us_crime_data_exploration

August 30, 2023

1 Exploratory Analysis of Crime Patterns in the USA (June 2015 - September 2018)

Crime analysis plays a crucial role in understanding patterns, trends, and factors influencing criminal activities within a specific region and timeframe. In this project, we delve into a dataset containing crime incidents in the USA from June 2015 to September 2018. By utilizing Python, pandas, matplotlib, and seaborn, we aim to uncover insightful information about the nature of these crimes, their distribution across various parameters, and trends that could aid law enforcement agencies and policymakers in crime prevention strategies.

1.1 Introduction

Crime is a complex and multifaceted social phenomenon that requires a comprehensive approach for effective analysis. This project focuses on analyzing a dataset encompassing crime incidents spanning three years in the USA. The dataset contains information such as offense type, location, date, and other relevant attributes. By applying data analysis techniques, we aim to shed light on various aspects of these crimes, helping us understand patterns and trends that may inform crime mitigation strategies.

1.1.1 Methods

```
Data Preprocessing: Load the dataset using pandas, clean and format data, handle missing values

Exploratory Data Analysis (EDA):
    Most Common Offense Group: Identify the most frequent crime types by grouping offenses.
    Top Ten Crimes in Offense Group: Visualize the top ten specific crimes within the most comm
    Least Common Offense Group: Identify and explore the least common offense group.
    Year-wise Crime Distribution: Analyze crime distribution across years to identify trends.
    Day-wise Crime Distribution: Examine crime occurrence patterns across days of the week.
    Hour-wise Crime Distribution: Explore patterns of crime occurrence throughout the day.
    Day and Hour-wise Heatmap: Create a heatmap of crimes based on days and hours.
```

Import necessary libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

```
from encodings.aliases import aliases
```

1.2 Read CSV file and Cleaning the data

Set up correct encoding for the dataset

[2]:
```
alias_values = set(aliases.values())

for encoding in set(aliases.values()):
    try:
        df = pd.read_csv('crime.csv', nrows= 10, encoding= encoding)
        print('sucessful', encoding)
    except:
        pass
```

```
sucessful mac_turkish
sucessful cp858
sucessful mac_iceland
sucessful cp037
sucessful iso8859_6
sucessful cp1254
sucessful cp862
sucessful cp1026
sucessful iso8859_11
sucessful cp1125
sucessful iso8859_2
sucessful cp1250
sucessful cp1256
sucessful latin_1
sucessful cp1257
sucessful cp949
sucessful mac_cyrillic
sucessful cp1252
sucessful iso8859_9
sucessful iso8859_10
sucessful iso8859_14
sucessful kz1048
sucessful cp865
sucessful cp860
sucessful iso8859_16
sucessful cp863
sucessful cp866
sucessful cp1255
sucessful gb18030
sucessful cp857
sucessful iso8859_4
sucessful cp855
sucessful utf_16_le
```

```
sucessful hp_roman8
sucessful ptcp154
sucessful utf_16_be
sucessful cp500
sucessful cp852
sucessful gbk
sucessful cp1251
sucessful cp273
sucessful iso8859_15
sucessful iso8859_3
sucessful cp850
sucessful mac_roman
sucessful iso8859_13
sucessful mac_latin2
sucessful cp775
sucessful cp932
sucessful cp1258
sucessful cp861
sucessful cp1253
sucessful iso8859_7
sucessful iso8859_8
sucessful mac_greek
sucessful cp1140
sucessful big5hkscs
sucessful iso8859_5
sucessful cp864
sucessful cp869
sucessful koi8_r
sucessful cp437
```

Read the dataset

[3]:
```
crime = pd.read_csv('crime.csv', encoding='ISO-8859-11').squeeze()
crime.head(10)
```

[3]:

	INCIDENT_NUMBER	OFFENSE_CODE	OFFENSE_CODE_GROUP	\
0	I182070945	619	Larceny	
1	I182070943	1402	Vandalism	
2	I182070941	3410	Towed	
3	I182070940	3114	Investigate Property	
4	I182070938	3114	Investigate Property	
5	I182070936	3820	Motor Vehicle Accident Response	
6	I182070933	724	Auto Theft	
7	I182070932	3301	Verbal Disputes	
8	I182070931	301	Robbery	
9	I182070929	3301	Verbal Disputes	

	OFFENSE_DESCRIPTION	DISTRICT	REPORTING_AREA	\

```
0                          LARCENY ALL OTHERS      D14            808
1                                   VANDALISM      C11            347
2                           TOWED MOTOR VEHICLE       D4            151
3                          INVESTIGATE PROPERTY       D4            272
4                          INVESTIGATE PROPERTY       B3            421
5  M/V ACCIDENT INVOLVING PEDESTRIAN - INJURY      C11            398
6                                  AUTO THEFT       B2            330
7                              VERBAL DISPUTE       B2            584
8                            ROBBERY - STREET       C6            177
9                              VERBAL DISPUTE      C11            364

  SHOOTING     OCCURRED_ON_DATE  YEAR  MONTH DAY_OF_WEEK  HOUR    UCR_PART  \
0      NaN  2018-09-02 13:00:00  2018      9      Sunday    13    Part One
1      NaN  2018-08-21 00:00:00  2018      8     Tuesday     0    Part Two
2      NaN  2018-09-03 19:27:00  2018      9      Monday    19  Part Three
3      NaN  2018-09-03 21:16:00  2018      9      Monday    21  Part Three
4      NaN  2018-09-03 21:05:00  2018      9      Monday    21  Part Three
5      NaN  2018-09-03 21:09:00  2018      9      Monday    21  Part Three
6      NaN  2018-09-03 21:25:00  2018      9      Monday    21    Part One
7      NaN  2018-09-03 20:39:37  2018      9      Monday    20  Part Three
8      NaN  2018-09-03 20:48:00  2018      9      Monday    20    Part One
9      NaN  2018-09-03 20:38:00  2018      9      Monday    20  Part Three

              STREET        Lat       Long                    Location
0         LINCOLN ST  42.357791 -71.139371  (42.35779134, -71.13937053)
1           HECLA ST  42.306821 -71.060300  (42.30682138, -71.06030035)
2        CAZENOVE ST  42.346589 -71.072429  (42.34658879, -71.07242943)
3         NEWCOMB ST  42.334182 -71.078664  (42.33418175, -71.07866441)
4           DELHI ST  42.275365 -71.090361  (42.27536542, -71.09036101)
5         TALBOT AVE  42.290196 -71.071590  (42.29019621, -71.07159012)
6        NORMANDY ST  42.306072 -71.082733  (42.30607218, -71.08273260)
7            LAWN ST  42.327016 -71.105551  (42.32701648, -71.10555088)
8  MASSACHUSETTS AVE  42.331521 -71.070853  (42.33152148, -71.07085307)
9          LESLIE ST  42.295147 -71.058608  (42.29514664, -71.05860832)
```

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

[4]: (319073, 17)

[5]:
```
crime.duplicated().sum()
```

[5]: 23

[6]:
```
crime.drop_duplicates(inplace= True)
```

[7]:
```
crime.shape
```

[7]: (319050, 17)

1.3 Exploring the dataset

[8]:
```
crime.head(10)
```

[8]:

	INCIDENT_NUMBER	OFFENSE_CODE	OFFENSE_CODE_GROUP
0	I182070945	619	Larceny
1	I182070943	1402	Vandalism
2	I182070941	3410	Towed
3	I182070940	3114	Investigate Property
4	I182070938	3114	Investigate Property
5	I182070936	3820	Motor Vehicle Accident Response
6	I182070933	724	Auto Theft
7	I182070932	3301	Verbal Disputes
8	I182070931	301	Robbery
9	I182070929	3301	Verbal Disputes

	OFFENSE_DESCRIPTION	DISTRICT	REPORTING_AREA
0	LARCENY ALL OTHERS	D14	808
1	VANDALISM	C11	347
2	TOWED MOTOR VEHICLE	D4	151
3	INVESTIGATE PROPERTY	D4	272
4	INVESTIGATE PROPERTY	B3	421
5	M/V ACCIDENT INVOLVING PEDESTRIAN - INJURY	C11	398
6	AUTO THEFT	B2	330
7	VERBAL DISPUTE	B2	584
8	ROBBERY - STREET	C6	177
9	VERBAL DISPUTE	C11	364

	SHOOTING	OCCURRED_ON_DATE	YEAR	MONTH	DAY_OF_WEEK	HOUR	UCR_PART
0	NaN	2018-09-02 13:00:00	2018	9	Sunday	13	Part One
1	NaN	2018-08-21 00:00:00	2018	8	Tuesday	0	Part Two
2	NaN	2018-09-03 19:27:00	2018	9	Monday	19	Part Three
3	NaN	2018-09-03 21:16:00	2018	9	Monday	21	Part Three
4	NaN	2018-09-03 21:05:00	2018	9	Monday	21	Part Three
5	NaN	2018-09-03 21:09:00	2018	9	Monday	21	Part Three
6	NaN	2018-09-03 21:25:00	2018	9	Monday	21	Part One
7	NaN	2018-09-03 20:39:37	2018	9	Monday	20	Part Three
8	NaN	2018-09-03 20:48:00	2018	9	Monday	20	Part One
9	NaN	2018-09-03 20:38:00	2018	9	Monday	20	Part Three

	STREET	Lat	Long	Location
0	LINCOLN ST	42.357791	-71.139371	(42.35779134, -71.13937053)
1	HECLA ST	42.306821	-71.060300	(42.30682138, -71.06030035)
2	CAZENOVE ST	42.346589	-71.072429	(42.34658879, -71.07242943)
3	NEWCOMB ST	42.334182	-71.078664	(42.33418175, -71.07866441)

```
4           DELHI ST  42.275365 -71.090361  (42.27536542, -71.09036101)
5         TALBOT AVE  42.290196 -71.071590  (42.29019621, -71.07159012)
6        NORMANDY ST  42.306072 -71.082733  (42.30607218, -71.08273260)
7            LAWN ST  42.327016 -71.105551  (42.32701648, -71.10555088)
8  MASSACHUSETTS AVE  42.331521 -71.070853  (42.33152148, -71.07085307)
9          LESLIE ST  42.295147 -71.058608  (42.29514664, -71.05860832)
```

[9]:
```
crime.tail(10)
```

[9]:
```
       INCIDENT_NUMBER  OFFENSE_CODE OFFENSE_CODE_GROUP  \
319063   I080542626-00          3125    Warrant Arrests
319064   I080542626-00          1848     Drug Violation
319065   I080542626-00          1849     Drug Violation
319066   I060168073-00          1864     Drug Violation
319067   I060168073-00          3125    Warrant Arrests
319068   I050310906-00          3125    Warrant Arrests
319069   I030217815-08           111           Homicide
319070   I030217815-08          3125    Warrant Arrests
319071   I010370257-00          3125    Warrant Arrests
319072       142052550          3125    Warrant Arrests

                                OFFENSE_DESCRIPTION DISTRICT  \
319063                                WARRANT ARREST       A1
319064  DRUGS - POSS CLASS B - INTENT TO MFR DIST DISP       A1
319065            DRUGS - POSS CLASS B - COCAINE, ETC.       A1
319066     DRUGS - POSS CLASS D - INTENT MFR DIST DISP      E13
319067                                WARRANT ARREST      E13
319068                                WARRANT ARREST       D4
319069             MURDER, NON-NEGLIGIENT MANSLAUGHTER      E18
319070                                WARRANT ARREST      E18
319071                                WARRANT ARREST      E13
319072                                WARRANT ARREST       D4

       REPORTING_AREA SHOOTING     OCCURRED_ON_DATE  YEAR  MONTH DAY_OF_WEEK  \
319063            111      NaN  2015-08-12 12:00:00  2015      8   Wednesday
319064            111      NaN  2015-08-12 12:00:00  2015      8   Wednesday
319065            111      NaN  2015-08-12 12:00:00  2015      8   Wednesday
319066            912      NaN  2018-01-27 14:01:00  2018      1    Saturday
319067            912      NaN  2018-01-27 14:01:00  2018      1    Saturday
319068            285      NaN  2016-06-05 17:25:00  2016      6      Sunday
319069            520      NaN  2015-07-09 13:38:00  2015      7    Thursday
319070            520      NaN  2015-07-09 13:38:00  2015      7    Thursday
319071            569      NaN  2016-05-31 19:35:00  2016      5     Tuesday
319072            903      NaN  2015-06-22 00:12:00  2015      6      Monday

        HOUR    UCR_PART             STREET        Lat       Long  \
319063    12  Part Three        BOYLSTON ST  42.352312 -71.063705
```

```
319064    12    Part Two        BOYLSTON ST  42.352312 -71.063705
319065    12    Part Two        BOYLSTON ST  42.352312 -71.063705
319066    14    Part Two          CENTRE ST  42.322838 -71.100967
319067    14  Part Three          CENTRE ST  42.322838 -71.100967
319068    17  Part Three        COVENTRY ST  42.336951 -71.085748
319069    13    Part One           RIVER ST  42.255926 -71.123172
319070    13  Part Three           RIVER ST  42.255926 -71.123172
319071    19  Part Three  NEW WASHINGTON ST  42.302333 -71.111565
319072     0  Part Three      WASHINGTON ST  42.333839 -71.080290

                          Location
319063  (42.35231190, -71.06370510)
319064  (42.35231190, -71.06370510)
319065  (42.35231190, -71.06370510)
319066  (42.32283759, -71.10096723)
319067  (42.32283759, -71.10096723)
319068  (42.33695098, -71.08574813)
319069  (42.25592648, -71.12317207)
319070  (42.25592648, -71.12317207)
319071  (42.30233307, -71.11156487)
319072  (42.33383935, -71.08029038)
```

[10]:
```
crime.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 319050 entries, 0 to 319072
Data columns (total 17 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   INCIDENT_NUMBER      319050 non-null  object
 1   OFFENSE_CODE         319050 non-null  int64
 2   OFFENSE_CODE_GROUP   319050 non-null  object
 3   OFFENSE_DESCRIPTION  319050 non-null  object
 4   DISTRICT             317285 non-null  object
 5   REPORTING_AREA       319050 non-null  object
 6   SHOOTING             1019 non-null    object
 7   OCCURRED_ON_DATE     319050 non-null  object
 8   YEAR                 319050 non-null  int64
 9   MONTH                319050 non-null  int64
 10  DAY_OF_WEEK          319050 non-null  object
 11  HOUR                 319050 non-null  int64
 12  UCR_PART             318960 non-null  object
 13  STREET               308179 non-null  object
 14  Lat                  299052 non-null  float64
 15  Long                 299052 non-null  float64
 16  Location             319050 non-null  object
dtypes: float64(2), int64(4), object(11)
```

```
memory usage: 43.8+ MB
```

[11]:
```
crime.OCCURRED_ON_DATE = pd.to_datetime(crime.OCCURRED_ON_DATE)
```

[12]:
```
crime.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 319050 entries, 0 to 319072
Data columns (total 17 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   INCIDENT_NUMBER      319050 non-null  object
 1   OFFENSE_CODE         319050 non-null  int64
 2   OFFENSE_CODE_GROUP   319050 non-null  object
 3   OFFENSE_DESCRIPTION  319050 non-null  object
 4   DISTRICT             317285 non-null  object
 5   REPORTING_AREA       319050 non-null  object
 6   SHOOTING             1019 non-null    object
 7   OCCURRED_ON_DATE     319050 non-null  datetime64[ns]
 8   YEAR                 319050 non-null  int64
 9   MONTH                319050 non-null  int64
 10  DAY_OF_WEEK          319050 non-null  object
 11  HOUR                 319050 non-null  int64
 12  UCR_PART             318960 non-null  object
 13  STREET               308179 non-null  object
 14  Lat                  299052 non-null  float64
 15  Long                 299052 non-null  float64
 16  Location             319050 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(4), object(10)
memory usage: 43.8+ MB
```

[13]:
```
crime.describe(include = object)
```

[13]:

	INCIDENT_NUMBER	OFFENSE_CODE_GROUP	OFFENSE_DESCRIPTION	DISTRICT	REPORTING_AREA	SHOOTING	DAY_OF_WEEK	UCR_PART	STREET	Location
count	319050	319050	319050	317285	319050	1019	319050	318960	308179	319050
unique	282517	67	244	12	879	1				
top	I162030584	Motor Vehicle Accident Response	SICK/INJURED/MEDICAL - PERSON	B2		Y				
freq	13	37132	18783	49940	20250	1019				

```
unique           7           4           4657                       18194
top         Friday  Part Three  WASHINGTON ST  (0.00000000, 0.00000000)
freq         48489      158537          14192                       19998
```

Checking the columns

[14]:
```
crime.columns
```

[14]:
```
Index(['INCIDENT_NUMBER', 'OFFENSE_CODE', 'OFFENSE_CODE_GROUP',
       'OFFENSE_DESCRIPTION', 'DISTRICT', 'REPORTING_AREA', 'SHOOTING',
       'OCCURRED_ON_DATE', 'YEAR', 'MONTH', 'DAY_OF_WEEK', 'HOUR', 'UCR_PART',
       'STREET', 'Lat', 'Long', 'Location'],
      dtype='object')
```

[15]:
```
crime.isnull()
```

[15]:
```
        INCIDENT_NUMBER  OFFENSE_CODE  OFFENSE_CODE_GROUP  \
0                 False         False               False
1                 False         False               False
2                 False         False               False
3                 False         False               False
4                 False         False               False
…                     …             …                   …
319068            False         False               False
319069            False         False               False
319070            False         False               False
319071            False         False               False
319072            False         False               False

        OFFENSE_DESCRIPTION  DISTRICT  REPORTING_AREA  SHOOTING  \
0                     False     False           False      True
1                     False     False           False      True
2                     False     False           False      True
3                     False     False           False      True
4                     False     False           False      True
…                         …         …               …         …
319068                False     False           False      True
319069                False     False           False      True
319070                False     False           False      True
319071                False     False           False      True
319072                False     False           False      True

        OCCURRED_ON_DATE   YEAR  MONTH  DAY_OF_WEEK   HOUR  UCR_PART  STREET  \
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
…                  …    …    …          …    …       …     …
319068             False  False  False        False  False     False   False
319069             False  False  False        False  False     False   False
319070             False  False  False        False  False     False   False
319071             False  False  False        False  False     False   False
319072             False  False  False        False  False     False   False

          Lat   Long  Location
0       False  False     False
1       False  False     False
2       False  False     False
3       False  False     False
4       False  False     False
…       …    …       …
319068  False  False     False
319069  False  False     False
319070  False  False     False
319071  False  False     False
319072  False  False     False

[319050 rows x 17 columns]
```

Checking columns with missing values

[16]:
```
crime.columns[np.sum(crime.isnull()) != 0]
```

[16]:
```
Index(['DISTRICT', 'SHOOTING', 'UCR_PART', 'STREET', 'Lat', 'Long'],
dtype='object')
```

Checking columns with no missing valuse

[17]:
```
crime.columns[np.sum(crime.isnull()) == 0]
```

[17]:
```
Index(['INCIDENT_NUMBER', 'OFFENSE_CODE', 'OFFENSE_CODE_GROUP',
       'OFFENSE_DESCRIPTION', 'REPORTING_AREA', 'OCCURRED_ON_DATE', 'YEAR',
       'MONTH', 'DAY_OF_WEEK', 'HOUR', 'Location'],
      dtype='object')
```

Checking number of unique values in each columns

[18]:
```
for col in crime.columns:
    unique_count = crime[col].nunique()
    print(col + ' has ' + str(unique_count)+ " unique values ")
```

```
INCIDENT_NUMBER has 282517 unique values
OFFENSE_CODE has 222 unique values
OFFENSE_CODE_GROUP has 67 unique values
```

```
OFFENSE_DESCRIPTION has 244 unique values
DISTRICT has 12 unique values
REPORTING_AREA has 879 unique values
SHOOTING has 1 unique values
OCCURRED_ON_DATE has 233229 unique values
YEAR has 4 unique values
MONTH has 12 unique values
DAY_OF_WEEK has 7 unique values
HOUR has 24 unique values
UCR_PART has 4 unique values
STREET has 4657 unique values
Lat has 18178 unique values
Long has 18178 unique values
Location has 18194 unique values
```

1. What are the most common crime in terms of offense group?

[19]:
```
crime.OFFENSE_CODE_GROUP.value_counts()
```

[19]:
```
OFFENSE_CODE_GROUP
Motor Vehicle Accident Response             37132
Larceny                                     25935
Medical Assistance                          23540
Investigate Person                          18749
Other                                       18073
                                            …
HUMAN TRAFFICKING                               7
INVESTIGATE PERSON                              4
Biological Threat                               2
HUMAN TRAFFICKING - INVOLUNTARY SERVITUDE       2
Burglary - No Property Taken                    2
Name: count, Length: 67, dtype: int64
```

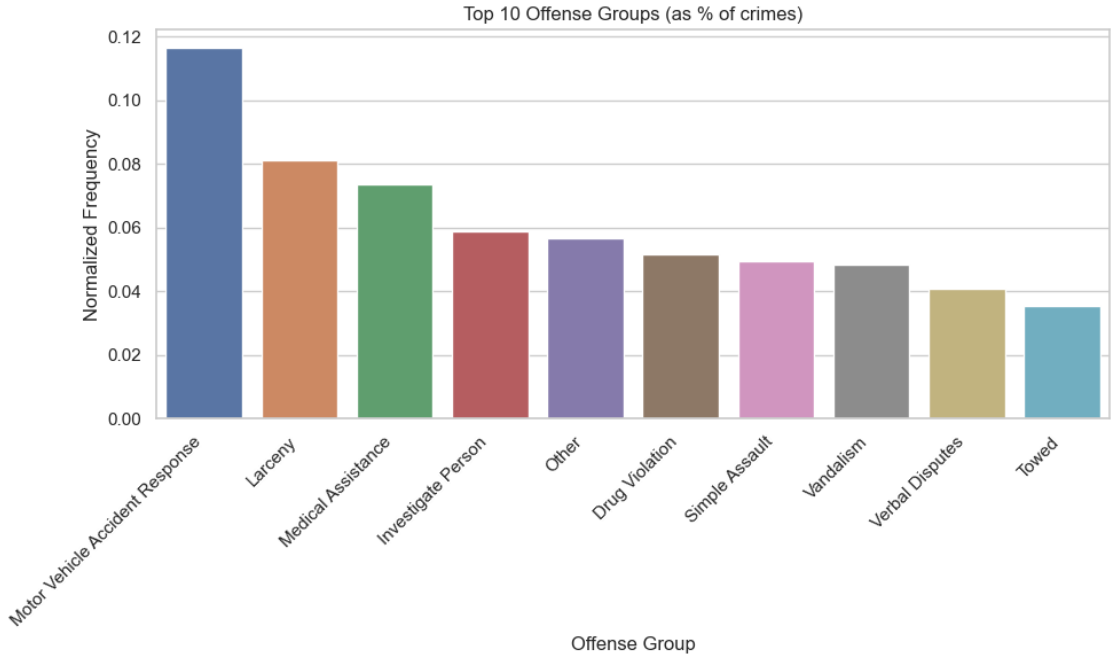
2. Top ten crimes in offense group

[20]:
```
offense_group_values = crime.OFFENSE_CODE_GROUP.value_counts().head(10)

display(offense_group_values / crime.shape[0])
```

```
OFFENSE_CODE_GROUP
Motor Vehicle Accident Response    0.116383
Larceny                            0.081288
Medical Assistance                 0.073782
Investigate Person                 0.058765
Other                              0.056646
Drug Violation                     0.051857
Simple Assault                     0.049604
Vandalism                          0.048312
Verbal Disputes                    0.041056
```

```
Towed                                0.035377
Name: count, dtype: float64
```

[21]:
```
# Calculate normalized values
normalized_values = offense_group_values / crime.shape[0]

# Create a bar plot
plt.figure(figsize=(10, 6))  # Set the figure size
sns.set(style="whitegrid")   # Set the style using seaborn

# Create the bar plot using seaborn's barplot function
sns.barplot(x=normalized_values.index, y=normalized_values.values)

# Add title and labels
plt.title('Top 10 Offense Groups (as % of crimes)')
plt.xlabel('Offense Group')
plt.ylabel('Normalized Frequency')

# Rotate x-labels for better readability
plt.xticks(rotation=45, ha="right")

# Display the plot
plt.tight_layout()  # Adjust layout to prevent clipping of labels
plt.show()
```



3. Least common offense group

[22]:
```
crime.OFFENSE_CODE_GROUP.value_counts().sort_values(ascending = True).head(10)
```

[22]:
```
OFFENSE_CODE_GROUP
Burglary - No Property Taken                    2
HUMAN TRAFFICKING - INVOLUNTARY SERVITUDE       2
Biological Threat                               2
INVESTIGATE PERSON                              4
HUMAN TRAFFICKING                               7
Gambling                                        8
Manslaughter                                    8
Explosives                                     27
Phone Call Complaints                          31
Aircraft                                       36
Name: count, dtype: int64
```

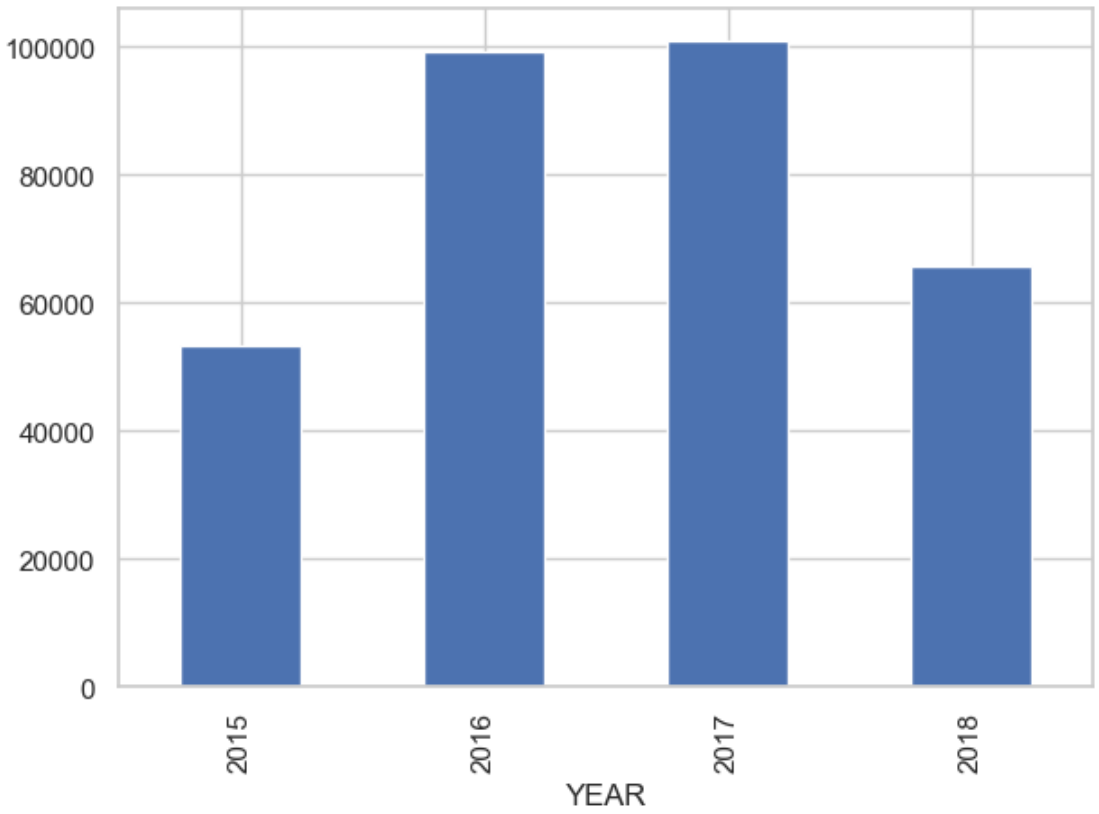
4.What are the most common offense descriptions?

[23]:
```
crime.OFFENSE_CODE_GROUP.value_counts().sort_values(ascending = False).head(10)
```

[23]:
```
OFFENSE_CODE_GROUP
Motor Vehicle Accident Response    37132
Larceny                            25935
Medical Assistance                 23540
Investigate Person                 18749
Other                              18073
Drug Violation                     16545
Simple Assault                     15826
Vandalism                          15414
Verbal Disputes                    13099
Towed                              11287
Name: count, dtype: int64
```

4. Which year most crimes are committed?

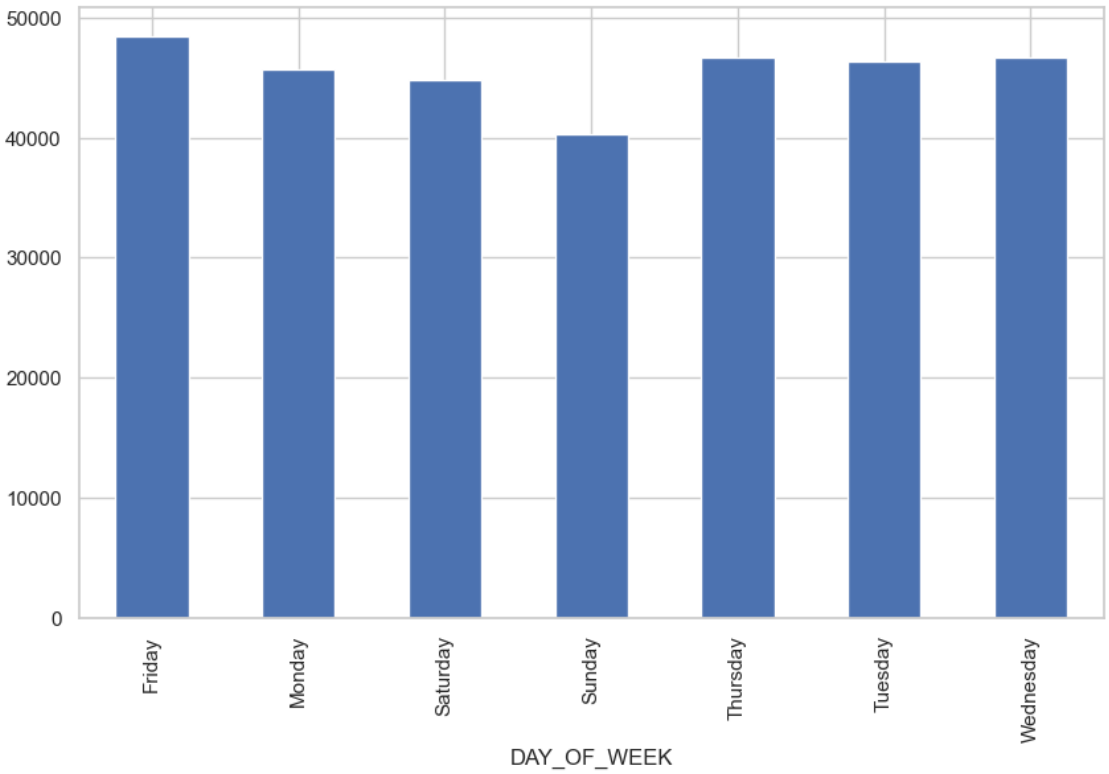
[24]:
```
crime.groupby('YEAR').count()['INCIDENT_NUMBER'].plot(kind = 'bar')

# Beautify the plot
plt.tight_layout()
```



5. Are there more crime comminted on specific days?

[25]:
```
plt.figure(figsize=(10, 6))  # Set the figure size
sns.set(style="whitegrid")   # Set the style using seaborn

crime.groupby('DAY_OF_WEEK').count()['INCIDENT_NUMBER'].plot(kind = 'bar')
```

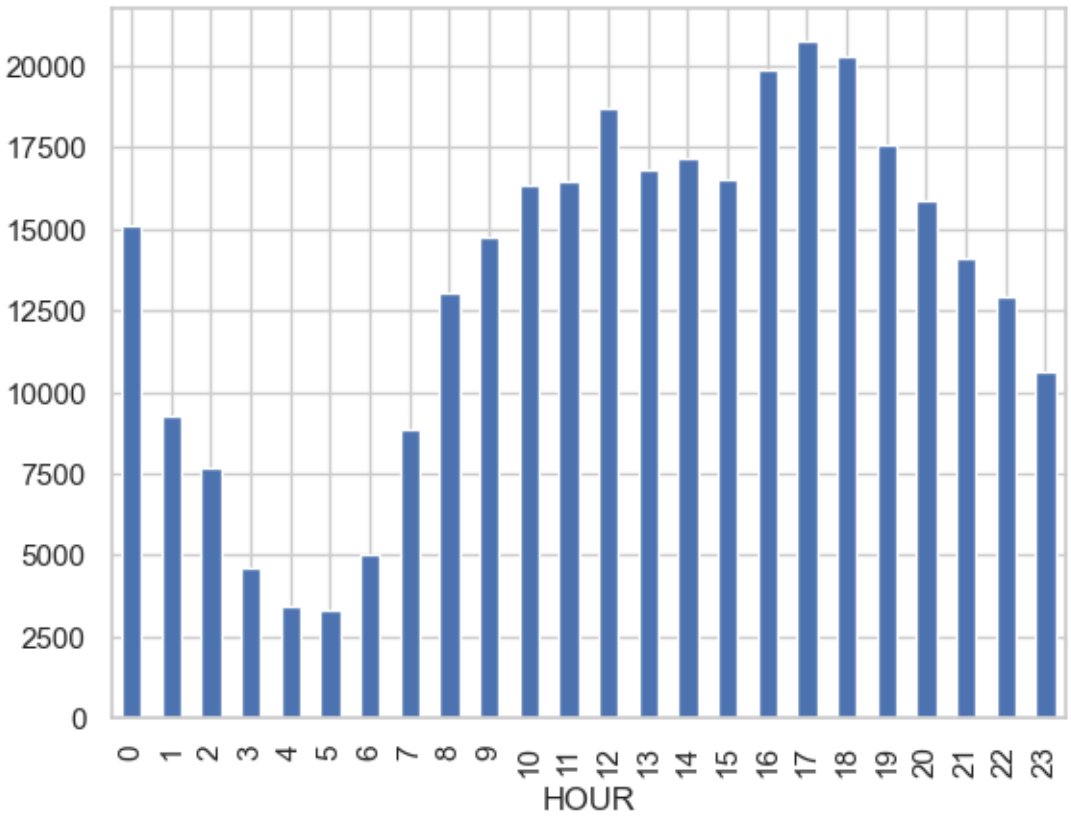
[25]: <Axes: xlabel='DAY_OF_WEEK'>



6. Crimes occured during specific hours

[26]:
```
crime.groupby('HOUR').count()['INCIDENT_NUMBER'].plot(kind = 'bar')
```

[26]: <Axes: xlabel='HOUR'>



7. On which hour of the day most crimes are committed?

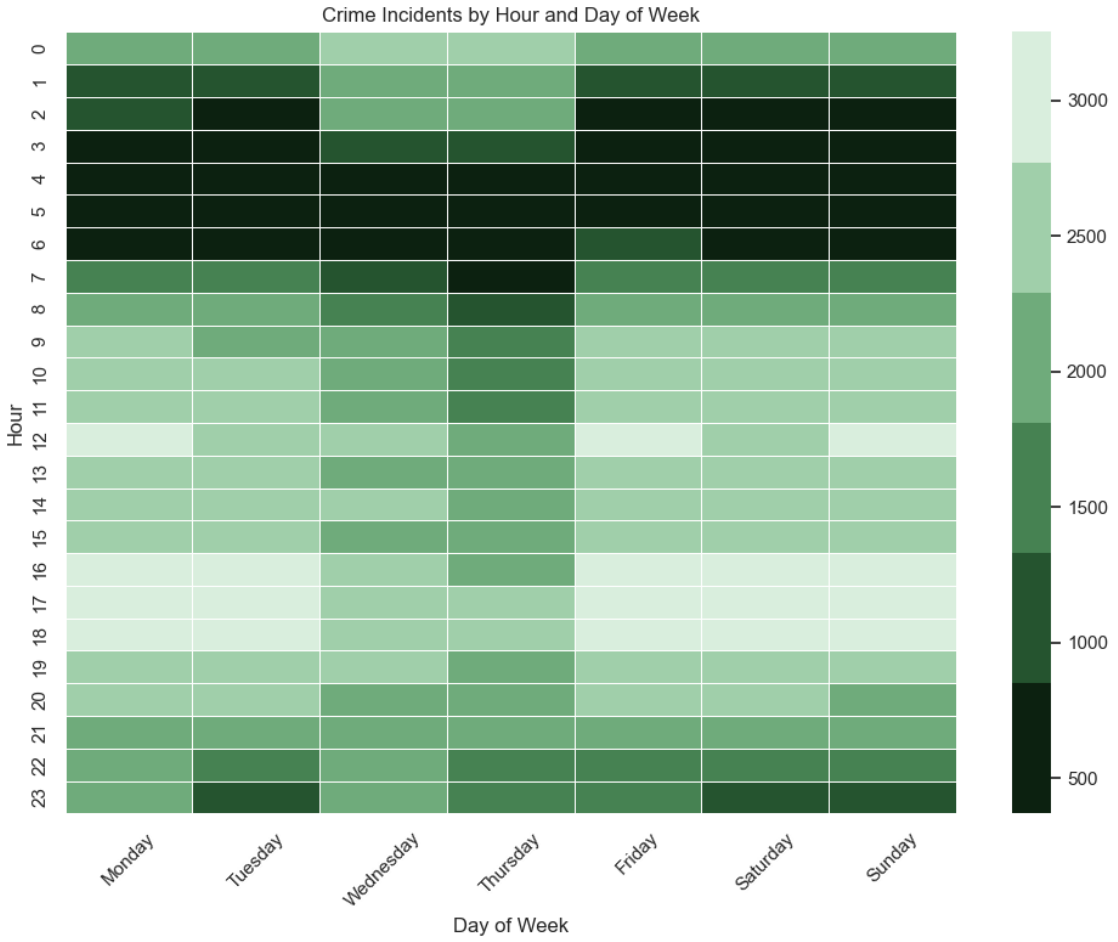
[27]:
```
crime.groupby(['HOUR','DAY_OF_WEEK']).count()['INCIDENT_NUMBER'].unstack()
```

[27]:

DAY_OF_WEEK	Friday	Monday	Saturday	Sunday	Thursday	Tuesday	Wednesday
HOUR							
0	2161	2000	2612	2400	2039	1897	1997
1	1275	1058	1855	2043	1077	1017	942
2	952	846	1827	1855	774	641	798
3	532	583	957	1119	526	460	412
4	441	386	672	704	436	399	370
5	485	417	478	517	508	462	444
6	768	709	530	543	866	787	823
7	1398	1352	1078	758	1405	1418	1441
8	2041	2046	1515	1123	2037	2145	2135
9	2299	2148	1812	1457	2325	2322	2377
10	2668	2432	2064	1778	2496	2414	2493
11	2552	2373	2042	1802	2548	2529	2599
12	2860	2746	2588	2135	2821	2681	2845
13	2499	2479	2223	1980	2576	2493	2595
14	2601	2485	2378	2029	2536	2555	2605

15	2566	2438	2084	1918	2531	2503	2479
16	3073	3029	2445	2216	2974	3080	3053
17	3252	3253	2555	2377	2931	3241	3153
18	3010	3089	2528	2326	3033	3217	3098
19	2564	2606	2301	2114	2510	2768	2724
20	2307	2319	2131	2109	2349	2369	2265
21	2089	2003	2077	1902	2070	1925	2043
22	2160	1634	2113	1728	1795	1757	1738
23	1936	1243	1951	1380	1492	1296	1298

[28]:
```
week_and_hour = crime.groupby(['HOUR','DAY_OF_WEEK']).
 ↪count()['INCIDENT_NUMBER'].unstack()
week_and_hour.columns = ['Monday', 'Tuesday',␣
 ↪'Wednesday','Thursday','Friday','Saturday','Sunday']
#sns.heatmap(week_and_hour, cmap = sns.cubehelix_palette(as_cmap= True))

# Create a custom color palette for the heatmap
custom_palette = sns.cubehelix_palette(start=2, rot=0, dark=0.1, light=0.9,␣
 ↪reverse=True)

# Create the heatmap
plt.figure(figsize=(10, 8))  # Adjust the figure size as needed
heatmap = sns.heatmap(week_and_hour, cmap=custom_palette, linewidths=0.5)

# Set labels and title
heatmap.set_title('Crime Incidents by Hour and Day of Week')
heatmap.set_xlabel('Day of Week')
heatmap.set_ylabel('Hour')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45)

plt.tight_layout()
```



1.4 Conclusion

This project's analysis enhances our understanding of crime incidents in the USA from 2015 to 2018. By employing data analysis techniques, we uncover valuable insights into crime patterns, distribution, and temporal trends. Law enforcement, policymakers, and researchers can utilize these findings to formulate effective strategies for crime prevention and resource allocation, contributing to safer communities and informed decision-making.