

Group9_FDA

October 16, 2024

IE6400 Foundations Data Analytics Engineering Fall Semester 2024

Group Projects

Topic: Cleaning and Analyzing Crime Data

Objective: In this project, you'll work with real-world data dataset containing crime data 2020. Your goal is to clean and prepare the dataset for analysis, perform exploratory data analysis (EDA), and answer specific questions related to crime trends, patterns, and factors influencing crime rates.

Dataset: You will use the crime dataset available at Crime Data from 2020 to present.

Tasks: - 1. Data Acquisition: Download the dataset from the provided link and load it into your preferred data analysis tool.

```
[1]: import pandas as pd
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")
print(cp)
```

	DR_NO	Date Rptd	DATE OCC	TIME OCC	\
0	190326475	03-01-2020 00:00	03-01-2020 00:00	2130	
1	200106753	02-09-2020 00:00	02-08-2020 00:00	1800	
2	200320258	11-11-2020 00:00	11-04-2020 00:00	1700	
3	200907217	05-10-2023 00:00	03-10-2020 00:00	2037	
4	220614831	08/18/2022 12:00:00 AM	08/17/2020 12:00:00 AM	1200	
...	
978623	240710284	07/24/2024 12:00:00 AM	07/23/2024 12:00:00 AM	1400	
978624	240104953	01/15/2024 12:00:00 AM	01/15/2024 12:00:00 AM	100	
978625	241711348	07/19/2024 12:00:00 AM	07/19/2024 12:00:00 AM	757	
978626	240309674	04/24/2024 12:00:00 AM	04/24/2024 12:00:00 AM	1500	
978627	240910892	08/13/2024 12:00:00 AM	08-12-2024 00:00	2300	

	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	\
0	7	Wilshire	784	1	510	
1	1	Central	182	1	330	
2	3	Southwest	356	1	480	
3	9	Van Nuys	964	1	343	
4	6	Hollywood	666	2	354	
...	
978623	7	Wilshire	788	1	510	
978624	1	Central	101	2	745	

978625	17	Devonshire	1751	2	888
978626	3	Southwest	358	1	230
978627	9	Van Nuys	914	1	510

	Crm	Cd	Desc	...	Status	\
0			VEHICLE - STOLEN	...	AA	
1			BURGLARY FROM VEHICLE	...	IC	
2			BIKE - STOLEN	...	IC	
3			SHOPLIFTING-GRAND THEFT (\$950.01 & OVER)	...	IC	
4			THEFT OF IDENTITY	...	IC	
...			
978623			VEHICLE - STOLEN	...	IC	
978624			VANDALISM - MISDEAMEANOR (\$399 OR UNDER)	...	IC	
978625			TRESPASSING	...	IC	
978626			ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT	...	IC	
978627			VEHICLE - STOLEN	...	IC	

	Status	Desc	Crm	Cd	1	Crm	Cd	2	Crm	Cd	3	Crm	Cd	4	\
0	Adult	Arrest			510.0			998.0			NaN			NaN	
1	Invest	Cont			330.0			998.0			NaN			NaN	
2	Invest	Cont			480.0			NaN			NaN			NaN	
3	Invest	Cont			343.0			NaN			NaN			NaN	
4	Invest	Cont			354.0			NaN			NaN			NaN	
...	
978623	Invest	Cont			510.0			NaN			NaN			NaN	
978624	Invest	Cont			745.0			NaN			NaN			NaN	
978625	Invest	Cont			888.0			NaN			NaN			NaN	
978626	Invest	Cont			230.0			NaN			NaN			NaN	
978627	Invest	Cont			510.0			NaN			NaN			NaN	

	LOCATION	\
0	1900 S LONGWOOD AV	
1	1000 S FLOWER ST	
2	1400 W 37TH ST	
3	14000 RIVERSIDE DR	
4	1900 TRANSIENT	
...	...	
978623	4000 W 23RD ST	
978624	1300 W SUNSET BL	
978625	10000 OLD DEPOT PLAZA RD	
978626	FLOWER ST	
978627	6900 VESPER AV	

	Cross Street	LAT	LON
0	NaN	34.0375	-118.3506
1	NaN	34.0444	-118.2628
2	NaN	34.0210	-118.3002
3	NaN	34.1576	-118.4387

```

4                NaN  34.0944 -118.3277
...
978623          NaN  34.0362 -118.3284
978624          NaN  34.0685 -118.2460
978625          NaN  34.2500 -118.5990
978626  JEFFERSON    BL  34.0215 -118.2868
978627          NaN  34.1961 -118.4510

```

[978628 rows x 28 columns]

2. Data Inspection: - Display the first few rows of the dataset?

```
[2]: #Display the first 10 rows of the dataframe
cp.head(10)
```

```
[2]:
      DR_NO      Date Rptd      DATE OCC  TIME OCC  AREA  \
0  190326475    03-01-2020 00:00    03-01-2020 00:00    2130    7
1  200106753    02-09-2020 00:00    02-08-2020 00:00    1800    1
2  200320258    11-11-2020 00:00    11-04-2020 00:00    1700    3
3  200907217    05-10-2023 00:00    03-10-2020 00:00    2037    9
4  220614831  08/18/2022 12:00:00 AM  08/17/2020 12:00:00 AM    1200    6
5  231808869    04-04-2023 00:00    12-01-2020 00:00    2300   18
6  230110144    04-04-2023 00:00    07-03-2020 00:00     900    1
7  220314085  07/22/2022 12:00:00 AM    05-12-2020 00:00    1110    3
8  231309864  04/28/2023 12:00:00 AM    12-09-2020 00:00    1400   13
9  211904005  12/31/2020 12:00:00 AM  12/31/2020 12:00:00 AM    1220   19

```

```

      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  Hollywood    666      2      354
5  Southeast   1826      2      354
6  Central      182      2      354
7  Southwest    303      2      354
8  Newton     1375      2      354
9  Mission     1974      2      624

```

```

      Crm Cd Desc  ... Status  Status Desc  \
0      VEHICLE - STOLEN  ...    AA  Adult Arrest
1  BURGLARY FROM VEHICLE  ...    IC  Invest Cont
2      BIKE - STOLEN  ...    IC  Invest Cont
3  SHOPLIFTING-GRAND THEFT ($950.01 & OVER)  ...    IC  Invest Cont
4      THEFT OF IDENTITY  ...    IC  Invest Cont
5      THEFT OF IDENTITY  ...    IC  Invest Cont
6      THEFT OF IDENTITY  ...    IC  Invest Cont
7      THEFT OF IDENTITY  ...    IC  Invest Cont

```

8		THEFT OF IDENTITY	...	IC	Invest Cont
9		BATTERY - SIMPLE ASSAULT	...	IC	Invest Cont

	Crm Cd 1	Crm Cd 2	Crm Cd 3	Crm Cd 4	\
0	510.0	998.0	NaN	NaN	
1	330.0	998.0	NaN	NaN	
2	480.0	NaN	NaN	NaN	
3	343.0	NaN	NaN	NaN	
4	354.0	NaN	NaN	NaN	
5	354.0	NaN	NaN	NaN	
6	354.0	NaN	NaN	NaN	
7	354.0	NaN	NaN	NaN	
8	354.0	NaN	NaN	NaN	
9	624.0	NaN	NaN	NaN	

	LOCATION	Cross Street	LAT	LON
0	1900 S	LONGWOOD AV	NaN	34.0375 -118.3506
1	1000 S	FLOWER ST	NaN	34.0444 -118.2628
2	1400 W	37TH ST	NaN	34.0210 -118.3002
3	14000	RIVERSIDE DR	NaN	34.1576 -118.4387
4		1900 TRANSIENT	NaN	34.0944 -118.3277
5	9900	COMPTON AV	NaN	33.9467 -118.2463
6	1100 S	GRAND AV	NaN	34.0415 -118.2620
7	2500 S	SYCAMORE AV	NaN	34.0335 -118.3537
8	1300 E	57TH ST	NaN	33.9911 -118.2521
9	9000	CEDROS AV	NaN	34.2336 -118.4535

[10 rows x 28 columns]

- Check the data types of each column?

```
[3]: #Display the datatypes of each column in the dataframe
cp.dtypes
```

```
[3]: DR_NO          int64
Date Rptd         object
DATE OCC          object
TIME OCC          int64
AREA              int64
AREA NAME         object
Rpt Dist No       int64
Part 1-2          int64
Crm Cd            int64
Crm Cd Desc       object
Mocodes           object
Vict Age          int64
Vict Sex          object
Vict Descent      object
```

```

Premis Cd      float64
Premis Desc    object
Weapon Used Cd float64
Weapon Desc    object
Status         object
Status Desc    object
Crm Cd 1       float64
Crm Cd 2       float64
Crm Cd 3       float64
Crm Cd 4       float64
LOCATION        object
Cross Street   object
LAT            float64
LON            float64
dtype: object

```

- Review column names and descriptions

```

[4]: #Display summary of the dataframe including column names, non-null counts, and
      ↪ data types
      cp.describe()

```

```

[4]:
count    DR_NO    TIME OCC    AREA    Rpt Dist No \
mean    9.786280e+05  978628.000000  978628.000000  978628.000000
std      2.196564e+08  1338.802627    10.702561    1116.686084
min      1.290395e+07   651.622947     6.107280     610.836054
25%      8.170000e+02    1.000000     1.000000     101.000000
50%      2.106073e+08   900.000000     5.000000     589.000000
75%      2.208116e+08  1420.000000    11.000000    1141.000000
max      2.309110e+08  1900.000000    16.000000    1617.000000
max      2.499253e+08  2359.000000    21.000000    2199.000000

```

```

count    Part 1-2    Crm Cd    Vict Age    Premis Cd \
mean      1.404785    500.810635    29.122904    306.181502
std        0.490851    206.309796    21.961531    218.908131
min        1.000000    110.000000    -4.000000    101.000000
25%        1.000000    331.000000     0.000000    101.000000
50%        1.000000    442.000000    30.000000    203.000000
75%        2.000000    626.000000    44.000000    501.000000
max        2.000000    956.000000   120.000000    976.000000

```

```

count    Weapon Used Cd    Crm Cd 1    Crm Cd 2    Crm Cd 3    Crm Cd 4 \
mean      325959.000000  978617.000000  68816.000000  2309.000000  64.00000
std        123.673988    206.107451    110.251477    51.506344    27.06985
min        101.000000    110.000000    210.000000    310.000000    821.00000
25%        311.000000    331.000000    998.000000    998.000000    998.00000

```

50%	400.000000	442.000000	998.000000	998.000000	998.000000
75%	400.000000	626.000000	998.000000	998.000000	998.000000
max	516.000000	956.000000	999.000000	999.000000	999.000000

	LAT	LON
count	978628.000000	978628.000000
mean	33.995399	-118.081108
std	1.640056	5.684520
min	0.000000	-118.667600
25%	34.014600	-118.430500
50%	34.058900	-118.322500
75%	34.164900	-118.273900
max	34.334300	0.000000

3.Data Cleaning: - Identify and handle missing data appropriately

```
[5]: #Check for null values in the dataframe
cp.isnull()
```

```
[5]:
```

	DR_NO	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	\
0	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	
...	
978623	False	False	False	False	False	False	False	
978624	False	False	False	False	False	False	False	
978625	False	False	False	False	False	False	False	
978626	False	False	False	False	False	False	False	
978627	False	False	False	False	False	False	False	

	Part 1-2	Crm Cd	Crm Cd Desc	...	Status	Status Desc	Crm Cd 1	\
0	False	False	False	...	False	False	False	
1	False	False	False	...	False	False	False	
2	False	False	False	...	False	False	False	
3	False	False	False	...	False	False	False	
4	False	False	False	...	False	False	False	
...	
978623	False	False	False	...	False	False	False	
978624	False	False	False	...	False	False	False	
978625	False	False	False	...	False	False	False	
978626	False	False	False	...	False	False	False	
978627	False	False	False	...	False	False	False	

	Crm Cd 2	Crm Cd 3	Crm Cd 4	LOCATION	Cross Street	LAT	LON
0	False	True	True	False	True	False	False
1	False	True	True	False	True	False	False

2	True	True	True	False	True	False	False
3	True	True	True	False	True	False	False
4	True	True	True	False	True	False	False
...
978623	True	True	True	False	True	False	False
978624	True	True	True	False	True	False	False
978625	True	True	True	False	True	False	False
978626	True	True	True	False	False	False	False
978627	True	True	True	False	True	False	False

[978628 rows x 28 columns]

```
[6]: #Drop rows with null values from the dataframe (handling missing data)
cp.dropna()
```

```
[6]:
```

	DR_NO	Date Rptd	DATE OCC	TIME OCC	\
66026	201904032	01-02-2020 00:00	01-01-2020 00:00	2135	
86496	200613424	08-02-2020 00:00	08-02-2020 00:00	2030	
363643	210617136	10-08-2021 00:00	10-07-2021 00:00	1950	
372408	210209196	05-08-2021 00:00	05-08-2021 00:00	230	
489920	220600626	04/27/2022 12:00:00 AM	04/23/2022 12:00:00 AM	2300	
537636	221718232	12/25/2022 12:00:00 AM	12/25/2022 12:00:00 AM	1150	
585780	221401314	11-10-2022 00:00	11-10-2022 00:00	2117	
728192	231717599	11/15/2023 12:00:00 AM	11/15/2023 12:00:00 AM	400	
809005	231915572	10/21/2023 12:00:00 AM	10/21/2023 12:00:00 AM	1	
922659	241905348	02-04-2024 00:00	02-03-2024 00:00	1100	

	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	\
66026	19	Mission	1924	1	761	
86496	6	Hollywood	657	1	761	
363643	6	Hollywood	659	1	121	
372408	2	Rampart	279	1	210	
489920	6	Hollywood	646	1	821	
537636	17	Devonshire	1797	1	122	
585780	14	Pacific	1452	2	910	
728192	17	Devonshire	1738	1	210	
809005	19	Mission	1902	1	210	
922659	19	Mission	1983	1	820	

	Crm Cd Desc	...	Status	\
66026	BRANDISH WEAPON	...	AA	
86496	BRANDISH WEAPON	...	AO	
363643	RAPE, FORCIBLE	...	IC	
372408	ROBBERY	...	AO	
489920	SODOMY/SEXUAL CONTACT B/W PENIS OF ONE PERS TO...	...	IC	
537636	RAPE, ATTEMPTED	...	AA	
585780	KIDNAPPING	...	IC	

728192	ROBBERY	...	IC
809005	ROBBERY	...	AA
922659	ORAL COPULATION	...	AO

	Status Desc	Crm Cd 1	Crm Cd 2	Crm Cd 3	Crm Cd 4	\
66026	Adult Arrest	761.0	930.0	997.0	998.0	
86496	Adult Other	761.0	920.0	930.0	998.0	
363643	Invest Cont	121.0	210.0	910.0	998.0	
372408	Adult Other	210.0	510.0	910.0	998.0	
489920	Invest Cont	230.0	821.0	910.0	998.0	
537636	Adult Arrest	122.0	230.0	910.0	998.0	
585780	Invest Cont	812.0	860.0	910.0	998.0	
728192	Invest Cont	210.0	230.0	761.0	998.0	
809005	Adult Arrest	210.0	250.0	761.0	998.0	
922659	Adult Other	761.0	820.0	910.0	998.0	

	LOCATION	Cross Street	\
66026	ASTORIA ST	SAN FERNANDO RD	
86496	WESTERN	ROMAINE	
363643	NORMANDIE	DE LONGPRE	
372408	JAMES M WOOD	GREEN	
489920	SELMA	LAS PALMAS	
537636	PARTHENIA ST	HAYVENHURST	
585780	WASHINGTON	SPEEDWAY	
728192	HASKELL AV	SAN FERNANDO BL	
809005	POLK	BORDEN	
922659	BURNET	PARTHENIA	

	LAT	LON
66026	34.2949	-118.4571
86496	34.0885	-118.3092
363643	34.0966	-118.3005
372408	34.0503	-118.2720
489920	34.0997	-118.3363
537636	34.2285	-118.4939
585780	33.9792	-118.4666
728192	34.2692	-118.4789
809005	34.3103	-118.4467
922659	34.2282	-118.4633

[10 rows x 28 columns]

- Check for and remove duplicate rows

```
[12]: cp.drop_duplicates().head()
```



```
[12]:      DR_NO      Date Rptd      DATE OCC  TIME OCC  AREA  \
0  190326475      03-01-2020 00:00      03-01-2020 00:00      2130.0      7
1  200106753      02-09-2020 00:00      02-08-2020 00:00      1800.0      1
2  200320258      11-11-2020 00:00      11-04-2020 00:00      1700.0      3
3  200907217      05-10-2023 00:00      03-10-2020 00:00      2037.0      9
4  220614831  08/18/2022 12:00:00 AM  08/17/2020 12:00:00 AM      1200.0      6
```

```
      AREA NAME  Rpt Dist No  Part 1-2  Crm Cd  \
0  Wilshire      784.0      1  510.0
1  Central      182.0      1  330.0
2  Southwest     356.0      1  480.0
3  Van Nuys      964.0      1  343.0
4  Hollywood     666.0      2  354.0
```

```
      Crm Cd Desc  ... Status  Status Desc  \
0      VEHICLE - STOLEN  ...    AA  Adult Arrest
1  BURGLARY FROM VEHICLE  ...    IC  Invest Cont
2      BIKE - STOLEN  ...    IC  Invest Cont
3  SHOPLIFTING-GRAND THEFT ($950.01 & OVER)  ...    IC  Invest Cont
4      THEFT OF IDENTITY  ...    IC  Invest Cont
```

```
      Crm Cd 1  Crm Cd 2  Crm Cd 3  Crm Cd 4  \
0      510.0      998.0      NaN      NaN
1      330.0      998.0      NaN      NaN
2      480.0      NaN      NaN      NaN
3      343.0      NaN      NaN      NaN
4      354.0      NaN      NaN      NaN
```

```
      LOCATION Cross Street      LAT      LON
0  1900 S LONGWOOD      AV      NaN  34.0375 -118.3506
1  1000 S FLOWER      ST      NaN  34.0444 -118.2628
2  1400 W 37TH      ST      NaN  34.0210 -118.3002
3  14000 RIVERSIDE      DR      NaN  34.1576 -118.4387
4      1900 TRANSIENT      NaN  34.0944 -118.3277
```

[5 rows x 28 columns]

- Convert data types if needed (e.g., dates to date format, numerical values to appropriate numeric types).

```
[13]: import pandas as pd
from datetime import datetime
# Sample data creation for demonstration (replace this with your actual data_
↳ loading)
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")
# Convert the 'Date Rptd' column to datetime format, coercing invalid entries_
↳ to NaT
```

```

cp['Date Rptd'] = pd.to_datetime(cp['Date Rptd'], errors='coerce')
# Convert the 'DATE OCC' column to datetime format, coercing invalid entries to
↳ NaT
cp['DATE OCC'] = pd.to_datetime(cp['DATE OCC'], errors='coerce')
# Function to process and convert 'TIME OCC' into HH:MM format
def process_time(x):
    try:
        # Ensure the value is treated as a string, fill with leading zeros if
↳ necessary
        time_str = str(int(x)).zfill(4) # Convert to string and pad
        # Convert the string to time format
        return (datetime.strptime(time_str, "%H%M").time()).strftime("%H:%M")
    except (ValueError, TypeError):
        # Return a default value if conversion fails
        return '00:00'
# Apply the function to 'TIME OCC'
cp['TIME OCC'] = cp['TIME OCC'].apply(process_time)
# Display the updated columns to verify conversion
print("Converted Dates and Times:")
print(cp[['Date Rptd', 'DATE OCC', 'TIME OCC']].head())# Display the first 5
↳ rows
print(cp[['Date Rptd', 'DATE OCC', 'TIME OCC']].tail())# Display the last 5 rows

```

Converted Dates and Times:

	Date Rptd	DATE OCC	TIME OCC
0	2020-03-01	2020-03-01	21:30
1	2020-02-09	2020-02-08	18:00
2	2020-11-11	2020-11-04	17:00
3	2023-05-10	2020-03-10	20:37
4	NaT	NaT	12:00

	Date Rptd	DATE OCC	TIME OCC
978623	NaT	NaT	14:00
978624	NaT	NaT	01:00
978625	NaT	NaT	07:57
978626	NaT	NaT	15:00
978627	NaT	2024-08-12	23:00

- Deal with outliers if relevant to your analysis.

```

[9]: import numpy as np
from scipy.stats import zscore
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")

# Z-score outlier detection and replacement for 'Crm Cd'
z_scores_crm_cd = zscore(cp['Crm Cd'])

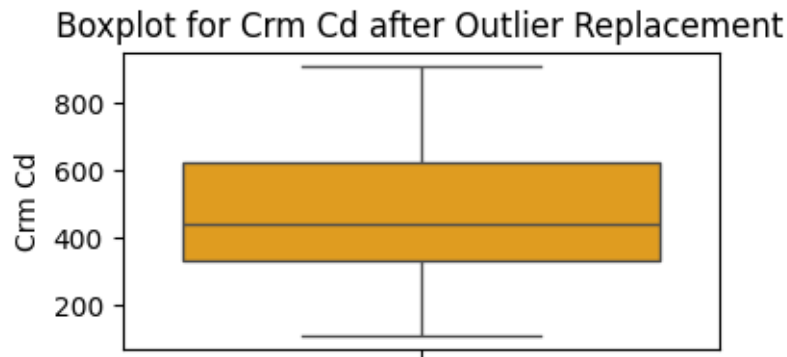
```

```

outliers_crm_cd = (np.abs(z_scores_crm_cd) > 2)
cp['Crm Cd'] = np.where(outliers_crm_cd, cp['Crm Cd'].median(), cp['Crm Cd'])

# Plot boxplot for 'Crm Cd'
plt.figure(figsize=(4, 2))
sns.boxplot(data=cp['Crm Cd'], color='orange')
plt.title('Boxplot for Crm Cd after Outlier Replacement')
plt.show()

```

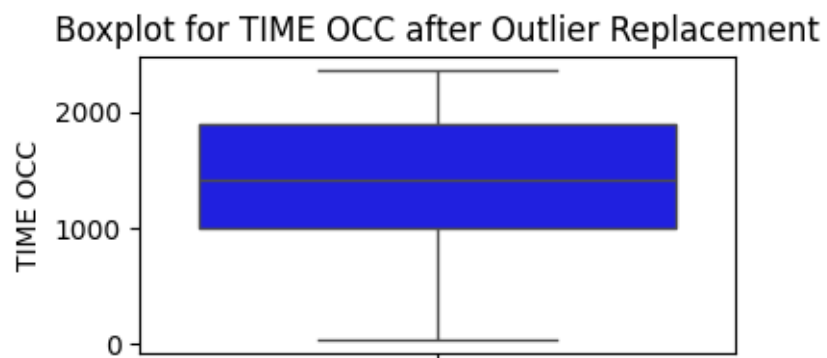


```

[10]: # Z-score outlier detection and replacement for 'TIME OCC'
z_scores_time_occ = zscore(cp['TIME OCC'])
outliers_time_occ = (np.abs(z_scores_time_occ) > 2)
cp['TIME OCC'] = np.where(outliers_time_occ, cp['TIME OCC'].median(), cp['TIME OCC'])

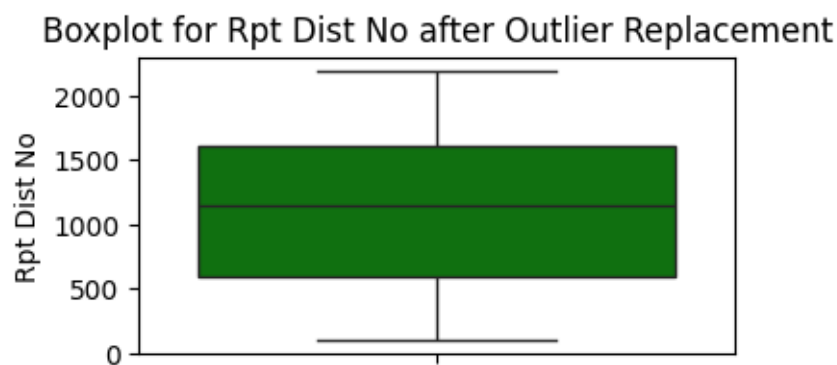
# Plot boxplot for 'TIME OCC'
plt.figure(figsize=(4, 2))
sns.boxplot(data=cp['TIME OCC'], color='blue')
plt.title('Boxplot for TIME OCC after Outlier Replacement')
plt.show()

```



```
[11]: # Z-score outlier detection and replacement for 'Rpt Dist No'
z_scores_rpt_dist_no = zscore(cp['Rpt Dist No'])
outliers_rpt_dist_no = (np.abs(z_scores_rpt_dist_no) > 2)
cp['Rpt Dist No'] = np.where(outliers_rpt_dist_no, cp['Rpt Dist No'].median(),
    ↪cp['Rpt Dist No'])

# Plot boxplot for 'Rpt Dist No'
plt.figure(figsize=(4, 2))
sns.boxplot(data=cp['Rpt Dist No'], color='green')
plt.title('Boxplot for Rpt Dist No after Outlier Replacement')
plt.show()
```



- Standardize or normalize numerical data as necessary.

```
[10]: import pandas as pd
from sklearn.preprocessing import StandardScaler

# Load the dataset
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")

# Select only the numerical columns for standardization
numerical_columns = cp.select_dtypes(include=['float64', 'int64']).columns

# Clean the dataset to remove NaN values before standardization
cp_cleaned = cp.dropna(subset=numerical_columns)

# Standardization: Scale the numerical data to have a mean of 0 and std of 1
scaler = StandardScaler()
cp_standardized = cp_cleaned.copy() # Make a copy to preserve the original data
cp_standardized[numerical_columns] = scaler.
    ↪fit_transform(cp_cleaned[numerical_columns])
```

```
print("Standardized Data:")
print(cp_standardized[numerical_columns].head())
```

Standardized Data:

	DR_NO	TIME OCC	AREA	Rpt Dist No	Part 1-2	Crm Cd	\
2198	-1.282787	-1.623306	-0.983972	-0.954631	-0.388514	0.836245	
4127	-1.166433	1.274569	1.356730	1.277183	-0.388514	1.040095	
36672	-1.283900	1.303119	-0.983972	-0.937938	-0.388514	0.836245	
37652	-1.284359	-2.037288	-0.983972	-0.996363	-0.388514	0.836245	
39344	-1.283625	-1.723233	-0.983972	-0.969654	-0.388514	0.836245	

	Vict Age	Premis Cd	Weapon Used Cd	Crm Cd 1	Crm Cd 2	Crm Cd 3	\
2198	0.924495	0.536197	-1.238294	1.223923	0.462166	0.646686	
4127	-0.409332	-0.326574	0.869554	-0.883803	0.714340	0.403706	
36672	-0.462685	0.536197	-1.238294	1.223923	0.462166	0.646686	
37652	-0.409332	0.536197	1.654691	0.730956	0.462166	0.646686	
39344	0.070846	0.531905	-0.538036	0.730956	0.462166	0.646686	

	Crm Cd 4	LAT	LON
2198	0.233138	-0.370817	0.662651
4127	0.233138	-0.510100	0.786173
36672	0.233138	-0.494117	0.772449
37652	0.233138	-0.325150	0.173553
39344	0.233138	-0.360542	0.793659

```
[11]: import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler

# Load the dataset
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")

# Step to identify numerical columns for normalization
numerical_columns = cp.select_dtypes(include=[np.number]).columns.tolist()

# Clean the dataset to remove NaN values before normalization
cp_cleaned = cp.dropna(subset=numerical_columns)

# Normalization: Scale the numerical data to [0, 1]
normalizer = MinMaxScaler()
cp_normalized = cp_cleaned.copy() # Make a copy to preserve the original data
cp_normalized[numerical_columns] = normalizer.
    ↪fit_transform(cp_cleaned[numerical_columns])

print("Normalized Data:")
print(cp_normalized[numerical_columns].head())
```

Normalized Data:

	DR_NO	TIME OCC	AREA	Rpt Dist No	Part 1-2	Crm Cd	Vict Age	\
2198	0.000455	0.127288	0.210526	0.208691	0.0	0.81375	0.645570	
4127	0.034124	0.991486	0.947368	0.925966	0.0	0.88750	0.329114	
36672	0.000133	1.000000	0.210526	0.214056	0.0	0.81375	0.316456	
37652	0.000000	0.003831	0.210526	0.195279	0.0	0.81375	0.329114	
39344	0.000212	0.097488	0.210526	0.203863	0.0	0.81375	0.443038	

	Premis Cd	Weapon Used Cd	Crm Cd 1	Crm Cd 2	Crm Cd 3	Crm Cd 4	\
2198	0.496287	0.000000	0.915954	0.748641	0.817204	0.994382	
4127	0.247525	0.726829	0.142450	0.828804	0.763441	0.994382	
36672	0.496287	0.000000	0.915954	0.748641	0.817204	0.994382	
37652	0.496287	0.997561	0.735043	0.748641	0.817204	0.994382	
39344	0.495050	0.241463	0.735043	0.748641	0.817204	0.994382	

	LAT	LON
2198	0.405982	0.743699
4127	0.372196	0.767237
36672	0.376073	0.764622
37652	0.417059	0.650499
39344	0.408474	0.768664

- Encode categorical data if present

```
[12]: #Import labelencoder from sklearn's preprocessing module
from sklearn.preprocessing import LabelEncoder
#Create an instance of labelEncoder
label_encoder = LabelEncoder()
#Transform the 'AREA NAME' column into numerical format
#Each unique category in 'AREA NAME' will be assigned a unique integer
cp['AREA NAME'] = label_encoder.fit_transform(cp['AREA NAME'])
#Display the first 10 rows of the dataframe to see the change in 'AREA NAME'
↳column
cp.head(10)
```

```
[12]:
```

	DR_NO	Date Rptd	DATE OCC	TIME OCC	AREA	\
0	190326475	03-01-2020 00:00	03-01-2020 00:00	2130	7	
1	200106753	02-09-2020 00:00	02-08-2020 00:00	1800	1	
2	200320258	11-11-2020 00:00	11-04-2020 00:00	1700	3	
3	200907217	05-10-2023 00:00	03-10-2020 00:00	2037	9	
4	220614831	08/18/2022 12:00:00 AM	08/17/2020 12:00:00 AM	1200	6	
5	231808869	04-04-2023 00:00	12-01-2020 00:00	2300	18	
6	230110144	04-04-2023 00:00	07-03-2020 00:00	900	1	
7	220314085	07/22/2022 12:00:00 AM	05-12-2020 00:00	1110	3	
8	231309864	04/28/2023 12:00:00 AM	12-09-2020 00:00	1400	13	
9	211904005	12/31/2020 12:00:00 AM	12/31/2020 12:00:00 AM	1220	19	

	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	\
0	20	784	1	510	

1	1	182	1	330
2	15	356	1	480
3	17	964	1	343
4	6	666	2	354
5	14	1826	2	354
6	1	182	2	354
7	15	303	2	354
8	9	1375	2	354
9	7	1974	2	624

	Crm Cd Desc	...	Status	Status Desc	\
0	VEHICLE - STOLEN	...	AA	Adult Arrest	
1	BURGLARY FROM VEHICLE	...	IC	Invest Cont	
2	BIKE - STOLEN	...	IC	Invest Cont	
3	SHOPLIFTING-GRAND THEFT (\$950.01 & OVER)	...	IC	Invest Cont	
4	THEFT OF IDENTITY	...	IC	Invest Cont	
5	THEFT OF IDENTITY	...	IC	Invest Cont	
6	THEFT OF IDENTITY	...	IC	Invest Cont	
7	THEFT OF IDENTITY	...	IC	Invest Cont	
8	THEFT OF IDENTITY	...	IC	Invest Cont	
9	BATTERY - SIMPLE ASSAULT	...	IC	Invest Cont	

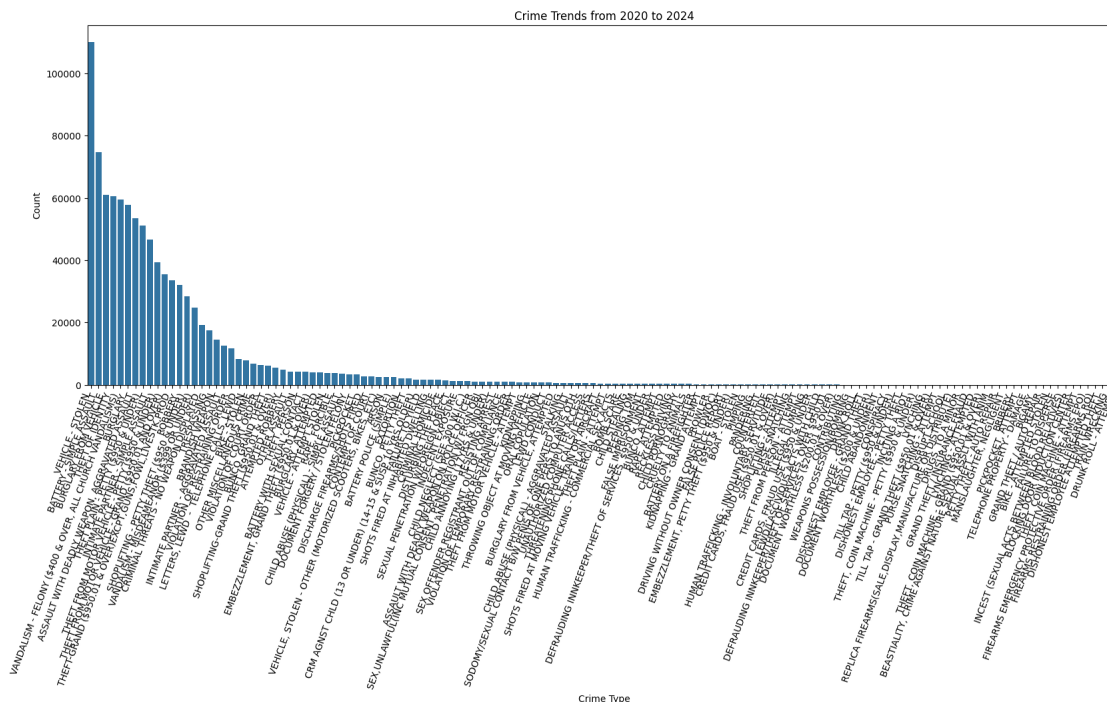
	Crm Cd 1	Crm Cd 2	Crm Cd 3	Crm Cd 4	\
0	510.0	998.0	NaN	NaN	
1	330.0	998.0	NaN	NaN	
2	480.0	NaN	NaN	NaN	
3	343.0	NaN	NaN	NaN	
4	354.0	NaN	NaN	NaN	
5	354.0	NaN	NaN	NaN	
6	354.0	NaN	NaN	NaN	
7	354.0	NaN	NaN	NaN	
8	354.0	NaN	NaN	NaN	
9	624.0	NaN	NaN	NaN	

	LOCATION	Cross Street	LAT	LON
0	1900 S LONGWOOD	AV	NaN	34.0375 -118.3506
1	1000 S FLOWER	ST	NaN	34.0444 -118.2628
2	1400 W 37TH	ST	NaN	34.0210 -118.3002
3	14000 RIVERSIDE	DR	NaN	34.1576 -118.4387
4		1900 TRANSIENT	NaN	34.0944 -118.3277
5	9900 COMPTON	AV	NaN	33.9467 -118.2463
6	1100 S GRAND	AV	NaN	34.0415 -118.2620
7	2500 S SYCAMORE	AV	NaN	34.0335 -118.3537
8	1300 E 57TH	ST	NaN	33.9911 -118.2521
9	9000 CEDROS	AV	NaN	34.2336 -118.4535

[10 rows x 28 columns]

4. Exploratory Data Analysis (EDA): - Visualize overall crime trends from 2020 to present year.

```
[13]: #Import seaborn and matplotlib for data visualization
import seaborn as sns
import matplotlib.pyplot as plt
#Set the figure size for plot
plt.figure(figsize=(20,7))
#Create a count plot for the 'Crm Cd Desc' column, ordering the bars by count
sns.countplot(data=cp, x='Crm Cd Desc', order=cp['Crm Cd Desc'].value_counts().
    ↪index)
plt.title('Crime Trends from 2020 to 2024') #Set the title for the plot
plt.xlabel('Crime Type') #Set the x-label for the plot
plt.ylabel('Count') #Set the y-label for the plot
plt.xticks(rotation=70, ha='right') #Rotate the x-axis labels for readability
plt.show() #Display the plot
```



- Analyze and visualize seasonal patterns in crime data

```
[26]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
cp = pd.read_csv(r"c:\ms\IE6400\Crimedata_till_sep29.csv")
# Convert the 'DATE OCC' column to datetime format, coercing invalid entries to NaT
```



```

cp['DATE OCC'] = pd.to_datetime(cp['DATE OCC'], errors='coerce')

# Extract the month and year from 'DATE OCC' and create new columns
cp['Month'] = cp['DATE OCC'].dt.month
cp['Year'] = cp['DATE OCC'].dt.year

# Drop rows where 'DATE OCC' is NaT
cp = cp.dropna(subset=['DATE OCC'])

# Group the dataframe by 'Month' and count the number of crimes per month
crimes_per_month = cp.groupby('Month').size()

# Print the year(s) of data being plotted
unique_years = cp['Year'].unique()
print(f"The data contains crimes from the following year(s): {unique_years}")

# Plot the number of crimes per month
plt.figure(figsize=(10, 6))
sns.lineplot(x=crimes_per_month.index, y=crimes_per_month.values, marker='o')

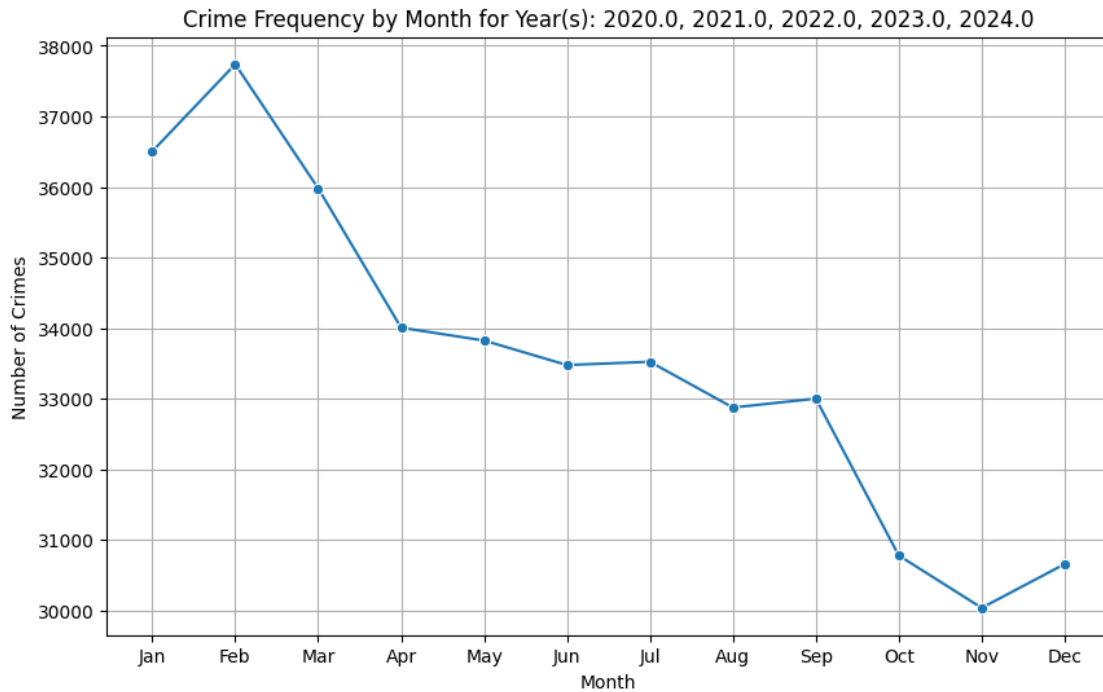
# Set the title and labels for the plot
plt.title(f'Crime Frequency by Month for Year(s): {"", ".join(map(str, unique_years))}')
plt.xlabel('Month')
plt.ylabel('Number of Crimes')

# Set the X-ticks to display month names
plt.xticks(ticks=range(1, 13), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])

plt.grid(True) # Enable grid lines for better readability
plt.show() # Display the plot

```

The data contains crimes from the following year(s): [2020. 2021. 2022. 2023. 2024.]

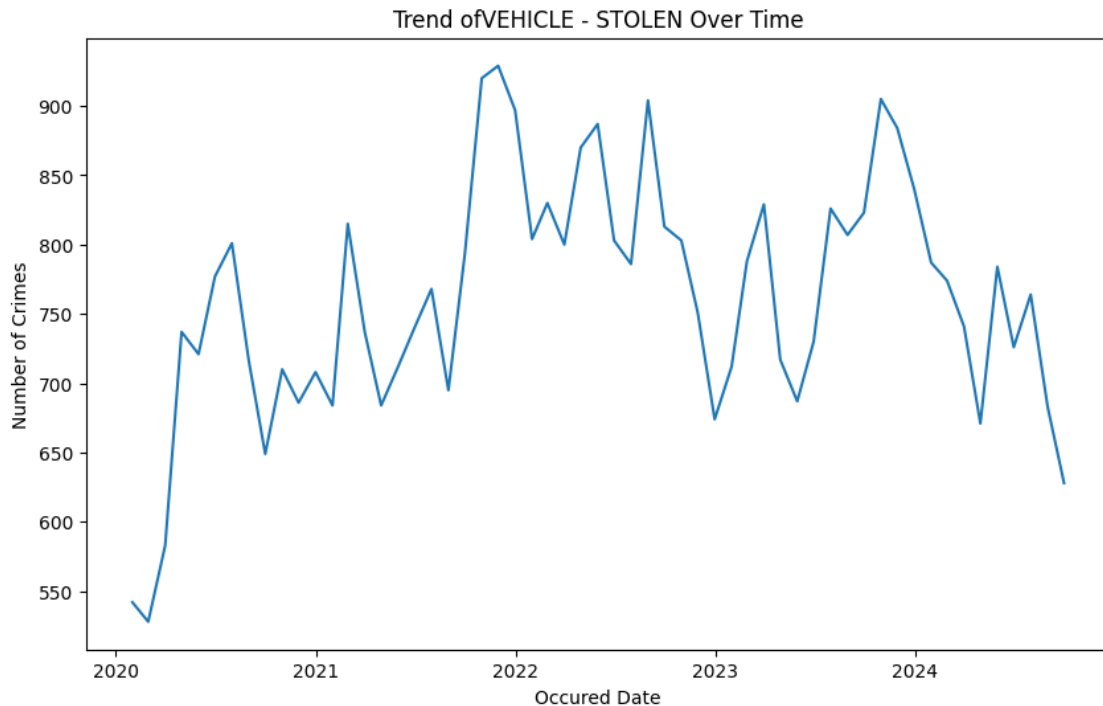


- Identify the most common type of crime and its trends over time.

```
[15]: import warnings # Import the warnings module to handle warning messages
# Suppress FutureWarning messages
warnings.simplefilter(action='ignore', category=FutureWarning)
# Identify the most common crime type from 'Crm Cd Desc' column
common_crime = cp['Crm Cd Desc'].value_counts().idxmax() # Display the most
    ↳ common crime
print(f"The most common crime is:{common_crime}")
# Filter the Dataframe to get data related to the most common crime
common_crime_data = cp[cp['Crm Cd Desc'] == common_crime]
# Convert the 'DATE OCC' column to datetime format, coercing invalid entries to
    ↳ NaT
common_crime_data.loc[:, 'DATE OCC'] = pd.to_datetime(common_crime_data['DATE_
    ↳ OCC'], errors='coerce')
# Resample the data to get the count of crimes per month, ME stands month-end
    ↳ frequency
crime_trends = common_crime_data.resample('ME', on='DATE OCC').size()
plt.figure(figsize=(10,6)) # set the figure size for plot
# Create a line plot for the trend of the most common crime over time
sns.lineplot(x=crime_trends.index, y=crime_trends.values)
#set the title and lables for the plot
plt.title(f"Trend of{ common_crime} Over Time")
plt.xlabel('Occured Date')
```

```
plt.ylabel('Number of Crimes')
plt.show() # Display the plot
```

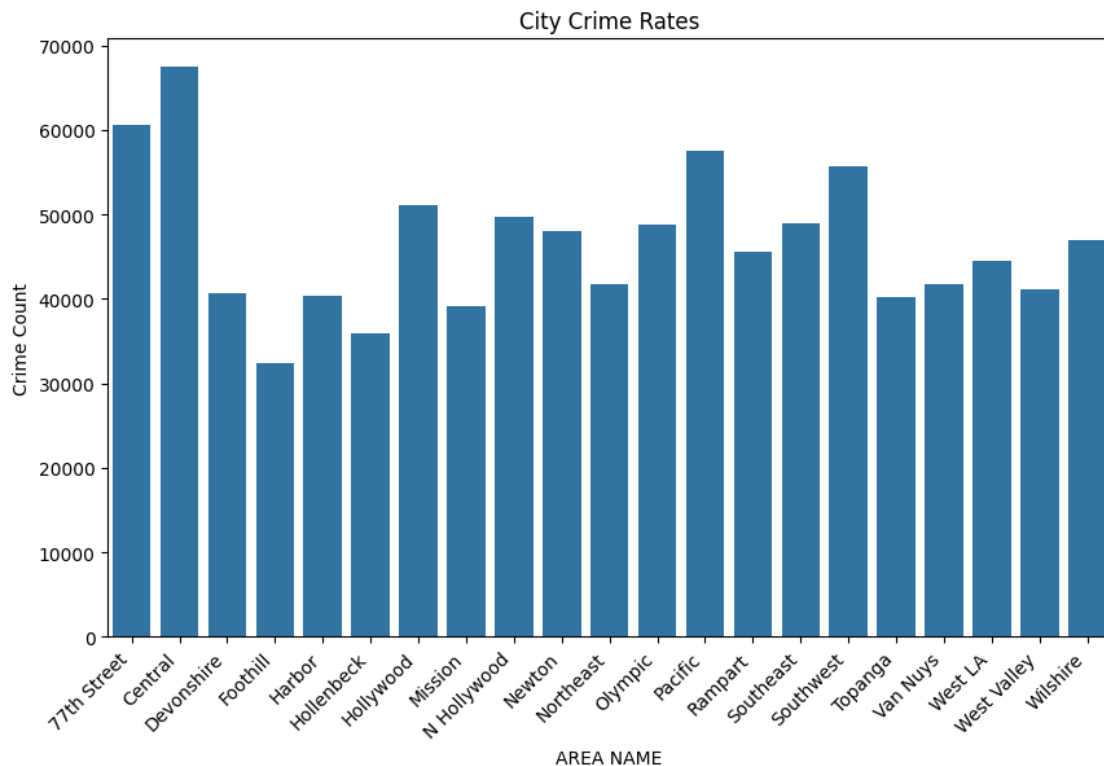
The most common crime is:VEHICLE - STOLEN



- Investigate if there are any notable differences in crime rates between regions or cities.

```
[4]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")
# Group the data by 'AREA NAME' and count the occurrences of 'Crm Cd Desc' (Crime_
↳types)
crime_by_streetname = cp.groupby('AREA NAME')['Crm Cd Desc'].count().
↳reset_index()
crime_by_streetname.columns = ['AREA NAME', 'Crime Count'] # Rename the columns_
↳for better understanding
plt.figure(figsize=(10,6)) # Set the figure size for the plot
# Create a bar plot for crime counts by area name
sns.barplot(x='AREA NAME', y='Crime Count', data=crime_by_streetname)
# Set the title and labels for the plot
plt.title('City Crime Rates')
plt.xlabel('AREA NAME')
plt.ylabel('Crime Count')
```

```
plt.xticks(rotation=45, ha='right') # rotate the x-axis for 45 degrees
plt.show() # display the plot
```



- Explore correlations between economic factors(if available) and crime rates.

```
[17]: import pandas as pd
# Read the crime data from specified csv file into a dataframe
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")
# Read the unemployment data from the specified csv file into a dataframe
uer = pd.read_csv(r"c:\ms\IE6400\unemployment_data.csv")
# Convert the 'DATE OCC' column in the crime dataframe to datetime format,
# coercing invalid entries to NaT
cp['DATE OCC'] = pd.to_datetime(cp['DATE OCC'], errors='coerce')
# Convert the 'DATE' column in the unemployment rate dataframe to datetime
# format, coercing invalid entries to NaT
uer['DATE'] = pd.to_datetime(uer['DATE'], errors='coerce')
# Create a new column 'month' in the crime dataframe representing the month of
# each crime occurrence
cp['month'] = cp['DATE OCC'].dt.to_period('M')
# Create a new column 'month' in the unemployment rate dataframe representing
# the month of each unemployment record
uer['month'] = uer['DATE'].dt.to_period('M')
```

```

# Merge the two dataframes on the 'month' column using inner join
merged_df = pd.merge(cp, uer, on='month', how='inner')
# save the merged dataframe to a new csv file named '
↳ crime_and_unemployment_rate.csv '
merged_df.to_csv('crime_and_unemploymentrate.csv', index=False)
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
# read the merged csv file containing crime and unemployment rate data into a
↳ dataframe
cer = pd.read_csv(r"C:\ms\jupyter\crime_and_unemploymentrate.csv")
cer.head() # Display first few rows of the dataframe

```

```

[17]:
      DR_NO      Date Rptd      DATE OCC      TIME OCC      AREA      AREA NAME \
0  190326475  03-01-2020 00:00  2020-03-01      2130      7      Wilshire
1  200106753  02-09-2020 00:00  2020-02-08      1800      1      Central
2  200320258  11-11-2020 00:00  2020-11-04      1700      3      Southwest
3  200907217  05-10-2023 00:00  2020-03-10      2037      9      Van Nuys
4  231808869  04-04-2023 00:00  2020-12-01      2300     18      Southeast

      Rpt Dist No      Part 1-2      Crm Cd      Crm Cd Desc \
0           784           1      510      VEHICLE - STOLEN
1           182           1      330      BURGLARY FROM VEHICLE
2           356           1      480      BIKE - STOLEN
3           964           1      343  SHOPLIFTING-GRAND THEFT ($950.01 & OVER)
4          1826           2      354      THEFT OF IDENTITY

      ... Crm Cd 2      Crm Cd 3      Crm Cd 4      LOCATION \
0  ...      998.0      NaN      NaN      1900 S      LONGWOOD      AV
1  ...      998.0      NaN      NaN      1000 S      FLOWER      ST
2  ...      NaN      NaN      NaN      1400 W      37TH      ST
3  ...      NaN      NaN      NaN      14000      RIVERSIDE      DR
4  ...      NaN      NaN      NaN      9900      COMPTON      AV

      Cross Street      LAT      LON      month      DATE UNRATE
0           NaN      34.0375 -118.3506  2020-03  2020-03-01      4.4
1           NaN      34.0444 -118.2628  2020-02  2020-02-01      3.5
2           NaN      34.0210 -118.3002  2020-11  2020-11-01      6.7
3           NaN      34.1576 -118.4387  2020-03  2020-03-01      4.4
4           NaN      33.9467 -118.2463  2020-12  2020-12-01      6.7

```

[5 rows x 31 columns]

```

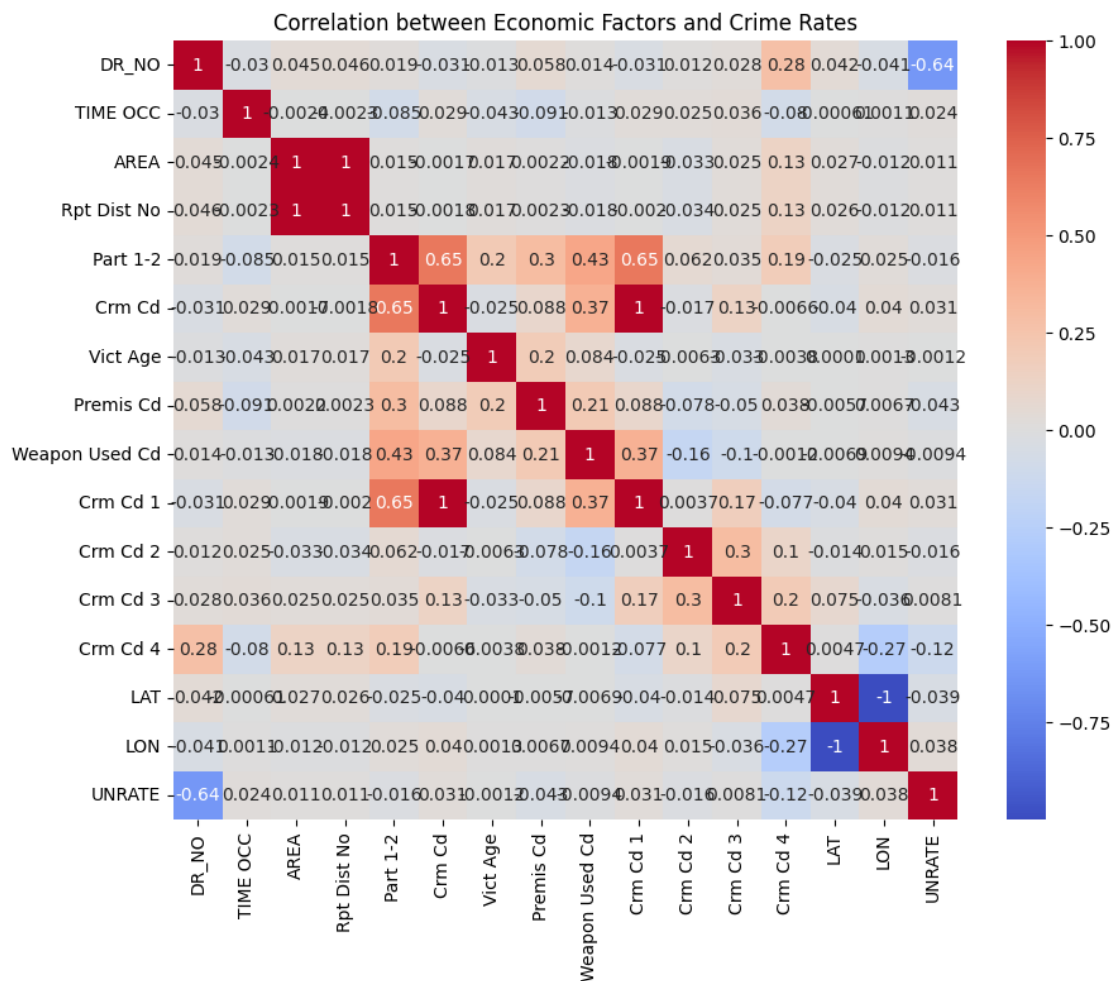
[18]: # Read the merged csv file containing crime and unemployment rate data
cer = pd.read_csv(r"C:\ms\jupyter\crime_and_unemploymentrate.csv")
# Identify the non numeric columns in dataframe
non_numeric_columns = cer.select_dtypes(exclude=['float64', 'int64']).columns

```

```

# Convert the 'DATE OCC' column to datetime format, coercing invalid entries to NaT
cer['DATE OCC'] = pd.to_datetime(cer['DATE OCC'], errors='coerce')
# Convert the 'DATE' column to datetime format, coercing invalid entries to NaT
cer['DATE'] = pd.to_datetime(cer['DATE'], errors='coerce')
# Identify numeric columns in the dataframe
numeric_columns = cer.select_dtypes(include=['float64', 'int64']).columns
# Calculate the correlation matrix for the numeric columns
correlation_matrix = cer[numeric_columns].corr()
plt.figure(figsize=(10, 8)) # set the figure size for the plot
# Create the heatmap to visualize the correlation matrix with annotations
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation between Economic Factors and Crime Rates') # set the
# title for heatmap
plt.show() # display the heatmap

```



- Analyze the relationship between the day of the week and the frequency of certain types of

crimes.

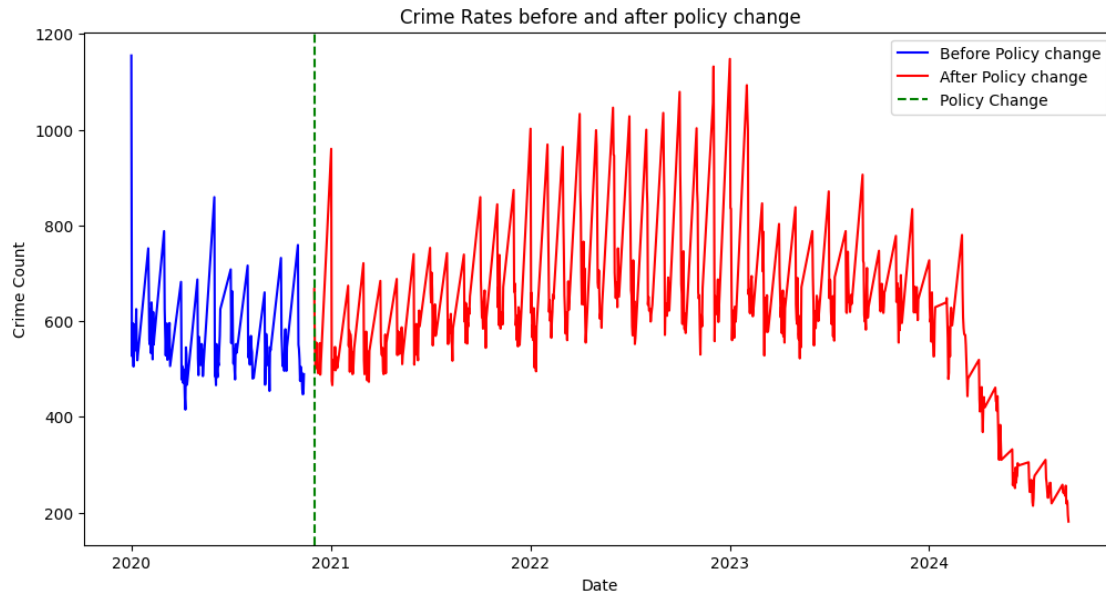
```
[19]: # Convert the 'DATE OCC' column to datetime format, coercing invalid entries to
      ↪ NaT
cp['DATE OCC'] = pd.to_datetime(cp['DATE OCC'], errors='coerce')
# Extract the day of week from 'DATE OCC' column and create a new column
      ↪ 'Day_of_Week'
cp['Day_of_Week'] = cp['DATE OCC'].dt.day_name()
# Group the data by 'Day_of_week' and 'Crm Cd Desc', to get crime count
crime_by_day = cp.groupby(['Day_of_Week', 'Crm Cd Desc']).size().
      ↪ reset_index(name='Crime Count')
plt.figure(figsize=(10,6)) # Set the size of figure for the plot
# specify the order of the days of the week for the x-axis
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
      ↪ 'Saturday', 'Sunday']
# Create a bar plot showing crime counts by day of the week, with hue for
      ↪ different crime types
sns.barplot(x='Day_of_Week', y='Crime Count', hue='Crm Cd Desc',
      ↪ data=crime_by_day, order=day_order)
# set the title and labels for the plot
plt.title('Crime Frequency by Day of the week and Crime Type')
plt.xlabel('Day of the Week')
plt.ylabel('Crime Count')
plt.xticks(rotation=45, ha='right') # rotate x-axis for 45 degrees
# Add a legend with a title for crime types, positioned outside the plot
plt.legend(title='Crime Type', bbox_to_anchor=(1,1), loc='upper left')
plt.show() # display the plot
```



- Investigate any impact of significant events or policy changes on crime rates.

```
[20]: # Convert the 'DATE OCC' column to datetime format, coercing invalid entries to
      ↪ NaT
cp['DATE OCC'] = pd.to_datetime(cp['DATE OCC'], errors='coerce')
# Group the data by date and count the occurrences to get crime counts
crime_by_date = cp.groupby(cp['DATE OCC'].dt.date).size().
      ↪ reset_index(name='Crime Count')
# Convert the "DATE OCC" column back to datetime for plotting
crime_by_date['DATE OCC'] = pd.to_datetime(crime_by_date['DATE OCC'],
      ↪ errors='coerce')
# define the date for policy change
# let's assume the policy had changed from 1st December 2020
event_date = pd.to_datetime('2020-12-01').date()
print(f"The crime rate policy has been changed from 01 December 2020")
# Filter the data to separate crime counts before and after the policy change
before_event = crime_by_date[crime_by_date['DATE OCC'].dt.date < event_date]
after_event = crime_by_date[crime_by_date['DATE OCC'].dt.date >= event_date]
plt.figure(figsize=(12,6)) # set the figure size for the plot
# plot the crime counts before the policy change
plt.plot(before_event['DATE OCC'], before_event['Crime Count'], label='Before',
      ↪ 'Policy change', color='blue')
# plot the crime counts after the policy change
plt.plot(after_event['DATE OCC'], after_event['Crime Count'], label='After',
      ↪ 'Policy change', color='red')
# add a vertical line to indicate the date of policy change
plt.axvline(event_date, color='green', linestyle='--', label='Policy Change')
# set the title and labels
plt.title('Crime Rates before and after policy change')
plt.xlabel('Date')
plt.ylabel('Crime Count')
plt.legend() # Add a legend to plot
plt.show() # display the plot
```

The crime rate policy has been changed from 01 December 2020



5. Advanced Analysis: - Use predictive modelling techniques (e.g., time series forecasting) to predict future crime trends.

```
[21]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# Load the dataset
cp = pd.read_csv(r"c:\ms\IE6400\Crimedate_till_sep29.csv")
cp['DATE OCC'] = pd.to_datetime(cp['DATE OCC'], errors='coerce')

# Group the data by date to get daily crime counts
crime_by_date = cp.groupby(cp['DATE OCC'].dt.date).size().
    ↪reset_index(name='Crime Count')

# Feature Engineering: Day of the week, month, year
crime_by_date['Day of Week'] = pd.to_datetime(crime_by_date['DATE OCC']).dt.
    ↪dayofweek
crime_by_date['Month'] = pd.to_datetime(crime_by_date['DATE OCC']).dt.month
crime_by_date['Year'] = pd.to_datetime(crime_by_date['DATE OCC']).dt.year

# Create lag features (lag 1 day, lag 7 days, etc.)
crime_by_date['Lag 1'] = crime_by_date['Crime Count'].shift(1)
crime_by_date['Lag 7'] = crime_by_date['Crime Count'].shift(7)
```

```

crime_by_date['Lag 30'] = crime_by_date['Crime Count'].shift(30)

# Drop rows with NaN values caused by lagging
crime_by_date.dropna(inplace=True)

# Create X and y datasets (X = features, y = target)
X = crime_by_date[['Day of Week', 'Month', 'Year', 'Lag 1', 'Lag 7', 'Lag 30']]
y = crime_by_date['Crime Count']
# Split the data into training and test sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪shuffle=False)
# Initialize Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model
rf_model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model using RMSE and R-squared
rmse = mean_squared_error(y_test, y_pred, squared=False)
r_squared = rf_model.score(X_test, y_test)

print(f'RMSE: {rmse}')
from sklearn.metrics import mean_absolute_error

# Calculate MAE
mae = mean_absolute_error(y_test, y_pred)

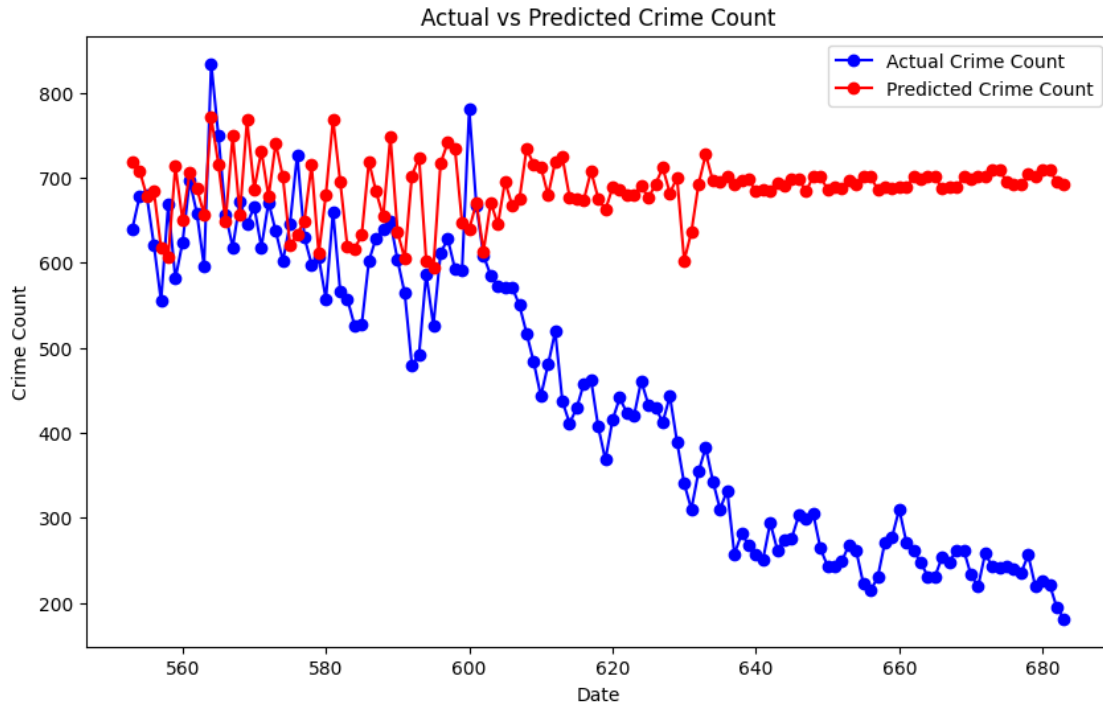
print(f'MAE: {mae}')

# Plot the actual vs predicted crime counts
plt.figure(figsize=(10, 6))
plt.plot(y_test.index, y_test.values, label='Actual Crime Count', color='blue',
    ↪marker='o')
plt.plot(y_test.index, y_pred, label='Predicted Crime Count', color='red',
    ↪marker='o')
plt.title('Actual vs Predicted Crime Count')
plt.xlabel('Date')
plt.ylabel('Crime Count')
plt.legend()
plt.show()

```

RMSE: 302.29649104937255

MAE: 250.9690076335878



```
[22]: # Import ARIMA model for time series forecasting
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error, r2_score # Import r2_score for
↳ R-squared

# Convert the 'DATE OCC' column to datetime format, coercing invalid entries to
↳ NaT
cp['DATE OCC'] = pd.to_datetime(cp['DATE OCC'], errors='coerce')

# Group the data by the date and count the occurrences to get daily crime counts
crime_by_date = cp.groupby(cp['DATE OCC'].dt.date).size().
↳ reset_index(name='Crime Count')

# Plot the daily crime counts
plt.plot(crime_by_date['DATE OCC'], crime_by_date['Crime Count'], marker='o')
plt.title('Crime Count over Time')
plt.xlabel('Date')
plt.ylabel('Crime Count')
plt.show()

# Split the data into training and testing sets (80% training, 20% testing)
train_size = int(len(crime_by_date) * 0.8)
train, test = crime_by_date[:train_size], crime_by_date[train_size:]
```

```

# Fit an ARIMA model to the training data
model = ARIMA(train['Crime Count'], order=(5, 1, 0)) # Order is (p, d, q)
model_fit = model.fit() # Fit the model to training data

# Forecast the test data period
predictions = model_fit.forecast(steps=len(test))

# Calculate the root mean squared error (RMSE) of the predictions
rmse = mean_squared_error(test['Crime Count'], predictions, squared=False)
print(f'RMSE: {rmse}')

# Forecast future values for the next 30 days
future_predictions = model_fit.forecast(steps=30)

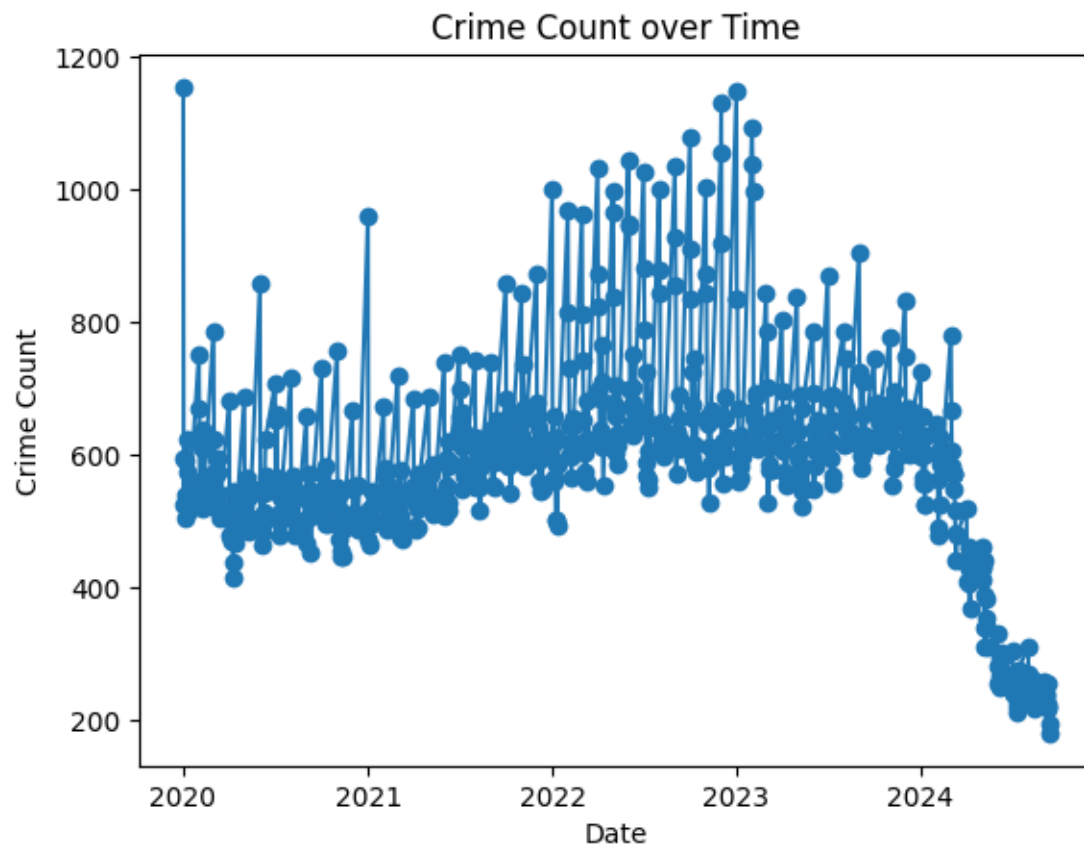
# Plot actual vs predicted values for the test set
plt.plot(test['DATE OCC'].values, test['Crime Count'], label='Actual',
         ↪marker='o')
plt.plot(test['DATE OCC'].values, predictions, label='Predicted', marker='o')

# Generate future dates for the forecasted values
future_dates = pd.date_range(start=test['DATE OCC'].values[-1] + pd.
         ↪Timedelta(days=1), periods=30)

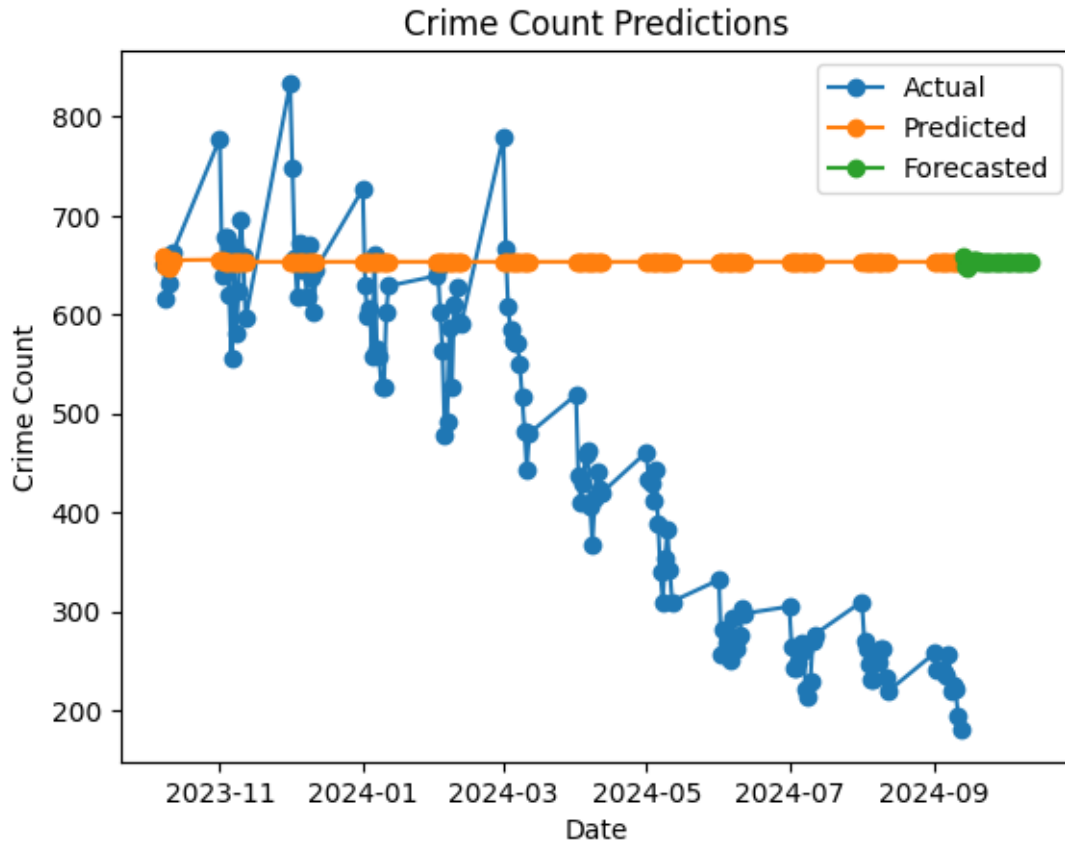
# Plot future predictions
plt.plot(future_dates, future_predictions, label='Forecasted', marker='o')

plt.legend() # Adding a legend
plt.title('Crime Count Predictions')
plt.xlabel('Date')
plt.ylabel('Crime Count')
plt.show() # Display the plot

```



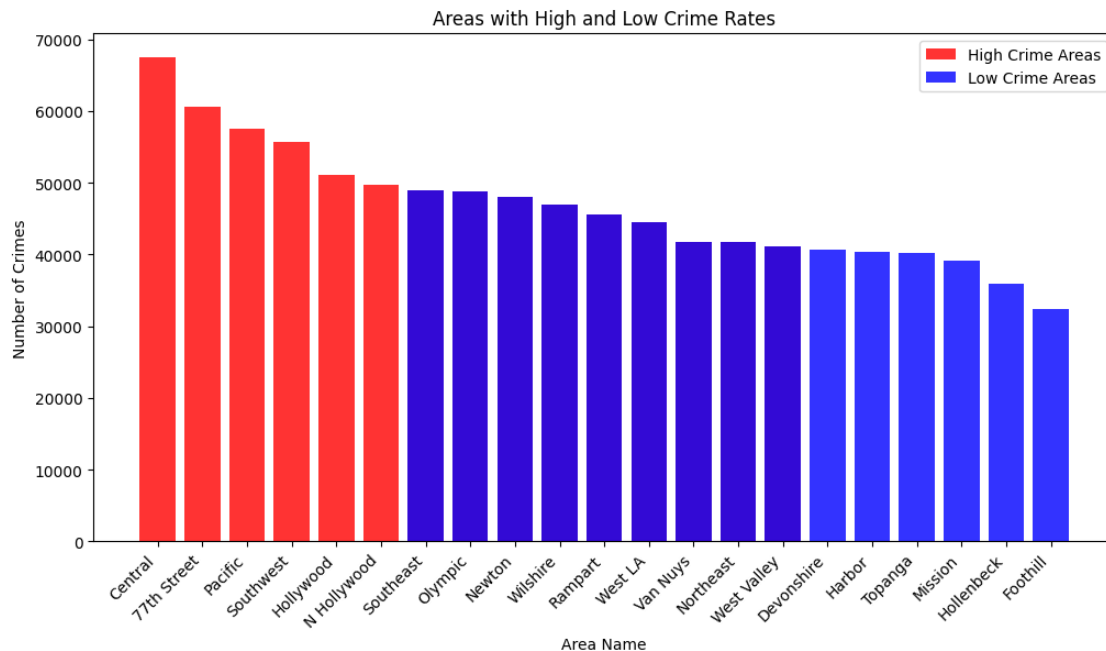
RMSE: 265.2728192163623



- Explore additional questions or hypothesis related to the dataset.
- Identify and compare areas with high and low crime rates based on the available dataset?

```
[23]: # count the crimes in each area
crime_by_area = cp['AREA NAME'].value_counts()
# sort the areas by number of crimes in descending order
crime_by_area = crime_by_area.sort_values(ascending=False)
top_15_areas = crime_by_area.head(15) # get top 15 areas with highest crime
# counts
bottom_15_areas = crime_by_area.tail(15) # get bottom 15 areas with lowest
# crime counts
plt.figure(figsize=(12,6)) # set the figure size for plot
# plot the top 15 areas with high crime rates
plt.bar(top_15_areas.index, top_15_areas.values, color='red', alpha=0.8,
# label='High Crime Areas')
# plot the bottom 15 areas with low crime rates
plt.bar(bottom_15_areas.index, bottom_15_areas.values, color='blue', alpha=0.8,
# label='Low Crime Areas')
# set the title and labels for the plot
```

```
plt.title('Areas with High and Low Crime Rates')
plt.xlabel('Area Name')
plt.ylabel('Number of Crimes')
plt.xticks(rotation=45, ha='right') # rotate the x-axis to 45 degrees for
↳ better readability
plt.legend() # add legend to differentiate between high and low crime areas
plt.show() # display the plot
```



Visualize geographic crime data using latitude and longitude coordinates.

```
[27]: import geopandas as gpd # import geopandas for geospatial data handling
import folium # import folium for creating interactive maps
from folium.plugins import FastMarkerCluster # import fastmarkercluster for
↳ clustering markers on the map
import pandas as pd # import pandas for data manipulation
# convert latitude and longitude columns to numeric type for proper formatting
cp['LAT'] = pd.to_numeric(cp['LAT'])
cp['LON'] = pd.to_numeric(cp['LON'])
# create a geodataframe using the latitude and longitude for geometry
gdf = gpd.GeoDataFrame(cp, geometry=gpd.points_from_xy(cp.LON, cp.LAT))
# create a base map centered on los angeles with a specified zoom level and
↳ tile style
m = folium.Map(location=[42.3601, -71.0589], zoom_start=10,
↳ tiles='openstreetmap')
# add clustered markers for crime locations on the map
```



```
FastMarkerCluster(data=list(zip(gdf['LAT'], gdf['LON']))).add_to(m)
#save map to html file for viewing in a web browser
m.save('crime_hotspots_map_boston.html')
m # display the map in a jupyter notebook
```

[27]: <folium.folium.Map at 0x187600b1820>

[]: