

# us\_crime\_data\_exploration

November 24, 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 common offense group.

- 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

```
[ ]: 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

```
[ ]: 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 iso8859_8
sucessful cp775
sucessful cp1257
sucessful gbk
sucessful cp860
sucessful cp1251
sucessful iso8859_14
sucessful cp1258
sucessful cp857
sucessful cp437
sucessful cp932
sucessful iso8859_13
sucessful kz1048
sucessful mac_latin2
sucessful cp1253
sucessful iso8859_15
sucessful cp1140
sucessful cp037
sucessful iso8859_5
sucessful cp949
sucessful utf_16_be
sucessful cp500
sucessful cp858
sucessful cp864
sucessful iso8859_10
sucessful mac_turkish
sucessful iso8859_2
sucessful iso8859_11
sucessful cp869
sucessful koi8_r
sucessful iso8859_7
sucessful ptcp154
sucessful cp1256
```

```

sucessful cp273
sucessful utf_16_le
sucessful cp866
sucessful iso8859_3
sucessful iso8859_4
sucessful mac_cyrillic
sucessful iso8859_6
sucessful iso8859_16
sucessful cp1254
sucessful cp863
sucessful mac_greek
sucessful cp850
sucessful cp1252
sucessful cp1255
sucessful big5hkscs
sucessful cp1250
sucessful hp_roman8
sucessful cp1026
sucessful iso8859_9
sucessful gb18030
sucessful cp855
sucessful cp1125
sucessful mac_roman
sucessful cp862
sucessful cp861
sucessful cp865
sucessful mac_iceland
sucessful cp852
sucessful latin_1

```

Read the dataset

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

```
[ ]: 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)

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

```
[ ]: (319073, 17)
```

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

```
[ ]: 23
```

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

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

```
[ ]: (319050, 17)
```

### 1.3 Exploring the dataset

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

```
[ ]: 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)

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

```
[ ]:
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)

```
[ ]: 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

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

```
[ ]: 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
```

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

```
[ ]:      INCIDENT_NUMBER      OFFENSE_CODE_GROUP \
count      319050      319050
unique      282517      67
top      I162030584  Motor Vehicle Accident Response
freq      13      37132

      OFFENSE_DESCRIPTION DISTRICT REPORTING_AREA SHOOTING \
count      319050      317285      319050      1019
unique      244      12      879      1
top      SICK/INJURED/MEDICAL - PERSON      B2      Y
freq      18783      49940      20250      1019

      DAY_OF_WEEK      UCR_PART      STREET      Location
count      319050      318960      308179      319050
```



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

## Checking the columns

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

```
[ ]: 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')
```

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

```
[ ]:
```

	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

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

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

### Checking columns with no missing value

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

```
[ ]: 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

```
[ ]: 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?

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

```
[ ]: 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

```
[ ]: 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  
Name: count, dtype: float64  
0.035377

```
[ ]: normalized_values = offense_group_values / crime.shape[0]

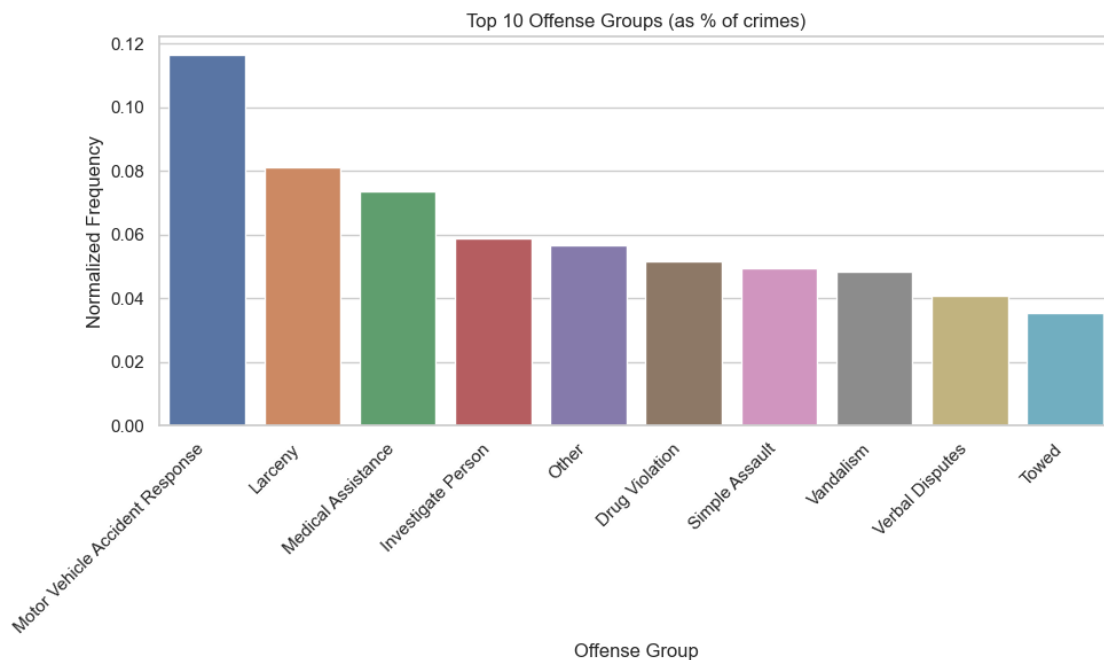
plt.figure(figsize=(10, 6)) # Set the figure size
sns.set(style="whitegrid") # Set the style using seaborn

sns.barplot(x=normalized_values.index, y=normalized_values.values)

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

plt.xticks(rotation=45, ha="right")

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



### 3. Least common offense group

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

```
[ ]: 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?

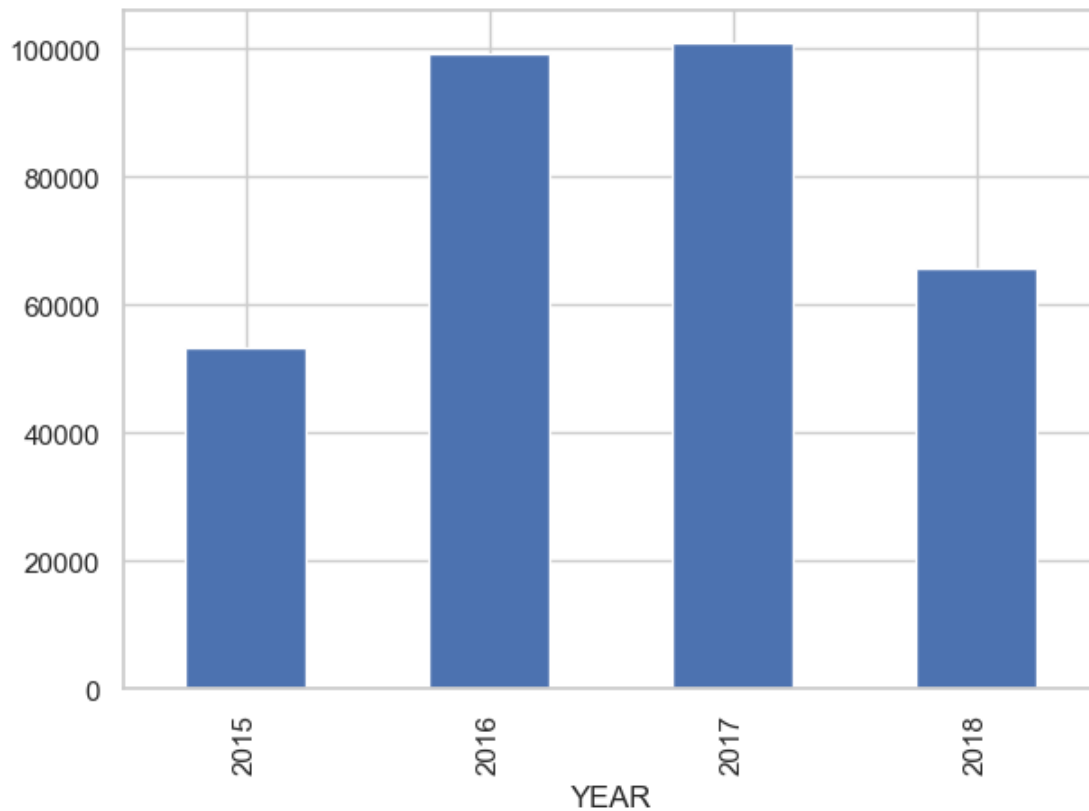
```
[ ]: crime.OFFENSE_CODE_GROUP.value_counts().sort_values(ascending = False).head(10)
```

```
[ ]: 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?

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

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

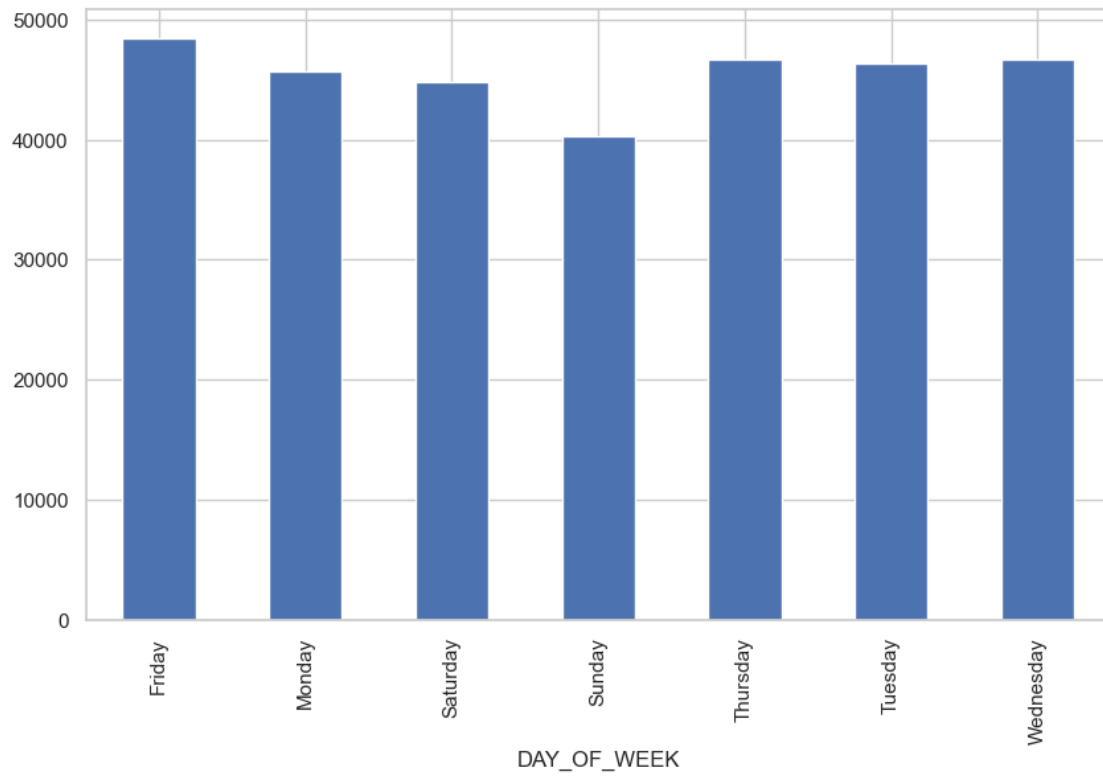


##### 5. Are there more crime committed on specific days?

```
[ ]: 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')
```

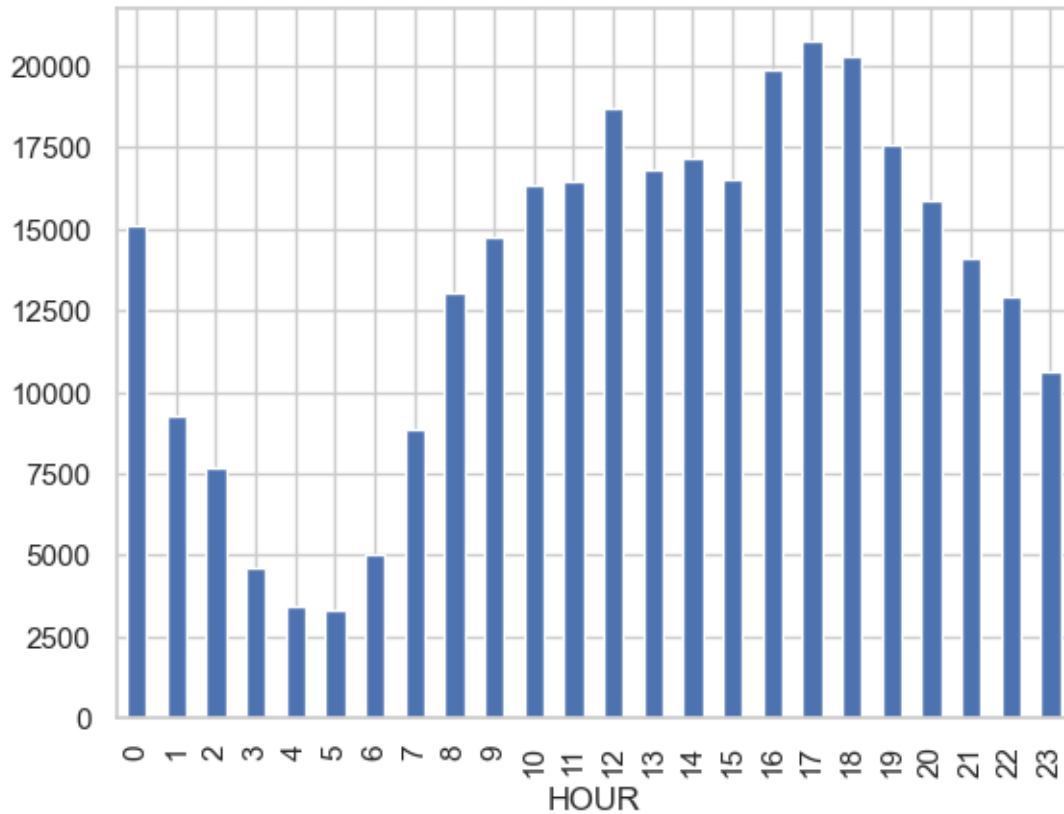
```
[ ]: <Axes: xlabel='DAY_OF_WEEK'>
```



## 6. Crimes occurred during specific hours

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

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



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

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

```
[ ]: 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

```
[ ]: 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))

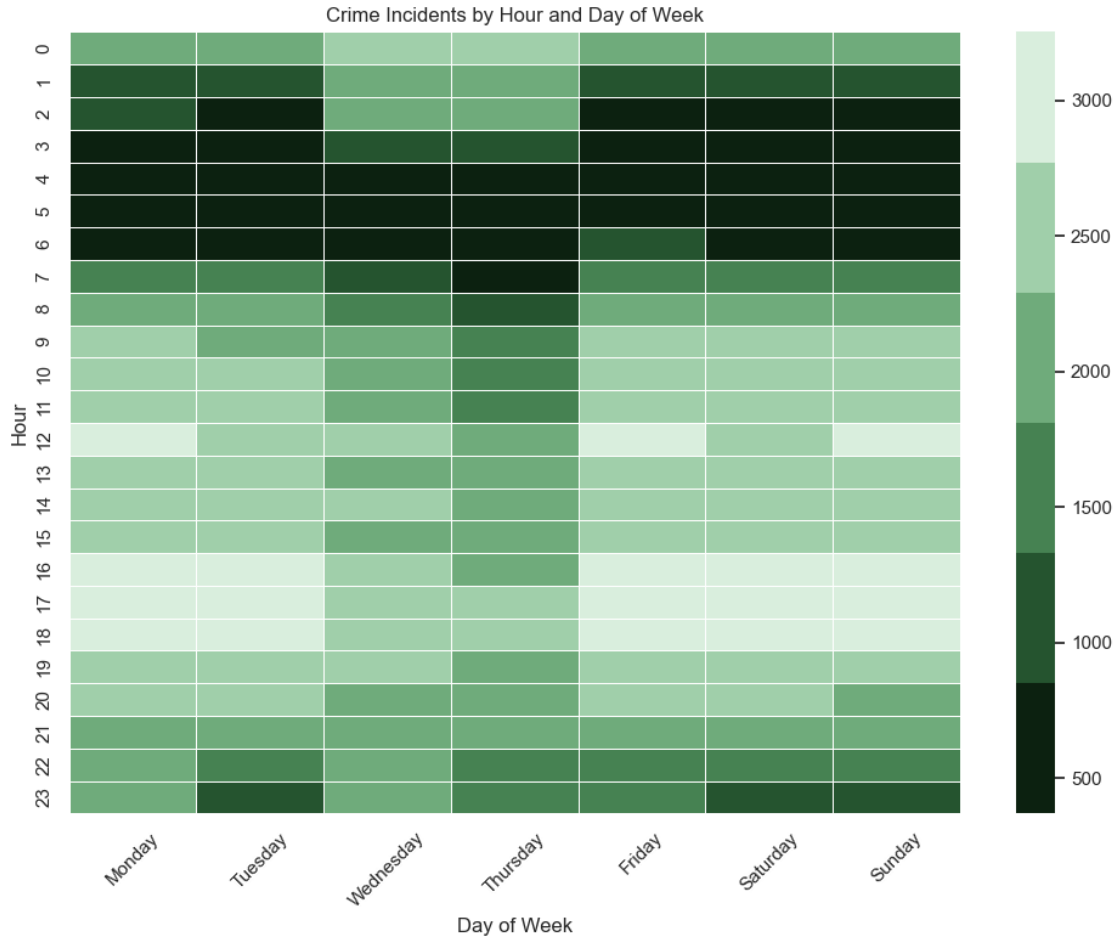
custom_palette = sns.cubehelix_palette(start=2, rot=0, dark=0.1, light=0.9,
      ↪reverse=True)

plt.figure(figsize=(10, 8))
heatmap = sns.heatmap(week_and_hour, cmap=custom_palette, linewidths=0.5)

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

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.