = (invalid_lat | invalid_lon).sum()
print("Invalid lat lon", count_invalid)
```

```
Invalid lat lon 1680
```

[225]:
```
df.drop(df[invalid_lat | invalid_lon].index, inplace=True)
```

[226]:
```
# Make sure 'DATE OCC' is in datetime format first
df['DATE OCC'] = pd.to_datetime(df['DATE OCC'], errors='coerce')

# Get min and max dates
min_date = df['DATE OCC'].min()
max_date = df['DATE OCC'].max()

print(f"Minimum DATE OCC: {min_date}")
print(f"Maximum DATE OCC: {max_date}")
```

```
C:\Users\dpamu\AppData\Local\Temp\ipykernel_22952\1535027545.py:2: UserWarning:
Could not infer format, so each element will be parsed individually, falling
back to `dateutil`. To ensure parsing is consistent and as-expected, please
specify a format.
  df['DATE OCC'] = pd.to_datetime(df['DATE OCC'], errors='coerce')
```

```
Minimum DATE OCC: 2020-01-01 00:00:00
Maximum DATE OCC: 2025-04-01 00:00:00
```

[227]:
```
# Ensure DATE OCC is datetime -
df['DATE OCC'] = pd.to_datetime(df['DATE OCC'], errors='coerce')

# Filter for years 2023, 2024, and 2025
df = df[df['DATE OCC'].dt.year.isin([2023, 2024, 2025])]
```

[228]:
```
print(len(df))  # Total number of rows
```

```
240556
```

0.7.1 Dropping redundant attriutes

[229]:
```
#Dropping due high cardinality for one hot encoding. will be using LAT/LONG,␣
↪zipcode instead
df.drop(['LOCATION'], axis=1, inplace=True)
```

[230]:
```
#dropping redundant code fields as we have descripton fields and unnecessary␣
↪fields
df.drop(['Crm Cd','Mocodes','AREA','Crm Cd 2', 'Crm Cd 3', 'Crm Cd 4','Rpt Dist␣
↪No','Cross Street','Weapon Used Cd', 'Status','Premis Cd','Weapon Desc',
       'Vict Descent','Status Desc','Premis Desc'], axis=1, inplace=True)
```

[231]:
```
# Checking TIME OCC is a 4-digit string
df['TIME OCC'] = df['TIME OCC'].astype(str).str.zfill(4)
# Extract hour
df['hour'] = df['TIME OCC'].str[:2].astype(int)
```

[232]:
```
#Dropping due to irrelevance and redundance
df.drop(['DATE OCC','TIME OCC'], axis=1, inplace=True)
```

[233]:
```
# Defining age bins and corresponding labels
age_bins = [0, 12, 18, 35, 60, 120]  # 0-12=Child, 13-18=Teen, 19-35=Young␣
↪Adult, etc.
age_labels = ['Child', 'Teen', 'Young Adult', 'Adult', 'Senior']

# Creating age group column
df['Victim_Age_Group'] = pd.cut(df['Vict Age'], bins=age_bins,␣
↪labels=age_labels, right=False)
```

[234]:
```
df.drop(['DR_NO', 'Date Rptd'], axis=1, inplace=True)
```

[235]:
```
df.head()
```

[235]:
```
         AREA NAME  Part 1-2  \
644982     Central         1
644983  N Hollywood        1
644984     Central         1
644985    Hollywood        2
644986     Topanga         1

                                           Crm Cd Desc  Vict Age Vict Sex  \
644982                THEFT PLAIN - PETTY ($950 & UNDER)        48        M
644983        ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT    36        F
644984  THEFT FROM MOTOR VEHICLE - GRAND ($950.01 AND …       25        F
644985                  INTIMATE PARTNER - SIMPLE ASSAULT       65        F
644986                                            ROBBERY       31        F

        Crm Cd 1   LAT     LON  hour Victim_Age_Group
644982    440.00 34.04 -118.27    16            Adult
644983    230.00 34.17 -118.36    10            Adult
644984    331.00 34.04 -118.27     8      Young Adult
644985    626.00 34.10 -118.31     1           Senior
644986    210.00 34.19 -118.56     7      Young Adult
```

[236]:
```
df.drop(['AREA NAME', 'Crm Cd Desc','Vict Age', 'Crm Cd 1'], axis=1,␣
↪inplace=True)
```

[237]:
```
fields = df.columns.tolist()
print(fields)
```

```
['Part 1-2', 'Vict Sex', 'LAT', 'LON', 'hour', 'Victim_Age_Group']
```

[238]:
```
df.head()
```

[238]:

	Part 1-2	Vict Sex	LAT	LON	hour	Victim_Age_Group
644982	1	M	34.04	-118.27	16	Adult
644983	1	F	34.17	-118.36	10	Adult
644984	1	F	34.04	-118.27	8	Young Adult
644985	2	F	34.10	-118.31	1	Senior
644986	1	F	34.19	-118.56	7	Young Adult

0.7.2 5. One Hot Encoding

One hot encoding will be applied to Victim sex (giving 2 columns) and Victim Age group (giving 5 groups)

[239]:
```
import pandas as pd

# 1. Keep only 'M' and 'F' values
df = df[df['Vict Sex'].isin(['M', 'F'])]

# 2. One-hot encode Vict Sex
df = pd.get_dummies(df, columns=['Vict Sex'], prefix='Vict_Sex',␣
↪drop_first=False)
```

[240]:
```
import pandas as pd

# 1. Keep only 'M' and 'F' values
df = df[df['Victim_Age_Group'].isin(['Child', 'Teen', 'Young Adult', 'Adult',␣
↪'Senior'])]

# 2. One-hot encode Vict Sex
df = pd.get_dummies(df, columns=['Victim_Age_Group'], prefix='Vict_Age',␣
↪drop_first=False)
```

[241]:
```
df.head()
```

[241]:

	Part 1-2	LAT	LON	hour	Vict_Sex_F	Vict_Sex_M	Vict_Age_Child \
644982	1	34.04	-118.27	16	False	True	False
644983	1	34.17	-118.36	10	True	False	False
644984	1	34.04	-118.27	8	True	False	False
644985	2	34.10	-118.31	1	True	False	False
644986	1	34.19	-118.56	7	True	False	False

```
        Vict_Age_Teen  Vict_Age_Young Adult  Vict_Age_Adult  Vict_Age_Senior
644982          False                 False            True            False
644983          False                 False            True            False
644984          False                  True           False            False
644985          False                 False           False             True
644986          False                  True           False            False
```

[242]:
```
fields = df.columns.tolist()
print(fields)
```

```
['Part 1-2', 'LAT', 'LON', 'hour', 'Vict_Sex_F', 'Vict_Sex_M', 'Vict_Age_Child',
'Vict_Age_Teen', 'Vict_Age_Young Adult', 'Vict_Age_Adult', 'Vict_Age_Senior']
```

0.7.3 6. Scaling

Scaling is need because some of the features have higher differences than the others. Without scaling these larger differences will dominate the distance metrics leading to biased clusters.

[243]:
```
df.isnull().sum()
```

[243]:
```
Part 1-2                0
LAT                     0
LON                     0
hour                    0
Vict_Sex_F              0
Vict_Sex_M              0
Vict_Age_Child          0
Vict_Age_Teen           0
Vict_Age_Young Adult    0
Vict_Age_Adult          0
Vict_Age_Senior         0
dtype: int64
```

[244]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaled_data = scaler.fit_transform(df[['Part 1-2', 'LAT', 'LON',  'Vict_Sex_F',␣
 ↪'Vict_Sex_M', 'Vict_Age_Child', 'Vict_Age_Teen', 'Vict_Age_Young Adult',␣
 ↪'Vict_Age_Adult', 'Vict_Age_Senior']])
```

[245]:
```
type(scaled_data)
```

[245]:
```
numpy.ndarray
```

0.8 7. Clustering

As we have 250k records we chose the following models for their ability to handle large datasets. We chose this option as opposed to sampling to get better accuracy.

MiniBatchKMeans : Faster, memory-efficient version of KMeans, using small random batches instead of the whole dataset for updates.

Gaussian Mixture : Flexible model that is probabilistic, allowing soft clustering (a point can belong to multiple clusters with different probabilities). This is useful as we belive there may be overlap in clusters.

Birch model (Balanced Iterative Reducing and Clustering using Hierarchies): Efficient at handling large datasets by incrementally builiding clustering tree and compressing data in memory.

Other algorithms took lot of compute resoures and long time process. The above mentioned models worked quickly and giving a moderate Silhoute scores.

[246]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import MiniBatchKMeans, Birch
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score
import pandas as pd
import numpy as np


# 1. MiniBatchKMeans
mini_kmeans = MiniBatchKMeans(n_clusters=5, batch_size=10000, random_state=42)
mini_labels = mini_kmeans.fit_predict(scaled_data)
mini_silhouette = silhouette_score(scaled_data, mini_labels)

# 2. Gaussian Mixture
gmm = GaussianMixture(n_components=5, random_state=42)
gmm_labels = gmm.fit_predict(scaled_data)
gmm_silhouette = silhouette_score(scaled_data, gmm_labels)

# 3. Birch
birch = Birch(n_clusters=5) an
birch_labels = birch.fit_predict(scaled_data)
birch_silhouette = silhouette_score(scaled_data, birch_labels)

# Prepare result summary
result_df = pd.DataFrame({
    'Algorithm': ['MiniBatchKMeans', 'GaussianMixture', 'Birch'],
    'Silhouette Score': [mini_silhouette, gmm_silhouette, birch_silhouette]
})

print("Clustering Comparison Results:")
print(result_df)
```

```
Clustering Comparison Results:
         Algorithm  Silhouette Score
0  MiniBatchKMeans              0.27
```

```
1  GaussianMixture             0.30
2            Birch             0.30
```

[247]:
```
from sklearn.cluster import MiniBatchKMeans

kmeans = MiniBatchKMeans(n_clusters=5, batch_size=10000, random_state=42)
df['cluster'] = kmeans.fit_predict(scaled_data)
```

[248]:
```
from sklearn.metrics import silhouette_score

score = silhouette_score(scaled_data, df['cluster'])
print(f"Silhouette Score: {score:.4f}")
```

```
Silhouette Score: 0.2652
```

[251]:
```
df['mini_labels'] = mini_labels
df['gmm_labels'] = gmm_labels
df['birch_labels'] = birch_labels
```

[252]:
```
print("MiniBatchKMeans label counts:")
print(df['mini_labels'].value_counts())

print("Gaussian label counts:")
print(df['gmm_labels'].value_counts())

print("Birch label counts:")
print(df['birch_labels'].value_counts())
```

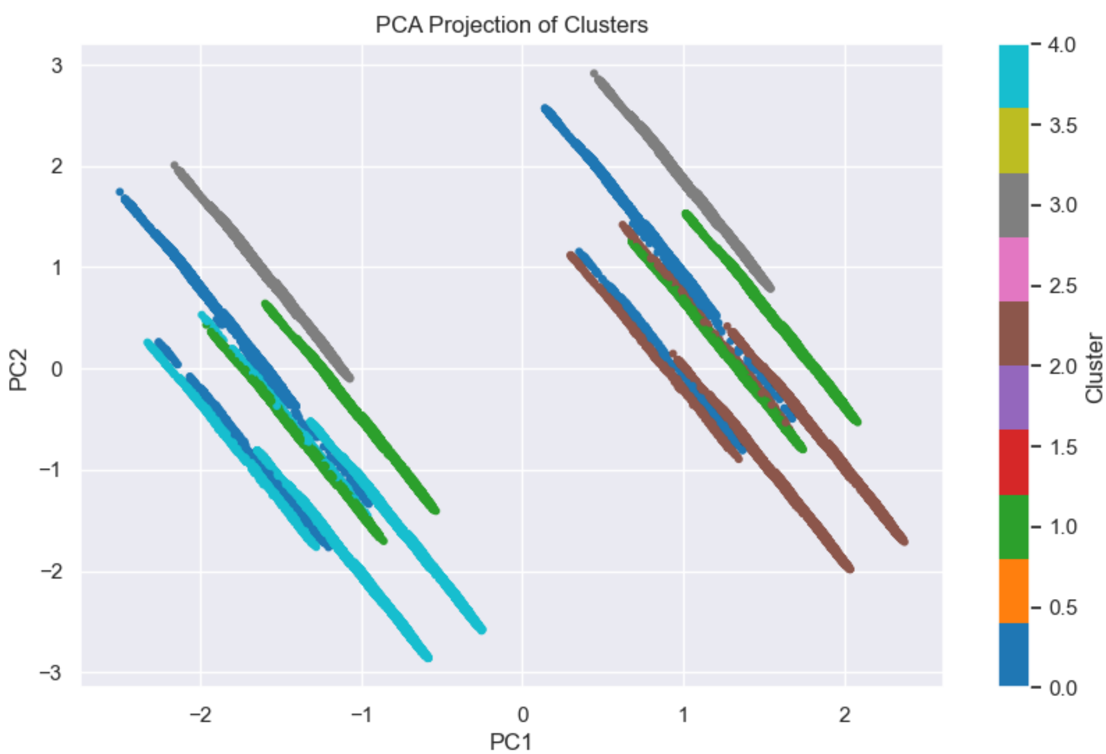
```
MiniBatchKMeans label counts:
mini_labels
3    83909
1    61848
4    51053
0    37236
2     6508
Name: count, dtype: int64
Gaussian label counts:
gmm_labels
2    58876
3    55575
4    51854
0    43555
1    30694
Name: count, dtype: int64
Birch label counts:
birch_labels
1    100304
4     94145
0     37711
```

```
2      6508
3      1886
Name: count, dtype: int64
```

0.9 8. Visualization

Using Guassian Mixture results due to high Silhouette scores

[255]:
```python
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Reduce to 2D for visualization
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_data)

# Scatter plot with cluster labels
plt.figure(figsize=(10, 6))
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=df['gmm_labels'],␣
 ↪cmap='tab10', s=10)
plt.title("PCA Projection of Clusters")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.colorbar(label='Cluster')
plt.grid(True)
plt.show()
```



[256]:
```
# Now group by cluster and describe the features
df.groupby('gmm_labels')[['Part 1-2','Vict_Age_Child', 'Vict_Age_Teen',
 ↪'Vict_Age_Young Adult','Vict_Age_Adult', 'Vict_Age_Senior',
                        'Vict_Sex_M', 'Vict_Sex_F', 'hour', 'LAT', 'LON']].mean()
```

[256]:
```
            Part 1-2  Vict_Age_Child  Vict_Age_Teen  Vict_Age_Young Adult  \
gmm_labels
0               1.99            0.04           0.00                  0.96
1               1.47            0.00           0.00                  0.00
2               1.39            0.00           0.05                  0.00
3               1.00            0.00           0.00                  1.00
4               1.55            0.00           0.07                  0.00

            Vict_Age_Adult  Vict_Age_Senior  Vict_Sex_M  Vict_Sex_F  hour  \
gmm_labels
0                     0.00             0.00        0.39        0.61 12.73
1                     0.00             1.00        0.54        0.46 13.02
2                     0.95             0.00        1.00        0.00 13.24
3                     0.00             0.00        0.54        0.46 13.57
4                     0.93             0.00        0.00        1.00 13.18

             LAT     LON
gmm_labels
0          34.07 -118.35
1          34.08 -118.38
2          34.09 -118.37
3          34.07 -118.35
4          34.07 -118.36
```

[257]:
```
df.groupby('gmm_labels')['Part 1-2'].value_counts(normalize=True)
```

[257]:
```
gmm_labels  Part 1-2
0           2           0.99
            1           0.01
1           1           0.53
            2           0.47
2           1           0.61
            2           0.39
3           1           1.00
4           2           0.55
            1           0.45
Name: proportion, dtype: float64
```

0.9.1 9. Business Value - Gaussian Mixture Model

From the above breakdown, we can see that for

Cluster 0 - Majority of the victims were female young adults and that the location of crime occurence is at Lat: 34.07 Long: -118.35 occuring around 1 pm with severity of crime being 2 (non serious crimes).This indicates some sort of petty theft or property crimes happening during lunch hours affecting young adults. So launching programs to make female commuters aware of the area will help combat the crime.

Cluster 1 - All of the victims are elderly with a mix of both male and female victims with server of crime being a mix of serious and non serious. This shows vulnerability for seniors so having Senior safety awareness would help reduce the crime.

Cluster 2- All of the victims are male with higher percentage of adults victims with small percentage of teenagers. Majority of the crimes in this cluster are of non serious crimes so this can be treated as lower priority incidents. This would save the police enforcement to focus on serious crime clusters.

Cluster 3 : This cluster captures serious crimes with young adults with equal mix of male and females happening around Lat: 34.07 Lon: -118.35 happening around 1 pm. These could be street violence or assaults. This would be helpful for police to survelience the area and priotize their resources

Cluster 4: All victims are Female with majority yound adults and small portion of teenagers as well with crime occruning around 1 pm . Since there is equal mix of serious and non serious crimes this could imply domestic violence or gender based crimes. This would be hellpful in planning and prioritising outreach programs for women to bring awareness.

Based on above insights from Clusters we have following recommendations:

1. Police departments should use cluster insights for proactive resource allocation.

2. Design tailored outreach and safety campaigns based on victim demographics.

3. Expand the model by incorporating real-time feeds, geographic trends, and repeat offense patterns.

4. Engage with local community organizations to raise awareness in areas identified as high-risk.

0.9.2 Deployment

The model can be transitioned into production through strategic integration into crime monitoring and public safety systems. The deployment plan involves:

Operationalizing cluster insights for use in daily or weekly police patrolling schedules, targeting identified high-risk zones and vulnerable demographics.

Launching targeted outreach programs, such as:

Senior safety awareness for clusters involving elderly victims.

Women's safety initiatives in areas with high female victimization rates.

Scheduling automated updates to ingest new crime data (weekly or monthly), enabling the system to reflect the latest crime trends and support dynamic resource allocation.

0.9.3 Implementation Steps:

To support this deployment, a crime analytics pipeline can be developed with the following components:

Data Ingestion: Automatically retrieve updated crime records.

Data Preprocessing: Filter relevant features, apply encoding, and scale inputs.

Cluster Labeling: Apply the trained Gaussian Mixture Model to assign clusters.

Visualization: Display crime patterns on an interactive map with clustering overlays.

Alert Generation: Identify and flag high-risk areas or vulnerable population groups like elderly or women.

0.9.4 Deployment Infrastructure:

This solution can be hosted on scalable cloud platforms such as AWS, Azure, or Google Cloud to ensure high availability and cost effective scaling along with real time integration with police enforcement systems.

0.9.5