In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import math
from scipy.stats import chi2_contingency
```

In [ ]:
```
# Replace 'your_dataset.csv' with the actual filename
file_path = '/content/Crime_Data_from_2020_to_Present_20241018.csv'

try:
  crime_data = pd.read_csv(file_path)
  print("Dataset loaded successfully.")
  # You can now work with the DataFrame 'df'
except FileNotFoundError:
  print(f"Error: File '{file_path}' not found.")
except pd.errors.ParserError:
  print(f"Error: Could not parse the file '{file_path}'. Check the file format."
except Exception as e:
  print(f"An unexpected error occurred: {e}")
```

```
Dataset loaded successfully.
```

In [ ]:
```
crime_data.head()
```

Out[ ]:

	DR_NO	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Desc
0	190326475	03/01/2020 12:00:00 AM	03/01/2020 12:00:00 AM	2130	7	Wilshire	784	1	510	VEHICLE - STOLEN
1	200106753	02/09/2020 12:00:00 AM	02/08/2020 12:00:00 AM	1800	1	Central	182	1	330	BURGLARY FROM VEHICLE
2	200320258	11/11/2020 12:00:00 AM	11/04/2020 12:00:00 AM	1700	3	Southwest	356	1	480	BIKE - STOLEN
3	200907217	05/10/2023 12:00:00 AM	03/10/2020 12:00:00 AM	2037	9	Van Nuys	964	1	343	SHOPLIFTING-GRAND THEFT ($950.01 & OVER)
4	220614831	08/18/2022 12:00:00 AM	08/17/2020 12:00:00 AM	1200	6	Hollywood	666	2	354	THEFT OF IDENTITY

5 rows × 28 columns

In [ ]:
```
crime_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 986500 entries, 0 to 986499
Data columns (total 28 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   DR_NO           986500 non-null  int64  
 1   Date Rptd       986500 non-null  object 
 2   DATE OCC        986500 non-null  object 
 3   TIME OCC        986500 non-null  int64  
 4   AREA            986500 non-null  int64  
 5   AREA NAME       986500 non-null  object 
 6   Rpt Dist No     986500 non-null  int64  
 7   Part 1-2        986500 non-null  int64  
 8   Crm Cd          986500 non-null  int64  
 9   Crm Cd Desc     986500 non-null  object 
 10  Mocodes         840065 non-null  object 
 11  Vict Age        986500 non-null  int64  
 12  Vict Sex        846925 non-null  object 
 13  Vict Descent    846914 non-null  object 
 14  Premis Cd       986486 non-null  float64
 15  Premis Desc     985915 non-null  object 
 16  Weapon Used Cd  326368 non-null  float64
 17  Weapon Desc     326368 non-null  object 
 18  Status          986499 non-null  object 
 19  Status Desc     986500 non-null  object 
 20  Crm Cd 1        986489 non-null  float64
 21  Crm Cd 2        68912 non-null   float64
 22  Crm Cd 3        2310 non-null    float64
 23  Crm Cd 4        64 non-null      float64
 24  LOCATION        986500 non-null  object 
 25  Cross Street    152270 non-null  object 
 26  LAT             986500 non-null  float64
 27  LON             986500 non-null  float64
dtypes: float64(8), int64(7), object(13)
memory usage: 210.7+ MB
```

In [ ]:

```
crime_data['DATE OCC'] = pd.to_datetime(crime_data['DATE OCC'])
# Filter data for November 2023
nov_2023_data = crime_data[(crime_data['DATE OCC'] >= '2024-01-01') & (crime_dat

nov_2023_data = nov_2023_data.sort_values(by='DATE OCC')

# Save the filtered data to a new CSV file
nov_2023_data.to_csv('crimedata_2024.csv', index=False)

print("November 2023 data extracted and saved as 'crime_data_nov_2023.csv'.")
```

```
<ipython-input-13-0da5cd8b9ba7>:1: 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.
  crime_data['DATE OCC'] = pd.to_datetime(crime_data['DATE OCC'])
November 2023 data extracted and saved as 'crime_data_nov_2023.csv'.
```

In [ ]:

```
df = pd.read_csv("/content/crimedata_2024.csv")
df.tail()
```

Out[ ]:

	DR_NO	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Des
109541	241216190	10/14/2024 12:00:00 AM	2024-10-14	230	12	77th Street	1266	1	510	VEHICLE STOLEI
109542	240119970	10/14/2024 12:00:00 AM	2024-10-14	905	1	Central	119	2	888	TRESPASSIN(
109543	241514626	10/14/2024 12:00:00 AM	2024-10-14	1435	15	N Hollywood	1548	1	510	VEHICLE STOLEI
109544	240410790	10/14/2024 12:00:00 AM	2024-10-14	1620	4	Hollenbeck	499	1	420	THEFT FROI MOTOI VEHICLE PETTY ($95 & UNDEF
109545	241313911	10/14/2024 12:00:00 AM	2024-10-14	800	13	Newton	1393	1	510	VEHICLE STOLEI

5 rows × 28 columns

In [ ]:

```
# Checking for the null values
df.isnull().sum()
```

Out[ ]:

	0
DR_NO	0
Date Rptd	0
DATE OCC	0
TIME OCC	0
AREA	0
AREA NAME	0
Rpt Dist No	0
Part 1-2	0
Crm Cd	0
Crm Cd Desc	0
Mocodes	24864
Vict Age	0
Vict Sex	24181
Vict Descent	24184
Premis Cd	4
Premis Desc	52
Weapon Used Cd	86537
Weapon Desc	86537
Status	1
Status Desc	0
Crm Cd 1	0
Crm Cd 2	104672
Crm Cd 3	109412
Crm Cd 4	109544
LOCATION	0
Cross Street	95754
LAT	0
LON	0

dtype: int64

DATA PRE-PROCESSING

In [ ]:

```
# Check for missing values in the dataset
missing_values = df.isnull().sum()
```

```
# Display columns with missing values
print(missing_values[missing_values > 0])

# Unwanted Columns
unwanted_columns = ['DR_NO', 'Mocodes', 'Cross Street', 'Crm Cd 1', 'Crm Cd 2',

# Drop unwanted columns
crime_data_cleaned = df.drop(columns=unwanted_columns)

# Verify the cleaning process
crime_data_cleaned.info()
```

```
Mocodes           24864
Vict Sex          24181
Vict Descent      24184
Premis Cd             4
Premis Desc          52
Weapon Used Cd    86537
Weapon Desc       86537
Status                1
Crm Cd 2         104672
Crm Cd 3         109412
Crm Cd 4         109544
Cross Street      95754
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109546 entries, 0 to 109545
Data columns (total 21 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Date Rptd       109546 non-null  object
 1   DATE OCC        109546 non-null  object
 2   TIME OCC        109546 non-null  int64
 3   AREA            109546 non-null  int64
 4   AREA NAME       109546 non-null  object
 5   Rpt Dist No     109546 non-null  int64
 6   Part 1-2        109546 non-null  int64
 7   Crm Cd          109546 non-null  int64
 8   Crm Cd Desc     109546 non-null  object
 9   Vict Age        109546 non-null  int64
 10  Vict Sex        85365 non-null   object
 11  Vict Descent    85362 non-null   object
 12  Premis Cd       109542 non-null  float64
 13  Premis Desc     109494 non-null  object
 14  Weapon Used Cd  23009 non-null   float64
 15  Weapon Desc     23009 non-null   object
 16  Status          109545 non-null  object
 17  Status Desc     109546 non-null  object
 18  LOCATION        109546 non-null  object
 19  LAT             109546 non-null  float64
 20  LON             109546 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 17.6+ MB
```

In [ ]:
```
crime_data_cleaned.head()
```

Out[ ]:

	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Desc	Vict Age	...	Vict Descent
0	01/22/2024 12:00:00 AM	2024-01-01	415	15	N Hollywood	1519	1	420	THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER)	0	...	X
1	01/02/2024 12:00:00 AM	2024-01-01	2000	12	77th Street	1269	1	330	BURGLARY FROM VEHICLE	49	...	B
2	01/01/2024 12:00:00 AM	2024-01-01	1437	18	Southeast	1863	1	440	THEFT PLAIN - PETTY ($950 & UNDER)	0	...	X
3	01/02/2024 12:00:00 AM	2024-01-01	1645	13	Newton	1341	2	624	BATTERY - SIMPLE ASSAULT	43	...	B
4	01/01/2024 12:00:00 AM	2024-01-01	200	21	Topanga	2107	2	624	BATTERY - SIMPLE ASSAULT	51	...	H

5 rows × 21 columns

Replacing the numerical columns with the mean of the data i.e., in this case we are replacing the missing values in the 'Vict Age' column with the mean of the column:

In [ ]:

```
crime_data_cleaned['Vict Age'].mean()
```

Out[ ]:

```
23.723905939057566
```

Replacing the null values from the categorical columns 'Vict Sex' and 'Vict Descent' with the mode of the data

In [ ]:

```
categorical_columns = ['Vict Sex', 'Vict Descent','Premis Cd']
for column in categorical_columns:
    crime_data_cleaned[column].fillna(crime_data_cleaned[column].mode()[0], inpl
```

```
<ipython-input-27-0a9030bc628a>:3: FutureWarning: A value is trying to be set o
n a copy of a DataFrame or Series through chained assignment using an inplace m
ethod.
The behavior will change in pandas 3.0. This inplace method will never work bec
ause the intermediate object on which we are setting values always behaves as a
copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.me
thod({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, t
o perform the operation inplace on the original object.


  crime_data_cleaned[column].fillna(crime_data_cleaned[column].mode()[0], inpla
ce=True)
```

Replacing the missing values from the other columns based on the analysis and context:

In [ ]:

```
# Replace missing values in 'Weapon Desc' with "Unknown"
crime_data_cleaned['Weapon Desc'].fillna('Unknown', inplace=True)

# Replace missing values in 'Weapon Used Cd' with "No Weapon Used"
crime_data_cleaned['Weapon Used Cd'].fillna("No Weapon Used", inplace=True)

# Replace missing values in 'Premis Desc' with a placeholder like "Unknown Premi
crime_data_cleaned['Premis Desc'].fillna("Unknown Premise", inplace=True)

# Replace missing values in 'Premis Desc' with a placeholder like "Unknown Premi
crime_data_cleaned['Status'].fillna("Unknown Premise", inplace=True)
```

In [ ]:

```
crime_data_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109546 entries, 0 to 109545
Data columns (total 21 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   Date Rptd       109546 non-null  object 
 1   DATE OCC        109546 non-null  object 
 2   TIME OCC        109546 non-null  int64  
 3   AREA            109546 non-null  int64  
 4   AREA NAME       109546 non-null  object 
 5   Rpt Dist No     109546 non-null  int64  
 6   Part 1-2        109546 non-null  int64  
 7   Crm Cd          109546 non-null  int64  
 8   Crm Cd Desc     109546 non-null  object 
 9   Vict Age        109546 non-null  int64  
 10  Vict Sex        109546 non-null  object 
 11  Vict Descent    109546 non-null  object 
 12  Premis Cd       109546 non-null  float64
 13  Premis Desc     109546 non-null  object 
 14  Weapon Used Cd  109546 non-null  object 
 15  Weapon Desc     109546 non-null  object 
 16  Status          109546 non-null  object 
 17  Status Desc     109546 non-null  object 
 18  LOCATION        109546 non-null  object 
 19  LAT             109546 non-null  float64
 20  LON             109546 non-null  float64
dtypes: float64(3), int64(6), object(12)
memory usage: 17.6+ MB
```

In [ ]:
```
# Checking if there are anymore missing values after the data cleaning.
crime_data_cleaned.isnull().sum()
```

Out[ ]:

	0
Date Rptd	0
DATE OCC	0
TIME OCC	0
AREA	0
AREA NAME	0
Rpt Dist No	0
Part 1-2	0
Crm Cd	0
Crm Cd Desc	0
Vict Age	0
Vict Sex	0
Vict Descent	0
Premis Cd	0
Premis Desc	0
Weapon Used Cd	0
Weapon Desc	0
Status	0
Status Desc	0
LOCATION	0
LAT	0
LON	0

dtype: int64

In [ ]:
```
crime_data_cleaned.head()
```

Out[ ]:

	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Desc	Vict Age	...	Vict Descent
0	01/22/2024 12:00:00 AM	2024-01-01	415	15	N Hollywood	1519	1	420	THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER)	0	...	X
1	01/02/2024 12:00:00 AM	2024-01-01	2000	12	77th Street	1269	1	330	BURGLARY FROM VEHICLE	49	...	B
2	01/01/2024 12:00:00 AM	2024-01-01	1437	18	Southeast	1863	1	440	THEFT PLAIN - PETTY ($950 & UNDER)	0	...	X
3	01/02/2024 12:00:00 AM	2024-01-01	1645	13	Newton	1341	2	624	BATTERY - SIMPLE ASSAULT	43	...	B
4	01/01/2024 12:00:00 AM	2024-01-01	200	21	Topanga	2107	2	624	BATTERY - SIMPLE ASSAULT	51	...	H

5 rows × 21 columns

Categorizing 'TIME OCC' into parts of the day: Morning (5-12), Afternoon (12-17), Evening (17-21), Night (21-5)

In [ ]:

```python
def categorize_time_of_day(hour):
    if 5 <= hour < 12:
        return 'Morning'
    elif 12 <= hour < 17:
        return 'Afternoon'
    elif 17 <= hour < 21:
        return 'Evening'
    else:
        return 'Night'

crime_data_cleaned['Time of Day'] = crime_data_cleaned['TIME OCC'].apply(lambda

# Checking the distribution of data across the newly created 'Time of Day' categ
crime_data_cleaned['Time of Day'].value_counts()
```

Out[ ]:

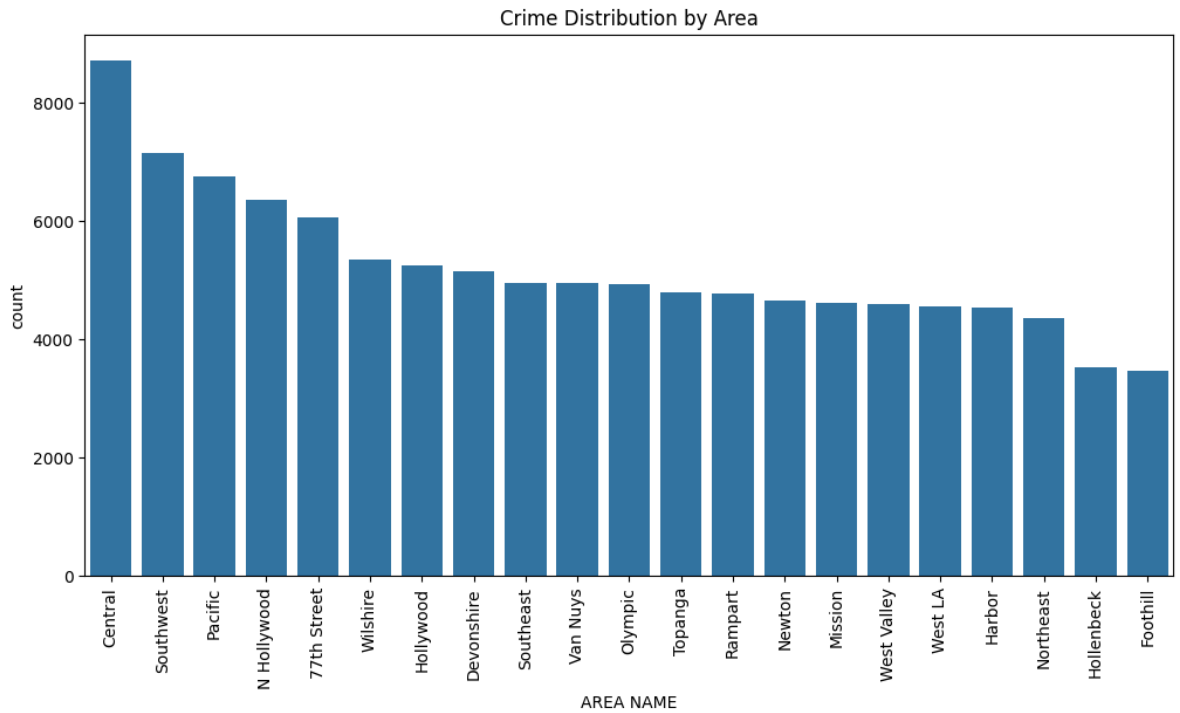
Time of Day	count
Afternoon	29269
Night	28849
Evening	26246
Morning	25182

dtype: int64

DATA - VISUALIzATIONS

Visualization 1. Crimes distributions by Area

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Count plot of crimes by area
plt.figure(figsize=(12, 6))
sns.countplot(x='AREA NAME', data=crime_data_cleaned, order=crime_data_cleaned['
plt.title('Crime Distribution by Area')
plt.xticks(rotation=90)
plt.show()
```

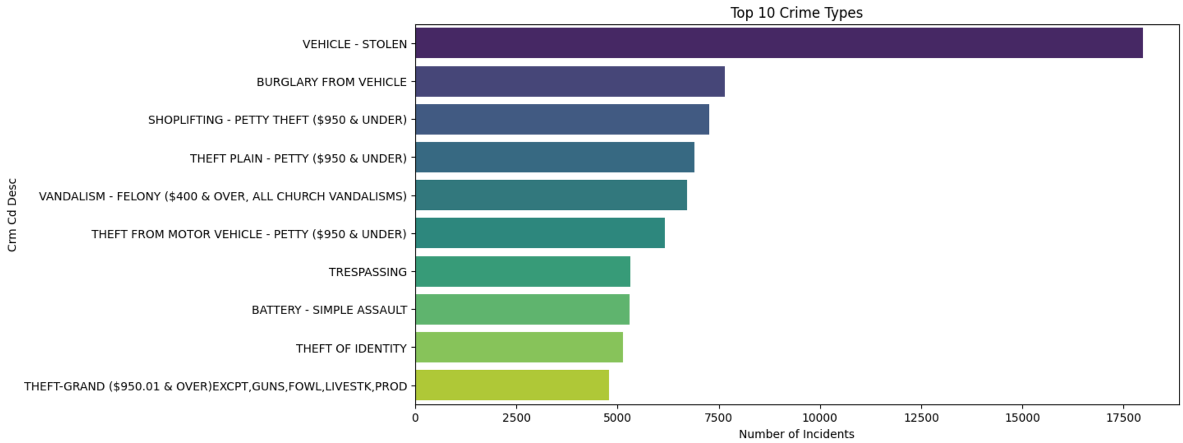


The bar chart shows the distribution of crime incidents across various areas, with the Central area having the highest crime count (over 1400 incidents). Other areas like 77th Street and Southwest also report high crime rates, each with over 1000 incidents. The areas with the lowest crime counts include Foothill, Hollenbeck, and Harbor, indicating fewer reported incidents in these regions. The chart highlights significant variation in crime distribution across different areas.

Visualization 2. Top 10 common crime descriptions

In [ ]:
```
# Bar plot of the most common crime descriptions
plt.figure(figsize=(12, 6))
top_crimes = crime_data_cleaned['Crm Cd Desc'].value_counts().head(10)
sns.barplot(x=top_crimes.values, y=top_crimes.index, palette='viridis')
plt.title('Top 10 Crime Types')
plt.xlabel('Number of Incidents')
plt.show()
```

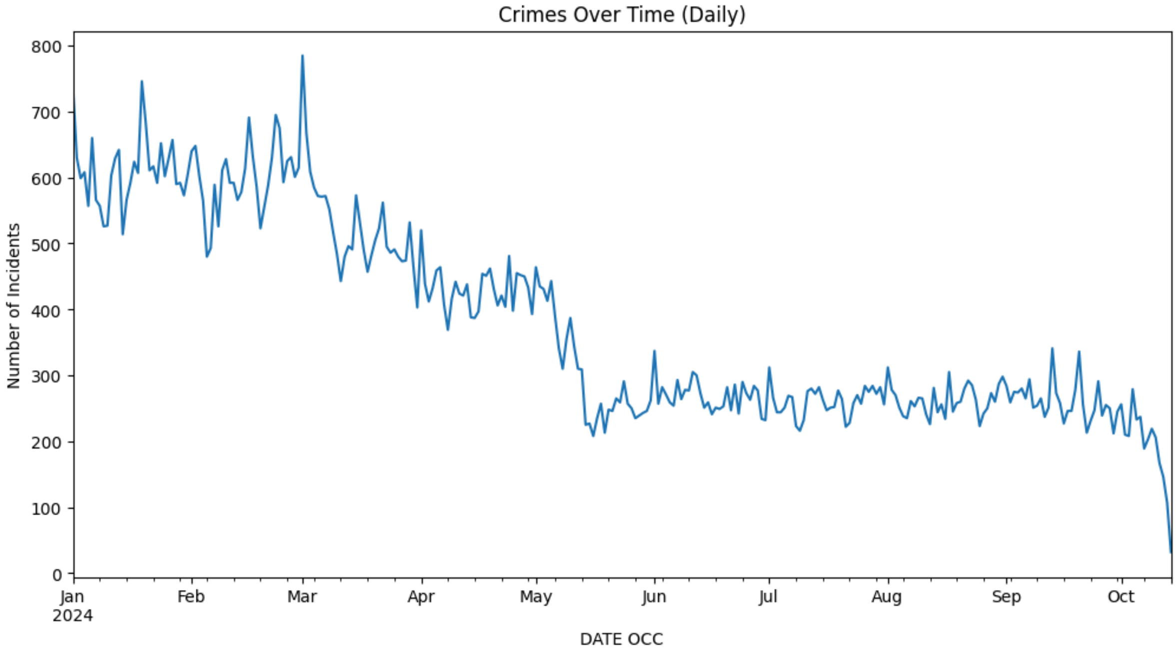
```
<ipython-input-34-0f35139f945f>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same e
ffect.

  sns.barplot(x=top_crimes.values, y=top_crimes.index, palette='viridis')
```



The bar chart shows the **Top 10 Crime Types** by number of incidents, with **Vehicle Stolen** being the most frequent, followed by **Battery - Simple Assault** and **Burglary from Vehicle**. The chart uses a gradient color scheme to differentiate the categories, making it clear that vehicle-related crimes are the most common. Incidents range from around 500 to over 2000.

Visualization 3. Crimes plotted over Time

In [ ]:
```
# Convert 'DATE OCC' to datetime format for better time-based analysis
crime_data_cleaned['DATE OCC'] = pd.to_datetime(crime_data_cleaned['DATE OCC'])

# Line plot of crimes over time
plt.figure(figsize=(12, 6))
crime_data_cleaned.set_index('DATE OCC').resample('D').size().plot()
plt.title('Crimes Over Time (Daily)')
plt.ylabel('Number of Incidents')
plt.show()
```

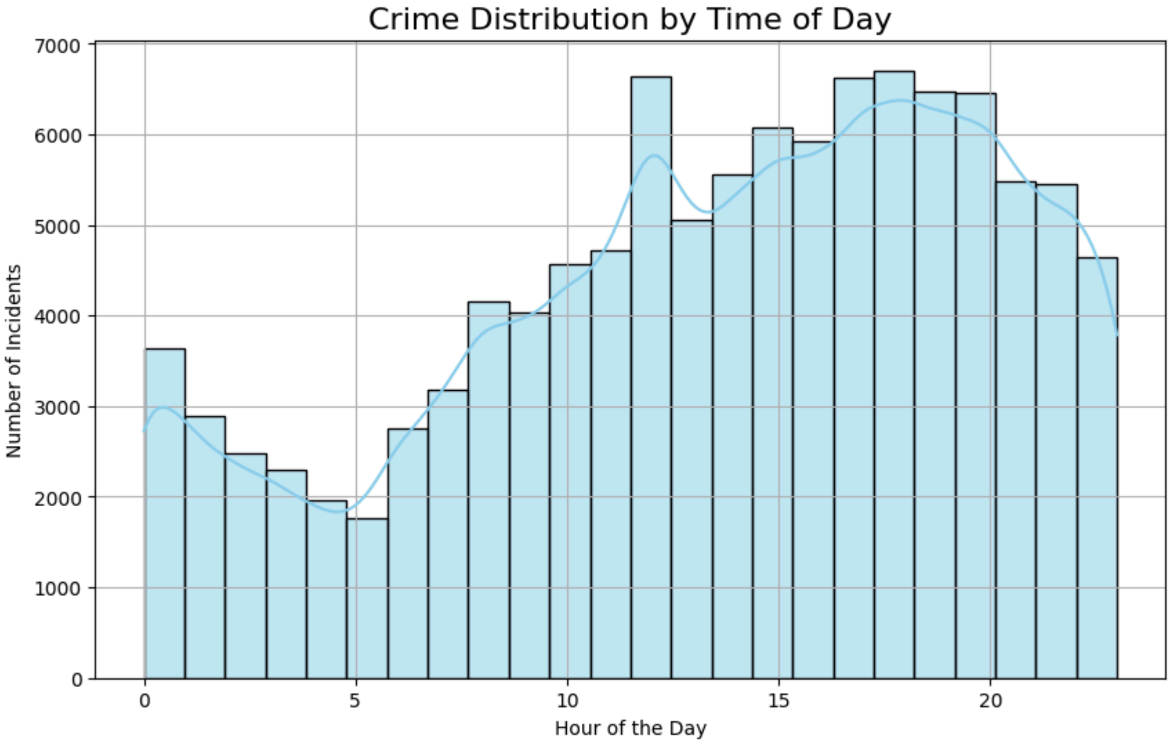


The line chart shows the **Crimes Over Time (Daily)** for November 2023. The Y-axis represents the **number of incidents**, ranging from approximately 500 to 675. The X-axis displays the dates throughout November. Crime rates fluctuate throughout the month, with noticeable peaks and drops. The highest number of incidents occurs at the start of the month, and a general downward trend is observed toward the end.

Visualization 4. Crime distribution by time of day

In [ ]:

```
# Convert the 'TIME OCC' into hours for better time analysis
crime_data_cleaned['Hour Occ'] = crime_data_cleaned['TIME OCC'] // 100

plt.figure(figsize=(10, 6))
sns.histplot(crime_data_cleaned['Hour Occ'], bins=24, color='skyblue', kde=True)
plt.title('Crime Distribution by Time of Day', fontsize=16)
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Incidents')
plt.grid(True)
plt.show()
```

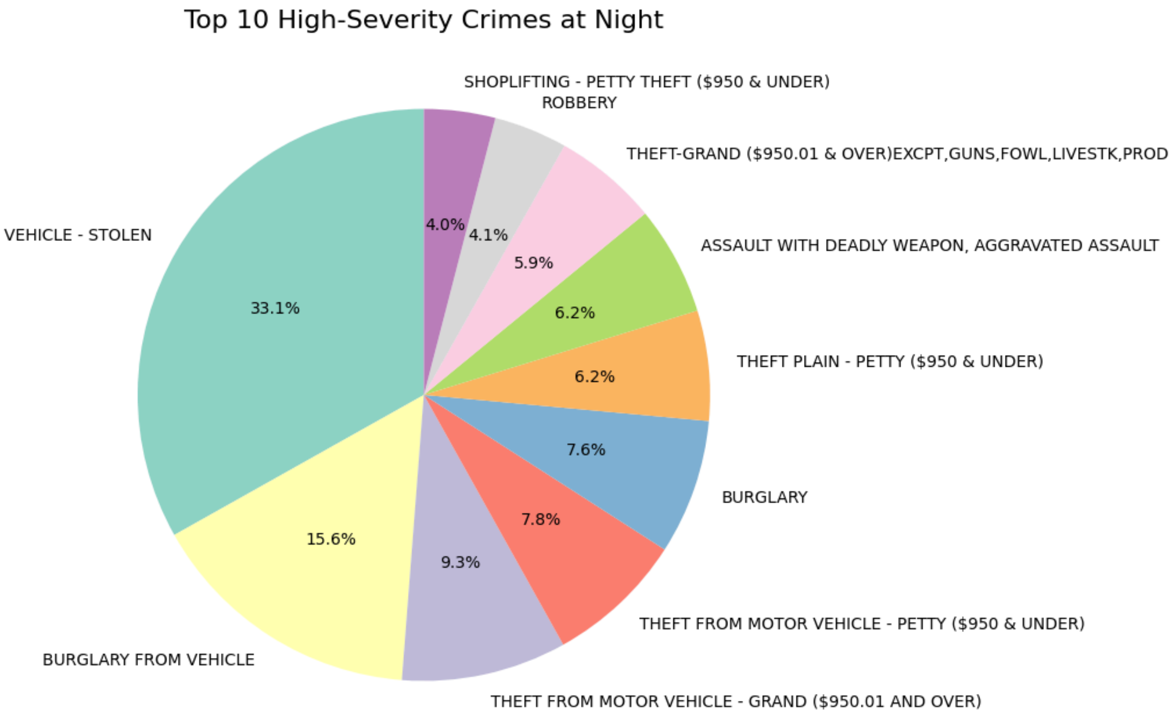


The histogram shows the **Crime Distribution by Time of Day**, with the X-axis representing the **hour of the day** (from 0 to 24), and the Y-axis indicating the **number of incidents**. Crimes are more frequent between **12 PM and 8 PM**, peaking around **3 PM**. There is a noticeable dip in crime activity between **2 AM and 6 AM**, indicating fewer incidents during the early morning hours. The graph also includes a **KDE (Kernel Density Estimation)** curve to smooth out the distribution pattern.

Visualization 5- Pie Chart of Top 10 High Severity Crimes at Night

In [ ]:

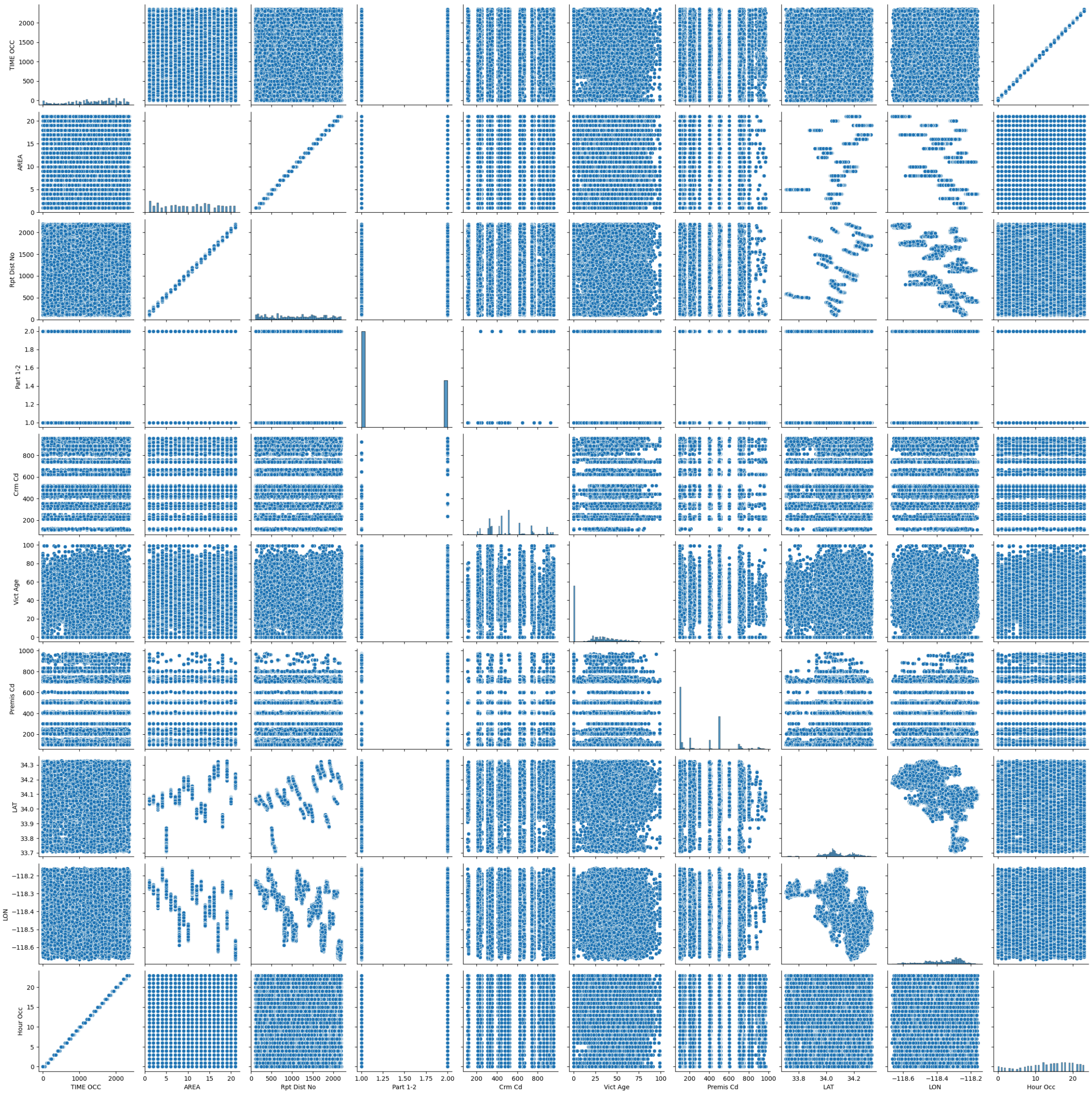
```
# Filtering the data for crimes that occurred at night (after 8 PM and before 6
night_crimes = crime_data_cleaned[(crime_data_cleaned['Hour Occ'] >= 20) | (crim

# Get the top 10 high-severity crimes that occur at night (assuming Part 1 crime
high_severity_night_crimes = night_crimes[night_crimes['Part 1-2'] == 1]

# Get the top 10 crime descriptions by frequency
top_10_high_severity_night_crimes = high_severity_night_crimes['Crm Cd Desc'].va

# Plotting a pie chart for the top 10 high-severity crimes at night
plt.figure(figsize=(8, 8))
plt.pie(top_10_high_severity_night_crimes, labels=top_10_high_severity_night_cri
plt.title('Top 10 High-Severity Crimes at Night', fontsize=16)
plt.show()
```



The pie chart shows the **Top 10 High-Severity Crimes at Night**. The largest portion of crimes at night is **Vehicle - Stolen**, accounting for **26.7%** of the total, followed by **Burglary from Vehicle** at **16%** and **Burglary** at **13.4%**. Other notable crimes include **Assault with Deadly Weapon, Aggravated Assault** and **Theft from Motor Vehicle**. Smaller crime categories, such as **Intimate Partner - Aggravated Assault**, make up a smaller portion of the total incidents.

Visualization 6

In [ ]:
```
sns.pairplot(crime_data_cleaned)
plt.show()
```

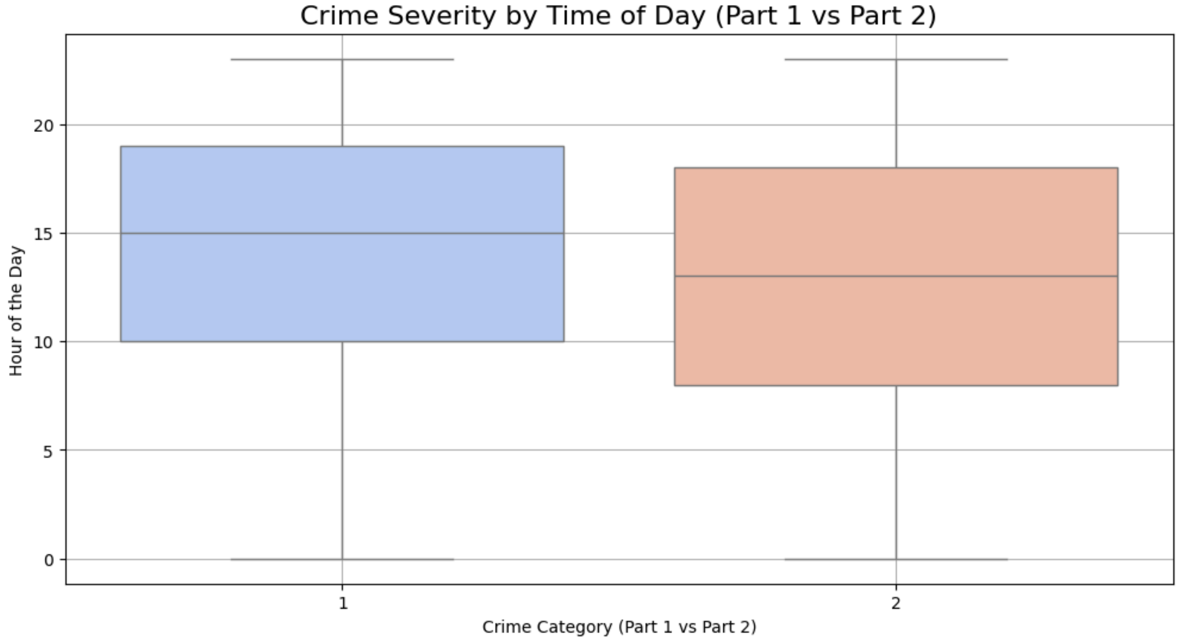


Visualization 7- Crime severity by time of the day

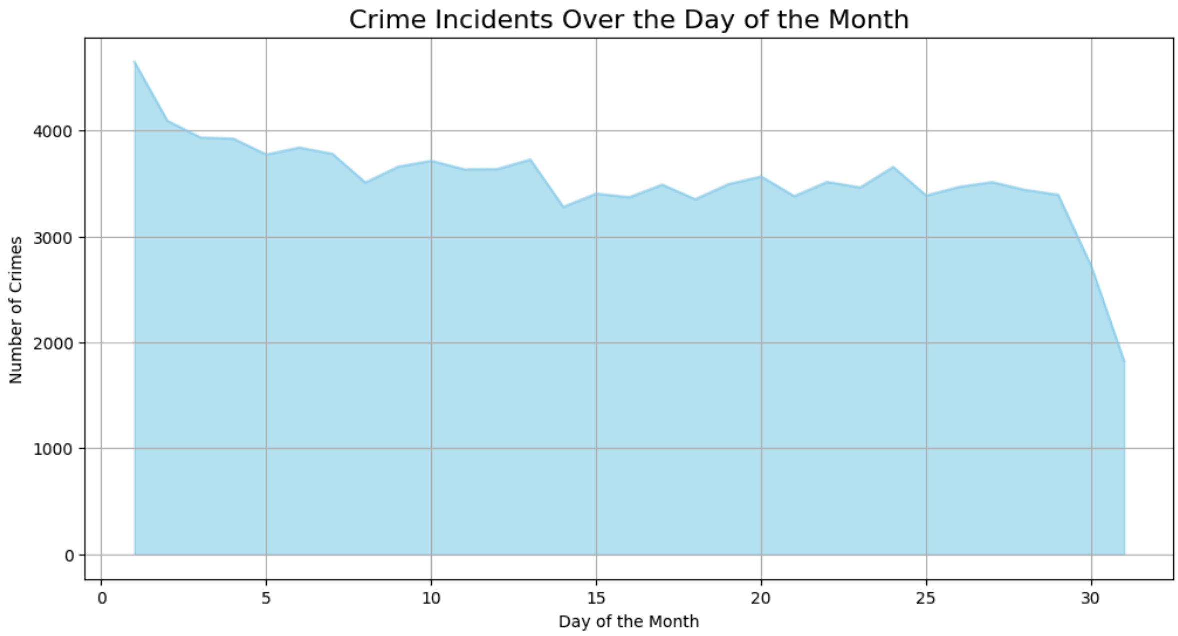
In [ ]:

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Part 1-2', y='Hour Occ', data=crime_data_cleaned, palette='coolwa
plt.title('Crime Severity by Time of Day (Part 1 vs Part 2)', fontsize=16)
plt.xlabel('Crime Category (Part 1 vs Part 2)')
plt.ylabel('Hour of the Day')
plt.grid(True)
plt.show()
```

```
<ipython-input-39-fa2a69f44b01>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same e
ffect.

  sns.boxplot(x='Part 1-2', y='Hour Occ', data=crime_data_cleaned, palette='coo
lwarm')
```



In [ ]:
```python
# Extract the day from the DATE OCC
crime_data_cleaned['Day'] = crime_data_cleaned['DATE OCC'].dt.day

crime_per_day = crime_data_cleaned.groupby('Day').size()

plt.figure(figsize=(12, 6))
crime_per_day.plot(kind='area', color='skyblue', alpha=0.6)
plt.title('Crime Incidents Over the Day of the Month', fontsize=16)
plt.xlabel('Day of the Month')
plt.ylabel('Number of Crimes')
plt.grid(True)
plt.show()
```

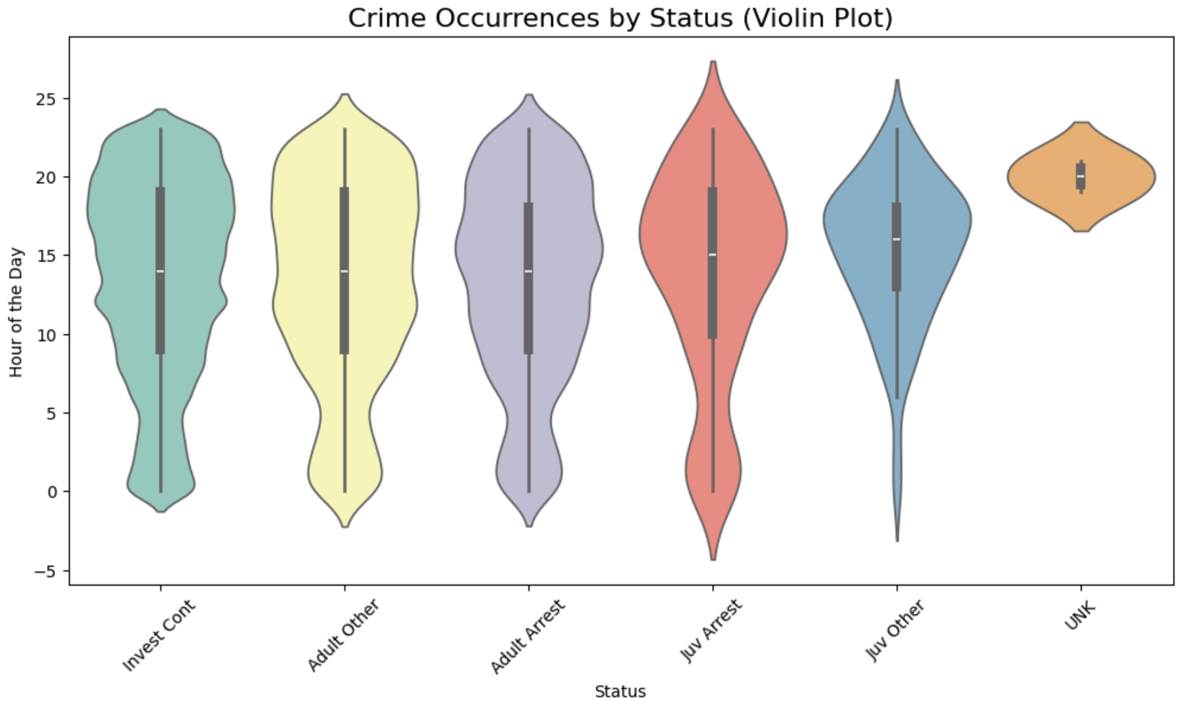


Visualization 8- Crime occurences by status

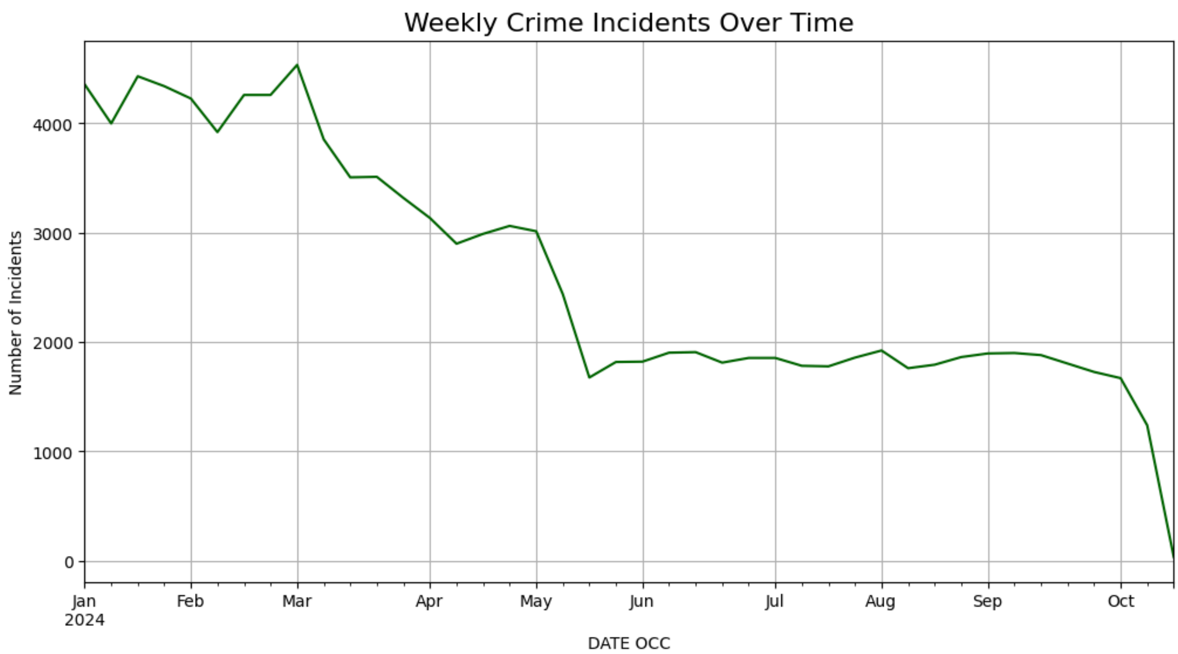
In [ ]:
```python
plt.figure(figsize=(12, 6))
sns.violinplot(x='Status Desc', y='Hour Occ', data=crime_data_cleaned, palette='
plt.title('Crime Occurrences by Status (Violin Plot)', fontsize=16)
plt.xlabel('Status')
plt.ylabel('Hour of the Day')
```

```
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-41-720b6017c177>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='Status Desc', y='Hour Occ', data=crime_data_cleaned, palette='Set3')
```



In [ ]:
```
plt.figure(figsize=(12, 6))
weekly_crime = crime_data_cleaned.set_index('DATE OCC').resample('W').size()
weekly_crime.plot(color='darkgreen')
plt.title('Weekly Crime Incidents Over Time', fontsize=16)
plt.ylabel('Number of Incidents')
plt.grid(True)
plt.show()
```



In [ ]:
```
!pip install geopandas matplotlib contextily
```

```
Requirement already satisfied: geopandas in /usr/local/lib/python3.10/dist-pack
ages (1.0.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-pac
kages (3.7.1)
Collecting contextily
  Downloading contextily-1.6.2-py3-none-any.whl.metadata (2.9 kB)
Requirement already satisfied: numpy>=1.22 in /usr/local/lib/python3.10/dist-pa
ckages (from geopandas) (1.26.4)
Requirement already satisfied: pyogrio>=0.7.2 in /usr/local/lib/python3.10/dist
-packages (from geopandas) (0.10.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-pack
ages (from geopandas) (24.1)
Requirement already satisfied: pandas>=1.4.0 in /usr/local/lib/python3.10/dist-
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Requirement already satisfied: pyproj>=3.3.0 in /usr/local/lib/python3.10/dist-
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ist-packages (from matplotlib) (4.54.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/d
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Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/di
st-packages (from matplotlib) (3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.1
0/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: geopy in /usr/local/lib/python3.10/dist-packages
(from contextily) (2.4.1)
Collecting mercantile (from contextily)
  Downloading mercantile-1.2.1-py3-none-any.whl.metadata (4.8 kB)
Collecting rasterio (from contextily)
  Downloading rasterio-1.4.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x8
6_64.whl.metadata (9.1 kB)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packa
ges (from contextily) (2.32.3)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-package
s (from contextily) (1.4.2)
Requirement already satisfied: xyzservices in /usr/local/lib/python3.10/dist-pa
ckages (from contextily) (2024.9.0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-p
ackages (from pandas>=1.4.0->geopandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist
-packages (from pandas>=1.4.0->geopandas) (2024.2)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-packag
es (from pyogrio>=0.7.2->geopandas) (2024.8.30)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packa
ges (from python-dateutil>=2.7->matplotlib) (1.16.0)
Requirement already satisfied: geographiclib<3,>=1.52 in /usr/local/lib/python
3.10/dist-packages (from geopy->contextily) (2.0)
Requirement already satisfied: click>=3.0 in /usr/local/lib/python3.10/dist-pac
kages (from mercantile->contextily) (8.1.7)
Collecting affine (from rasterio->contextily)
  Downloading affine-2.4.0-py3-none-any.whl.metadata (4.0 kB)
Requirement already satisfied: attrs in /usr/local/lib/python3.10/dist-packages
(from rasterio->contextily) (24.2.0)
Collecting cligj>=0.5 (from rasterio->contextily)
```
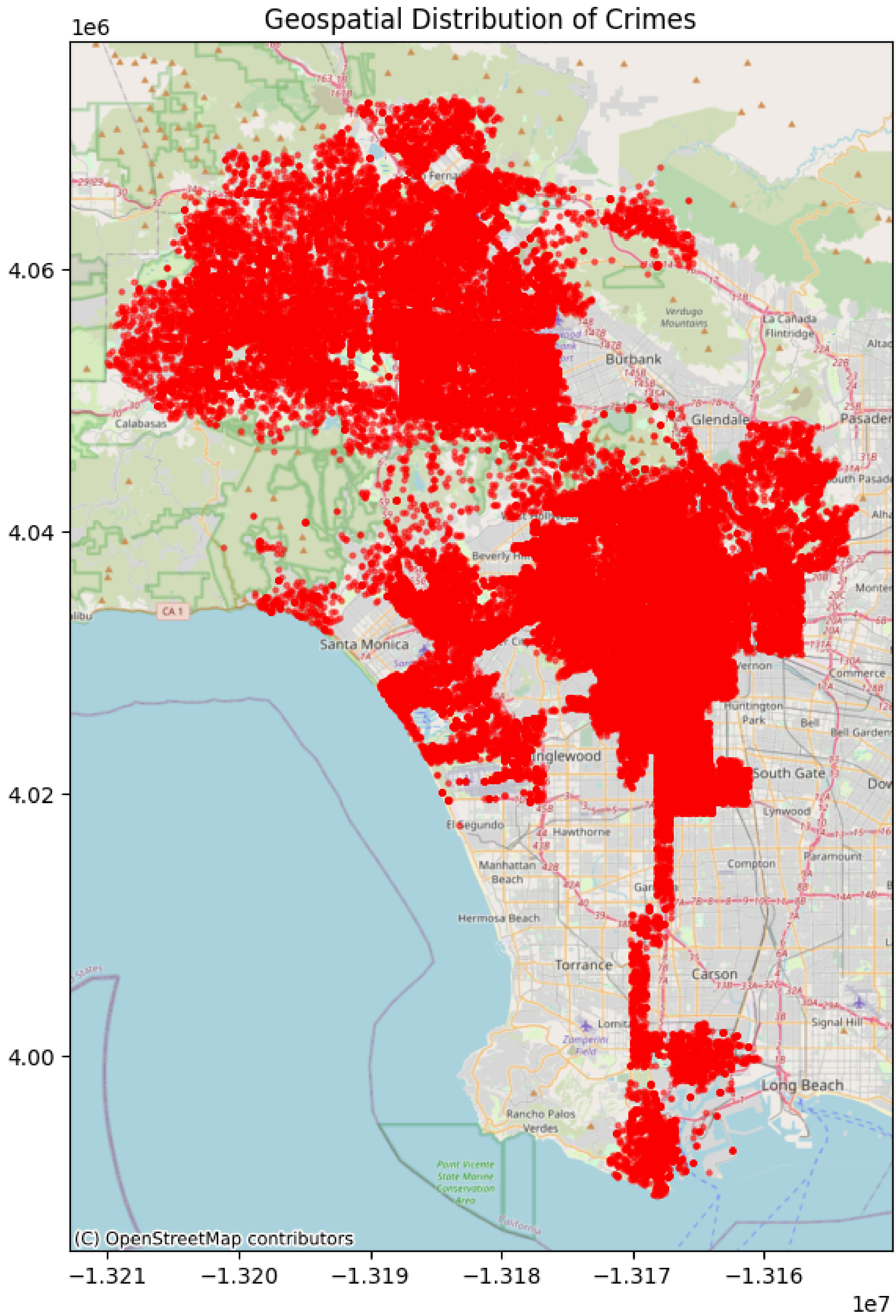

```
  Downloading cligj-0.7.2-py3-none-any.whl.metadata (5.0 kB)
Collecting click-plugins (from rasterio->contextily)
  Downloading click_plugins-1.1.1-py2.py3-none-any.whl.metadata (6.4 kB)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/pytho
n3.10/dist-packages (from requests->contextily) (3.4.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-p
ackages (from requests->contextily) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/
dist-packages (from requests->contextily) (2.2.3)
Downloading contextily-1.6.2-py3-none-any.whl (17 kB)
Downloading mercantile-1.2.1-py3-none-any.whl (14 kB)
Downloading rasterio-1.4.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_
64.whl (22.2 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 22.2/22.2 MB 45.5 MB/s eta 0:00:00
Downloading cligj-0.7.2-py3-none-any.whl (7.1 kB)
Downloading affine-2.4.0-py3-none-any.whl (15 kB)
Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
Installing collected packages: mercantile, cligj, click-plugins, affine, raster
io, contextily
Successfully installed affine-2.4.0 click-plugins-1.1.1 cligj-0.7.2 contextily-
1.6.2 mercantile-1.2.1 rasterio-1.4.1
```

Visualization - Geospatial Distributions of crime in NY-city

In [ ]:

```python
import geopandas as gpd
import contextily as ctx
import matplotlib.pyplot as plt
from shapely.geometry import Point

# Create a GeoDataFrame with crime data points
crime_data_cleaned['Coordinates'] = list(zip(crime_data_cleaned['LON'], crime_da
crime_data_cleaned['Coordinates'] = crime_data_cleaned['Coordinates'].apply(Poir
geo_crime_data = gpd.GeoDataFrame(crime_data_cleaned, geometry='Coordinates')

# Set the coordinate reference system (CRS) for latitude/longitude (EPSG:4326) a
geo_crime_data = geo_crime_data.set_crs(epsg=4326)
geo_crime_data = geo_crime_data.to_crs(epsg=3857)

# Plot the crime locations on a map
fig, ax = plt.subplots(figsize=(10, 10))
geo_crime_data.plot(ax=ax, markersize=5, color='red', alpha=0.5)

# Add a basemap using OpenStreetMap tiles
ctx.add_basemap(ax, source=ctx.providers.OpenStreetMap.Mapnik)

plt.title('Geospatial Distribution of Crimes')
plt.show()
```



CORRELATION ANALYSIS

Let's find the correlation between all the variables in the dataset by finding the correlation matrix.

In [ ]:
```
crime_data_cleaned.head()
```

Out[ ]:

	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Desc	Vict Age	...	Weapor Desc
0	01/22/2024 12:00:00 AM	2024-01-01	415	15	N Hollywood	1519	1	420	THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER)	0	...	Unknowr
1	01/02/2024 12:00:00 AM	2024-01-01	2000	12	77th Street	1269	1	330	BURGLARY FROM VEHICLE	49	...	Unknowr
2	01/01/2024 12:00:00 AM	2024-01-01	1437	18	Southeast	1863	1	440	THEFT PLAIN - PETTY ($950 & UNDER)	0	...	Unknowr
3	01/02/2024 12:00:00 AM	2024-01-01	1645	13	Newton	1341	2	624	BATTERY - SIMPLE ASSAULT	43	...	STRONG-ARM (HANDS FIST FEET OF BODILY FORCE)
4	01/01/2024 12:00:00 AM	2024-01-01	200	21	Topanga	2107	2	624	BATTERY - SIMPLE ASSAULT	51	...	STRONG-ARM (HANDS FIST FEET OF BODILY FORCE)

5 rows × 25 columns

In [ ]:
```
# Convert 'DATE OCC' from datetime to string
crime_data_cleaned['DATE OCC'] = crime_data_cleaned['DATE OCC'].astype(str)
```

In [ ]:
```
crime_data_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109546 entries, 0 to 109545
Data columns (total 25 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   Date Rptd       109546 non-null  object 
 1   DATE OCC        109546 non-null  object 
 2   TIME OCC        109546 non-null  int64  
 3   AREA            109546 non-null  int64  
 4   AREA NAME       109546 non-null  object 
 5   Rpt Dist No     109546 non-null  int64  
 6   Part 1-2        109546 non-null  int64  
 7   Crm Cd          109546 non-null  int64  
 8   Crm Cd Desc     109546 non-null  object 
 9   Vict Age        109546 non-null  int64  
 10  Vict Sex        109546 non-null  object 
 11  Vict Descent    109546 non-null  object 
 12  Premis Cd       109546 non-null  float64
 13  Premis Desc     109546 non-null  object 
 14  Weapon Used Cd  109546 non-null  object 
 15  Weapon Desc     109546 non-null  object 
 16  Status          109546 non-null  object 
 17  Status Desc     109546 non-null  object 
 18  LOCATION        109546 non-null  object 
 19  LAT             109546 non-null  float64
 20  LON             109546 non-null  float64
 21  Time of Day     109546 non-null  object 
 22  Hour Occ        109546 non-null  int64  
 23  Day             109546 non-null  int32  
 24  Coordinates     109546 non-null  object 
dtypes: float64(3), int32(1), int64(7), object(14)
memory usage: 20.5+ MB
```

In [ ]:

```
# Select only numeric columns for correlation calculation
numeric_columns = crime_data_cleaned.select_dtypes(include=['float64', 'int64'])

# Calculate the correlation matrix
correlation_matrix = numeric_columns.corr()

# Display the correlation matrix
correlation_matrix
```

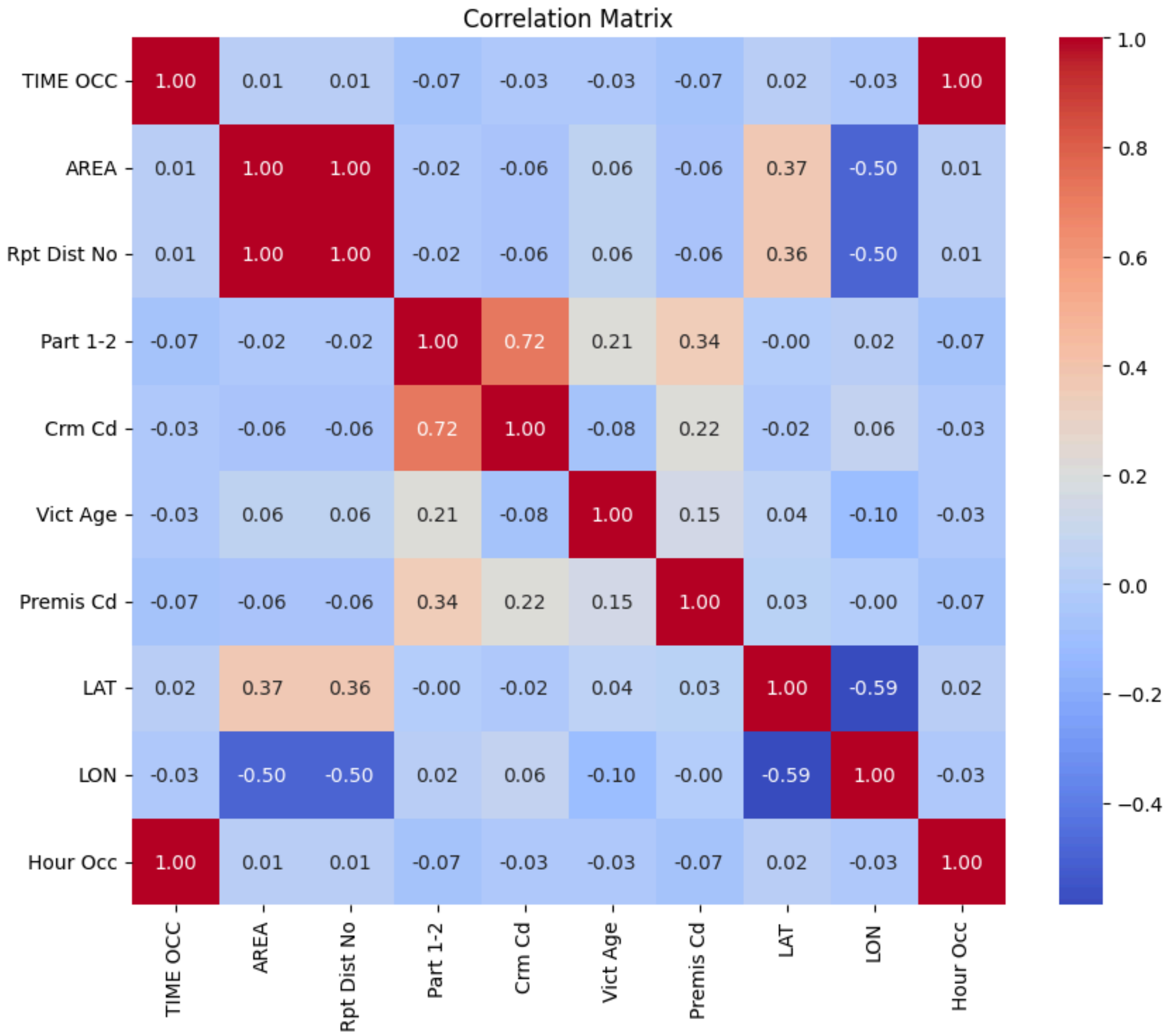
Out[ ]:

	TIME OCC	AREA	Rpt Dist No	Part 1-2	Crm Cd	Vict Age	Premis Cd	LAT
TIME OCC	1.000000	0.012218	0.012529	-0.072466	-0.028837	-0.027109	-0.067121	0.015479
AREA	0.012218	1.000000	0.999074	-0.023739	-0.056206	0.056220	-0.059417	0.365647
Rpt Dist No	0.012529	0.999074	1.000000	-0.024392	-0.056860	0.056754	-0.060447	0.362508
Part 1-2	-0.072466	-0.023739	-0.024392	1.000000	0.719261	0.212778	0.342876	-0.004170
Crm Cd	-0.028837	-0.056206	-0.056860	0.719261	1.000000	-0.083470	0.216846	-0.019670
Vict Age	-0.027109	0.056220	0.056754	0.212778	-0.083470	1.000000	0.154307	0.038630
Premis Cd	-0.067121	-0.059417	-0.060447	0.342876	0.216846	0.154307	1.000000	0.027271
LAT	0.015479	0.365647	0.362508	-0.004170	-0.019670	0.038630	0.027271	1.000000
LON	-0.027266	-0.496637	-0.498042	0.021883	0.060516	-0.104988	-0.000076	-0.587734
Hour Occ	0.999589	0.012799	0.013107	-0.074615	-0.029780	-0.028373	-0.070059	0.015362

HeatMap of the Correlation Matrix:

In [ ]:

```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



According to the above correlation matrix that shows the correlation coefficients between different variables in the dataset and the heatmap of the correlation matrix, Here are some insights based on the correlations:

TIME OCC (Time of Occurrence) and Other Variables:

- TIME OCC has very weak correlations with other variables (all coefficients are close to zero). This suggests that the time of occurrence is not strongly correlated with the other variables in the dataset.

AREA, Rpt Dist No (Reporting District Number), and Other Variables:

- AREA and Rpt Dist No are highly positively correlated (correlation coefficient of approximately 1), which is expected since they likely represent similar location information.
- AREA and Rpt Dist No both have weak negative correlations with other variables, indicating that the area or reporting district number is not strongly correlated with the other variables.

Part 1-2 (Part Type) and Other Variables:

- Part 1-2 has a moderate positive correlation with Crm Cd (Crime Code) and a strong positive correlation with Vict Age. This suggests that certain crime types (Part 1-2) may be correlated with specific crime codes and the age of victims.

Crm Cd (Crime Code) and Other Variables:

- Crm Cd has a moderate positive correlation with Part 1-2 and a weak positive correlation with Premis Cd (Premise Code). This indicates that specific crime codes may be associated with certain types of crime (Part 1-2) and locations (Premis Cd).

Vict Age and Other Variables:

- Vict Age has a weak positive correlation with Premis Cd, indicating a slight association between the age of victims and the location where the crime occurred.

Premis Cd (Premise Code) and Other Variables:

- Premis Cd has a moderate positive correlation with Part 1-2 and a weak positive correlation with Crm Cd. This suggests that certain premises may be associated with specific crime types and codes.

In [ ]:
```
import pandas as pd
crime_data_cleaned.to_csv('crime_data_cleaned_final_2024.csv', index=False)
```