LA Crime 2020 - 2023

May 6, 2024

1 Unveiling Patterns of Crime in Los Angeles: An Analysis of Crime Incidents from 2020 to 2023

1.1 Abstract:

This analysis explores a comprehensive dataset of crime incidents in the City of Los Angeles from 2020 to 2023, sourced from original crime reports. The dataset offers a wealth of information for understanding the trends, patterns, and dynamics of criminal activity within the city. By leveraging data-driven insights, this analysis aims to uncover valuable insights that can inform law enforcement strategies, resource allocation, and public safety initiatives.

The study begins by performing data cleaning and preprocessing steps to ensure data integrity and consistency. This includes handling missing values, removing irrelevant columns, converting data types, and filtering out invalid data points. Despite potential inaccuracies inherent in manually recorded crime reports and privacy measures limiting address specificity, the cleaned dataset remains a reliable resource for examining crime patterns in Los Angeles.

Through exploratory data analysis and visualization techniques, this study investigates various aspects of crime in the city. It examines the temporal distribution of crime incidents, revealing trends over time and seasonal variations. The analysis also delves into the demographic characteristics of crime victims, shedding light on the age distribution and identifying vulnerable populations.

Furthermore, the study explores the geographical distribution of crime, identifying areas with the highest crime rates during different time periods, such as nighttime hours. By uncovering these spatial patterns, the analysis provides actionable insights for targeted law enforcement interventions and community-based crime prevention strategies.

The findings of this analysis have significant implications for public safety, law enforcement resource allocation, and policy development. By understanding the temporal, demographic, and spatial dimensions of crime in Los Angeles, stakeholders can make data-driven decisions to enhance public safety, optimize law enforcement efforts, and develop targeted interventions in high-risk areas.

For these reasons, this analysis contributes to a deeper understanding of the crime landscape in Los Angeles and serves as a valuable resource for researchers, policymakers, and law enforcement agencies in their efforts to combat crime and promote public safety in the city.

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
crime = pd.read_csv('../data_course/Crime_Data_from_2020_to_Present.csv')
```

```python
# Suppress the SettingWithCopyWarning
pd.options.mode.chained_assignment = None
```

2 Understand and Clean the Data

In this section, we perform initial data exploration and cleaning steps. This includes examining the data schema, checking for null values, removing irrelevant columns, converting data types, and filtering out invalid data points.

2.1 Key observations:

- The dataset contains 27 columns with information about crime incidents.
- Several columns have high null values and are removed for analysis.
- Date columns are converted to datetime format for easier manipulation.
- Invalid victim ages (negative or 0) are filtered out.

[2]:
```python
crime.head()
```

[2]:
```
   division_number date_reported        date_occurred  area    area_name  \
0         10304468    2020-01-08  2020-01-08 22:30:00     3    Southwest
1        190101086    2020-01-02  2020-01-01 03:30:00     1      Central
2        200110444    2020-04-14  2020-02-13 12:00:00     1      Central
3        191501505    2020-01-01  2020-01-01 17:30:00    15  N Hollywood
4        191921269    2020-01-01  2020-01-01 04:15:00    19      Mission

   reporting_district  part  crime_code  \
0                 377     2         624
1                 163     2         624
2                 155     2         845
3                1543     2         745
4                1998     2         740

                                crime_description  modus_operandi  …  \
0                        BATTERY - SIMPLE ASSAULT       0444 0913  …
1                        BATTERY - SIMPLE ASSAULT  0416 1822 1414  …
2          SEX OFFENDER REGISTRANT OUT OF COMPLIANCE            1501  …
3           VANDALISM - MISDEAMEANOR ($399 OR UNDER)       0329 1402  …
4  VANDALISM - FELONY ($400 & OVER, ALL CHURCH VA…            0329  …

   status status_description crime_code_1  crime_code_2 crime_code_3  \
0      AO        Adult Other        624.0           NaN          NaN
1      IC        Invest Cont        624.0           NaN          NaN
2      AA       Adult Arrest        845.0           NaN          NaN
3      IC        Invest Cont        745.0         998.0          NaN
4      IC        Invest Cont        740.0           NaN          NaN

   crime_code_4                                  location cross_street  \
```

```
0           NaN   1100 W  39TH                          PL          NaN
1           NaN    700 S  HILL                          ST          NaN
2           NaN    200 E  6TH                           ST          NaN
3           NaN   5400    CORTEEN                       PL          NaN
4           NaN  14400    TITUS                         ST          NaN

  latitude  longitude
0  34.0141  -118.2978
1  34.0459  -118.2545
2  34.0448  -118.2474
3  34.1685  -118.4019
4  34.2198  -118.4468

[5 rows x 27 columns]
```

[3]:
```
crime.columns
```

[3]:
```
Index(['division_number', 'date_reported', 'date_occurred', 'area',
       'area_name', 'reporting_district', 'part', 'crime_code',
       'crime_description', 'modus_operandi', 'victim_age', 'victim_sex',
       'victim_descent', 'premise_code', 'premise_description', 'weapon_code',
       'weapon_description', 'status', 'status_description', 'crime_code_1',
       'crime_code_2', 'crime_code_3', 'crime_code_4', 'location',
       'cross_street', 'latitude', 'longitude'],
      dtype='object')
```

[4]:
```
crime.shape
```

[4]:
```
(852950, 27)
```

[5]:
```
crime.dtypes
```

[5]:
```
division_number          int64
date_reported           object
date_occurred           object
area                     int64
area_name               object
reporting_district       int64
part                     int64
crime_code               int64
crime_description       object
modus_operandi          object
victim_age               int64
victim_sex              object
victim_descent          object
premise_code           float64
premise_description     object
```

```
weapon_code              float64
weapon_description        object
status                    object
status_description        object
crime_code_1             float64
crime_code_2             float64
crime_code_3             float64
crime_code_4             float64
location                  object
cross_street              object
latitude                 float64
longitude                float64
dtype: object
```

[6]:
```python
#Check for Null values
crime.isna().sum()
```

[6]:
```
division_number              0
date_reported                0
date_occurred                0
area                         0
area_name                    0
reporting_district           0
part                         0
crime_code                   0
crime_description            0
modus_operandi          118311
victim_age                   0
victim_sex              112606
victim_descent          112614
premise_code                10
premise_description        518
weapon_code             556202
weapon_description      556202
status                       0
status_description           0
crime_code_1                11
crime_code_2            790429
crime_code_3            850837
crime_code_4            852888
location                     0
cross_street            717289
latitude                     0
longitude                    0
dtype: int64
```

[7]:
```
#Remove high null and irrelevant columns
df = crime.drop(labels = ['modus_operandi', 'weapon_description',\
                          'weapon_code', 'crime_code_2',\
                          'crime_code_3', 'crime_code_4',\
                          'cross_street'], axis = 1)
```

[8]:
```
df
```

[8]:
```
        division_number date_reported       date_occurred  area    area_name  \
0              10304468    2020-01-08 2020-01-08 22:30:00     3    Southwest
1             190101086    2020-01-02 2020-01-01 03:30:00     1      Central
2             200110444    2020-04-14 2020-02-13 12:00:00     1      Central
3             191501505    2020-01-01 2020-01-01 17:30:00    15  N Hollywood
4             191921269    2020-01-01 2020-01-01 04:15:00    19      Mission
…                   …           …                 …   …          …
852945        231606525    2023-03-22 2023-03-22 10:00:00    16     Foothill
852946        231210064    2023-04-12 2023-04-12 16:30:00    12  77th Street
852947        230115220    2023-07-02 2023-07-01 00:01:00     1      Central
852948        230906458    2023-03-05 2023-03-05 09:00:00     9    Van Nuys
852949        230319786    2023-11-10 2023-11-09 23:00:00     3    Southwest

        reporting_district  part  crime_code  \
0                      377     2         624
1                      163     2         624
2                      155     2         845
3                     1543     2         745
4                     1998     2         740
…                      …   …         …
852945                1602     1         230
852946                1239     1         230
852947                 154     1         352
852948                 914     2         745
852949                 395     1         331

                                    crime_description  victim_age  \
0                            BATTERY - SIMPLE ASSAULT          36
1                            BATTERY - SIMPLE ASSAULT          25
2             SEX OFFENDER REGISTRANT OUT OF COMPLIANCE           0
3              VANDALISM - MISDEAMEANOR ($399 OR UNDER)          76
4       VANDALISM - FELONY ($400 & OVER, ALL CHURCH VA…        31
…                                                   …          …
852945     ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT          25
852946     ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT          29
852947                                         PICKPOCKET          24
852948         VANDALISM - MISDEAMEANOR ($399 OR UNDER)          53
852949  THEFT FROM MOTOR VEHICLE - GRAND ($950.01 AND …        38
```

```
       victim_sex victim_descent  premise_code  \
0               F              B         501.0
1               M              H         102.0
2               X              X         726.0
3               F              W         502.0
4               X              X         409.0
…             …              …             …
852945          F              H         102.0
852946          M              B         222.0
852947          F              H         735.0
852948          F              H         502.0
852949          M              W         501.0

                                  premise_description status  \
0                              SINGLE FAMILY DWELLING     AO
1                                            SIDEWALK     IC
2                                     POLICE FACILITY     AA
3       MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)     IC
4                                 BEAUTY SUPPLY STORE     IC
…                                                 …    …
852945                                       SIDEWALK     IC
852946                                     LAUNDROMAT     IC
852947                NIGHT CLUB (OPEN EVENINGS ONLY)     IC
852948  MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)     IC
852949                         SINGLE FAMILY DWELLING     IC

       status_description  crime_code_1  \
0             Adult Other         624.0
1             Invest Cont         624.0
2            Adult Arrest         845.0
3             Invest Cont         745.0
4             Invest Cont         740.0
…                     …           …
852945        Invest Cont         230.0
852946        Invest Cont         230.0
852947        Invest Cont         352.0
852948        Invest Cont         745.0
852949        Invest Cont         331.0

                                        location  latitude  longitude
0        1100 W  39TH                         PL   34.0141  -118.2978
1         700 S  HILL                         ST   34.0459  -118.2545
2         200 E  6TH                          ST   34.0448  -118.2474
3         5400    CORTEEN                     PL   34.1685  -118.4019
4        14400    TITUS                       ST   34.2198  -118.4468
…                                            …       …        …
852945  12800    FILMORE                      ST   34.2790  -118.4116
```

```
852946   6100 S  VERMONT                     AV   33.9841  -118.2915
852947    500 S  MAIN                        ST   34.0467  -118.2485
852948  14500    HARTLAND                    ST   34.1951  -118.4487
852949   4100 S  HOBART                      BL   34.0091  -118.3078

[852950 rows x 20 columns]
```

[9]:
```
df.sort_values(by = 'date_reported')
```

[9]:
```
        division_number date_reported         date_occurred  area    area_name  \
39025         201004026    2020-01-01  2020-01-01 18:23:00    10  West Valley
137157        202100503    2020-01-01  2020-01-01 13:15:00    21     Topanga
2389          200304056    2020-01-01  2020-01-01 14:37:00     3   Southwest
103594        201804032    2020-01-01  2020-01-01 12:50:00    18   Southeast
25891         200104434    2020-01-01  2020-01-01 02:50:00     1     Central
…                   …           …                   …   …          …
770235        230125557    2023-12-04  2023-12-04 06:50:00     1     Central
692345        231917421    2023-12-04  2023-12-03 09:45:00    19     Mission
835683        232117291    2023-12-04  2023-03-01 12:00:00    21     Topanga
825607        231116467    2023-12-04  2023-12-01 22:30:00    11   Northeast
676338        231116462    2023-12-04  2023-11-17 12:00:00    11   Northeast

        reporting_district  part  crime_code  \
39025                 1091     1         310
137157                2189     1         343
2389                   329     2         888
103594                1823     1         210
25891                  128     1         330
…                      …   …          …
770235                 111     1         330
692345                1936     1         420
835683                2125     2         354
825607                1141     1         331
676338                1173     2         354

                                     crime_description  victim_age  \
39025                                         BURGLARY          44
137157            SHOPLIFTING-GRAND THEFT ($950.01 & OVER)          75
2389                                       TRESPASSING          19
103594                                         ROBBERY          50
25891                               BURGLARY FROM VEHICLE          26
…                                                    …         …
770235                              BURGLARY FROM VEHICLE           0
692345     THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER)           0
835683                                  THEFT OF IDENTITY           0
825607   THEFT FROM MOTOR VEHICLE - GRAND ($950.01 AND …           0
676338                                  THEFT OF IDENTITY           0
```

```
       victim_sex victim_descent  premise_code  \
39025           M              O         504.0
137157          M              X         402.0
2389            X              X         255.0
103594          M              B         102.0
25891           F              W         108.0
…             …              …           …
770235        NaN            NaN         717.0
692345        NaN            NaN         101.0
835683        NaN            NaN         502.0
825607        NaN            NaN         101.0
676338        NaN            NaN         502.0

                                   premise_description status  \
39025                                  OTHER RESIDENCE     IC
137157                                          MARKET     AA
2389    AUTO DEALERSHIP (CHEVY, FORD, BMW, MERCEDES, E…     IC
103594                                        SIDEWALK     IC
25891                                      PARKING LOT     AO
…                                                   …    …
770235                                 HEALTH SPA/GYM     IC
692345                                          STREET     IC
835683       MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)     IC
825607                                          STREET     IC
676338       MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)     IC

       status_description  crime_code_1  \
39025         Invest Cont         310.0
137157       Adult Arrest         343.0
2389          Invest Cont         888.0
103594        Invest Cont         210.0
25891         Adult Other         330.0
…                    …            …
770235        Invest Cont         330.0
692345        Invest Cont         420.0
835683        Invest Cont         354.0
825607        Invest Cont         331.0
676338        Invest Cont         354.0

                                         location  latitude  longitude
39025    3800    WINFORD                       DR   34.1386  -118.5525
137157  20000 W  VENTURA                       BL   34.1719  -118.5684
2389     3300 S  FIGUEROA                      ST   34.0225  -118.2796
103594                                    CENTURY   33.9456  -118.2652
25891     300 E  2ND                           ST   34.0498  -118.2400
…                                             …        …          …
```

```
770235    700 W  CESAR E CHAVEZ                AV   34.0606  -118.2439
692345  11400    AMBOY                         AV   34.2767  -118.4477
835683  21400    SATICOY                       ST   34.2119  -118.6017
825607         N  KENMORE                      AV   34.1018  -118.2973
676338   1900    ALLESANDRO                    ST   34.0900  -118.2587

[852950 rows x 20 columns]
```

[10]:
```
#Convert objects to datetimes where relevant and update datatypes
df['date_reported'] = pd.to_datetime(df['date_reported'], format = '%Y-%m-%d')
df['date_occurred'] = pd.to_datetime(df['date_occurred'], format = '%Y-%m-%d')
```

[11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 852950 entries, 0 to 852949
Data columns (total 20 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   division_number       852950 non-null  int64
 1   date_reported         852950 non-null  datetime64[ns]
 2   date_occurred         852950 non-null  datetime64[ns]
 3   area                  852950 non-null  int64
 4   area_name             852950 non-null  object
 5   reporting_district    852950 non-null  int64
 6   part                  852950 non-null  int64
 7   crime_code            852950 non-null  int64
 8   crime_description     852950 non-null  object
 9   victim_age            852950 non-null  int64
 10  victim_sex            740344 non-null  object
 11  victim_descent        740336 non-null  object
 12  premise_code          852940 non-null  float64
 13  premise_description   852432 non-null  object
 14  status                852950 non-null  object
 15  status_description    852950 non-null  object
 16  crime_code_1          852939 non-null  float64
 17  location              852950 non-null  object
 18  latitude              852950 non-null  float64
 19  longitude             852950 non-null  float64
dtypes: datetime64[ns](2), float64(4), int64(6), object(8)
memory usage: 130.1+ MB
```

[12]:
```
df.describe(include = ['float64', 'int64'])
```

[12]:
```
       division_number           area  reporting_district           part  \
count     8.529500e+05  852950.000000       852950.000000  852950.000000
mean      2.166969e+08      10.707354         1117.165490       1.412575
std       1.100081e+07       6.097178          609.716073       0.492298
```

```
min       8.170000e+02       1.000000         101.000000        1.000000
25%       2.102184e+08       6.000000         615.000000        1.000000
50%       2.202184e+08      11.000000        1141.000000        1.000000
75%       2.301094e+08      16.000000        1617.000000        2.000000
max       2.399306e+08      21.000000        2199.000000        2.000000

          crime_code     victim_age   premise_code   crime_code_1  \
count  852950.000000  852950.000000  852940.000000  852939.000000
mean      500.746338      29.742191     305.974292     500.486350
std       207.705242      21.799470     216.950442     207.493864
min       110.000000      -3.000000     101.000000     110.000000
25%       331.000000       5.000000     101.000000     331.000000
50%       442.000000      31.000000     203.000000     442.000000
75%       626.000000      45.000000     501.000000     626.000000
max       956.000000     120.000000     976.000000     956.000000

            latitude      longitude
count  852950.000000  852950.000000
mean       33.983232    -118.040106
std         1.756263       6.089068
min         0.000000    -118.667600
25%        34.014100    -118.429700
50%        34.058500    -118.321500
75%        34.163200    -118.273900
max        34.334300       0.000000
```

[13]:
```
# Extract the 'victim_age' column into a new DataFrame
df['victim_age'].value_counts()
```

[13]:
```
 0      211842
 30      19421
 35      19008
 31      18603
 29      18552
         …
 97         63
-1          60
-2          13
 120         1
-3           1
Name: victim_age, Length: 103, dtype: int64
```

[14]:
```
# Filter out invalid negative ages and age 0
df_age = df[df['victim_age'] > 0]
```

[15]:
```
df_age['victim_age'].value_counts()
```

[15]:
```
30     19421
35     19008
31     18603
29     18552
28     18266
       …
95        89
96        88
98        67
97        63
120        1
Name: victim_age, Length: 99, dtype: int64
```

[16]:
```
#Adding year and month columns
df['year'] = df['date_occurred'].dt.year
df['month'] = df['date_occurred'].dt.month
```

[17]:
```
df.sort_values(by = 'date_reported')
```

[17]:
```
        division_number date_reported       date_occurred  area    area_name  \
39025         201004026    2020-01-01 2020-01-01 18:23:00    10  West Valley
137157        202100503    2020-01-01 2020-01-01 13:15:00    21      Topanga
2389          200304056    2020-01-01 2020-01-01 14:37:00     3    Southwest
103594        201804032    2020-01-01 2020-01-01 12:50:00    18    Southeast
25891         200104434    2020-01-01 2020-01-01 02:50:00     1      Central
…                   …           …                 …    …          …
770235        230125557    2023-12-04 2023-12-04 06:50:00     1      Central
692345        231917421    2023-12-04 2023-12-03 09:45:00    19      Mission
835683        232117291    2023-12-04 2023-03-01 12:00:00    21      Topanga
825607        231116467    2023-12-04 2023-12-01 22:30:00    11    Northeast
676338        231116462    2023-12-04 2023-11-17 12:00:00    11    Northeast

        reporting_district  part  crime_code  \
39025                 1091     1         310
137157                2189     1         343
2389                   329     2         888
103594                1823     1         210
25891                  128     1         330
…                     …    …          …
770235                 111     1         330
692345                1936     1         420
835683                2125     2         354
825607                1141     1         331
676338                1173     2         354

                                   crime_description  victim_age  …  \
39025                                       BURGLARY          44  …
```

```
137157          SHOPLIFTING-GRAND THEFT ($950.01 & OVER)          75  …
2389                                         TRESPASSING          19  …
103594                                           ROBBERY          50  …
25891                               BURGLARY FROM VEHICLE          26  …
…                                                     …          …   …
770235                              BURGLARY FROM VEHICLE           0  …
692345    THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER)           0  …
835683                                  THEFT OF IDENTITY           0  …
825607  THEFT FROM MOTOR VEHICLE - GRAND ($950.01 AND …          0  …
676338                                  THEFT OF IDENTITY           0  …

       premise_code                               premise_description  \
39025         504.0                                   OTHER RESIDENCE
137157        402.0                                            MARKET
2389          255.0  AUTO DEALERSHIP (CHEVY, FORD, BMW, MERCEDES, E…
103594        102.0                                          SIDEWALK
25891         108.0                                       PARKING LOT
…             …                                                     …
770235        717.0                                    HEALTH SPA/GYM
692345        101.0                                            STREET
835683        502.0       MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)
825607        101.0                                            STREET
676338        502.0       MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)

        status status_description crime_code_1  \
39025       IC        Invest Cont        310.0
137157      AA       Adult Arrest        343.0
2389        IC        Invest Cont        888.0
103594      IC        Invest Cont        210.0
25891       AO        Adult Other        330.0
…         …                …           …
770235      IC        Invest Cont        330.0
692345      IC        Invest Cont        420.0
835683      IC        Invest Cont        354.0
825607      IC        Invest Cont        331.0
676338      IC        Invest Cont        354.0

                                                location  latitude longitude  year  \
39025    3800    WINFORD                               DR   34.1386 -118.5525  2020
137157  20000 W  VENTURA                               BL   34.1719 -118.5684  2020
2389     3300 S  FIGUEROA                              ST   34.0225 -118.2796  2020
103594                                            CENTURY   33.9456 -118.2652  2020
25891     300 E  2ND                                   ST   34.0498 -118.2400  2020
…                                                   …         …         …    …
770235    700 W  CESAR E CHAVEZ                        AV   34.0606 -118.2439  2023
692345  11400    AMBOY                                 AV   34.2767 -118.4477  2023
835683  21400    SATICOY                               ST   34.2119 -118.6017  2023
```

```
825607         N   KENMORE                      AV    34.1018 -118.2973   2023
676338    1900     ALLESANDRO                   ST    34.0900 -118.2587   2023

        month
39025       1
137157      1
2389        1
103594      1
25891       1
…       …
770235     12
692345     12
835683      3
825607     12
676338     11

[852950 rows x 22 columns]
```

2.2 Feature Understanding

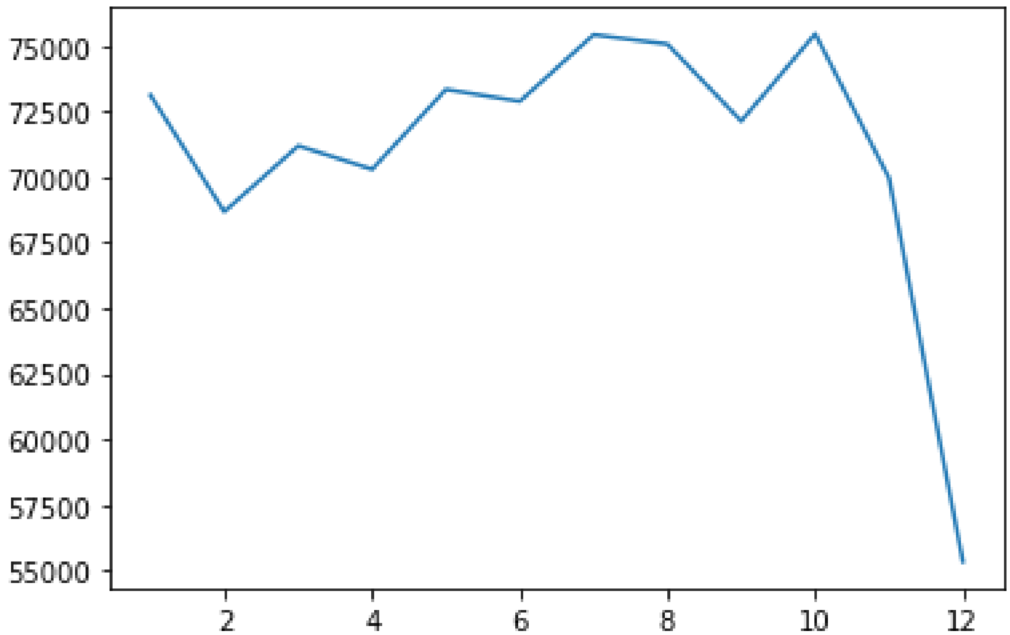
2.2.1 In this section, we explore and visualize various features of the crime data to gain insights into patterns and trends.

2.2.2 Key findings:

- The count of crime incidents varies by month, with higher counts generally observed in the middle months of the year.
- There is an increasing trend in the number of crime incidents from 2020 to 2022.
- The distribution of victim ages shows a peak in the 20-40 age range.
- The top 20 most frequent crimes are identified, with theft-related crimes being the most prevalent.

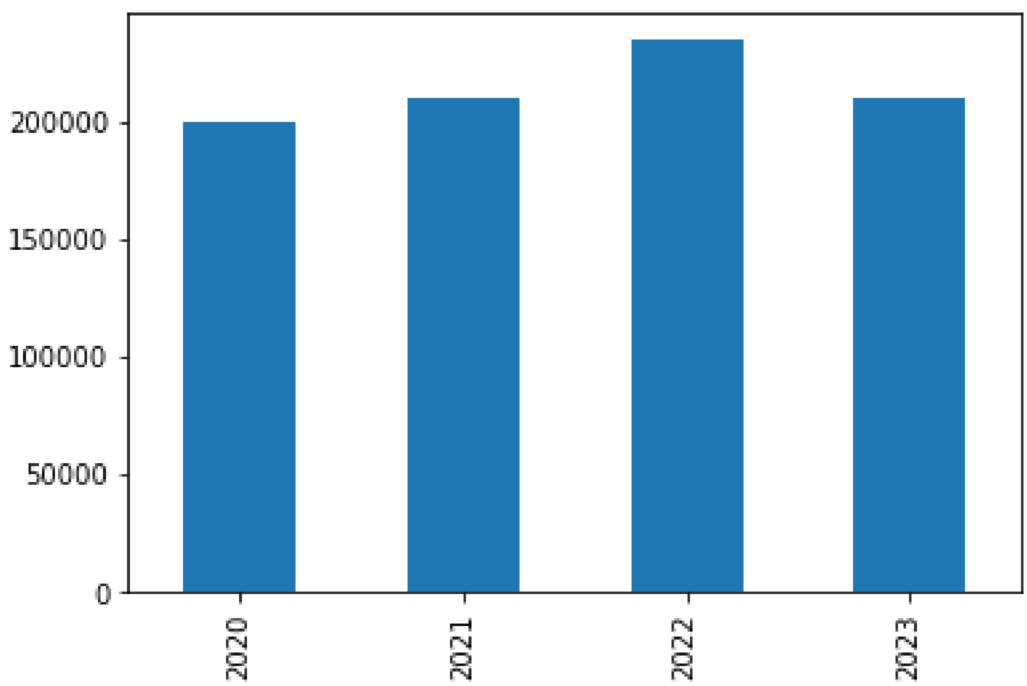
[18]:
```
# Plot the count of crime incidents by month
df['month'].value_counts().sort_index().plot()
```

[18]: <AxesSubplot:>



[19]:
```
# Plot the count of crime incidents by year as a bar chart
df['year'].value_counts().sort_index().plot(kind = 'bar')
```

[19]: <AxesSubplot:>



[20]:
```
# Remove rows where month is 12 and year is 2023 (incomplete data)
df = df[~((df['month'] == 12) & (df['year'] == 2023))]
```

[21]:
```
# Sort the DataFrame by the 'date_occurred' column
df.sort_values(by = 'date_occurred')
```

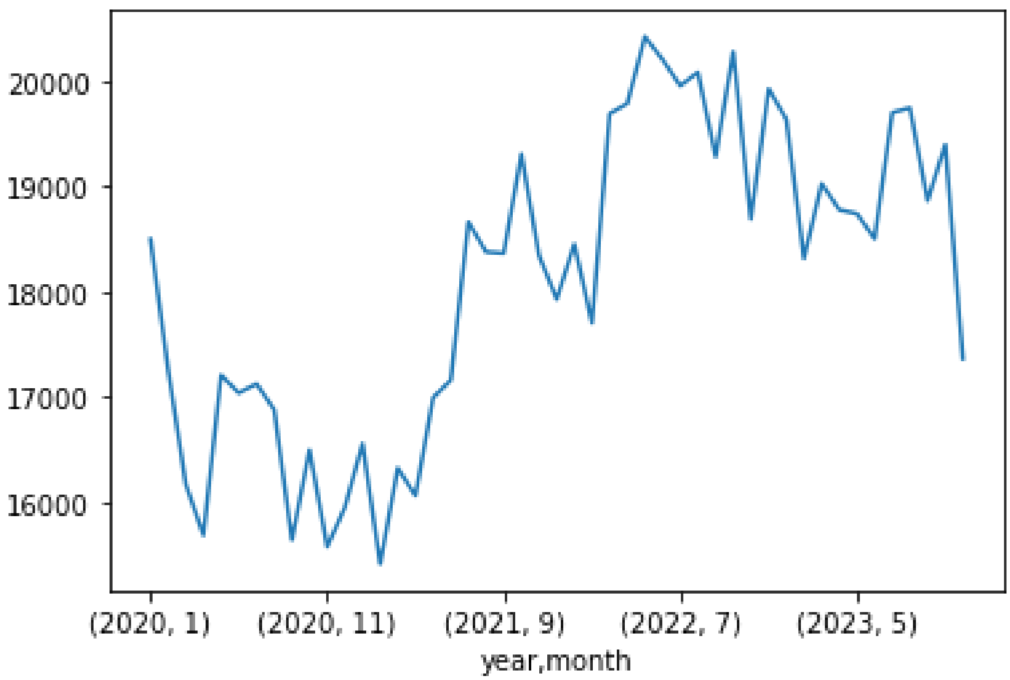
[21]:
```
        division_number date_reported       date_occurred  area   area_name  \
168264        201810982    2020-05-11 2020-01-01 00:01:00    18   Southeast
196441        220706832    2022-03-16 2020-01-01 00:01:00     7    Wilshire
1559          210708670    2021-05-11 2020-01-01 00:01:00     7    Wilshire
199361        221818077    2022-09-28 2020-01-01 00:01:00    18   Southeast
129124        201704365    2020-01-02 2020-01-01 00:01:00    17  Devonshire
…                   …           …                   …   …     …
672120        230717815    2023-12-01 2023-11-30 23:45:00     7    Wilshire
766816        230917064    2023-12-04 2023-11-30 23:48:00     9    Van Nuys
770137        230221843    2023-12-01 2023-11-30 23:50:00     2     Rampart
726894        231116332    2023-12-01 2023-11-30 23:50:00    11   Northeast
743649        232018618    2023-12-01 2023-11-30 23:59:00    20     Olympic

        reporting_district  part  crime_code  \
168264                1822     2         810
196441                 782     2         668
1559                   775     2         812
199361                1801     1         820
129124                1761     2         740
…                     …   …         …
672120                 702     1         310
766816                 984     1         310
770137                 216     1         510
726894                1132     2         888
743649                2044     2         930

                                         crime_description  victim_age  …  \
168264  SEX,UNLAWFUL(INC MUTUAL CONSENT, PENETRATION W…          17   …
196441         EMBEZZLEMENT, GRAND THEFT ($950.01 & OVER)           0  …
1559    CRM AGNST CHLD (13 OR UNDER) (14-15 & SUSP 10 …          13   …
199361                                      ORAL COPULATION           6  …
129124  VANDALISM - FELONY ($400 & OVER, ALL CHURCH VA…          23   …
…                                                      …         …  …
672120                                             BURGLARY          30  …
766816                                             BURGLARY           0  …
770137                                      VEHICLE - STOLEN           0  …
726894                                          TRESPASSING           0  …
743649                   CRIMINAL THREATS - NO WEAPON DISPLAYED          55  …
```

```
       premise_code                              premise_description  status  \
168264        501.0                            SINGLE FAMILY DWELLING      AO
196441        203.0                                    OTHER BUSINESS      IC
1559          710.0                                     OTHER PREMISE      AO
199361        501.0                            SINGLE FAMILY DWELLING      AO
129124        122.0                          VEHICLE, PASSENGER/TRUCK      IC
…             …                                                   …     …
672120        501.0                            SINGLE FAMILY DWELLING      IC
766816        501.0                            SINGLE FAMILY DWELLING      IC
770137        101.0                                            STREET      IC
726894        203.0                                    OTHER BUSINESS      IC
743649        502.0  MULTI-UNIT DWELLING (APARTMENT, DUPLEX, ETC)      IC

       status_description crime_code_1  \
168264        Adult Other        810.0
196441        Invest Cont        668.0
1559          Adult Other        812.0
199361        Adult Other        812.0
129124        Invest Cont        740.0
…                     …          …
672120        Invest Cont        310.0
766816        Invest Cont        310.0
770137        Invest Cont        510.0
726894        Invest Cont        888.0
743649        Invest Cont        930.0

                                        location  latitude longitude  year  \
168264    400 W  CENTURY                      BL   33.9456 -118.2808  2020
196441   1800 S  FAIRFAX                      AV   34.0431 -118.3692  2020
1559     1700 S  LONGWOOD                     AV   34.0437 -118.3440  2020
199361    500 W  92ND                         ST   33.9528 -118.2827  2020
129124   9500    OWENSMOUTH                   AV   34.2427 -118.6021  2020
…                                          …        …         …    …
672120    700 N  VISTA                        ST   34.0836 -118.3523  2023
766816  14600    SUTTON                       ST   34.1477 -118.4530  2023
770137   1000    CORONADO                     TR   34.0777 -118.2688  2023
726894   3200    RIVERSIDE                    DR   34.1143 -118.2695  2023
743649    900 S  KINGSLEY                     DR   34.0559 -118.3031  2023

        month
168264      1
196441      1
1559        1
199361      1
129124      1
…       …
672120     11
```

```
766816      11
770137      11
726894      11
743649      11

[851405 rows x 22 columns]
```

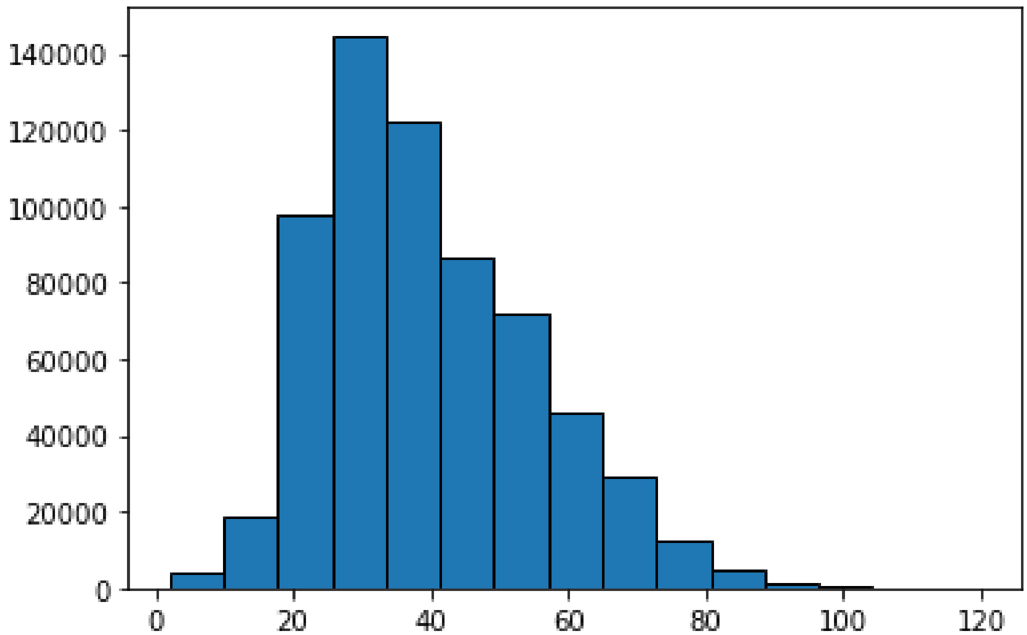
[22]:
```python
# Plot the count of crime incidents by year and month
crime_over_time = df.groupby(['year', 'month']).size().plot()
crime_over_time
```

[22]:
```
<AxesSubplot:xlabel='year,month'>
```



[23]:
```python
# Plot a histogram of victim ages
plt.hist(df_age['victim_age'], edgecolor = 'black', bins = 15)
```

[23]:
```
(array([3.96800e+03, 1.86630e+04, 9.81120e+04, 1.44858e+05, 1.22469e+05,
        8.64850e+04, 7.20760e+04, 4.59690e+04, 2.94150e+04, 1.28000e+04,
        4.50300e+03, 1.27400e+03, 4.41000e+02, 0.00000e+00, 1.00000e+00]),
 array([  2.        ,   9.86666667,  17.73333333,  25.6       ,
         33.46666667,  41.33333333,  49.2       ,  57.06666667,
         64.93333333,  72.8       ,  80.66666667,  88.53333333,
         96.4       , 104.26666667, 112.13333333, 120.        ]),
 <BarContainer object of 15 artists>)
```



[24]:
```python
df['date_occurred_no_time'] = df['date_occurred'].dt.date
```

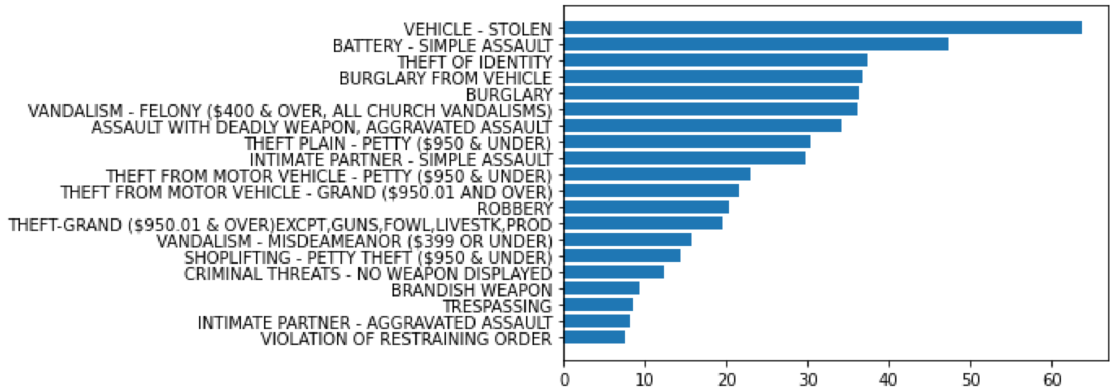
[25]:
```python
#Calculate average daily count of crimes
crime_count_per_day = df.groupby(['date_occurred_no_time',␣
↪'crime_description']).size()
```

[26]:
```python
#Calculate top 20 daily crimes
top_20_crimes = crime_count_per_day.groupby('crime_description').mean()\
.reset_index(name = 'average_daily_count').\
sort_values(by = 'average_daily_count', ascending = False).head(20)
```

[27]:
```python
top_20_sorted = top_20_crimes.sort_values(by = 'average_daily_count', ascending␣
↪= True)
```

[28]:
```python
#Plot the top 20 cri'Oomes
plt.barh(top_20_sorted['crime_description'],␣
↪top_20_sorted['average_daily_count'])
```

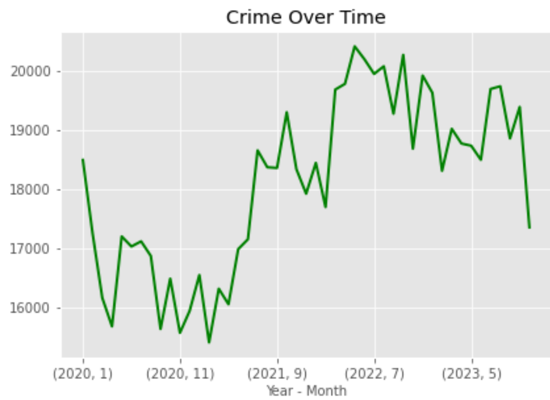
[28]:
```
<BarContainer object of 20 artists>
```

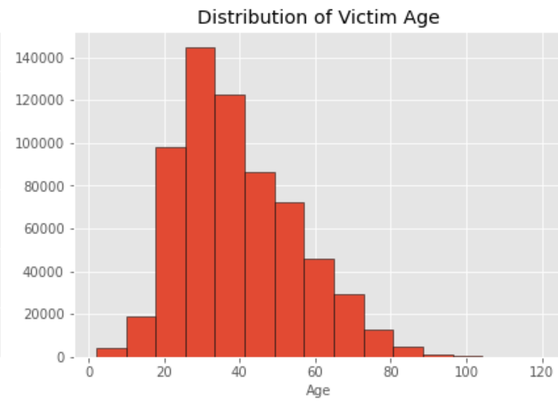


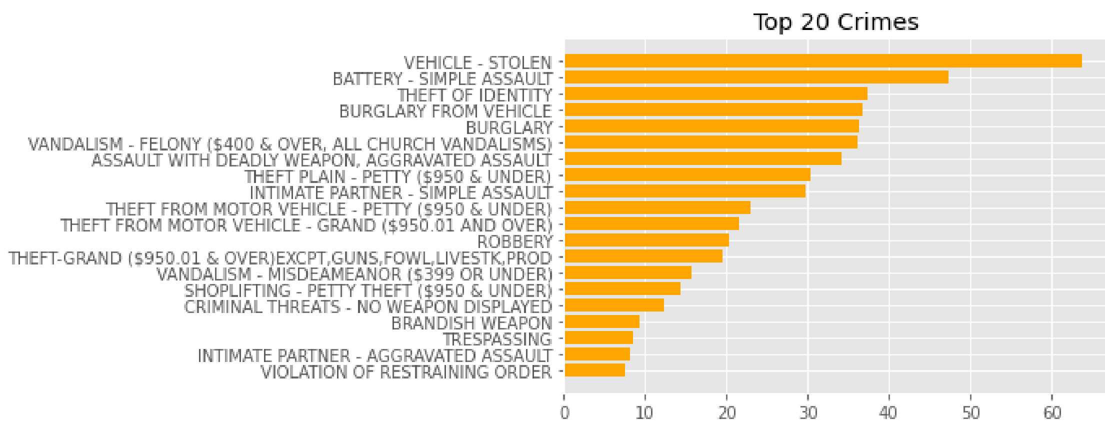
[29]:
```python
plt.style.use('ggplot')
```

[30]:
```python
plt.figure(figsize = (12, 8))

# Plot 1, line chart
plt.subplot(2, 2, 1)
crime_plot = df.groupby(['year', 'month']).size().plot(color = 'green',␣
 ↪linewidth = 2)
crime_plot.set_xlabel('Year - Month', fontsize = 10)
crime_plot.set_title('Crime Over Time')
# Plot 2, histogram of victim ages
plt.subplot(2, 2, 2)
plt.hist(df_age['victim_age'], edgecolor = 'black', bins = 15)
plt.xlabel('Age', fontsize = 10)
plt.tight_layout()
plt.title('Distribution of Victim Age')
#Plot 3, top 20 crimes
plt.figure()
plt.barh(top_20_sorted['crime_description'],␣
 ↪top_20_sorted['average_daily_count'], color = 'orange')
plt.title('Top 20 Crimes')
```

[30]:
```
Text(0.5, 1.0, 'Top 20 Crimes')
```







2.3 Time Taken to Report Crime

2.3.1 In this section, we analyze the time difference between when a crime occurred and when it was reported.

2.3.2 Key observations:

- A large number of crimes are reported on the same day they occur (time difference of 0 days).
- Some crime types have longer average reporting times than others.

[31]:
```
# Show the difference in time for crime reported vs occurred
df['Time to report'] = (pd.to_datetime(df['date_reported']) - pd.
↪to_datetime(df['date_occurred_no_time'])).dt.days
```

[32]:
```
df
```

[32]:
```
   division_number date_reported       date_occurred  area   area_name  \
0         10304468    2020-01-08 2020-01-08 22:30:00     3   Southwest
1        190101086    2020-01-02 2020-01-01 03:30:00     1     Central
```

```
2            200110444   2020-04-14 2020-02-13 12:00:00     1      Central
3            191501505   2020-01-01 2020-01-01 17:30:00    15  N Hollywood
4            191921269   2020-01-01 2020-01-01 04:15:00    19      Mission
…                …           …                   …   …         …
852945       231606525   2023-03-22 2023-03-22 10:00:00    16     Foothill
852946       231210064   2023-04-12 2023-04-12 16:30:00    12  77th Street
852947       230115220   2023-07-02 2023-07-01 00:01:00     1      Central
852948       230906458   2023-03-05 2023-03-05 09:00:00     9     Van Nuys
852949       230319786   2023-11-10 2023-11-09 23:00:00     3    Southwest

        reporting_district  part  crime_code  \
0                      377     2         624
1                      163     2         624
2                      155     2         845
3                     1543     2         745
4                     1998     2         740
…                      …   …           …
852945                1602     1         230
852946                1239     1         230
852947                 154     1         352
852948                 914     2         745
852949                 395     1         331

                                     crime_description  victim_age  …  \
0                             BATTERY - SIMPLE ASSAULT          36  …
1                             BATTERY - SIMPLE ASSAULT          25  …
2             SEX OFFENDER REGISTRANT OUT OF COMPLIANCE          0  …
3              VANDALISM - MISDEAMEANOR ($399 OR UNDER)         76  …
4       VANDALISM - FELONY ($400 & OVER, ALL CHURCH VA…         31  …
…                                                   …         …  …
852945     ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT       25  …
852946     ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT       29  …
852947                                        PICKPOCKET       24  …
852948         VANDALISM - MISDEAMEANOR ($399 OR UNDER)         53  …
852949  THEFT FROM MOTOR VEHICLE - GRAND ($950.01 AND …         38  …

       status status_description  crime_code_1  \
0          AO        Adult Other         624.0
1          IC        Invest Cont         624.0
2          AA       Adult Arrest         845.0
3          IC        Invest Cont         745.0
4          IC        Invest Cont         740.0
…       …                 …             …
852945     IC        Invest Cont         230.0
852946     IC        Invest Cont         230.0
852947     IC        Invest Cont         352.0
852948     IC        Invest Cont         745.0
```

```
852949      IC        Invest Cont         331.0

                                         location latitude longitude   year  \
0        1100 W  39TH                          PL  34.0141 -118.2978  2020
1         700 S  HILL                          ST  34.0459 -118.2545  2020
2         200 E  6TH                           ST  34.0448 -118.2474  2020
3        5400    CORTEEN                       PL  34.1685 -118.4019  2020
4       14400    TITUS                         ST  34.2198 -118.4468  2020
…                                           …       …         …    …
852945  12800    FILMORE                       ST  34.2790 -118.4116  2023
852946   6100 S  VERMONT                       AV  33.9841 -118.2915  2023
852947    500 S  MAIN                          ST  34.0467 -118.2485  2023
852948  14500    HARTLAND                      ST  34.1951 -118.4487  2023
852949   4100 S  HOBART                        BL  34.0091 -118.3078  2023

       month  date_occurred_no_time  Time to report
0          1             2020-01-08               0
1          1             2020-01-01               1
2          2             2020-02-13              61
3          1             2020-01-01               0
4          1             2020-01-01               0
…        …                    …               …
852945     3             2023-03-22               0
852946     4             2023-04-12               0
852947     7             2023-07-01               1
852948     3             2023-03-05               0
852949    11             2023-11-09               1

[851405 rows x 24 columns]
```

[33]:
```python
df['Time to report'].value_counts().head(10)
```

[33]:
```
0    419620
1    185029
2     52808
3     30894
4     19932
5     14416
6     10837
7      9722
8      7053
9      5660
Name: Time to report, dtype: int64
```

[34]:
```python
#Group by crime description and reporting times
df.groupby(['crime_description'])['Time to report'].mean().
 ↪sort_values(ascending = False).head(10)
```

[34]:
```
crime_description
CRM AGNST CHLD (13 OR UNDER) (14-15 & SUSP 10 YRS OLDER)    128.181013
SEX OFFENDER REGISTRANT OUT OF COMPLIANCE                   123.779056
SEX,UNLAWFUL(INC MUTUAL CONSENT, PENETRATION W/ FRGN OBJ    110.913921
LEWD/LASCIVIOUS ACTS WITH CHILD                              97.324675
DISHONEST EMPLOYEE ATTEMPTED THEFT                           87.000000
BIGAMY                                                       77.666667
SEXUAL PENETRATION W/FOREIGN OBJECT                          66.092946
ORAL COPULATION                                              62.078616
EMBEZZLEMENT, PETTY THEFT ($950 & UNDER)                     61.322581
EMBEZZLEMENT, GRAND THEFT ($950.01 & OVER)                   59.657109
Name: Time to report, dtype: float64
```

2.3.3 Identify the top 3 crimes with the highest average victim age

[35]:
```python
df_age.groupby('crime_description')['victim_age'].mean().reset_index().
 ↪sort_values(by = 'victim_age', ascending = False).head(3)
```

[35]:

	crime_description	victim_age
45	DISHONEST EMPLOYEE ATTEMPTED THEFT	60.000000
12	BLOCKING DOOR INDUCTION CENTER	54.666667
77	LYNCHING	53.000000

2.4 Areas With the Highest Crime Rates at Night

In this section, we identify the areas with the highest crime rates during nighttime hours (8 PM to 6 AM).

2.4.1 Key finding:

The top five areas with the highest nighttime crime rates are:

- Central (55,315 crimes)
- 77th Street (51,137 crimes)
- Pacific (47,889 crimes)
- Southwest (45,718 crimes)
- Hollywood (42,763 crimes)

The areas with the lowest nighttime crime rates are Foothill (27,267 crimes) and Hollenbeck (30,549 crimes). There is a significant variation in nighttime crime rates across different areas of Los Angeles.

[36]:
```python
crimes_at_night = df[(df['date_occurred'].dt.hour) >= 20 | (df['date_occurred'].
 ↪dt.hour <= 6)]
```

[37]:
```python
crimes_at_night['area_name'].value_counts().reset_index()
```

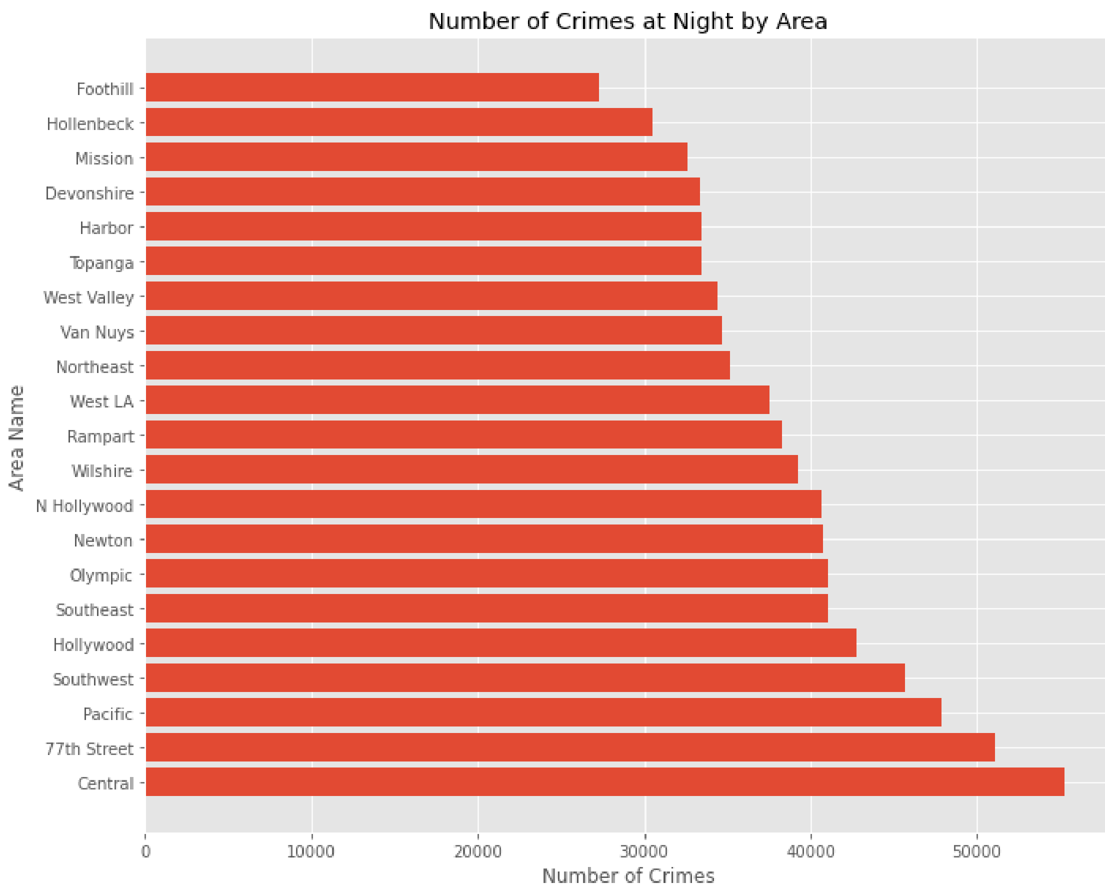
[37]:

	index	area_name
0	Central	55315

```
1    77th Street     51137
2        Pacific     47889
3      Southwest     45718
4      Hollywood     42763
5      Southeast     41080
6        Olympic     41050
7         Newton     40779
8    N Hollywood     40628
9       Wilshire     39196
10       Rampart     38310
11       West LA     37575
12     Northeast     35174
13      Van Nuys     34651
14  West Valley      34383
15       Topanga     33475
16        Harbor     33435
17    Devonshire     33340
18       Mission     32630
19    Hollenbeck     30549
20      Foothill     27267
```

[38]:

```python
crimes_at_night_counts = crimes_at_night['area_name'].value_counts().
 ↪reset_index()
crimes_at_night_counts.columns = ['area_name', 'count']

plt.figure(figsize=(10, 8))
plt.barh(crimes_at_night_counts['area_name'], crimes_at_night_counts['count'])
plt.xlabel('Number of Crimes')
plt.ylabel('Area Name')
plt.title('Number of Crimes at Night by Area')
plt.tight_layout()
plt.show()
```



2.5 Crime by the Hour

In this section, we analyze the distribution of crimes across different hours of the day.

2.5.1 Key observations:

- There is a notable peak in crime incidents around noon (12 PM).
- Identity theft is a significant contributor to the crime count at this hour.

[39]:
```
hourly_crime = df['date_occurred'].dt.hour.value_counts().sort_index().
    ↪reset_index()
hourly_crime.columns = ['hour', 'crime_count']
```

[40]:
```
hourly_crime
```

[40]:

	hour	crime_count
0	0	35061
1	1	25740
2	2	21801
3	3	19040

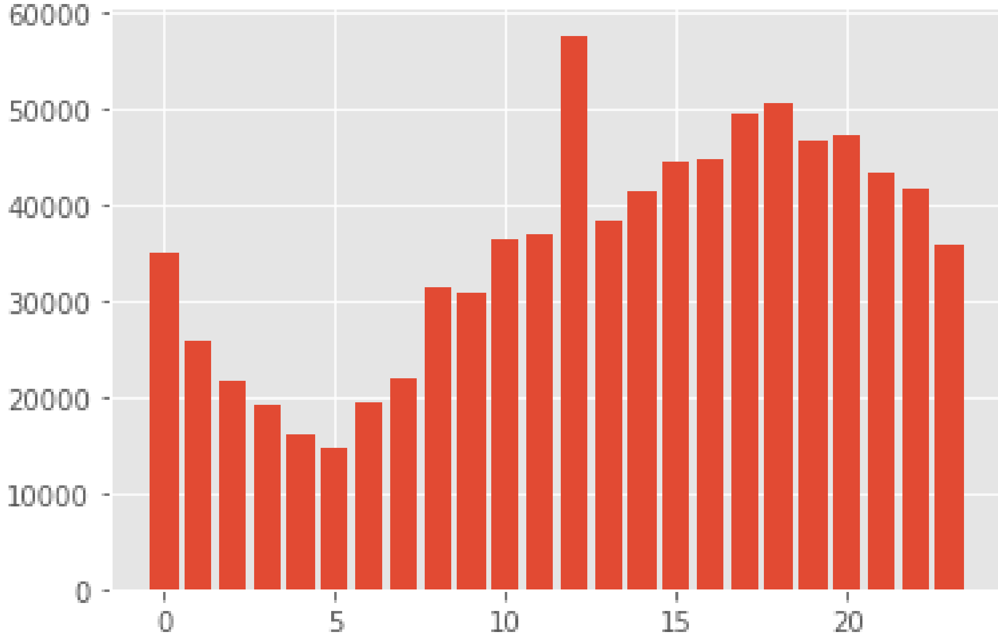
```
4      4          16099
5      5          14829
6      6          19484
7      7          21985
8      8          31428
9      9          30812
10     10         36461
11     11         36967
12     12         57683
13     13         38422
14     14         41494
15     15         44394
16     16         44754
17     17         49492
18     18         50606
19     19         46701
20     20         47399
21     21         43270
22     22         41704
23     23         35779
```

[41]:
```
hourly_crime.columns
```

[41]:
```
Index(['hour', 'crime_count'], dtype='object')
```

[42]:
```
#Crimes including identity theft
plt.bar(hourly_crime['hour'], hourly_crime['crime_count'])
```

[42]:
```
<BarContainer object of 24 artists>
```



[43]:
```
df[df['date_occurred'].dt.hour == 12]['crime_description'].value_counts()
```

[43]:
```
THEFT OF IDENTITY                                  9098
VEHICLE - STOLEN                                   4048
BATTERY - SIMPLE ASSAULT                           3958
THEFT PLAIN - PETTY ($950 & UNDER)                 3785
BURGLARY                                           2945
                                                   …
DRUGS, TO A MINOR                                     1
THEFT, COIN MACHINE - GRAND ($950.01 & OVER)          1
BIGAMY                                                1
GRAND THEFT / INSURANCE FRAUD                         1
INCITING A RIOT                                       1
Name: crime_description, Length: 124, dtype: int64
```

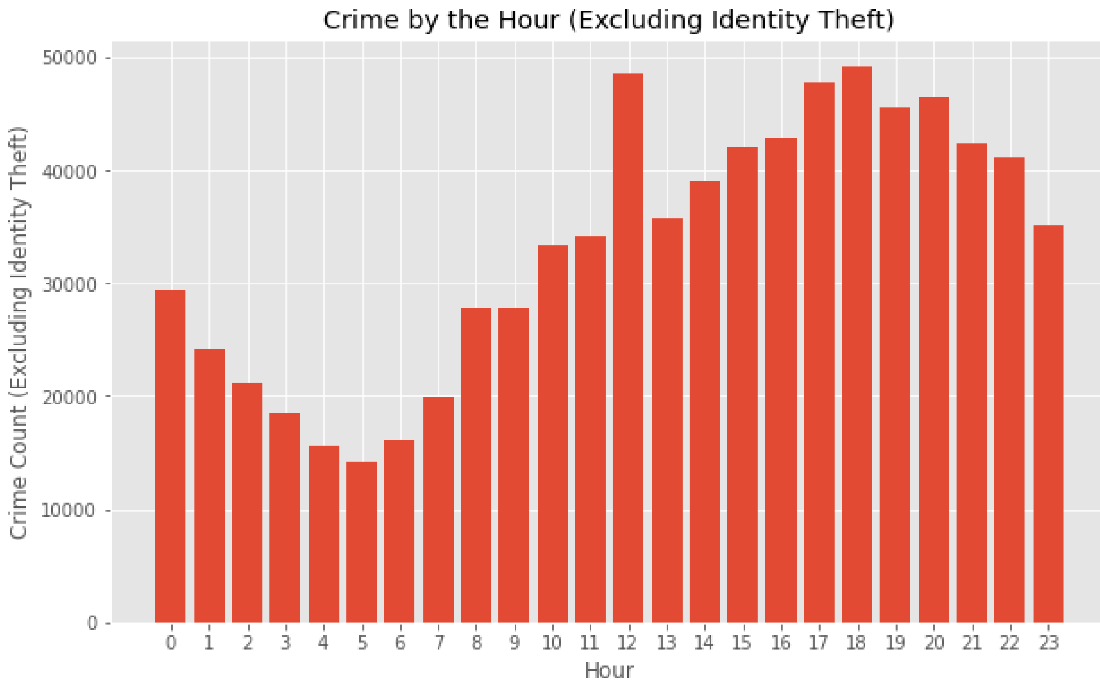
[44]:
```
#Filter out identity theft to focus on active crime reporting
no_id_theft = df[~(df['crime_description'] == 'THEFT OF IDENTITY')]
```

[45]:
```
new_hourly_count = no_id_theft['date_occurred'].dt.hour.value_counts().
  ↪sort_index().reset_index()
```

[46]:
```
new_hourly_count.columns = ['hour', 'crime_count']
```

[47]:
```
plt.figure(figsize=(10, 6))
plt.bar(new_hourly_count['hour'], new_hourly_count['crime_count'])
plt.xlabel('Hour')
```

```
plt.ylabel('Crime Count (Excluding Identity Theft)')
plt.title('Crime by the Hour (Excluding Identity Theft)')
plt.xticks(new_hourly_count['hour'])
plt.show()
```



3 Conclusion

3.0.1 This analysis provides a comprehensive overview of crime patterns in Los Angeles from 2020 to 2023. Key insights include:

- An increasing trend in crime incidents over the years.
- Seasonal variations in crime counts, with higher incidents in the middle months.
- Theft-related crimes being the most prevalent.
- Specific areas experiencing higher crime rates during nighttime hours.
- A significant peak in crime incidents around noon, largely driven by identity theft.

These findings can inform law enforcement strategies, resource allocation, and crime prevention initiatives in the City of Los Angeles. Further analysis could explore additional factors such as location-specific trends, demographic correlations, and the impact of socioeconomic conditions on crime rates.

3.1 Further Insights and Recommendations

The analysis of crime incidents in Los Angeles from 2020 to 2023 reveals several noteworthy patterns and trends that warrant further attention. While the overall increasing trend in crime incidents is concerning, it is crucial to delve deeper into the underlying factors contributing to this rise. Socioeconomic conditions, such as unemployment rates, income inequality, and housing affordability, may play a significant role in shaping crime patterns across different areas of the city. Investigating these factors and their correlation with crime rates could provide valuable insights for targeted interventions and support programs.

Moreover, the prominence of theft-related crimes highlights the need for enhanced crime prevention strategies. Strengthening community policing efforts, increasing surveillance in high-risk areas, and promoting public awareness campaigns could help deter potential offenders and reduce the incidence of theft. Additionally, the peak in crime incidents around noon, largely attributed to identity theft, underscores the importance of digital security and fraud prevention measures. Collaborating with financial institutions, educating the public about online safety, and enforcing stricter penalties for identity theft could help mitigate this specific crime category.

To further enhance the effectiveness of law enforcement efforts, it is recommended to conduct a more granular analysis of crime patterns at the neighborhood level. Identifying specific hotspots within each area and understanding the unique characteristics and challenges of these locations can enable more targeted and efficient deployment of resources. Furthermore, analyzing the temporal patterns of crime, such as seasonal variations and peak hours, can help optimize patrol schedules and ensure a more proactive approach to crime prevention.

Lastly, it is crucial to recognize the importance of community engagement and collaboration in addressing crime. Strengthening partnerships between law enforcement agencies, community organizations, and local residents can foster trust, encourage information sharing, and develop tailored solutions to address the specific needs and concerns of each neighborhood. By adopting a holistic and data-driven approach, the City of Los Angeles can work towards creating safer communities and reducing the overall impact of crime on its residents.

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