Crimes in Chicago Data Analysis

Group Members:

Apeksha Shetty

Shraddha Shahane

Bhavesh Yadav

Problem Statement: Analyzing the factors that affect the Crimes in Chicago based on five years data(2012-2017)

This dataset reflects reported incidents of crime (with the exception of murders where data exists for each victim) that occurred in the City of Chicago from 2012 to 2017. Data is extracted from the Chicago Police Department's CLEAR (Citizen Law Enforcement Analysis and Reporting) system. In order to protect the privacy of crime victims, addresses are shown at the block level only and specific locations are not identified. This data includes unverified reports supplied to the Police Department. The dataset consists of 23 columns.

Parameters

ID - Unique identifier for the record.

Case Number - The Chicago Police Department RD Number (Records Division Number), which is unique to the incident.

Date - Date when the incident occurred. this is sometimes a best estimate.

Block - The partially redacted address where the incident occurred, placing it on the same block as the actual address.

Primary Type - The primary description of the IUCR code.

Description - The secondary description of the IUCR code, a subcategory of the primary description.

Location Description - Description of the location where the incident occurred.

Arrest - Indicates whether an arrest was made.

Domestic - Indicates whether the incident was domestic-related as defined by the Illinois Domestic Violence Act.

Updated On - Date and time the record was last updated.

Latitude - The latitude of the location where the incident occurred. This location is shifted from the actual location for partial redaction but falls on the same block.

Longitude - The longitude of the location where the incident occurred. This location is shifted from the actual location for partial redaction but falls on the same block.

Target Audience

We analyze this data from a perspective of a Chicago resident who wants to know more about their area so they can better navigate their way through the city and it can also help the Police Department to ensure the safety of the residents.

Questions:

(1)How has crime in Chicago changed across years? Is it Increasing or Decreasing?

(2)Which types of crimes are more likely to happen in specific locations or specific time of the day or specific day of the week than other types of crimes?

(3) Which crimes are most common among the top 20 most frequent crime types?

Importing Libraries

```
In [71]:
```

```
import numpy as np
from io import StringIO
import pandas as pd
import folium
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('seaborn')
import seaborn as sns
```

Reading the dataset

```
In [79]:
```

```
crimes = pd.read_csv("C:\\Users\\APEKSHA\\Desktop\\Chicago_Crimes_2012_to_2017.csv")
crimes
```

Out[79]:

	Unnamed:	ID	Case Number	Date	Block	IUCR	Primary Type	Description	
0	3	10508693	HZ250496	05/03/2016 11:40:00 PM	013XX S SAWYER AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	А
1	89	10508695	HZ250409	05/03/2016 09:40:00 PM	061XX S DREXEL AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	R
2	197	10508697	HZ250503	05/03/2016 11:31:00 PM	053XX W CHICAGO AVE	0470	PUBLIC PEACE VIOLATION	RECKLESS CONDUCT	s
3	673	10508698	HZ250424	05/03/2016 10:10:00 PM	049XX W FULTON ST	0460	BATTERY	SIMPLE	s
4	911	10508699	HZ250455	05/03/2016 10:00:00 PM	003XX N LOTUS AVE	0820	THEFT	\$500 AND UNDER	R
5	1108	10508702	HZ250447	05/03/2016 10:35:00 PM	082XX S MARYLAND AVE	041A	BATTERY	AGGRAVATED: HANDGUN	s
6	1130	10508703	HZ250489	05/03/2016 10:30:00 PM	027XX S STATE ST	0460	BATTERY	SIMPLE	С
7	1801	10508704	HZ250514	05/03/2016 09:30:00 PM	002XX E 46TH ST	0460	BATTERY	SIMPLE	R
8	1868	10508709	HZ250523	05/03/2016 04:00:00 PM	014XX W DEVON AVE	0460	BATTERY	SIMPLE	s
9	1891	10508982	HZ250667	05/03/2016 10:30:00 PM	069XX S ASHLAND AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	s
10	1935	10508710	HZ250469	05/03/2016 09:44:00 PM	074XX S SOUTH SHORE DR	143A	WEAPONS VIOLATION	UNLAWFUL POSS OF HANDGUN	٧
				05/03/2016	006XX N				T

11	2150 Unnamed:	10508715 ID	HZ250541 Case	11:11:00	WABASH AVE Block	0486	BATTERY Primary	DOMESTIC BATTERY SIMPLE	S
	0	טו	Number	PM Date		IUCR	Туре	Description	Ļ
12	2193	10508717	HZ250415	05/03/2016 05:30:00 PM	JACKSON BLVD	0890	THEFT	FROM BUILDING	О
13	2279	10508724	HZ250513	05/03/2016 09:00:00 AM	028XX S DR MARTIN LUTHER KING JR DR	0820	THEFT	\$500 AND UNDER	s
14	2477	10508728	HZ250505	05/03/2016 10:08:00 PM	016XX N CLAREMONT AVE	0810	THEFT	OVER \$500	s
15	2847	10508732	HZ250535	05/03/2016 04:00:00 PM	072XX S RICHMOND ST	0486	BATTERY	DOMESTIC BATTERY SIMPLE	R
16	3023	10508738	HZ250440	05/03/2016 09:45:00 PM	020XX W LE MOYNE ST	0810	THEFT	OVER \$500	s
17	3088	10508741	HZ250587	05/03/2016 10:00:00 PM	055XX S STATE ST	0313	ROBBERY	ARMED: OTHER DANGEROUS WEAPON	s
18	3242	10508747	HZ250577	05/03/2016 08:00:00 PM	S 100XX S SANGAMON ST	0910	MOTOR VEHICLE THEFT	AUTOMOBILE	s
19	3264	10508752	HZ250500	05/03/2016 11:00:00 PM	043XX S ELLIS AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	А
20	3307	10508755	HZ250531	05/03/2016 11:37:00 PM	015XX N DAMEN AVE	0560	ASSAULT	SIMPLE	s
21	3416	10508757	HZ250601	05/03/2016 01:30:00 PM	057XX S COTTAGE GROVE AVE	0560	ASSAULT	SIMPLE	О
22	4333	10508987	HZ250698	05/03/2016 06:30:00 PM	025XX N GREENVIEW AVE	0810	THEFT	OVER \$500	R
23	4377	10509011	HZ250748		068XX W HIGHLAND AVE	0820	THEFT	\$500 AND UNDER	s
24	4571	10509016	HZ250610	05/03/2016 11:30:00 PM	003XX W HUBBARD ST	5002	OTHER OFFENSE	OTHER VEHICLE OFFENSE	s
25	4701	10509030	HZ250659	05/03/2016 07:00:00 AM	010XX W 95TH ST	0820	THEFT	\$500 AND UNDER	V
26	5138	10509071	HZ250713		012XX W FULLERTON AVE	0820	THEFT	\$500 AND UNDER	P L
27	5225	10509077	HZ250776	05/03/2016 12:01:00 AM	002XX W 33RD ST	1130	DECEPTIVE PRACTICE	FRAUD OR CONFIDENCE GAME	R
28	5423	10509078	HZ250611	05/03/2016 12:01:00 AM	043XX S SAWYER AVE	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER \$ 300	R
29	5770	10509094	HZ250662	05/03/2016 11:00:00 PM	084XX S MORGAN ST	0910	MOTOR VEHICLE THEFT	AUTOMOBILE	s

0 883 003 288 484 506 678 722 046 219	10508641 10508642 10508643 10508644 10508646 10508647	Number HZ250458 HZ250462 HZ250498 HZ250510 HZ250401 HZ250244 HZ250244 HZ250244 HZ250404 HZ250404	05/03/2016 10:32:00 PM 05/03/2016 10:07:00 PM 05/03/2016 10:31:00 PM 05/03/2016 10:45:00 PM 05/03/2016 07:13:00 PM 05/03/2016 07:45:00 PM 05/03/2016 07:45:00 PM 05/03/2016 07:45:00 PM	HERMITAGE AVE 035XX W ROOSEVELT RD 066XX S WOLCOTT AVE 027XX W FLOURNOY ST 075XX S PARNELL AVE 076XX S HALSTED ST 080XX S VERNON AVE	051A 1811 143A 051A 0560 0460	Type ASSAULT NARCOTICS WEAPONS VIOLATION ASSAULT BATTERY BATTERY BATTERY ASSAULT	AGGRAVATED: HANDGUN POSS: CANNABIS 30GMS OR LESS UNLAWFUL POSS OF HANDGUN AGGRAVATED: HANDGUN SIMPLE SIMPLE SIMPLE AGGRAVATED: KNIFE/CUTTING INSTR
003 288 484 506 678 722 046	10508640 10508641 10508642 10508643 10508644 10508646 10508647	HZ250462 HZ250498 HZ250510 HZ250401 HZ250244 HZ250293 HZ250404 HZ250445	PM 05/03/2016 10:07:00 PM 05/03/2016 10:31:00 PM 05/03/2016 10:45:00 PM 05/03/2016 09:00:00 PM 05/03/2016 07:13:00 PM 05/03/2016 07:45:00 PM 05/03/2016 08:56:00 PM 05/03/2016 10:10:00 PM 05/03/2016	AVE 035XX W ROOSEVELT RD 066XX S WOLCOTT AVE 027XX W FLOURNOY ST 075XX S PARNELL AVE 076XX S HALSTED ST 080XX S VERNON AVE 063XX S GREENWOOD AVE 073XX S	1811 143A 051A 0560 0460 0460	NARCOTICS WEAPONS VIOLATION ASSAULT ASSAULT BATTERY BATTERY	POSS: CANNABIS 30GMS OR LESS UNLAWFUL POSS OF HANDGUN AGGRAVATED: HANDGUN SIMPLE SIMPLE SIMPLE AGGRAVATED: KNIFE/CUTTING
288 484 506 678 722 046	10508641 10508642 10508643 10508644 10508646 10508647	HZ250498 HZ250510 HZ250401 HZ250244 HZ250293 HZ250404 HZ250445	10:07:00 PM 05/03/2016 10:31:00 PM 05/03/2016 10:45:00 PM 05/03/2016 09:00:00 PM 05/03/2016 07:13:00 PM 05/03/2016 07:45:00 PM 05/03/2016 08:56:00 PM 05/03/2016 10:10:00 PM	ROOSEVELT RD 066XX S WOLCOTT AVE 027XX W FLOURNOY ST 075XX S PARNELL AVE 076XX S HALSTED ST 080XX S VERNON AVE 063XX S GREENWOOD AVE 073XX S	143A 051A 0560 0460 0460	WEAPONS VIOLATION ASSAULT ASSAULT BATTERY BATTERY	UNLAWFUL POSS OF HANDGUN AGGRAVATED: HANDGUN SIMPLE SIMPLE SIMPLE AGGRAVATED: KNIFE/CUTTING
484 506 678 722 046	10508642 10508643 10508644 10508646 10508647	HZ250510 HZ250401 HZ250244 HZ250293 HZ250404 HZ250445	10:31:00 PM 05/03/2016 10:45:00 PM 05/03/2016 09:00:00 PM 05/03/2016 07:13:00 PM 05/03/2016 07:45:00 PM 05/03/2016 08:56:00 PM 05/03/2016 10:10:00 PM	WOLCOTT AVE 027XX W FLOURNOY ST 075XX S PARNELL AVE 076XX S HALSTED ST 080XX S VERNON AVE 063XX S GREENWOOD AVE 073XX S	051A 0560 0460 0460	ASSAULT ASSAULT BATTERY BATTERY BATTERY	HANDGUN AGGRAVATED: HANDGUN SIMPLE SIMPLE SIMPLE AGGRAVATED: KNIFE/CUTTING
506 678 722 046 219	10508644 10508646 10508647 10508648	HZ250401 HZ250244 HZ250293 HZ250404 HZ250445	10:45:00 PM 05/03/2016 09:00:00 PM 05/03/2016 07:13:00 PM 05/03/2016 07:45:00 PM 05/03/2016 08:56:00 PM 05/03/2016 10:10:00 PM	FLOURNOY ST 075XX S PARNELL AVE 076XX S HALSTED ST 080XX S VERNON AVE 063XX S GREENWOOD AVE 073XX S	0560 0460 0460	ASSAULT BATTERY BATTERY BATTERY	SIMPLE SIMPLE SIMPLE AGGRAVATED:KNIFE/CUTTING
678 722 046 219	10508644 10508646 10508647 10508648	HZ250244 HZ250293 HZ250404 HZ250445	09:00:00 PM 05/03/2016 07:13:00 PM 05/03/2016 07:45:00 PM 05/03/2016 08:56:00 PM 05/03/2016 10:10:00 PM	PARNELL AVE 076XX S HALSTED ST 080XX S VERNON AVE 063XX S GREENWOOD AVE 073XX S	0460 0460 0460	BATTERY BATTERY	SIMPLE SIMPLE SIMPLE AGGRAVATED:KNIFE/CUTTING
722 046 219	10508646 10508647 10508648	HZ250293 HZ250404 HZ250445	07:13:00 PM 05/03/2016 07:45:00 PM 05/03/2016 08:56:00 PM 05/03/2016 10:10:00 PM 05/03/2016	HALSTED ST 080XX S VERNON AVE 063XX S GREENWOOD AVE 073XX S	0460	BATTERY	SIMPLE SIMPLE AGGRAVATED:KNIFE/CUTTING
046 219	10508647 10508648	HZ250404 HZ250445	07:45:00 PM 05/03/2016 08:56:00 PM 05/03/2016 10:10:00 PM 05/03/2016	VERNON AVE 063XX S GREENWOOD AVE 073XX S	0460	BATTERY	SIMPLE AGGRAVATED:KNIFE/CUTTING
219	10508648	HZ250445	08:56:00 PM 05/03/2016 10:10:00 PM 05/03/2016	GREENWOOD AVE 073XX S			AGGRAVATED:KNIFE/CUTTING
			10:10:00 PM 05/03/2016		0520	ASSAULT	
370	10508649	HZ250442					
			10:15:00 PM	041XX W CERMAK RD	4387	OTHER OFFENSE	VIOLATE ORDER OF PROTECTION
478	10508650	HZ250022	05/03/2016 05:00:00 PM		031A	ROBBERY	ARMED: HANDGUN
521	10508653	HZ250512	05/03/2016 11:58:00 PM	026XX W LE MOYNE ST	0520	ASSAULT	AGGRAVATED:KNIFE/CUTTING INSTR
563	10508656	HZ250476	05/03/2016 03:15:00 PM	014XX N OGDEN AVE	1720	OFFENSE INVOLVING CHILDREN	CONTRIBUTE DELINQUENCY OF A CHILD
798	10508658	HZ250506	05/03/2016 11:50:00 PM	018XX S KEDZIE AVE	4625	OTHER OFFENSE	PAROLE VIOLATION
016	10508659	HZ250499		038XX S PRINCETON AVE	0460	BATTERY	SIMPLE
192	10508661	HZ250344	05/03/2016 08:44:00 PM	070XX S WABASH AVE	041A	BATTERY	AGGRAVATED: HANDGUN
278	10508662	HZ250477		057XX S MICHIGAN AVE	5001	OTHER OFFENSE	OTHER CRIME INVOLVING PROPERTY
	10508663	HZ250466		033XX W MARQUETTE RD	1563	SEX OFFENSE	CRIMINAL SEXUAL ABUSE
19	2	2 10508661 8 10508662	2 10508661 HZ250344 8 10508662 HZ250477	6 10508659 HZ250499 11:38:00 PM 2 10508661 HZ250344 05/03/2016 08:44:00 PM 8 10508662 HZ250477 08:00:00 AM 3 10508663 HZ250466 10:10:00 PM	2 10508661 HZ250344 05/03/2016 070XX S WABASH AVE 8 10508662 HZ250477 08:00:00 MICHIGAN AW AVE 3 10508663 HZ250466 05/03/2016 033XX W MARQUETTE	6 10508659 HZ250499 11:38:00 PM PRINCETON AVE 0460 2 10508661 HZ250344 05/03/2016 070XX S WABASH AVE PM 041A 8 10508662 HZ250477 05/03/2016 057XX S MICHIGAN AVE 05/03/2016 AVE 3 10508663 HZ250466 05/03/2016 033XX W MARQUETTE PM 1563 PM	6 10508659 HZ250499 11:38:00 PRINCETON AVE 0460 BATTERY 2 10508661 HZ250344 05/03/2016 08:44:00 PM 070XX S WABASH AVE 041A BATTERY 8 10508662 HZ250477 05/03/2016 057XX S MICHIGAN AVE 5001 OFFENSE 3 10508663 HZ250466 05/03/2016 033XX W MARQUETTE RD 1563 OFFENSE

	Unnamed:		Case	PM 5 1	ST	шор	Primary	5	Γ
	0	ID	Number	Date 05/03/2016	Block	IUCK	Туре		T
1456703	6248999	10508665	HZ250448	10:15:00 PM	1095XX S LOOMIS ST	1310	CRIMINAL DAMAGE	TO PROPERTY	R
1456704	6249417	10508666	HZ250497	05/03/2016 11:30:00 PM	053XX S PULASKI RD	10320 IRC		STRONGARM - NO WEAPON	
1456705	6249592	10508671	HZ250526	05/03/2016 11:50:00 PM	036XX E 106TH ST	502P	OTHER OFFENSE	FALSE/STOLEN/ALTERED TRP	Α
1456706	6249615	10508672	HZ250441	05/03/2016 10:25:00 PM	071XX S MOZART ST	0460	BATTERY	SIMPLE	s
1456707	6249936	10508675	HZ250502	05/03/2016 11:00:00 PM	085XX S MAY ST	0320	ROBBERY	STRONGARM - NO WEAPON	s
1456708	6250154	10508678	HZ250481	05/03/2016 11:28:00 PM	088XX S LAFLIN ST	041A	BATTERY	AGGRAVATED: HANDGUN	s
1456709	6250330	10508679	HZ250507	05/03/2016 11:33:00 PM	026XX W 23RD PL	0486	BATTERY	DOMESTIC BATTERY SIMPLE	А
1456710	6251089	10508680	HZ250491	05/03/2016 11:30:00 PM	073XX S HARVARD AVE	1310	CRIMINAL DAMAGE	TO PROPERTY	А
1456711	6251349	10508681	HZ250479	05/03/2016 12:15:00 AM	024XX W 63RD ST	041A	BATTERY	AGGRAVATED: HANDGUN	s
1456712	6253257	10508690	HZ250370	05/03/2016 09:07:00 PM			DOMESTIC BATTERY SIMPLE	s	
1456713	6253474	10508692	HZ250517	05/03/2016 11:38:00 PM	1001XX F 75TH L LOTHER L		OTHER WEAPONS VIOLATION	P L	

1456714 rows × 23 columns

For simplicity, display subset of the datset using head() function

In [3]:

crimes.head()

Out[3]:

	Unnamed: 0	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arrest	 Ward	Cı
0	3	10508693	HZ250496	05/03/2016 11:40:00 PM	013XX S SAWYER AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	APARTMENT	True	 24.0	29
1	89	10508695	HZ250409	05/03/2016 09:40:00 PM	061XX S DREXEL AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	RESIDENCE	False	 20.0	42
2	197	10508697	HZ250503	05/03/2016 11:31:00 PM	053XX W CHICAGO AVE	0470	PUBLIC PEACE VIOLATION	RECKLESS CONDUCT	STREET	False	 37.0	25
2	670	10500600	ロマつをロルウル	05/03/2016	049XX W	0460	DATTEDV	OIMDLE	CIDEMALK	Ealaa	20.0	25

3	Unnamed:	ID	Case		ST Block	IUCR	Type	Description	Location	Arrest	 Ward	Ci
4	911	10508699	HZ250455	05/03/2016 10:00:00 PM		0820	THEFT	\$500 AND UNDER	RESIDENCE	False	 28.0	25

5 rows × 23 columns

· ·

To print the index of columns of the dataset

```
In [4]:
```

```
crimes.columns
```

Out[4]:

Data Preprocessing and Cleaning

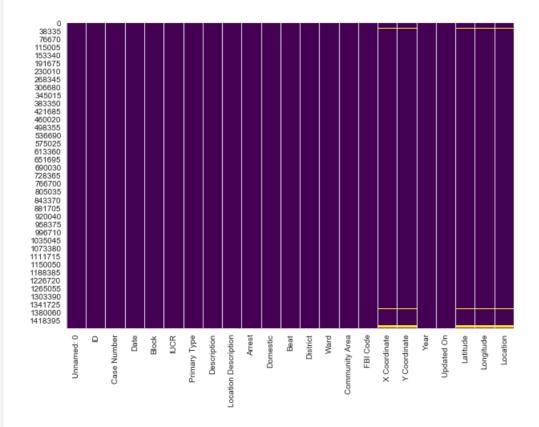
Determining null values in our dataset.

In [5]:

```
plt.figure(figsize=(10,7))
sns.heatmap(crimes.isnull(), cbar = False, cmap = 'viridis')
```

Out[5]:

<matplotlib.axes._subplots.AxesSubplot at 0x2490dba2ef0>



We will not be using any of those columns in our analysis; so we filter them out.

```
In [6]:
```

```
crimes.drop(['Unnamed: 0', 'Case Number', 'IUCR', 'X Coordinate', 'Y Coordinate', 'Updated
On', 'Year', 'FBI Code', 'Beat', 'Ward', 'Community Area', 'Location', 'District'], inplace=True, axis
=1)
```

We will use the 'Date' column to explore temporal patterns, 'Primary Type' and 'Location Description' to investigate their relationship with time (month of the year, time of the day, hour of the day, .. etc).

We need to convert the 'Date' column into a date format that is understandable by Python (and pandas).

```
In [7]:
```

```
# convert dates to pandas datetime format
crimes.Date = pd.to_datetime(crimes.Date, format='%m/%d/%Y %I:%M:%S %p')
# setting the index to be the date will help us a lot later on
crimes.index = pd.DatetimeIndex(crimes.Date)
```

To display records and its corresponding features

```
In [8]:
```

```
crimes.shape
Out[8]:
(1456714, 10)
In [9]:
crimes.info()
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1456714 entries, 2016-05-03 23:40:00 to 2016-05-03 23:38:00
Data columns (total 10 columns):
                       1456714 non-null int64
ΤD
Date
                       1456714 non-null datetime64[ns]
Block
                       1456714 non-null object
Primary Type
                      1456714 non-null object
Description
                      1456714 non-null object
Location Description 1455056 non-null object
Arrest
                        1456714 non-null bool
Domestic
                       1456714 non-null bool
                       1419631 non-null float64
Latitude
                       1419631 non-null float64
dtypes: bool(2), datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 102.8+ MB
```

As 'Location Description', 'Description' and 'Primary Type' columns are actually categorical columns, we will only keep the most frequent categories and then cast them to a categorical type.

```
In [10]:
```

```
loc_to_change = list(crimes['Location Description'].value_counts()[20:].index)
desc_to_change = list(crimes['Description'].value_counts()[20:].index)
#type_to_change = list(crimes['Primary Type'].value_counts()[20:].index)

crimes.loc[crimes['Location Description'].isin(loc_to_change) , crimes.columns=='Location
Description'] = 'OTHER'
crimes.loc[crimes['Description'].isin(desc_to_change) , crimes.columns=='Description'] = 'OTHER'
#crimes.loc[crimes['Primary Type'].isin(type_to_change) , crimes.columns=='Primary Type'] = 'OTHER'
'
```

In [11]:

```
# we convert those 3 columns into 'Categorical' types -- works like 'factor' in R
crimes['Primary Type'] = pd.Categorical(crimes['Primary Type'])
crimes['Location Description'] = pd.Categorical(crimes['Location Description'])
```

Data Exploration and Visualization

In [12]:

```
pd.value counts(crimes['Location Description'])[:10]
Out[12]:
STREET
                                   330471
RESIDENCE
                                   233530
                                   202047
OTHER
APARTMENT
                                   185023
SIDEWALK
                                   160891
                                   41768
PARKING LOT/GARAGE (NON.RESID.)
                                    31771
RESIDENTIAL YARD (FRONT/BACK)
                                    30645
SMALL RETAIL STORE
                                    28803
SCHOOL, PUBLIC, BUILDING
                                    25959
Name: Location Description, dtype: int64
```

In [13]:

```
pd.value_counts(crimes['Primary Type'])[:10]
```

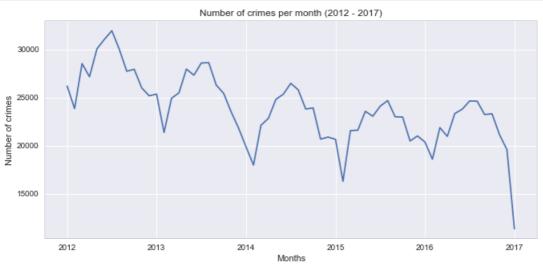
Out[13]:

THEFT	329460
BATTERY	263700
CRIMINAL DAMAGE	155455
NARCOTICS	135240
ASSAULT	91289
OTHER OFFENSE	87874
BURGLARY	83397
DECEPTIVE PRACTICE	75495
MOTOR VEHICLE THEFT	61138
ROBBERY	57313
Name: Primary Type,	dtype: int64

To plot the number of crimes per month

In [14]:

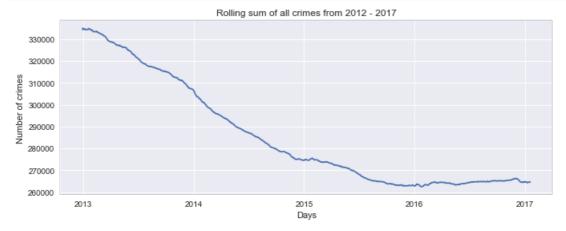
```
plt.figure(figsize=(11,5))
crimes.resample('M').size().plot(legend=False)
plt.title('Number of crimes per month (2012 - 2017)')
plt.xlabel('Months')
plt.ylabel('Number of crimes')
plt.show()
```



The previous graph shows monthly crime records. For more finer results, we take into consideration the rolling sum of crimes of the past year. The idea is, for each day, we calculate the sum of crimes of the past year. If this rolling sum is decreasing, then we know for sure that crime rates have been decreasing during that year. On the other hand, if the rolling sum stays the same during a given year, then we can conclude that crime rates stayed the same.

In [15]:

```
plt.figure(figsize=(11,4))
crimes.resample('D').size().rolling(365).sum().plot()
plt.title('Rolling sum of all crimes from 2012 - 2017')
plt.ylabel('Number of crimes')
plt.xlabel('Days')
plt.show()
```

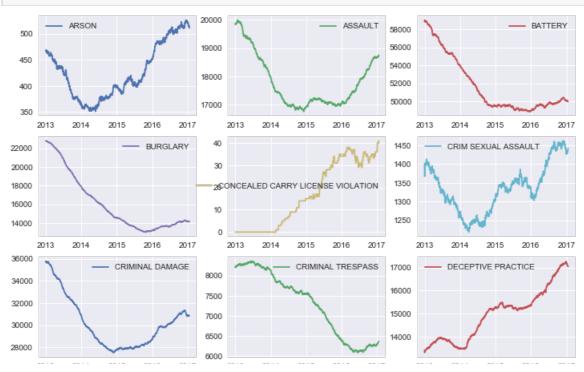


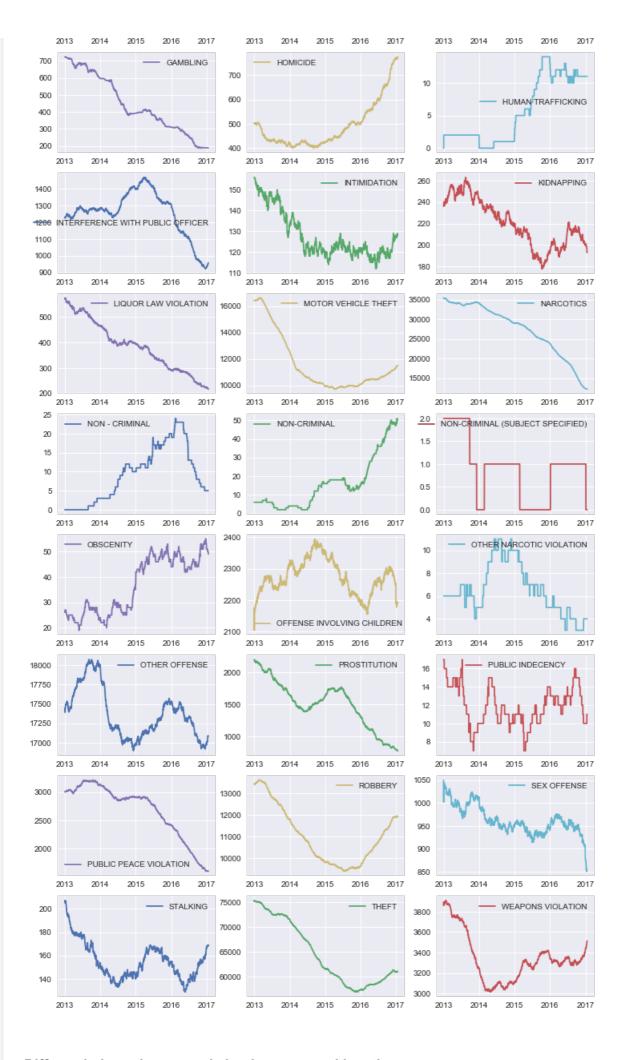
We see the line decreasing from 2013 up to some point around 2017 after which it stays around the same number of crimes. This all means that 2017 is really no better than 2016, but both years show a much better crime record (in total) than the previous years.

Separating crimes by type

In [16]:

```
crimes_count_date = crimes.pivot_table('ID', aggfunc=np.size, columns='Primary Type', index=crimes.
index.date, fill_value=0)
crimes_count_date.index = pd.DatetimeIndex(crimes_count_date.index)
plo = crimes_count_date.rolling(365).sum().plot(figsize=(12, 30), subplots=True, layout=(-1, 3), sh
arex=False, sharey=False)
```

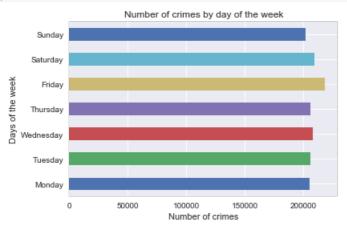




Is there a difference in the number of crimes during specific days of the week. Are there more crimes during weekdays or weekend?

In [17]:

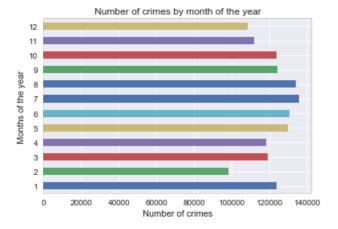
```
days = ['Monday','Tuesday','Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
crimes.groupby([crimes.index.dayofweek]).size().plot(kind='barh')
plt.ylabel('Days of the week')
plt.yticks(np.arange(7), days)
plt.xlabel('Number of crimes')
plt.title('Number of crimes by day of the week')
plt.show()
```



Here we can see that the highest number of crimes occur on Friday.

In [18]:

```
crimes.groupby([crimes.index.month]).size().plot(kind='barh')
plt.ylabel('Months of the year')
plt.xlabel('Number of crimes')
plt.title('Number of crimes by month of the year')
plt.show()
```

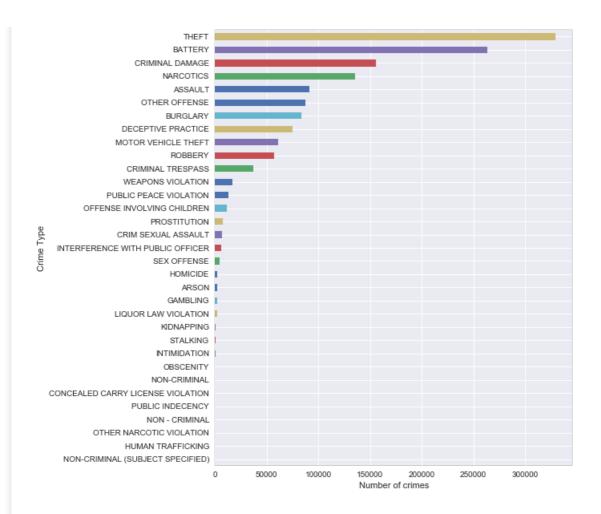


Here we can see that July has the highest no of crimes per month,

Which crimes are most common among the top 20 most frequent crime types?

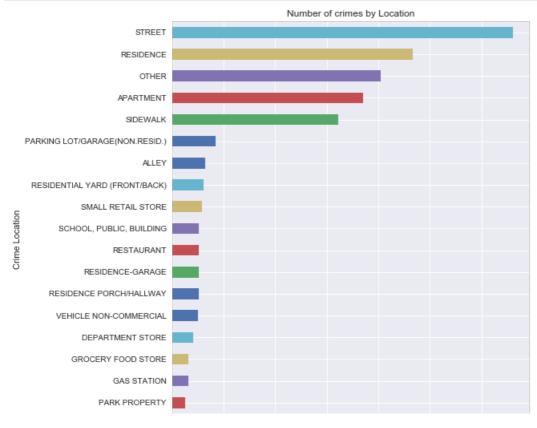
In [19]:

```
plt.figure(figsize=(8,10))
crimes.groupby([crimes['Primary Type']]).size().sort_values(ascending=True).plot(kind='barh')
plt.title('Number of crimes by type')
plt.ylabel('Crime Type')
plt.xlabel('Number of crimes')
plt.show()
```



In [20]:

```
plt.figure(figsize=(8,10))
  crimes.groupby([crimes['Location Description']]).size().sort_values(ascending=True).plot(kind='bar
h')
  plt.title('Number of crimes by Location')
  plt.ylabel('Crime Location')
  plt.xlabel('Number of crimes')
  plt.show()
```



Creating Heatmaps for each crime to get an idea of where the crimes were generally committed.

```
In [86]:
```

```
x = crimes.sample(30000)
```

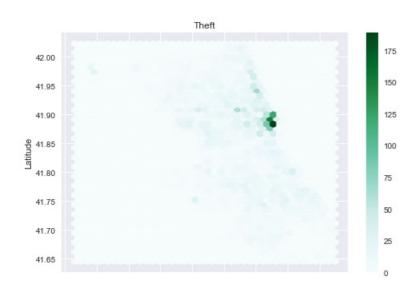
In [87]:

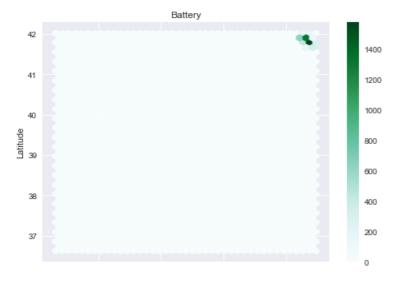
```
x theft = x[x['Primary Type'] == "THEFT"]
x_battery = x[x['Primary Type'] == "BATTERY"]
x_cd = x[x['Primary Type'] == "CRIMINAL DAMAGE"]
x narc = x[(x['Primary Type'] == "NARCOTICS")]
```

In [89]:

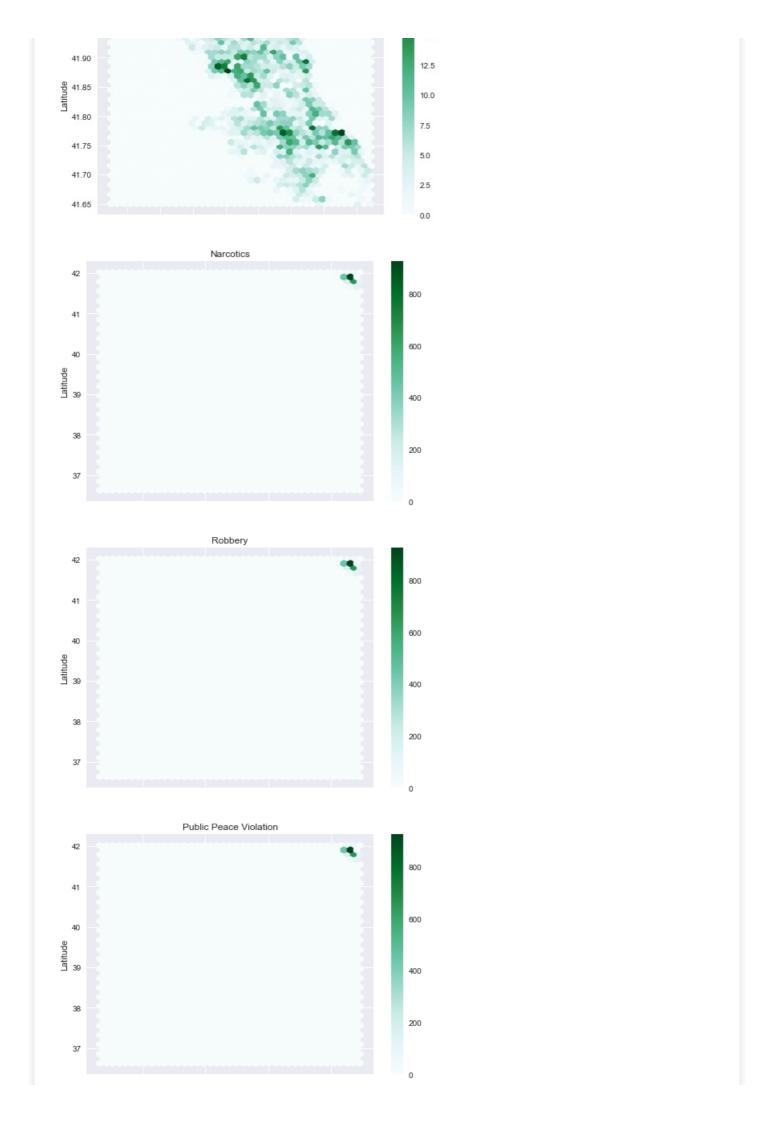
```
print("Heat map over cooridantes of crimes")
x.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Overall crimes")
plt.show()
x theft.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Theft")
x battery.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Battery")
x cd.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Criminal Damage")
plt.show()
x narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Narcotics")
plt.show()
x narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Robbery")
plt.show()
x_narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Public Peace Violation")
plt.show()
x narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Weapons Violation")
plt.show()
x narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Motor Vehicle Theft")
plt.show()
x narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Other Offense")
plt.show()
x narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Deceptive Practice")
plt.show()
x_narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Offense Involving Children")
plt.show()
x narc.plot.hexbin(x='Longitude', y='Latitude', gridsize=40)
plt.title("Sex Offense")
plt.show()
```

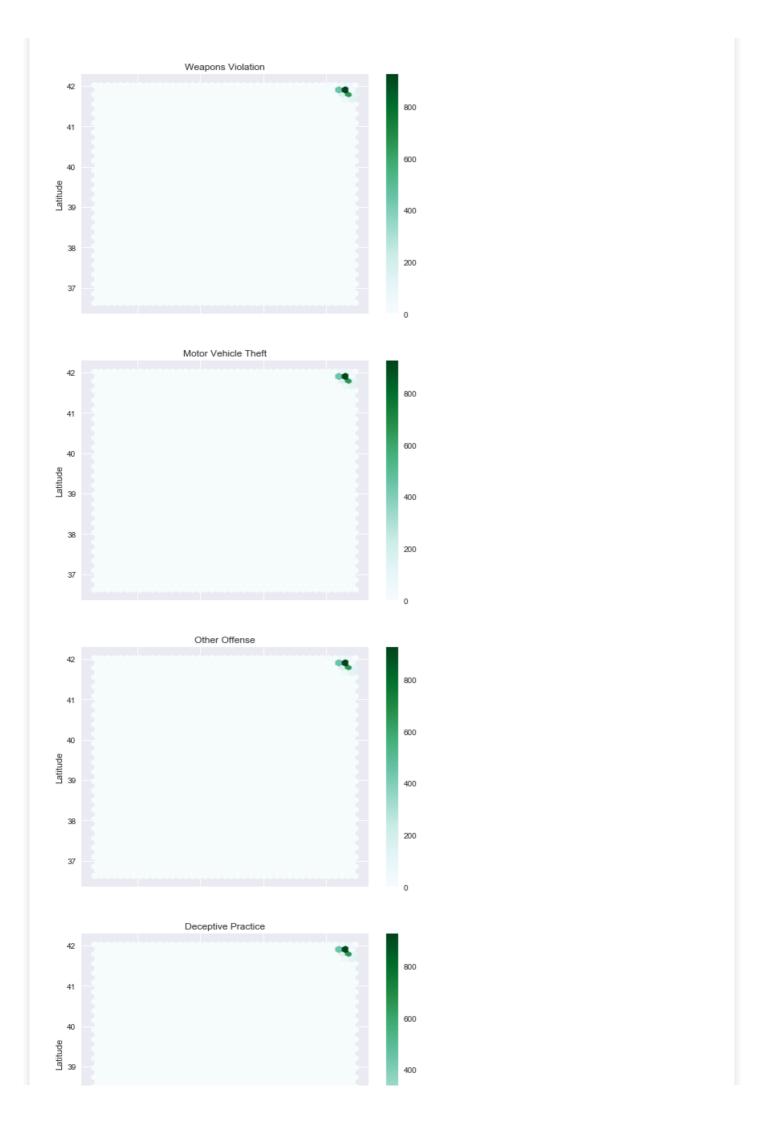


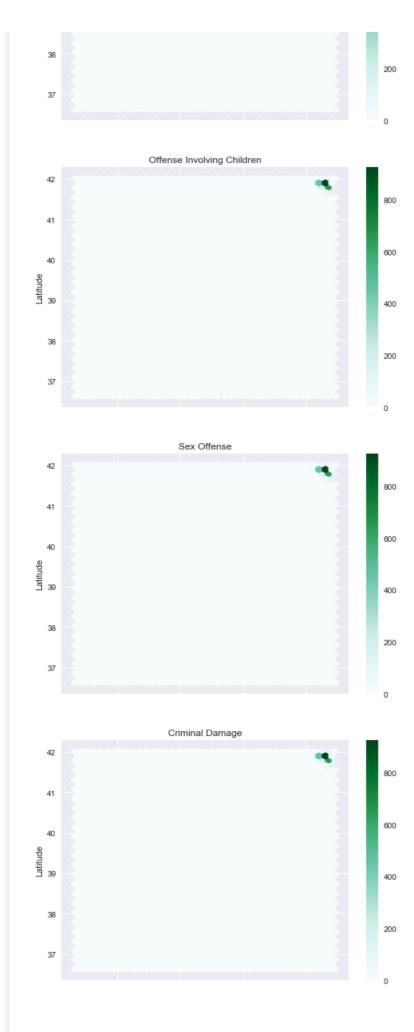












Analyzing thefts

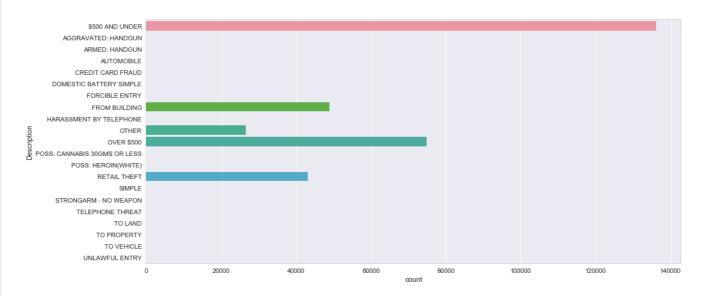
```
crimes_theft = crimes[crimes['Primary Type'] == 'THEFT']
```

In [23]:

```
plt.figure(figsize = (15, 7))
sns.countplot(y = crimes_theft['Description'])
```

Out[23]:

<matplotlib.axes._subplots.AxesSubplot at 0x2490fb14320>



In [24]:

```
crimes_theft_data = pd.DataFrame({"Counts": crimes_theft['Description'].value_counts(),
    "Description" : crimes_theft['Description'].value_counts().index})
```

In [25]:

```
crimes_theft_data.reset_index(inplace=True)
```

In [26]:

```
crimes_theft_data = crimes_theft_data.drop(columns=['index'], axis = 1)
crimes_theft_data.head()
```

Out[26]:

	Counts	Description
0	136036	\$500 AND UNDER
1	74906	OVER \$500
2	48835	FROM BUILDING
3	43109	RETAIL THEFT
4	26574	OTHER

In [27]:

```
%%time
crimes_theft['Date'] = pd.to_datetime(crimes_theft['Date'])
```

Wall time: 146 ms

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
"""Entry point for launching an IPython kernel.
```

In [28]:

```
crimes_theft['Month'] = crimes_theft['Date'].apply(lambda x : x.month)

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
"""Entry point for launching an IPython kernel.
```

In [29]:

```
theft_in_months = pd.DataFrame({"thefts" : crimes_theft['Month'].value_counts(), "month" :
crimes_theft["Month"].value_counts().index}, index = range(12))
```

In [30]:

```
theft_in_months.head()
```

Out[30]:

	thefts	month
0	NaN	7
1	26982.0	8
2	20667.0	6
3	24702.0	9
4	25686.0	10

In [31]:

```
plt.figure(figsize = (15,7))
plt.plot(theft_in_months['month'], theft_in_months['thefts'], label = 'Total In Month')
plt.plot(theft_in_months['month'], theft_in_months['thefts'].rolling(window = 2).mean(),color='red',
linewidth=5, label='2-months Moving Average')

plt.title('Thefts per month', fontsize=16)
plt.xlabel('Months')
plt.legend(prop={'size':16})
plt.tick_params(labelsize=16);
```



In [32]:

```
print (max (crimes_theft['Date']))
print (min (crimes_theft['Date']))

2017-01-18 23:00:00
```

2012-01-01 00:00:00

In [33]:

```
crimes_theft['Date'].iloc[0].date()
```

Out[33]:

datetime.date(2016, 5, 3)

Conclusion

According to our analysis,

- 1.It can be concluded that the Crime has decreased over the years from 2012-2017.
- 2. Theft is the highest committed crime.
- 3. Weekdays encountered more number of crimes as compared to weekends.
- 4.It is observed that crimes committed were highest on street and lowest on Business/Commercial Office.