ABOUT THE PROJECT

> The project about **Chicago Crime Analysis** where we explore and visualize the dataset for the cri
> the years 2001 to 2017.

> We also would like to demonstrate the application of basic Machine Learning Models and some l
> to perform classification task with Chicago Crime Dataset.

```
from google.colab import drive

drive.mount('/content/drive', force_remount=True)
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=9473189

Enter your authorization code:
··········
Mounted at /content/drive
```

```
cd drive
```

```
/content/drive
```

```
cd My\ Drive
```

```
/content/drive/My Drive
```

```
cd Chicago\ Crime\ Analysis
```

```
/content/drive/My Drive/Chicago Crime Analysis
```

```
ls
```

```
Chicago_Crimes_2001_to_2004.csv  Chicago_Crimes_2008_to_2011.csv
Chicago_Crimes_2005_to_2007.csv  Chicago_Crimes_2012_to_2017.csv
```

Importing the Required Libraries

```
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sea
import numpy as np
import datetime as dt
import folium # for 3d visualization
```

Reading the Data and concatenating

```
data1 = pd.read_csv('Chicago_Crimes_2001_to_2004.csv',error_bad_lines=False)
data2 = pd.read_csv('Chicago_Crimes_2005_to_2007.csv',error_bad_lines=False)
data3 = pd.read_csv('Chicago_Crimes_2008_to_2011.csv',error_bad_lines=False)
data4 = pd.read_csv('Chicago_Crimes_2012_to_2017.csv',error_bad_lines=False)
data = pd.concat([data1, data2, data3, data4], ignore_index=False, axis=0)
```

```
b'Skipping line 1513591: expected 23 fields, saw 24\n'
/usr/local/lib/python3.6/dist-packages/IPython/core/interactiveshell.py:2718: DtypeWarni
  interactivity=interactivity, compiler=compiler, result=result)
b'Skipping line 533719: expected 23 fields, saw 24\n'
b'Skipping line 1149094: expected 23 fields, saw 41\n'
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7941282 entries, 0 to 1456713
Data columns (total 23 columns):
Unnamed: 0              int64
ID                      int64
Case Number             object
Date                    object
Block                   object
IUCR                    object
Primary Type            object
Description             object
Location Description    object
Arrest                  bool
Domestic                bool
Beat                    int64
District                float64
Ward                    float64
Community Area          float64
FBI Code                object
X Coordinate            float64
Y Coordinate            object
Year                    float64
Updated On              object
Latitude                object
Longitude               float64
Location                object
dtypes: bool(2), float64(6), int64(3), object(12)
memory usage: 1.3+ GB
```

```
data.head(5)
```

	Unnamed: 0	ID	Case Number	Date	Block	IUCR	Primary Type	Description
0	879	4786321	HM399414	01/01/2004 12:01:00 AM	082XX S COLES AVE	0840	THEFT	FINANCIAL ID THEFT: OVER $300
1	2544	4676906	HM278933	03/01/2003 12:00:00 AM	004XX W 42ND PL	2825	OTHER OFFENSE	HARASSMENT BY TELEPHONE
2	2919	4789749	HM402220	06/20/2004 11:00:00 AM	025XX N KIMBALL AVE	1752	OFFENSE INVOLVING CHILDREN	AGG CRIM SEX ABUSE FAM MEMBER
3	2927	4789765	HM402058	12/30/2004 08:00:00 PM	045XX W MONTANA ST	0840	THEFT	FINANCIAL ID THEFT: OVER $300
4	3302	4677901	HM275615	05/01/2003 01:00:00 AM	111XX S NORMAL AVE	0841	THEFT	FINANCIAL ID THEFT:$300 &UNDER

```
data.shape
```

```
(7941282, 23)
```

Preprocessing

Our dataset is huge with nearly ~8 million rows. Firstly we try to preprocessing the data by looking int

```
null_data=data.isnull().sum()
print(null_data)
```

```
Unnamed: 0                  0
ID                          0
Case Number                 7
Date                        0
Block                       0
IUCR                        0
Primary Type                0
Description                 0
Location Description     1990
Arrest                      0
Domestic                    0
Beat                        0
District                   91
Ward                   700224
Community Area         702091
FBI Code                    0
X Coordinate           105573
Y Coordinate           105573
Year                        0
Updated On                  0
Latitude               105573
Longitude              105574
Location               105574
dtype: int64
```

Collectively there are many rows with **NaN** values, so we tend to delete them.

```
data = data.dropna(how = 'any', axis = 'rows')
```

```
data.shape
```

```
# df = data.sample(n=1000000)
df = data
```

```
df.shape
```

```
(7145213, 23)
```

```
print('Dataset Shape before drop_duplicate : ', df.shape)
df.drop_duplicates(subset=['ID', 'Case Number'], inplace=True)
print('Dataset Shape after drop_duplicate: ', df.shape)
```

```
Dataset Shape before drop_duplicate :  (7145213, 23)
Dataset Shape after drop_duplicate:  (5478329, 23)
```

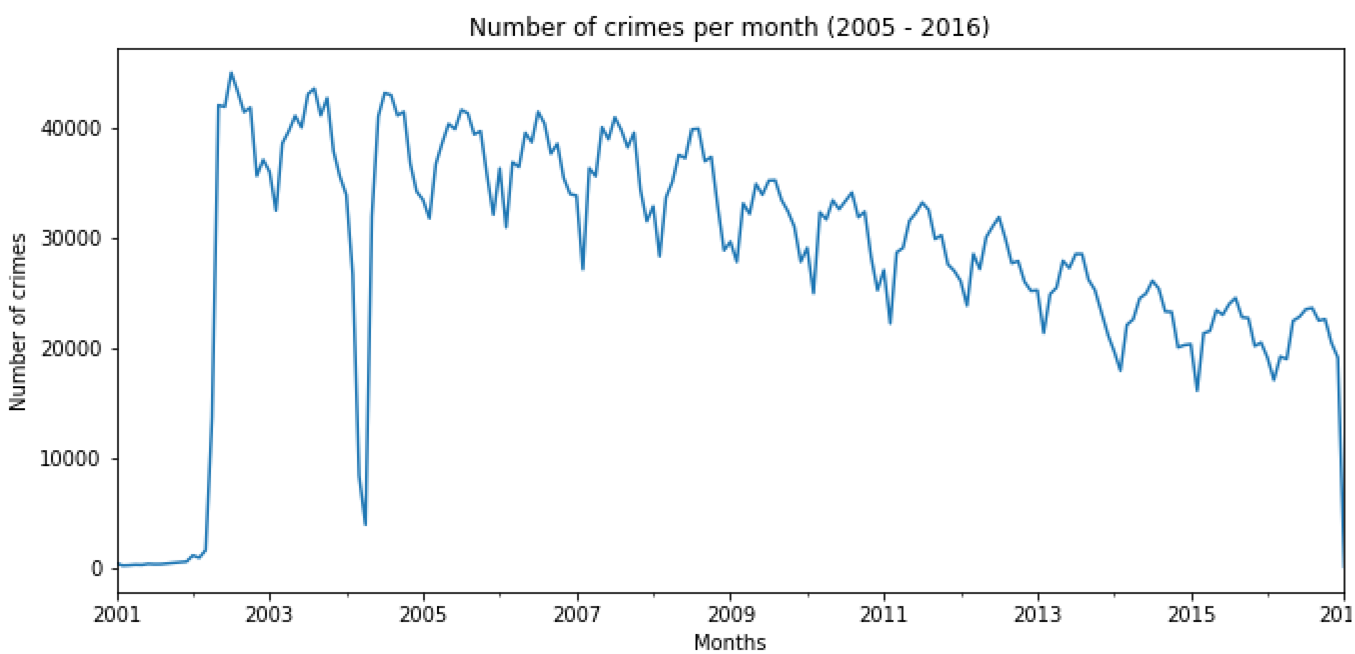
Getting Community Number to Name Mapping.

```
community_mapping = {0.0: 'Rogers Park ', 1.0: 'West Ridge ', 2.0: 'Uptown ', 3.0: 'Lincoln S

df['Community'] = df['Community Area'].map(community_mapping)

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

Plotting

> Let us first plot the crime lineage through the years.

```
plt.figure(figsize=(11,5))
df.resample('M').size().plot(legend=False)
plt.title('Number of crimes per month (2005 - 2016)')
plt.xlabel('Months')
plt.ylabel('Number of crimes')
plt.show()
```



As we can see in the above chart, there is a periodic pattern in the crimes over all the years. On a who decreasing from 2002 to 2017.

> Let us see the same for each crime.

```
crimes_count_date = df.pivot_table('ID', aggfunc=np.size, columns='Primary Type', index=df.in
```

```
%matplotlib inline
plt.style.use('seaborn')
```

> Crimes grouped by Day of Week.

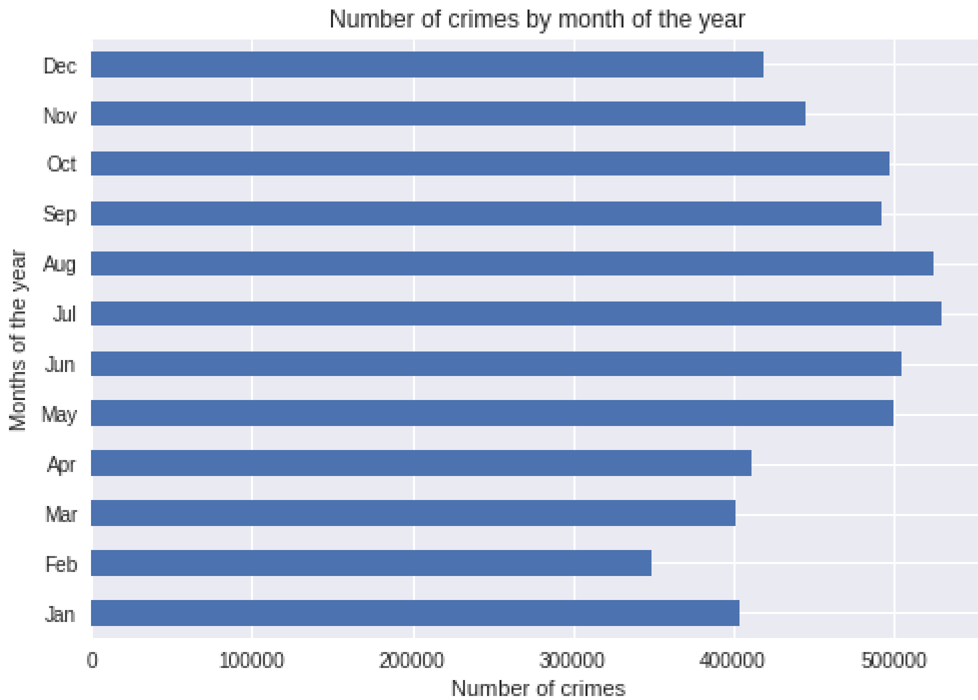
```
days = ['Monday','Tuesday','Wednesday',  'Thursday', 'Friday', 'Saturday', 'Sunday']
df.groupby([df.index.dayofweek]).size().plot(kind='barh')
plt.ylabel('Days of the week')
plt.yticks(np.arange(7), days)
plt.xlabel('Number of crimes')
plt.title('Number of crimes by day of the week')
plt.show()
```

> We don't see any significant difference between days, maybe friday has higher number of crime t cannot really say much more in this relation.

> Crimes grouped by Month.

```
months = ['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']
df.groupby([df.index.month]).size().plot(kind='barh')
plt.ylabel('Months of the year')
plt.xlabel('Number of crimes')
```

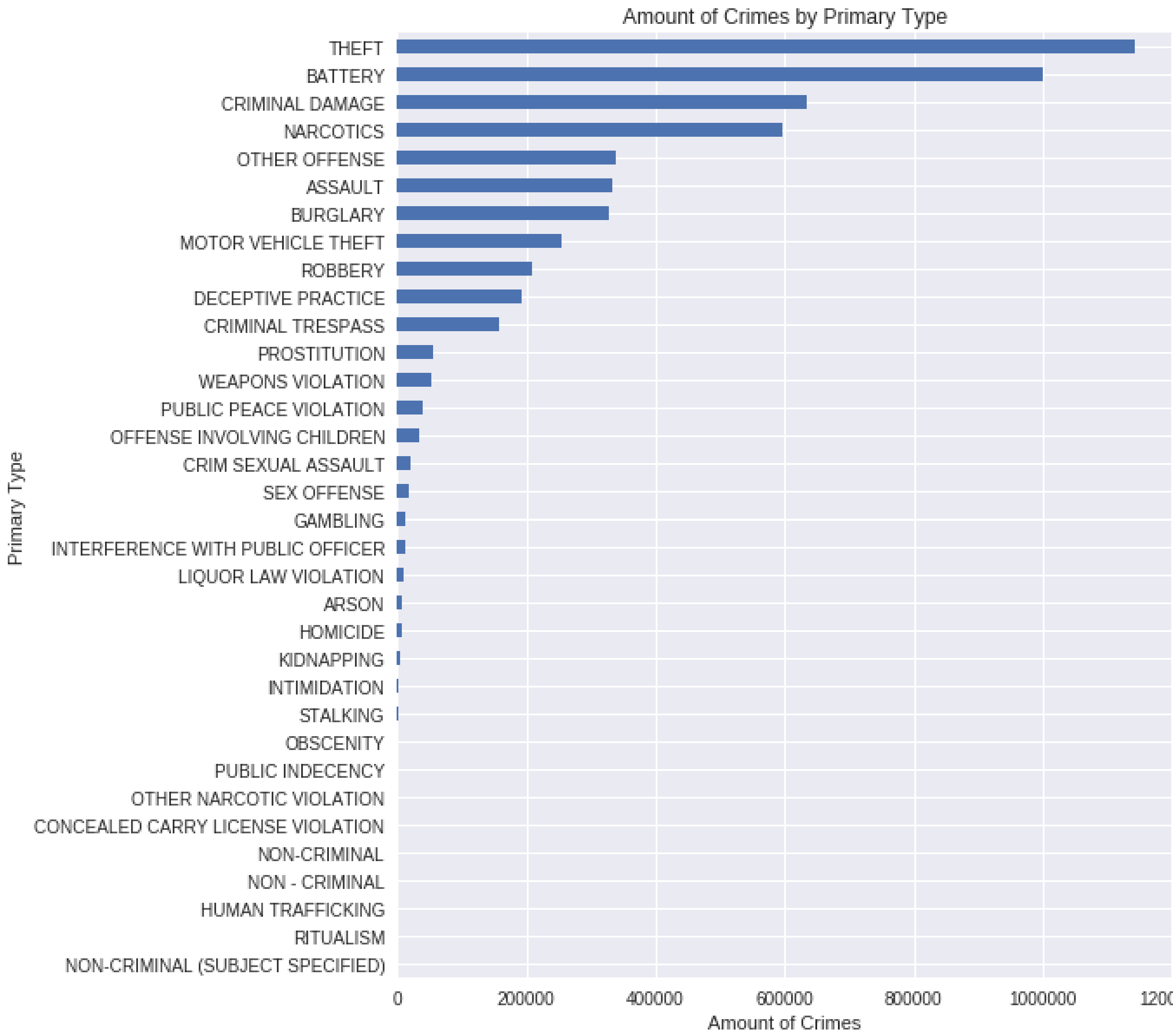
```
plt.yticks(np.arange(12), months)
plt.title('Number of crimes by month of the year')
plt.show()
```



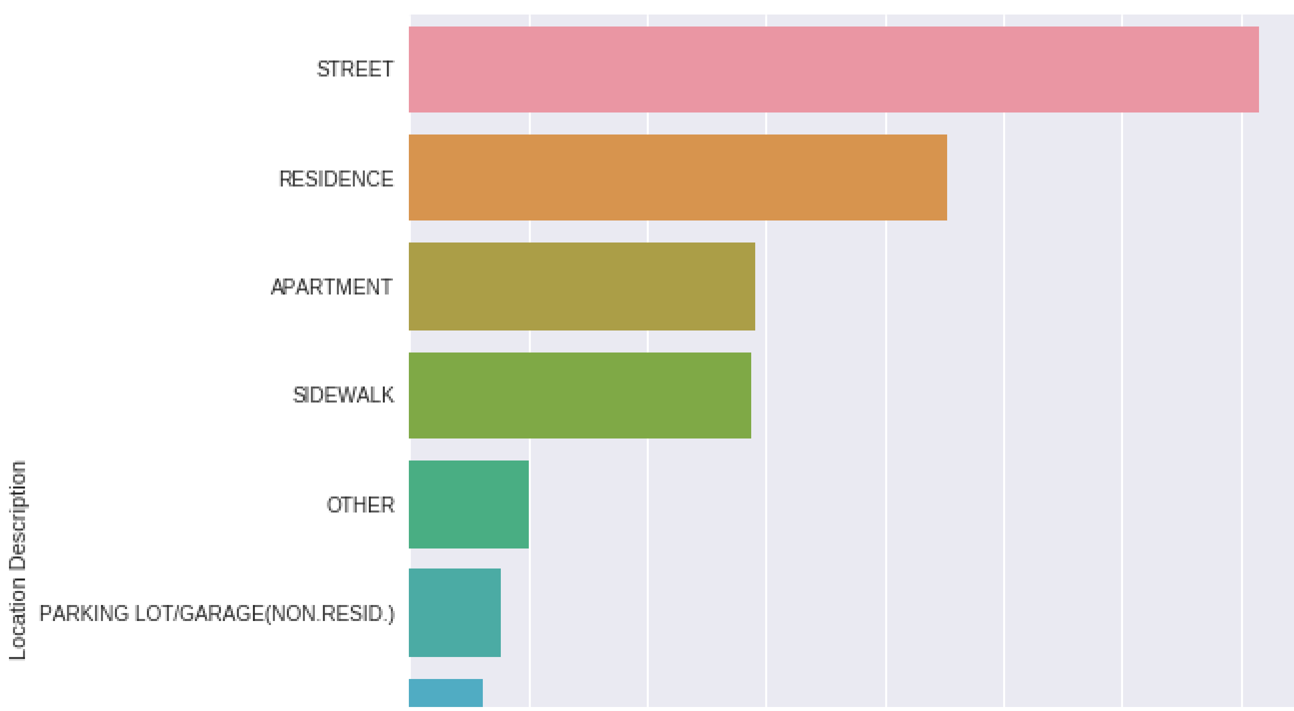
> In here, we can see a clear segmentation where in the months of May - August, the crime rate is h
> October.

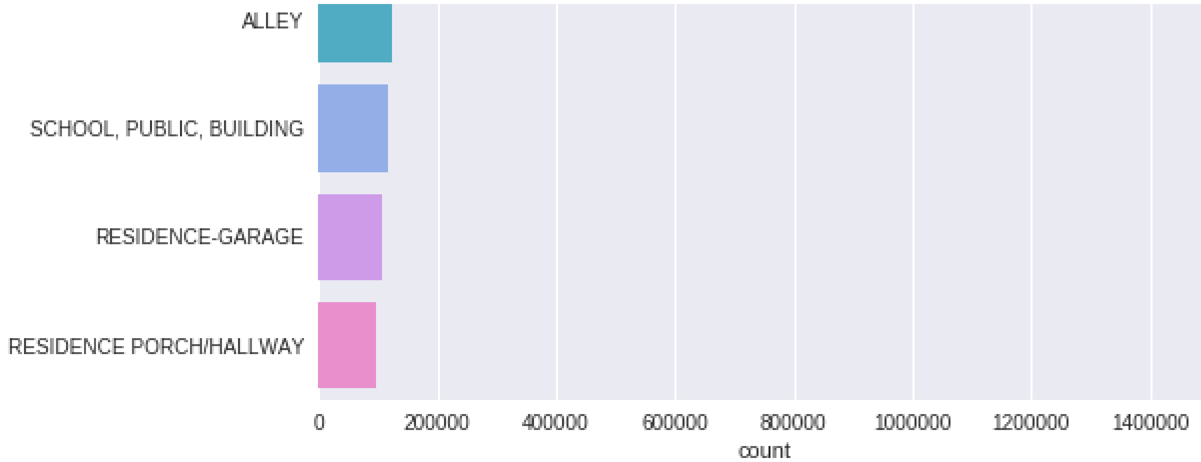
> Let us plot the distribution of the crimes based on the type.

```
plt.figure(figsize=(8,10))
plt.title('Amount of Crimes by Primary Type')
plt.ylabel('Crime Type')
plt.xlabel('Amount of Crimes')

df.groupby([df['Primary Type']]).size().sort_values(ascending=True).plot(kind='barh')

plt.show()

import seaborn as sns
plt.figure(figsize = (8, 10))
sns.countplot(y= 'Location Description', data = df, order = df['Location Description'].value_
```



<matplotlib.axes._subplots.AxesSubplot at 0x7f94a4a86a58>





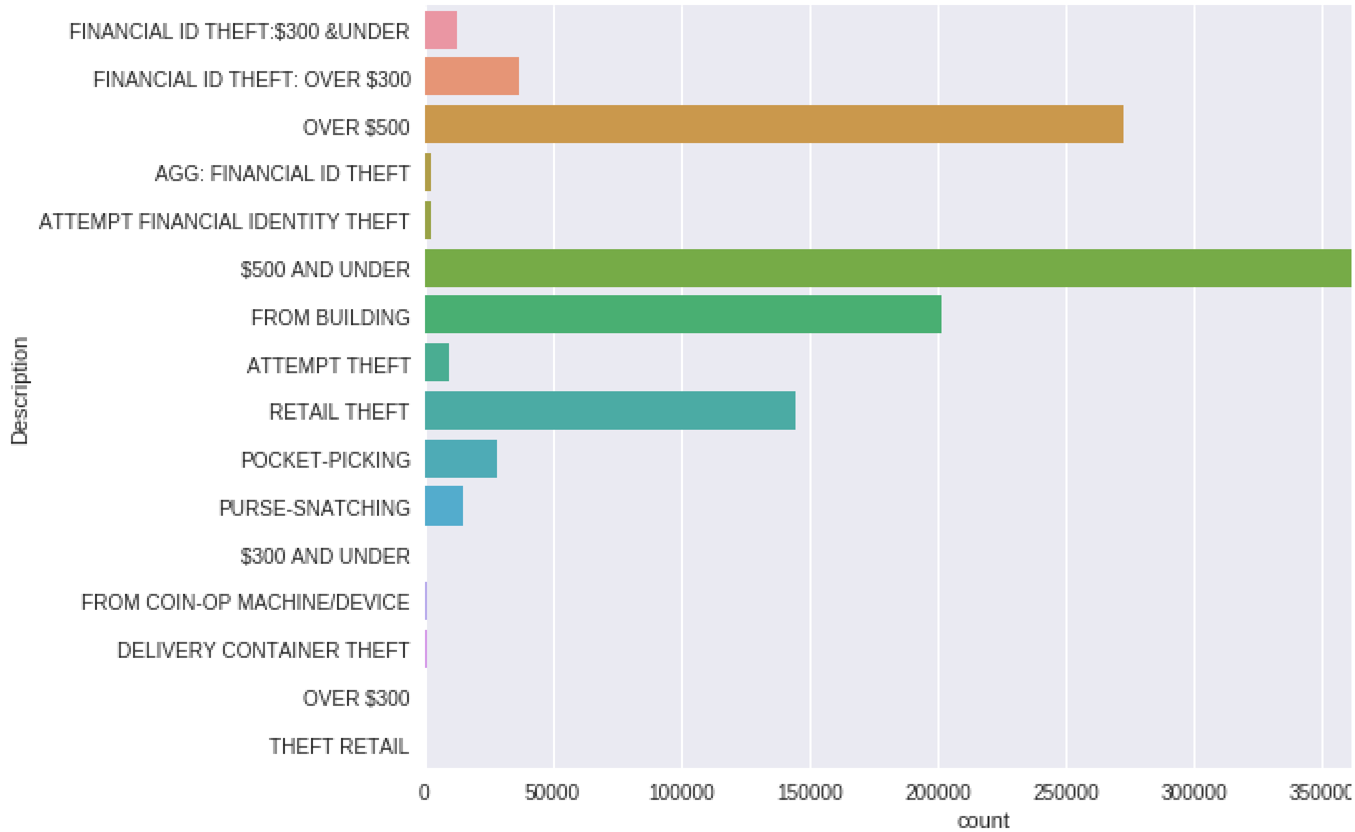
We can see that the 'theft', 'battery', 'criminal damage', 'narcotics' topped the most committed crime li which is the most dangerous one, it says that these are more in number in chicago. Most of the crime mostly in residences/ streets.

> Let us take a closer look on 'theft'

```
df_theft = df[df['Primary Type'] == 'THEFT']
```

```
plt.figure(figsize = (10, 7))
# sns.countplot(y= 'Description', data = df_theft, order = df['Description'].value_counts().i
sns.countplot(y = df_theft['Description'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f94a4a24198>
```



In here we can see that the small theft are of high in number followed by huge buglaries over 500$. Re
follow up next. These four constitute most of the percentage of thefts.

> Now let us do post-processing on the Descriptions, we have huge number of them and the trailin
> So we club those and sum-up those entries into OTHERS.

```
#getting all the classes
all_classes = df.groupby(['Primary Type'])['Block'].size().reset_index()
all_classes['Count'] = all_classes['Block']
all_classes = all_classes.drop(['Block'], axis=1)
all_classes = all_classes.sort_values(['Count'], ascending=[False])
all_classes
```

	Primary Type	Count
32	THEFT	1143153
2	BATTERY	998674
6	CRIMINAL DAMAGE	633246
17	NARCOTICS	597701
24	OTHER OFFENSE	337754
1	ASSAULT	334045
3	BURGLARY	326234
16	MOTOR VEHICLE THEFT	254388
29	ROBBERY	207996
8	DECEPTIVE PRACTICE	194091
7	CRIMINAL TRESPASS	159349
25	PROSTITUTION	56985
33	WEAPONS VIOLATION	54516
27	PUBLIC PEACE VIOLATION	41041
22	OFFENSE INVOLVING CHILDREN	35484
5	CRIM SEXUAL ASSAULT	20166
30	SEX OFFENSE	18975
9	GAMBLING	12669
12	INTERFERENCE WITH PUBLIC OFFICER	12250
15	LIQUOR LAW VIOLATION	11291
0	ARSON	8863
10	HOMICIDE	7812
14	KIDNAPPING	5022
13	INTIMIDATION	3171
31	STALKING	2626
21	OBSCENITY	363
26	PUBLIC INDECENCY	124
23	OTHER NARCOTIC VIOLATION	101
4	CONCEALED CARRY LICENSE VIOLATION	84
19	NON-CRIMINAL	80

18	NON - CRIMINAL	38
11	HUMAN TRAFFICKING	20
28	RITUALISM	13
20	NON-CRIMINAL (SUBJECT SPECIFIED)	4

```
#These are the unwanted classes, trailing at the last
unwanted_classes = all_classes.tail(13)
unwanted_classes
```

	Primary Type	Count
10	HOMICIDE	7812
14	KIDNAPPING	5022
13	INTIMIDATION	3171
31	STALKING	2626
21	OBSCENITY	363
26	PUBLIC INDECENCY	124
23	OTHER NARCOTIC VIOLATION	101
4	CONCEALED CARRY LICENSE VIOLATION	84
19	NON-CRIMINAL	80
18	NON - CRIMINAL	38
11	HUMAN TRAFFICKING	20
28	RITUALISM	13
20	NON-CRIMINAL (SUBJECT SPECIFIED)	4

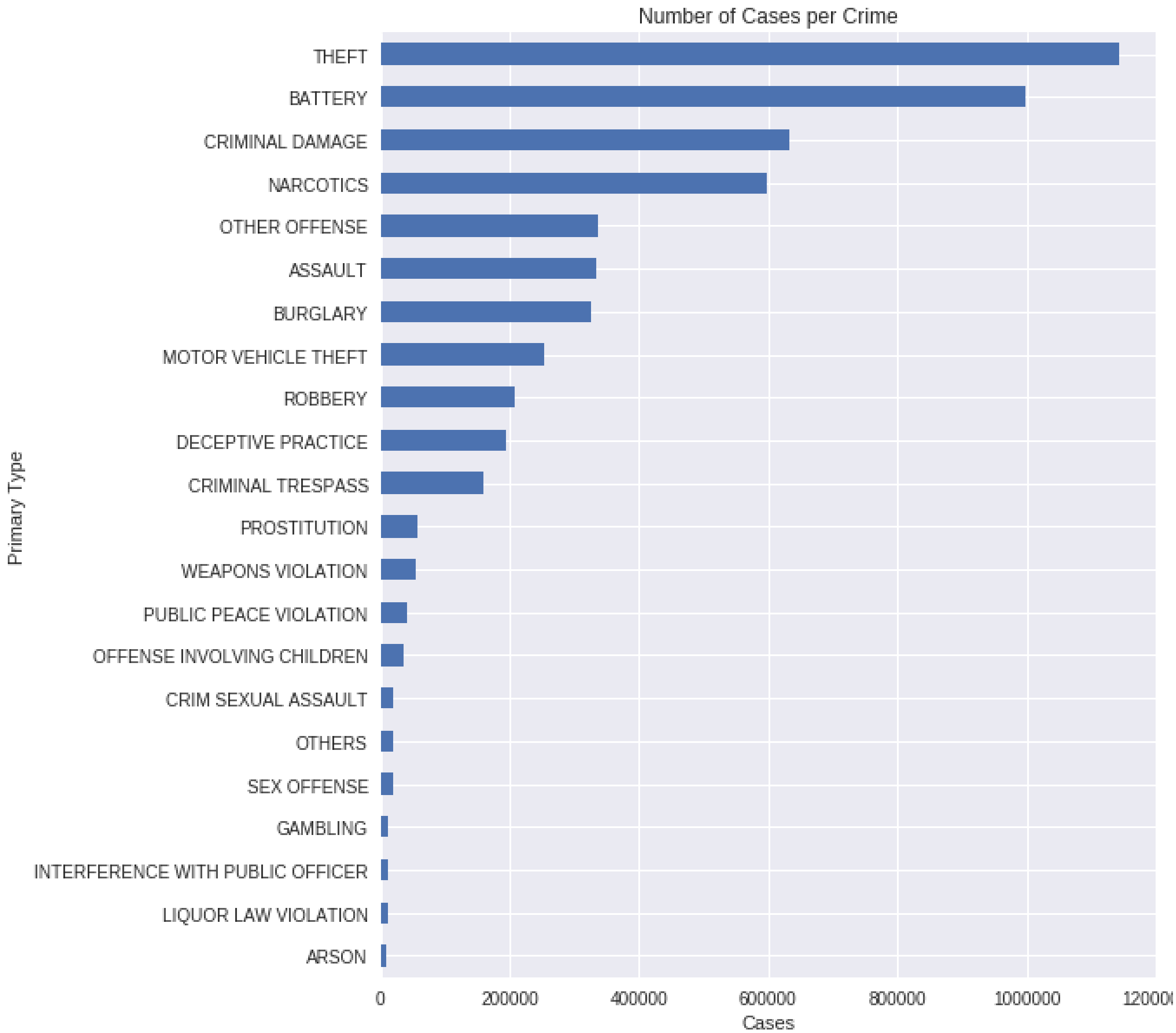
> Replacing them with OTHERS

```
df.loc[df['Primary Type'].isin(unwanted_classes['Primary Type']), 'Primary Type'] = 'OTHERS'
```

Now, Let's check the number of cases per crime.

```
plt.figure(figsize=(8,10))
plt.title('Number of Cases per Crime')
plt.ylabel('Crime Type')
plt.xlabel('Cases')

df.groupby([df['Primary Type']]).size().sort_values(ascending=True).plot(kind='barh')
```

```
df.groupby([df['Primary Type']]).size().sort_values(ascending=True).plot(kind='barh')

plt.show()
```




```
print('Total niumber of Crimes Now : ',len(df['Primary Type'].unique()))
```

```
Total niumber of Crimes Now :  22
```

> Let us split up the Date

```
# Splitting the Date to Day, Month, Year, Hour, Minute, Second
df['temp_date'] = pd.to_datetime(df['Date'])
df['Year'] = df['temp_date'].dt.year
df['Month'] = df['temp_date'].dt.month
df['Day'] = df['temp_date'].dt.day
df['Hour'] = df['temp_date'].dt.hour
df['Minute'] = df['temp_date'].dt.minute
df['Second'] = df['temp_date'].dt.second
```

```
df['Second'] = df['temp_date'].dt.second


df = df.drop(['temp_date'], axis=1)
df = df.drop(['Updated On'], axis=1)


df.head(5)
```

	Unnamed: 0	ID	Case Number	Date	Block	IUCR	Primary Type	Descripti
Date								
2003-03-01 00:00:00	2544	4676906	HM278933	2003-03-01 00:00:00	004XX W 42ND PL	2825	OTHER OFFENSE	HARASSME I TELEPHO
2003-05-01 01:00:00	3302	4677901	HM275615	2003-05-01 01:00:00	111XX S NORMAL AVE	0841	THEFT	FINANCIAL THEFT:$3 &UND
2001-01-01 11:00:00	3756	4791194	HM403711	2001-01-01 11:00:00	114XX S ST LAWRENCE AVE	0266	CRIM SEXUAL ASSAULT	PREDATO
2003-03-15 00:00:00	4502	4679521	HM216293	2003-03-15 00:00:00	090XX S RACINE AVE	5007	OTHER OFFENSE	OTH WEAPO VIOLATI
2003-01-01 00:00:00	4904	4680124	HM282389	2003-01-01 00:00:00	009XX S SPAULDING AVE	0840	THEFT	FINANCIAL THEFT: OV $3

Let us count the total cases punished/ not punished per year

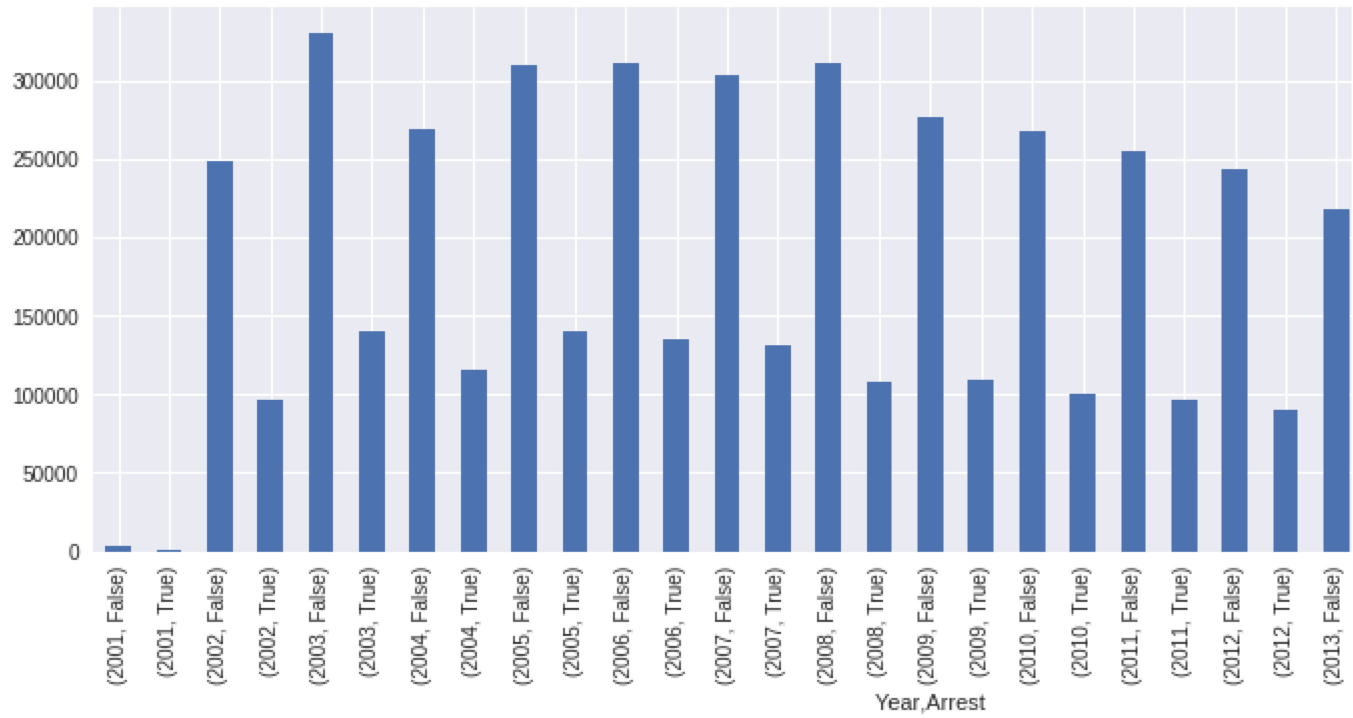
```
df_arrest = df[['Year', 'Arrest']].copy()


# grouping by year for arrest column
week_groups = df_arrest.groupby([df.Year, 'Arrest']).count()


# import seaborn as sns
# sns.set(style="whitegrid")

# # Draw a nested barplot to show survival for class and sex
# g = sns.catplot(x="Year", y="Year", hue="Arrest", data=df,
#                  height=6, kind="bar", palette="muted")
# g.despine(left=True)
# g.set_ylabels("survival probability")
week_groups
```

		Year
Year	Arrest	
2001	**False**	3104
	True	710
2002	**False**	248761
	True	96140
2003	**False**	330745
	True	140277
2004	**False**	268738
	True	116098
2005	**False**	309663
	True	140207
2006	**False**	310852
	True	134643
2007	**False**	303864
	True	131663
2008	**False**	311702
	True	108085
2009	**False**	277066
	True	108764
2010	**False**	268330
	True	100080
2011	**False**	254414
	True	96058
2012	**False**	243957
	True	90440
2013	**False**	218225
	True	86042
2014	**False**	191291
	True	78038
2015	**False**	191294

	True	68316
2016	**False**	202511
	True	48221
2017	**False**	30

```
# Visualizing
week_groups.plot(kind='bar',figsize=(15,5),legend=None)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f94a2161550>
```




```
i=0
map = {}
j=1
# turning dataframe into array
temp = week_groups.values
while i <= len(temp):
  if j<10:
    map['200'+str(j)] = [temp[i], temp[i+1]]
  elif i==32:
    map['20'+str(j)] = [0, temp[i]]
  else:
    map['20'+str(j)] = [temp[i], temp[i+1]]
  i+=2

  j+=1

print('Year    Total        Punished         Not Punished')
# Calculating the percentage
for key, array in map.items():
```

```
for key, array in map.items():
  st = key + '     '
  total = array[0]+array[1]
  tr_per = (array[0]/total)*100
  fl_per = 100 - tr_per
  print(st+str(total)+'    '+str(tr_per)+'%    '+str(fl_per)+'%    ')
```

As we can see in the year 2001, the punished percent is greater than the rest, but the total number of the later years.

We can see a small-scale increase in the punished percent in the years down from 2005 to 2016, whic measures through the years.

Now, let's see which district has the highest and lowest crime-rate.

```
crime_rate_per_district = df.Community.value_counts(normalize=True)
print(crime_rate_per_district * 100)
```

Proving the well-known fact, The South Side has the highest crime rate which is significantly more tha
North Park, West Lawn, North Side with almost similar percent in crime cases.

Rogers Park, Albany Park, Armour Square, North Center have the lowest recorded crime rate down the

```
df_year_split = [pd.DataFrame(y) for x, y in df.groupby('Year', as_index=False)]
```

```
len(df_year_split)
```

```
df_year_split[0]['Year'][0]
```

```
2001
```

Let's check which district has more crime rate per each year.

```
for i,df_year in enumerate(df_year_split):
  print('\n----------- ',df_year['Year'][0],' -----------')
  crime_rate_per_district = df_year.Community.value_counts(normalize=True)
  print(crime_rate_per_district * 100)
```

```
-----------  2001  -----------
Near South Side     6.895648
Near North Side     5.820661
Hermosa             3.093865
Loop                2.962769
Humboldt Park       2.779234
                      ...
Archer Heights      0.183534
Brighton Park       0.183534
Armour Square       0.157315
North Center        0.131096
Albany Park         0.104877
Name: Community, Length: 77, dtype: float64

-----------  2002  -----------
Near South Side     5.911841
North Park          3.486218
Loop                3.451135
Near North Side     3.157138
West Lawn           3.097121
                      ...
Woodlawn            0.206146
North Center        0.175993
Armour Square       0.133662
Albany Park         0.091331
Rogers Park         0.001740
Name: Community, Length: 78, dtype: float64

-----------  2003  -----------
Near South Side     6.490780
Austin              3.306852
Near North Side     3.254625
Loop                3.232333
North Park          3.218321
                      ...
Archer Heights      0.188951
North Center        0.177062
Armour Square       0.143518
Albany Park         0.089592
Rogers Park         0.001486
Name: Community, Length: 78, dtype: float64

-----------  2004  -----------
Near South Side     6.164964
North Park          3.344801
Austin              3.149134
Near North Side     3.069359
West Lawn           3.049611
                      ...
Archer Heights      0.189431
North Center        0.169163
Armour Square       0.160328
Albany Park         0.084711
Rogers Park         0.002339
Name: Community, Length: 78, dtype: float64
```

```
-----------  2005  -----------
Near South Side     6.257363
Near North Side     3.266055
North Park          3.236268
West Lawn           3.184920
South Chicago       3.001756
                      ...
Archer Heights      0.193834
North Center        0.192055
Armour Square       0.158490
Albany Park         0.102029
Rogers Park         0.000445
Name: Community, Length: 78, dtype: float64

-----------  2006  -----------
Near South Side     6.441374
West Lawn           3.315189
North Park          3.177813
South Chicago       3.061763
Near North Side     3.057273
                      ...
Archer Heights      0.178678
North Center        0.175535
Armour Square       0.149272
Albany Park         0.097195
Rogers Park         0.002469
Name: Community, Length: 78, dtype: float64

-----------  2007  -----------
Near South Side     6.532086
West Lawn           3.264551
North Park          3.179596
South Chicago       3.108188
Pullman             3.050787
                      ...
Woodlawn            0.197003
North Center        0.168761
Armour Square       0.168531
Albany Park         0.095516
Rogers Park         0.001148
Name: Community, Length: 78, dtype: float64

-----------  2008  -----------
Near South Side     6.381331
West Lawn           3.345506
South Chicago       3.179946
North Park          3.168750
Near North Side     3.097047
                      ...
West Pullman        0.220350
North Center        0.185809
Armour Square       0.175565
Albany Park         0.110056
Rogers Park         0.001668
Name: Community, Length: 78, dtype: float64

-----------  2009  -----------
Near South Side     6.638934
```

```
West Lawn           3.333593
Near North Side     3.240546
North Park          3.137651
Loop                3.018687
                      ...
Woodlawn            0.209159
North Center        0.191794
Armour Square       0.155250
Albany Park         0.098748
Rogers Park         0.001296
Name: Community, Length: 78, dtype: float64

-----------  2010  -----------
Near South Side     6.561168
West Lawn           3.330528
Near North Side     3.192910
North Park          3.129394
Loop                3.074021
                      ...
Woodlawn            0.206292
North Center        0.188377
Armour Square       0.123504
Albany Park         0.082245
Rogers Park         0.000814
Name: Community, Length: 78, dtype: float64

-----------  2011  -----------
Near South Side     6.463284
West Lawn           3.442786
North Park          3.188557
Near North Side     3.174861
South Chicago       3.083841
                      ...
West Pullman        0.206579
North Center        0.171768
Armour Square       0.129825
Albany Park         0.104145
Rogers Park         0.001427
Name: Community, Length: 78, dtype: float64

-----------  2012  -----------
Near South Side        6.362198
West Lawn              3.458464
North Park             3.361872
Near North Side        3.339743
West Garfield Park     3.094525
                         ...
West Pullman           0.210827
North Center           0.178530
Armour Square          0.158793
Albany Park            0.095994
Rogers Park            0.000299
Name: Community, Length: 78, dtype: float64

-----------  2013  -----------
Near South Side        6.606040
West Lawn              3.442371
Near North Side        3.348046
```

```
Near North Side        3.348046
North Park             3.295790
West Garfield Park     3.189304
                         ...
Irving Park            0.205083
West Pullman           0.204426
Armour Square          0.153155
North Center           0.144281
Albany Park            0.095640
Name: Community, Length: 77, dtype: float64

-----------  2014  -----------
Near South Side        6.852957
West Lawn              3.370227
Near North Side        3.342381
North Park             3.263666
West Garfield Park     3.155991
                         ...
Woodlawn               0.227231
Irving Park            0.188988
North Center           0.167453
Armour Square          0.147032
Albany Park            0.088368
Name: Community, Length: 77, dtype: float64

-----------  2015  -----------
Near South Side        6.594892
West Lawn              3.445168
North Park             3.428219
West Garfield Park     3.155117
Near North Side        3.106583
                         ...
Irving Park            0.220330
Woodlawn               0.195293
North Center           0.169485
Armour Square          0.146759
Albany Park            0.097069
Name: Community, Length: 77, dtype: float64

-----------  2016  -----------
Near South Side        6.268845
North Park             3.904966
Austin                 3.538041
North Lawndale         3.360959
West Garfield Park     3.220570
                         ...
West Pullman           0.222947
Woodlawn               0.216566
North Center           0.210185
Armour Square          0.147568
Albany Park            0.112870
Name: Community, Length: 77, dtype: float64

-----------  2017  -----------
Near South Side            26.666667
West Town                  13.333333
Humboldt Park               6.666667
Austin                      6.666667
```

```
Chicago Lawn              6.666667
East Garfield Park        3.333333
Loop                      3.333333
Lincoln Square            3.333333
Mount Greenwood           3.333333
Uptown                    3.333333
Burnside                  3.333333
Avalon Park               3.333333
New City                  3.333333
West Garfield Park        3.333333
Near North Side           3.333333
Greater Grand Crossing    3.333333
Gage Park                 3.333333
Name: Community, dtype: float64
```

By the above details split by year we can observe the following:

- South Side tops every year with highest crime rate and it's consistant through out the years.
- It is followed by Westside and North Park which have equivalent crime rate.
- Armour Square, Albany Park, Rogers Park have the lowest crime rate recorded over the years.
- It is followed by North Center which a slightly fluctuating crime rate but it's still on the lower end

Let's find the highest and lowest crimes rates in each district.

```
df_district_split = [pd.DataFrame(y) for x, y in df.groupby('Community', as_index=False)]
```

```
len(df_district_split)
```

```
78
```

```
for i,df_district in enumerate(df_district_split):
  print('\n----------- ',df_district['Community'][0],' -----------\n')
  crime_per_district = df_district['Primary Type'].value_counts(normalize=True)

  print("\n***Highest***\n")
  crime_per_district_hjigh = crime_per_district.head(3)
  print(crime_per_district_hjigh * 100)

  print("\n***Lowest***\n")
  crime_per_district_low = crime_per_district.tail(3)
  print(crime_per_district_low * 100)
```

```
-----------  Albany Park   -----------


***Highest***

THEFT              21.931322
CRIMINAL DAMAGE    21.684690
BATTERY            16.695124
Name: Primary Type, dtype: float64

***Lowest***

PROSTITUTION                        0.094859
GAMBLING                            0.037943
INTERFERENCE WITH PUBLIC OFFICER    0.037943
Name: Primary Type, dtype: float64

-----------  Archer Heights   -----------


***Highest***

BATTERY            22.179185
THEFT              16.992253
CRIMINAL DAMAGE    11.923206
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.151566
INTERFERENCE WITH PUBLIC OFFICER    0.101044
LIQUOR LAW VIOLATION                0.016841
Name: Primary Type, dtype: float64

-----------  Armour Square   -----------


***Highest***

BATTERY            20.164609
THEFT              14.294360
CRIMINAL DAMAGE    14.209634
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.133140
LIQUOR LAW VIOLATION                0.096829
PROSTITUTION                        0.024207
Name: Primary Type, dtype: float64

-----------  Ashburn   -----------


***Highest***
```

```
THEFT              25.658237
CRIMINAL DAMAGE    16.538195
BATTERY            14.762688
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.134246
PROSTITUTION                        0.121254
GAMBLING                            0.038975
Name: Primary Type, dtype: float64

-----------  Auburn Gresham   -----------


***Highest***

THEFT              21.062512
CRIMINAL DAMAGE    18.338984
BATTERY            16.327160
Name: Primary Type, dtype: float64

***Lowest***

LIQUOR LAW VIOLATION                0.268990
INTERFERENCE WITH PUBLIC OFFICER    0.154109
GAMBLING                            0.050436
Name: Primary Type, dtype: float64

-----------  Austin   -----------


***Highest***

THEFT              32.524793
BATTERY            14.699008
CRIMINAL DAMAGE     9.538248
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.132651
GAMBLING                            0.128229
ARSON                               0.057482
Name: Primary Type, dtype: float64

-----------  Avalon Park   -----------


***Highest***

BATTERY            19.774032
THEFT              14.623603
CRIMINAL DAMAGE    12.428978
Name: Primary Type, dtype: float64

***Lowest***
```

```
INTERFERENCE WITH PUBLIC OFFICER    0.280472
ARSON                               0.204571
LIQUOR LAW VIOLATION                0.154694
Name: Primary Type, dtype: float64

-----------  Avondale   -----------


***Highest***

THEFT              23.084496
CRIMINAL DAMAGE    15.381103
BATTERY            15.275519
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.184060
INTERFERENCE WITH PUBLIC OFFICER    0.164084
GAMBLING                            0.039951
Name: Primary Type, dtype: float64

-----------  Belmont Cragin   -----------


***Highest***

THEFT              23.328909
BATTERY            15.982842
CRIMINAL DAMAGE    13.499529
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.261604
INTERFERENCE WITH PUBLIC OFFICER    0.130802
GAMBLING                            0.051936
Name: Primary Type, dtype: float64

-----------  Beverly   -----------


***Highest***

BATTERY      21.507067
THEFT        16.078896
NARCOTICS    13.634793
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.313612
LIQUOR LAW VIOLATION                0.252272
ARSON                               0.235857
Name: Primary Type, dtype: float64

-----------  Bridgeport   -----------
```

```
***Highest***

THEFT               23.870422
CRIMINAL DAMAGE     17.386545
BATTERY             13.027468
Name: Primary Type, dtype: float64

***Lowest***

ARSON                                0.243830
INTERFERENCE WITH PUBLIC OFFICER    0.079618
GAMBLING                             0.034833
Name: Primary Type, dtype: float64

-----------  Brighton Park   -----------


***Highest***

THEFT        18.287099
BATTERY      18.254781
NARCOTICS    16.962025
Name: Primary Type, dtype: float64

***Lowest***

PROSTITUTION            0.183140
ARSON                   0.102343
LIQUOR LAW VIOLATION    0.070024
Name: Primary Type, dtype: float64

-----------  Burnside   -----------


***Highest***

BATTERY      25.045813
THEFT        13.188886
NARCOTICS    12.251731
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.282292
ARSON                                0.198750
LIQUOR LAW VIOLATION                 0.086911
Name: Primary Type, dtype: float64

-----------  Calumet Heights   -----------


***Highest***

BATTERY             22.407960
THEFT               14.312729
CRIMINAL DAMAGE     10.894841
```

```
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING                 0.245243
ARSON                    0.146998
LIQUOR LAW VIOLATION     0.106370
Name: Primary Type, dtype: float64

-----------  Chatham   -----------


***Highest***

THEFT              31.616094
CRIMINAL DAMAGE    16.043307
BATTERY            12.574419
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.074419
GAMBLING                            0.064817
PROSTITUTION                        0.045612
Name: Primary Type, dtype: float64

-----------  Chicago Lawn   -----------


***Highest***

THEFT              21.174253
BATTERY            18.699922
CRIMINAL DAMAGE    10.203713
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING                 0.160078
ARSON                    0.115325
LIQUOR LAW VIOLATION     0.088646
Name: Primary Type, dtype: float64

-----------  Clearing   -----------


***Highest***

BATTERY      21.237156
THEFT        13.343255
NARCOTICS    12.894613
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.317332
ARSON                               0.121461
LIQUOR LAW VIOLATION                0.089728
```

```
Name: Primary Type, dtype: float64

-----------  Douglas   -----------


***Highest***

THEFT              20.686179
BATTERY            16.613461
CRIMINAL DAMAGE    13.411069
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.110891
ARSON                               0.094089
PROSTITUTION                        0.006721
Name: Primary Type, dtype: float64

-----------  Dunning   -----------


***Highest***

THEFT              19.530677
BATTERY            17.204595
CRIMINAL DAMAGE    13.786360
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.307015
LIQUOR LAW VIOLATION                0.298216
GAMBLING                            0.052799
Name: Primary Type, dtype: float64

-----------  East Garfield Park   -----------


***Highest***

BATTERY            20.464265
THEFT              16.518877
CRIMINAL DAMAGE    11.994240
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.292331
INTERFERENCE WITH PUBLIC OFFICER    0.173233
GAMBLING                            0.043308
Name: Primary Type, dtype: float64

-----------  East Side   -----------


***Highest***
```

```
BATTERY            18.813771
THEFT              17.542591
CRIMINAL DAMAGE    12.516351
Name: Primary Type, dtype: float64

***Lowest***

PROSTITUTION            0.172363
ARSON                   0.135428
LIQUOR LAW VIOLATION    0.060019
Name: Primary Type, dtype: float64

-----------  Edgewater   -----------


***Highest***

THEFT              23.687367
CRIMINAL DAMAGE    16.969641
BATTERY            14.644274
Name: Primary Type, dtype: float64

***Lowest***

CRIM SEXUAL ASSAULT    0.161484
GAMBLING               0.064594
PROSTITUTION           0.041524
Name: Primary Type, dtype: float64

-----------  Edison Park   -----------


***Highest***

THEFT              27.551287
BATTERY            15.078039
CRIMINAL DAMAGE    14.720468
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING                            0.138331
INTERFERENCE WITH PUBLIC OFFICER    0.122671
ARSON                               0.088740
Name: Primary Type, dtype: float64

-----------  Englewood   -----------


***Highest***

BATTERY            22.015243
THEFT              14.666512
CRIMINAL DAMAGE    12.316233
Name: Primary Type, dtype: float64

***Lowest***
```

```
GAMBLING                0.179898
LIQUOR LAW VIOLATION    0.175062
ARSON                   0.172160
Name: Primary Type, dtype: float64

-----------  Forest Glen   -----------


***Highest***

THEFT              44.312718
CRIMINAL DAMAGE    12.139389
BATTERY             9.106015
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.062459
ARSON                               0.053031
GAMBLING                            0.017677
Name: Primary Type, dtype: float64

-----------  Fuller Park   -----------


***Highest***

BATTERY            22.525425
THEFT              17.753440
CRIMINAL DAMAGE    12.277392
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING                0.115043
LIQUOR LAW VIOLATION    0.055221
PROSTITUTION            0.018407
Name: Primary Type, dtype: float64

-----------  Gage Park   -----------


***Highest***

THEFT              32.560349
BATTERY            12.141097
CRIMINAL DAMAGE    10.442709
Name: Primary Type, dtype: float64

***Lowest***

ARSON                   0.074230
LIQUOR LAW VIOLATION    0.065323
PROSTITUTION            0.011877
Name: Primary Type, dtype: float64

-----------  Garfield Ridge   -----------
```

```
***Highest***

NARCOTICS    19.167629
BATTERY      19.011438
THEFT        18.625840
Name: Primary Type, dtype: float64

***Lowest***

PROSTITUTION           0.120398
ARSON                  0.058572
LIQUOR LAW VIOLATION   0.045556
Name: Primary Type, dtype: float64

-----------  Grand Boulevard   -----------


***Highest***

BATTERY           18.659573
THEFT             17.955863
CRIMINAL DAMAGE   14.471092
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING               0.182965
LIQUOR LAW VIOLATION   0.171705
PROSTITUTION           0.019704
Name: Primary Type, dtype: float64

-----------  Greater Grand Crossing   -----------


***Highest***

BATTERY           17.815628
THEFT             15.707161
CRIMINAL DAMAGE   14.385244
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.291518
INTERFERENCE WITH PUBLIC OFFICER    0.194346
GAMBLING                            0.031169
Name: Primary Type, dtype: float64

-----------  Hegewisch   -----------


***Highest***

THEFT            30.676296
OTHER OFFENSE    20.329374
BATTERY           9.121895
```

```
BATTERY           9.121895
Name: Primary Type, dtype: float64

***Lowest***

LIQUOR LAW VIOLATION    0.043871
ARSON                   0.023623
GAMBLING                0.003375
Name: Primary Type, dtype: float64

-----------  Hermosa   -----------


***Highest***

THEFT              27.990463
BATTERY            15.091179
CRIMINAL DAMAGE    12.401942
Name: Primary Type, dtype: float64

***Lowest***

ARSON                                   0.218762
INTERFERENCE WITH PUBLIC OFFICER    0.141854
GAMBLING                            0.024782
Name: Primary Type, dtype: float64

-----------  Humboldt Park   -----------


***Highest***

NARCOTICS    29.130504
BATTERY      19.524935
THEFT        11.088161
Name: Primary Type, dtype: float64

***Lowest***

SEX OFFENSE             0.198606
ARSON                   0.145975
LIQUOR LAW VIOLATION    0.119163
Name: Primary Type, dtype: float64

-----------  Hyde Park   -----------


***Highest***

BATTERY            30.361364
CRIMINAL DAMAGE    13.812901
ASSAULT            10.376562
Name: Primary Type, dtype: float64

***Lowest***

ARSON                   0.151976
LIQUOR LAW VIOLATION    0.059102
```

```
PROSTITUTION            0.016886
Name: Primary Type, dtype: float64

-----------  Irving Park   -----------


***Highest***

THEFT              23.768786
CRIMINAL DAMAGE    16.524085
BATTERY            15.437380
Name: Primary Type, dtype: float64

***Lowest***

PROSTITUTION                        0.100193
INTERFERENCE WITH PUBLIC OFFICER    0.100193
GAMBLING                            0.092486
Name: Primary Type, dtype: float64

-----------  Jefferson Park   -----------


***Highest***

THEFT              36.977597
BATTERY            12.228797
CRIMINAL DAMAGE    10.727178
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.125600
ARSON                               0.074430
GAMBLING                            0.016747
Name: Primary Type, dtype: float64

-----------  Kenwood   -----------


***Highest***

CRIMINAL DAMAGE    20.337702
BATTERY            18.127160
THEFT              14.210109
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.144009
GAMBLING                            0.021601
PROSTITUTION                        0.010801
Name: Primary Type, dtype: float64

-----------  Lakeview   -----------


***Highest***
```

```
***Highest***

THEFT              28.939970
CRIMINAL DAMAGE    14.883413
BATTERY            12.176837
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING                             0.143322
ARSON                                0.132297
INTERFERENCE WITH PUBLIC OFFICER    0.110248
Name: Primary Type, dtype: float64

-----------  Lincoln Park   -----------


***Highest***

THEFT              20.124028
BATTERY            18.341119
CRIMINAL DAMAGE    14.567226
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.206034
ARSON                                0.183595
GAMBLING                             0.122397
Name: Primary Type, dtype: float64

-----------  Lincoln Square   -----------


***Highest***

THEFT        24.121398
BATTERY      16.741634
NARCOTICS    12.600712
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.168059
GAMBLING                             0.112451
ARSON                                0.079087
Name: Primary Type, dtype: float64

-----------  Logan Square   -----------


***Highest***

THEFT              22.049561
BATTERY            16.803983
CRIMINAL DAMAGE    15.708105
Name: Primary Type, dtype: float64

***Lowest***
```

```
***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.135195
PROSTITUTION                        0.128833
GAMBLING                            0.060440
Name: Primary Type, dtype: float64

-----------  Loop   -----------


***Highest***

THEFT              32.017579
BATTERY            13.505256
CRIMINAL DAMAGE    13.305269
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.174679
INTERFERENCE WITH PUBLIC OFFICER    0.116659
GAMBLING                            0.058638
Name: Primary Type, dtype: float64

-----------  Lower West Side   -----------


***Highest***

THEFT              26.080118
BATTERY            14.721062
CRIMINAL DAMAGE    12.219218
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.172032
CRIM SEXUAL ASSAULT                 0.172032
ARSON                               0.167117
Name: Primary Type, dtype: float64

-----------  McKinley Park   -----------


***Highest***

BATTERY      21.677745
THEFT        16.434628
NARCOTICS    11.442741
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.174029
ARSON                               0.090286
LIQUOR LAW VIOLATION                0.077201
Name: Primary Type, dtype: float64
```

```
-----------  Montclare   -----------


***Highest***

BATTERY            19.583767
THEFT              15.079530
CRIMINAL DAMAGE    12.876468
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.324067
LIQUOR LAW VIOLATION                0.312175
GAMBLING                            0.026758
Name: Primary Type, dtype: float64

-----------  Morgan Park   -----------


***Highest***

CRIMINAL DAMAGE    20.294681
THEFT              19.323054
BATTERY            15.879026
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.114041
GAMBLING                            0.072986
PROSTITUTION                        0.041055
Name: Primary Type, dtype: float64

-----------  Mount Greenwood   -----------


***Highest***

BATTERY            17.218904
THEFT              16.965971
CRIMINAL DAMAGE    14.998930
Name: Primary Type, dtype: float64

***Lowest***

LIQUOR LAW VIOLATION                0.276281
INTERFERENCE WITH PUBLIC OFFICER    0.190673
GAMBLING                            0.071989
Name: Primary Type, dtype: float64

-----------  Near North Side   -----------


***Highest***

NARCOTICS    23.650183
BATTERY      19.953315
```

```
THEFT        13.075300
Name: Primary Type, dtype: float64

***Lowest***

SEX OFFENSE             0.270797
ARSON                   0.230551
LIQUOR LAW VIOLATION    0.155234
Name: Primary Type, dtype: float64

-----------  Near South Side   -----------


***Highest***

NARCOTICS    23.933415
BATTERY      19.866705
THEFT        12.905791
Name: Primary Type, dtype: float64

***Lowest***

SEX OFFENSE             0.239101
ARSON                   0.161010
LIQUOR LAW VIOLATION    0.148515
Name: Primary Type, dtype: float64

-----------  Near West Side   -----------


***Highest***

THEFT              21.849883
BATTERY            17.670862
CRIMINAL DAMAGE    14.314219
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.234965
INTERFERENCE WITH PUBLIC OFFICER    0.160373
GAMBLING                            0.016783
Name: Primary Type, dtype: float64

-----------  New City   -----------


***Highest***

THEFT              24.193445
BATTERY            19.171681
CRIMINAL DAMAGE    11.349379
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.073614
```

```
LIQUOR LAW VIOLATION                 0.038407
PROSTITUTION                         0.032006
Name: Primary Type, dtype: float64

-----------  North Center   -----------


***Highest***

THEFT              26.015593
CRIMINAL DAMAGE    20.958145
BURGLARY           11.622897
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.092327
PROSTITUTION                        0.082068
ARSON                               0.071810
Name: Primary Type, dtype: float64

-----------  North Lawndale   -----------


***Highest***

THEFT                 51.721065
DECEPTIVE PRACTICE    11.090571
BATTERY                8.167526
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.103157
ARSON                               0.018156
GAMBLING                            0.016505
Name: Primary Type, dtype: float64

-----------  North Park   -----------


***Highest***

THEFT                 41.090055
BATTERY               13.153718
DECEPTIVE PRACTICE     8.905212
Name: Primary Type, dtype: float64

***Lowest***

OTHERS      0.189899
GAMBLING    0.053461
ARSON       0.030072
Name: Primary Type, dtype: float64

-----------  Norwood Park   -----------
```

```
***Highest***

THEFT              31.160725
CRIMINAL DAMAGE    14.028928
BATTERY            10.307886
Name: Primary Type, dtype: float64

***Lowest***

ARSON                                0.129036
INTERFERENCE WITH PUBLIC OFFICER     0.126035
GAMBLING                             0.087024
Name: Primary Type, dtype: float64

-----------  Oakland   -----------


***Highest***

BATTERY      21.290309
THEFT        14.738606
NARCOTICS    12.029624
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING                0.235741
ARSON                   0.183960
LIQUOR LAW VIOLATION    0.062683
Name: Primary Type, dtype: float64

-----------  O’Hare   -----------


***Highest***

THEFT              26.654641
CRIMINAL DAMAGE    18.708929
BATTERY            14.212086
Name: Primary Type, dtype: float64

***Lowest***

PROSTITUTION                         0.124554
INTERFERENCE WITH PUBLIC OFFICER     0.077310
GAMBLING                             0.051540
Name: Primary Type, dtype: float64

-----------  Portage Park   -----------


***Highest***

THEFT              22.329584
CRIMINAL DAMAGE    18.449881
BATTERY            14.637728
Name: Primary Type, dtype: float64
```

```
***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.117478
GAMBLING                            0.108667
PROSTITUTION                        0.026432
Name: Primary Type, dtype: float64

-----------  Pullman   -----------


***Highest***

BATTERY      21.170115
THEFT        15.013779
NARCOTICS    11.451274
Name: Primary Type, dtype: float64

***Lowest***

SEX OFFENSE            0.278782
ARSON                  0.147742
LIQUOR LAW VIOLATION    0.115624
Name: Primary Type, dtype: float64

-----------  Riverdale   -----------


***Highest***

THEFT             20.248789
BATTERY           18.179337
CRIMINAL DAMAGE    12.821504
Name: Primary Type, dtype: float64

***Lowest***

ARSON                  0.136447
LIQUOR LAW VIOLATION    0.115980
PROSTITUTION           0.020467
Name: Primary Type, dtype: float64

-----------  Rogers Park   -----------


***Highest***

THEFT             19.672131
BATTERY           19.672131
CRIMINAL DAMAGE    16.393443
Name: Primary Type, dtype: float64

***Lowest***

ASSAULT                3.278689
CRIM SEXUAL ASSAULT    1.639344
CRIMINAL TRESPASS      1.639344
Name: Primary Type, dtype: float64
```

```
-----------  Roscoe Village  -----------


***Highest***

THEFT              28.199550
BATTERY            16.418438
CRIMINAL DAMAGE    11.457578
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.115282
ARSON                               0.107845
GAMBLING                            0.092970
Name: Primary Type, dtype: float64

-----------  Roseland   -----------


***Highest***

THEFT              19.536510
CRIMINAL DAMAGE    16.296074
BATTERY            15.960444
Name: Primary Type, dtype: float64

***Lowest***

LIQUOR LAW VIOLATION    0.115873
GAMBLING                0.107881
PROSTITUTION            0.081910
Name: Primary Type, dtype: float64

-----------  South Chicago   -----------


***Highest***

BATTERY      23.757875
NARCOTICS    13.787751
THEFT        13.517824
Name: Primary Type, dtype: float64

***Lowest***

SEX OFFENSE             0.278516
ARSON                   0.214715
LIQUOR LAW VIOLATION    0.101223
Name: Primary Type, dtype: float64

-----------  South Deering   -----------


***Highest***

THEFT              26.964824
```

```
CRIMINAL DAMAGE    15.025126
BATTERY            11.221106
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.100503
GAMBLING                            0.020101
PROSTITUTION                        0.010050
Name: Primary Type, dtype: float64

-----------  South Lawndale   -----------


***Highest***

THEFT                29.073781
CRIMINAL TRESPASS    16.345462
BATTERY              13.756652
Name: Primary Type, dtype: float64

***Lowest***

LIQUOR LAW VIOLATION    0.115058
GAMBLING                0.076705
ARSON                   0.069514
Name: Primary Type, dtype: float64

-----------  South Shore   -----------


***Highest***

THEFT              20.073341
CRIMINAL DAMAGE    16.319490
BATTERY            13.936987
Name: Primary Type, dtype: float64

***Lowest***

ARSON                               0.184438
INTERFERENCE WITH PUBLIC OFFICER    0.151890
GAMBLING                            0.075945
Name: Primary Type, dtype: float64

-----------  Uptown   -----------


***Highest***

THEFT              24.686752
CRIMINAL DAMAGE    15.652864
BATTERY            15.479531
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.182147
```

```
INTERFERENCE WITH PUBLIC OFFICER    0.182147
ARSON                               0.138079
GAMBLING                            0.098418
Name: Primary Type, dtype: float64

-----------  Washington Heights   -----------


***Highest***

THEFT              22.297140
CRIMINAL DAMAGE    19.037433
BATTERY            12.797024
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.130202
GAMBLING                            0.037201
PROSTITUTION                        0.032551
Name: Primary Type, dtype: float64

-----------  Washington Park   -----------


***Highest***

BATTERY            22.097766
CRIMINAL DAMAGE    13.342006
THEFT              12.681631
Name: Primary Type, dtype: float64

***Lowest***

ARSON                   0.233722
GAMBLING                0.195136
LIQUOR LAW VIOLATION    0.089299
Name: Primary Type, dtype: float64

-----------  West Elsdon   -----------


***Highest***

BATTERY      24.622869
THEFT        13.531091
NARCOTICS    10.981975
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.211159
LIQUOR LAW VIOLATION                0.106424
ARSON                               0.094599
Name: Primary Type, dtype: float64

-----------  West Englewood   -----------
```

```
***Highest***

THEFT              20.683206
BATTERY            19.532766
CRIMINAL DAMAGE    11.352648
Name: Primary Type, dtype: float64

***Lowest***

GAMBLING                0.116456
LIQUOR LAW VIOLATION    0.063521
PROSTITUTION            0.049405
Name: Primary Type, dtype: float64

-----------  West Garfield Park   -----------


***Highest***

NARCOTICS    22.860530
BATTERY      22.200986
THEFT        12.749678
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.237125
ARSON                               0.177520
LIQUOR LAW VIOLATION                0.132168
Name: Primary Type, dtype: float64

-----------  West Lawn   -----------


***Highest***

BATTERY            21.788445
THEFT              15.763764
CRIMINAL DAMAGE    11.715896
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.212459
ARSON                               0.126025
LIQUOR LAW VIOLATION                0.069147
Name: Primary Type, dtype: float64

-----------  West Pullman   -----------


***Highest***

THEFT              24.793989
CRIMINAL DAMAGE    16.779771
BATTERY            15.018581
Name: Primary Type, dtype: float64
```

```
***Lowest***

ARSON           0.105025
GAMBLING        0.024237
PROSTITUTION    0.016158
Name: Primary Type, dtype: float64

-----------  West Ridge   -----------


***Highest***

THEFT              20.526447
BATTERY            18.582587
CRIMINAL DAMAGE    11.834362
Name: Primary Type, dtype: float64

***Lowest***

OTHERS      0.277015
GAMBLING    0.191414
ARSON       0.102246
Name: Primary Type, dtype: float64

-----------  West Town   -----------


***Highest***

NARCOTICS    24.872523
BATTERY      20.806666
THEFT        12.268366
Name: Primary Type, dtype: float64

***Lowest***

SEX OFFENSE            0.237255
ARSON                  0.127237
LIQUOR LAW VIOLATION   0.117671
Name: Primary Type, dtype: float64

-----------  Woodlawn   -----------


***Highest***

THEFT              19.508475
BATTERY            17.754237
CRIMINAL DAMAGE    16.686441
Name: Primary Type, dtype: float64

***Lowest***

INTERFERENCE WITH PUBLIC OFFICER    0.135593
GAMBLING                            0.093220
PROSTITUTION                        0.016949
Name: Primary Type, dtype: float64
```

```
Name: Primary Type, dtype: float64
```

By the above data we observe the following:

- Theft is classified as the highest crime having a considerable ~20% in most of the districts.
- Criminal Damage, Battery trail Theft with almost similar percentages.
- In a few districts, Narcotics has the highest percent to cases recorded and mostly above ~25% (
- The crimes with least percentage have been varying acroos the districts.
- Interferance with a Public Officer. Arson, Prostitution have somewhat consistantly at their lowes
- Gambling and Liquor Law Violation follow them with slightly more percentage.

Let's find the highest and lowest crimes rates in each location per district.

```
for i,df_district in enumerate(df_district_split):
  print('\n----------- ',df_district['Community'][0],' -----------\n')
  crime_per_location = df_district['Location Description'].value_counts(normalize=True)
  print("\n***Highest***\n")
  crime_per_location_high = crime_per_location.head(3)
  print(crime_per_location_high * 100)

  print("\n***Lowest***\n")
  crime_per_location_low = crime_per_location.tail(3)
  print(crime_per_location_low * 100)
```

```
-----------  Albany Park   -----------


***Highest***

RESIDENCE    31.455132
STREET       23.145513
APARTMENT     4.989566
Name: Location Description, dtype: float64

***Lowest***

ABANDONED BUILDING               0.018972
VEHICLE - OTHER RIDE SERVICE     0.018972
GOVERNMENT BUILDING/PROPERTY     0.018972
Name: Location Description, dtype: float64

-----------  Archer Heights   -----------


***Highest***

STREET       25.463119
RESIDENCE    18.625800
APARTMENT    18.053217
Name: Location Description, dtype: float64

***Lowest***

CTA TRAIN         0.00842
HOUSE             0.00842
DELIVERY TRUCK    0.00842
Name: Location Description, dtype: float64

-----------  Armour Square   -----------


***Highest***

RESIDENCE    33.321230
STREET       26.143791
SIDEWALK     10.239651
Name: Location Description, dtype: float64

***Lowest***

CHA APARTMENT                       0.012104
BANK                                0.012104
POLICE FACILITY/VEH PARKING LOT     0.012104
Name: Location Description, dtype: float64

-----------  Ashburn   -----------


***Highest***
```

```
STREET       27.996709
RESIDENCE    15.611467
APARTMENT     8.245280
Name: Location Description, dtype: float64

***Lowest***

OFFICE           0.004331
CHA APARTMENT    0.004331
PAWN SHOP        0.004331
Name: Location Description, dtype: float64

-----------  Auburn Gresham   -----------


***Highest***

STREET       30.404326
RESIDENCE    18.904985
APARTMENT    12.040124
Name: Location Description, dtype: float64

***Lowest***

RIVER BANK      0.002802
CTA PROPERTY    0.002802
DUMPSTER        0.002802
Name: Location Description, dtype: float64

-----------  Austin   -----------


***Highest***

STREET       29.252732
RESIDENCE     7.708926
SIDEWALK      6.918704
Name: Location Description, dtype: float64

***Lowest***

BARBER SHOP/BEAUTY SALON    0.000632
YARD                        0.000632
VACANT LOT                  0.000632
Name: Location Description, dtype: float64

-----------  Avalon Park   -----------


***Highest***

STREET       25.969726
RESIDENCE    22.232503
SIDEWALK     11.912128
Name: Location Description, dtype: float64

***Lowest***
```

```
BOWLING ALLEY                0.000723
BASEMENT                     0.000723
BARBER SHOP/BEAUTY SALON     0.000723
Name: Location Description, dtype: float64

-----------  Avondale   -----------


***Highest***

STREET       28.857404
RESIDENCE    21.814628
APARTMENT     7.864623
Name: Location Description, dtype: float64

***Lowest***

CEMETARY                    0.001427
VESTIBULE                   0.001427
JAIL / LOCK-UP FACILITY     0.001427
Name: Location Description, dtype: float64

-----------  Belmont Cragin   -----------


***Highest***

STREET       27.735780
RESIDENCE    14.370900
APARTMENT    13.670725
Name: Location Description, dtype: float64

***Lowest***

COLLEGE/UNIVERSITY RESIDENCE HALL    0.001924
AIRPORT/AIRCRAFT                     0.001924
JAIL / LOCK-UP FACILITY              0.001924
Name: Location Description, dtype: float64

-----------  Beverly   -----------


***Highest***

STREET       30.294260
RESIDENCE    18.067699
APARTMENT    11.008398
Name: Location Description, dtype: float64

***Lowest***

HOTEL           0.000864
DRIVEWAY        0.000864
RETAIL STORE    0.000864
Name: Location Description, dtype: float64

-----------  Bridgeport   -----------
```

```
***Highest***

STREET                            26.119626
RESIDENCE                         16.465963
PARKING LOT/GARAGE(NON.RESID.)     7.678145
Name: Location Description, dtype: float64

***Lowest***

HOSPITAL BUILDING/GROUNDS    0.004976
FOREST PRESERVE              0.004976
SAVINGS AND LOAN             0.004976
Name: Location Description, dtype: float64

-----------  Brighton Park   -----------


***Highest***

STREET       28.618368
RESIDENCE    12.954484
SIDEWALK      8.047401
Name: Location Description, dtype: float64

***Lowest***

PARKING LOT         0.005386
FEDERAL BUILDING    0.005386
FACTORY             0.005386
Name: Location Description, dtype: float64

-----------  Burnside   -----------


***Highest***

STREET       26.434365
RESIDENCE    19.425580
APARTMENT    15.574555
Name: Location Description, dtype: float64

***Lowest***

BRIDGE               0.000674
RAILROAD PROPERTY    0.000674
STAIRWELL            0.000674
Name: Location Description, dtype: float64

-----------  Calumet Heights   -----------


***Highest***

STREET       26.200360
APARTMENT    17.828862
RESIDENCE    15.976244
```

```
Name: Location Description, dtype: float64

***Lowest***

BOAT/WATERCRAFT    0.000739
HOTEL              0.000739
VESTIBULE          0.000739
Name: Location Description, dtype: float64

-----------  Chatham   -----------


***Highest***

RESIDENCE           20.561264
STREET              20.446034
DEPARTMENT STORE    12.490398
Name: Location Description, dtype: float64

***Lowest***

PAWN SHOP                         0.002401
AIRPORT EXTERIOR - SECURE AREA    0.002401
SCHOOL YARD                       0.002401
Name: Location Description, dtype: float64

-----------  Chicago Lawn   -----------


***Highest***

STREET       23.492809
RESIDENCE    16.301326
APARTMENT    16.228172
Name: Location Description, dtype: float64

***Lowest***

CLUB               0.000861
BRIDGE             0.000861
FOREST PRESERVE    0.000861
Name: Location Description, dtype: float64

-----------  Clearing   -----------


***Highest***

STREET       23.989189
APARTMENT    21.933098
SIDEWALK     13.238207
Name: Location Description, dtype: float64

***Lowest***

CTA TRACKS - RIGHT OF WAY    0.001094
MOVIE HOUSE/THEATER          0.001094
PARKING LOT                  0.001094
```

```
Name: Location Description, dtype: float64

-----------  Douglas   -----------


***Highest***

STREET       28.710642
RESIDENCE    27.245539
SIDEWALK      6.932357
Name: Location Description, dtype: float64

***Lowest***

GANGWAY      0.00336
DRIVEWAY     0.00336
NEWSSTAND    0.00336
Name: Location Description, dtype: float64

-----------  Dunning   -----------


***Highest***

STREET       26.283060
RESIDENCE    17.785383
APARTMENT    10.597898
Name: Location Description, dtype: float64

***Lowest***

PUBLIC HIGH SCHOOL            0.000978
VACANT LOT                    0.000978
COLLEGE/UNIVERSITY GROUNDS    0.000978
Name: Location Description, dtype: float64

-----------  East Garfield Park   -----------


***Highest***

STREET       31.785061
SIDEWALK     14.356709
RESIDENCE    13.645370
Name: Location Description, dtype: float64

***Lowest***

AIRPORT/AIRCRAFT    0.001083
VESTIBULE           0.001083
AIRCRAFT            0.001083
Name: Location Description, dtype: float64

-----------  East Side   -----------


***Highest***
```

```
RESIDENCE    29.917358
STREET       28.583081
SIDEWALK      6.306653
Name: Location Description, dtype: float64

***Lowest***

NEWSSTAND    0.001539
BRIDGE       0.001539
CEMETARY     0.001539
Name: Location Description, dtype: float64

-----------  Edgewater   -----------


***Highest***

STREET       26.114238
RESIDENCE    25.089970
APARTMENT     6.334779
Name: Location Description, dtype: float64

***Lowest***

COIN OPERATED MACHINE    0.004614
BASEMENT                 0.004614
BRIDGE                   0.004614
Name: Location Description, dtype: float64

-----------  Edison Park   -----------


***Highest***

STREET       26.864854
RESIDENCE    14.496007
APARTMENT    10.821110
Name: Location Description, dtype: float64

***Lowest***

MOTEL                        0.00261
PARKING LOT                  0.00261
CTA TRACKS - RIGHT OF WAY    0.00261
Name: Location Description, dtype: float64

-----------  Englewood   -----------


***Highest***

STREET       25.265978
RESIDENCE    21.938835
APARTMENT    14.710036
Name: Location Description, dtype: float64

***Lowest***
```

```
GAS STATION DRIVE/PROP.     0.000967
HIGHWAY/EXPRESSWAY          0.000967
VEHICLE - DELIVERY TRUCK    0.000967
Name: Location Description, dtype: float64

-----------  Forest Glen   -----------


***Highest***

STREET       29.038607
RESIDENCE    10.465966
APARTMENT     5.827520
Name: Location Description, dtype: float64

***Lowest***

AUTO                        0.001178
SAVINGS AND LOAN            0.001178
JAIL / LOCK-UP FACILITY     0.001178
Name: Location Description, dtype: float64

-----------  Fuller Park   -----------


***Highest***

RESIDENCE                   24.605402
STREET                      21.945608
SCHOOL, PUBLIC, BUILDING     9.364502
Name: Location Description, dtype: float64

***Lowest***

CREDIT UNION    0.004602
CTA TRAIN       0.004602
YARD            0.004602
Name: Location Description, dtype: float64

-----------  Gage Park   -----------


***Highest***

STREET       27.931352
APARTMENT    13.961222
RESIDENCE    13.780100
Name: Location Description, dtype: float64

***Lowest***

LAKE                                                0.002969
AIRPORT BUILDING NON-TERMINAL - NON-SECURE AREA     0.002969
PARKING LOT                                         0.002969
Name: Location Description, dtype: float64

-----------  Garfield Ridge   -----------
```

```
***Highest***

STREET                      20.947562
CHA PARKING LOT/GROUNDS    14.525812
RESIDENCE                   8.753234
Name: Location Description, dtype: float64

***Lowest***

VEHICLE - OTHER RIDE SERVICE    0.001627
NEWSSTAND                       0.001627
JAIL / LOCK-UP FACILITY         0.001627
Name: Location Description, dtype: float64

-----------  Grand Boulevard   -----------


***Highest***

RESIDENCE    29.544559
STREET       22.408940
SIDEWALK      6.623318
Name: Location Description, dtype: float64

***Lowest***

CHA PARKING LOT               0.002815
RIVER                         0.002815
COLLEGE/UNIVERSITY GROUNDS    0.002815
Name: Location Description, dtype: float64

-----------  Greater Grand Crossing   -----------


***Highest***

STREET       32.945253
RESIDENCE    17.417770
APARTMENT    10.756848
Name: Location Description, dtype: float64

***Lowest***

HIGHWAY/EXPRESSWAY            0.001833
PARKING LOT                   0.001833
COLLEGE/UNIVERSITY GROUNDS    0.001833
Name: Location Description, dtype: float64

-----------  Hegewisch   -----------


***Highest***

AIRPORT/AIRCRAFT                                   34.904833
AIRPORT TERMINAL UPPER LEVEL - SECURE AREA    10.522408
```

```
RESIDENCE                                       6.712338
Name: Location Description, dtype: float64

***Lowest***

CTA TRACKS - RIGHT OF WAY    0.003375
CEMETARY                     0.003375
COIN OPERATED MACHINE        0.003375
Name: Location Description, dtype: float64

-----------  Hermosa   -----------


***Highest***

STREET       30.086650
RESIDENCE    13.221446
APARTMENT    12.348960
Name: Location Description, dtype: float64

***Lowest***

YARD            0.000855
RETAIL STORE    0.000855
YMCA            0.000855
Name: Location Description, dtype: float64

-----------  Humboldt Park   -----------


***Highest***

STREET       28.240750
SIDEWALK     21.589442
RESIDENCE    11.471470
Name: Location Description, dtype: float64

***Lowest***

COLLEGE/UNIVERSITY RESIDENCE HALL    0.000993
VEHICLE - DELIVERY TRUCK             0.000993
BARBER SHOP/BEAUTY SALON             0.000993
Name: Location Description, dtype: float64

-----------  Hyde Park   -----------


***Highest***

RESIDENCE                    18.355285
CHA PARKING LOT/GROUNDS      18.009119
STREET                       17.886694
Name: Location Description, dtype: float64

***Lowest***

BARBERSHOP      0.004222
FIRE STATION    0.004222
```

```
PARKING LOT     0.004222
Name: Location Description, dtype: float64

-----------  Irving Park   -----------


***Highest***

STREET       25.803468
RESIDENCE    25.556840
APARTMENT     7.668593
Name: Location Description, dtype: float64

***Lowest***

CREDIT UNION    0.007707
HOUSE           0.007707
CTA PLATFORM    0.007707
Name: Location Description, dtype: float64

-----------  Jefferson Park   -----------


***Highest***

STREET       24.277102
RESIDENCE    12.069703
SIDEWALK      9.724238
Name: Location Description, dtype: float64

***Lowest***

BRIDGE                                            0.00093
AIRPORT BUILDING NON-TERMINAL - NON-SECURE AREA    0.00093
FOREST PRESERVE                                   0.00093
Name: Location Description, dtype: float64

-----------  Kenwood   -----------


***Highest***

STREET       28.341014
RESIDENCE    26.584101
APARTMENT     6.808036
Name: Location Description, dtype: float64

***Lowest***

PORCH                         0.0036
GARAGE                        0.0036
COLLEGE/UNIVERSITY GROUNDS    0.0036
Name: Location Description, dtype: float64

-----------  Lakeview   -----------


***Highest***
```

```
***Highest***

STREET       24.293038
RESIDENCE    14.469985
APARTMENT     9.508847
Name: Location Description, dtype: float64

***Lowest***

AUTO             0.005512
RIVER BANK       0.005512
CHA APARTMENT    0.005512
Name: Location Description, dtype: float64

-----------  Lincoln Park   -----------


***Highest***

STREET       27.886008
APARTMENT    15.187369
RESIDENCE    13.561535
Name: Location Description, dtype: float64

***Lowest***

TAVERN                            0.00204
BOAT/WATERCRAFT                   0.00204
VEHICLE - OTHER RIDE SERVICE    0.00204
Name: Location Description, dtype: float64

-----------  Lincoln Square   -----------


***Highest***

STREET       22.154120
SIDEWALK     14.896693
RESIDENCE    11.342741
Name: Location Description, dtype: float64

***Lowest***

FOREST PRESERVE    0.001236
PARKING LOT        0.001236
RETAIL STORE       0.001236
Name: Location Description, dtype: float64

-----------  Logan Square   -----------


***Highest***

STREET       29.536201
RESIDENCE    15.420219
APARTMENT    12.862642
Name: Location Description, dtype: float64

***Lowest***
```

```
***Lowest***

FIRE STATION                  0.001591
AIRCRAFT                      0.001591
COLLEGE/UNIVERSITY GROUNDS    0.001591
Name: Location Description, dtype: float64

-----------  Loop   -----------


***Highest***

STREET       33.679195
RESIDENCE    11.372067
SIDEWALK      9.547500
Name: Location Description, dtype: float64

***Lowest***

COLLEGE/UNIVERSITY RESIDENCE HALL    0.000617
CHA PARKING LOT                      0.000617
JAIL / LOCK-UP FACILITY              0.000617
Name: Location Description, dtype: float64

-----------  Lower West Side   -----------


***Highest***

STREET       31.427869
RESIDENCE     8.110101
SIDEWALK      7.156550
Name: Location Description, dtype: float64

***Lowest***

FEDERAL BUILDING         0.004915
AIRPORT/AIRCRAFT         0.004915
COIN OPERATED MACHINE    0.004915
Name: Location Description, dtype: float64

-----------  McKinley Park   -----------


***Highest***

STREET       28.212342
RESIDENCE    14.607977
APARTMENT    13.058725
Name: Location Description, dtype: float64

***Lowest***

VESTIBULE           0.001308
CREDIT UNION        0.001308
AIRPORT/AIRCRAFT    0.001308
Name: Location Description, dtype: float64
```

```
-----------  Montclare   -----------


***Highest***

STREET       29.915267
RESIDENCE    16.646351
APARTMENT    13.973539
Name: Location Description, dtype: float64

***Lowest***

CHA HALLWAY/STAIRWELL/ELEVATOR    0.002973
SAVINGS AND LOAN                  0.002973
BRIDGE                            0.002973
Name: Location Description, dtype: float64

-----------  Morgan Park   -----------


***Highest***

RESIDENCE           28.145242
STREET              24.103640
RESIDENCE-GARAGE     7.955479
Name: Location Description, dtype: float64

***Lowest***

MOVIE HOUSE/THEATER             0.004562
NEWSSTAND                       0.004562
NURSING HOME/RETIREMENT HOME    0.004562
Name: Location Description, dtype: float64

-----------  Mount Greenwood   -----------


***Highest***

STREET       28.740977
RESIDENCE    20.734673
SIDEWALK      8.543300
Name: Location Description, dtype: float64

***Lowest***

BOAT/WATERCRAFT     0.001946
PORCH               0.001946
AIRPORT/AIRCRAFT    0.001946
Name: Location Description, dtype: float64

-----------  Near North Side   -----------


***Highest***

STREET       28.544653
SIDEWALK     19.442193
```

```
RESIDENCE    13.997505
Name: Location Description, dtype: float64

***Lowest***

SEWER                           0.000575
AIRPORT VENDING ESTABLISHMENT    0.000575
GARAGE/AUTO REPAIR              0.000575
Name: Location Description, dtype: float64

-----------  Near South Side   -----------


***Highest***

STREET       26.441707
SIDEWALK     19.537870
RESIDENCE    14.221416
Name: Location Description, dtype: float64

***Lowest***

AIRPORT BUILDING NON-TERMINAL - NON-SECURE AREA    0.000284
DRIVEWAY                                           0.000284
CLEANERS/LAUNDROMAT                                0.000284
Name: Location Description, dtype: float64

-----------  Near West Side   -----------


***Highest***

STREET       32.427040
RESIDENCE    13.717483
SIDEWALK      9.245688
Name: Location Description, dtype: float64

***Lowest***

CREDIT UNION                0.001865
AIRCRAFT                    0.001865
VEHICLE - DELIVERY TRUCK    0.001865
Name: Location Description, dtype: float64

-----------  New City   -----------


***Highest***

STREET       25.976187
APARTMENT    17.744207
RESIDENCE    17.513763
Name: Location Description, dtype: float64

***Lowest***

YARD                   0.003201
```

```
NEWSSTAND              0.003201
AIRPORT PARKING LOT    0.003201
Name: Location Description, dtype: float64

-----------  North Center   -----------


***Highest***

RESIDENCE           30.242101
STREET              26.661879
RESIDENCE-GARAGE     5.960197
Name: Location Description, dtype: float64

***Lowest***

DAY CARE CENTER                                0.010259
AIRPORT TERMINAL UPPER LEVEL - SECURE AREA    0.010259
JAIL / LOCK-UP FACILITY                        0.010259
Name: Location Description, dtype: float64

-----------  North Lawndale   -----------


***Highest***

STREET              11.848979
DEPARTMENT STORE    11.116980
RESTAURANT          10.163813
Name: Location Description, dtype: float64

***Lowest***

PARKING LOT         0.000825
RIVER               0.000825
CTA "L" PLATFORM    0.000825
Name: Location Description, dtype: float64

-----------  North Park   -----------


***Highest***

STREET        19.433755
SIDEWALK       7.057454
RESTAURANT     6.556254
Name: Location Description, dtype: float64

***Lowest***

TAVERN           0.000557
TRUCK            0.000557
CHA STAIRWELL    0.000557
Name: Location Description, dtype: float64

-----------  Norwood Park   -----------
```

```
***Highest***

STREET       28.018845
RESIDENCE    14.353019
APARTMENT     6.169728
Name: Location Description, dtype: float64

***Lowest***

VEHICLE - OTHER RIDE SERVICE    0.003001
SAVINGS AND LOAN                0.003001
CHA GROUNDS                     0.003001
Name: Location Description, dtype: float64

-----------  Oakland   -----------


***Highest***

RESIDENCE    27.872672
STREET       26.901091
SIDEWALK      9.914084
Name: Location Description, dtype: float64

***Lowest***

VACANT LOT                 0.000681
FOREST PRESERVE            0.000681
JAIL / LOCK-UP FACILITY    0.000681
Name: Location Description, dtype: float64

-----------  O’Hare   -----------


***Highest***

RESIDENCE                   27.427737
STREET                      22.900829
SCHOOL, PUBLIC, BUILDING     4.887686
Name: Location Description, dtype: float64

***Lowest***

STAIRWELL        0.004295
PARKING LOT      0.004295
CHA APARTMENT    0.004295
Name: Location Description, dtype: float64

-----------  Portage Park   -----------


***Highest***

RESIDENCE           28.156480
STREET              27.947957
RESIDENCE-GARAGE     6.194015
Name: Location Description, dtype: float64
```

```
***Lowest***

GANGWAY                              0.002937
OTHER RAILROAD PROP / TRAIN DEPOT    0.002937
HOSPITAL                             0.002937
Name: Location Description, dtype: float64

-----------  Pullman   -----------


***Highest***

STREET       27.725997
RESIDENCE    22.461250
APARTMENT    12.886297
Name: Location Description, dtype: float64

***Lowest***

RAILROAD PROPERTY               0.000642
VEHICLE - OTHER RIDE SERVICE    0.000642
HIGHWAY/EXPRESSWAY              0.000642
Name: Location Description, dtype: float64

-----------  Riverdale   -----------


***Highest***

RESIDENCE    31.517067
STREET       25.306438
SIDEWALK      5.771724
Name: Location Description, dtype: float64

***Lowest***

VEHICLE - OTHER RIDE SERVICE    0.002274
GAS STATION DRIVE/PROP.         0.002274
COIN OPERATED MACHINE           0.002274
Name: Location Description, dtype: float64

-----------  Rogers Park   -----------


***Highest***

RESIDENCE                       26.229508
STREET                          24.590164
COMMERCIAL / BUSINESS OFFICE     8.196721
Name: Location Description, dtype: float64

***Lowest***

CTA BUS                              1.639344
CHURCH/SYNAGOGUE/PLACE OF WORSHIP    1.639344
TAXICAB                              1.639344
Name: Location Description, dtype: float64
```

```
-----------  Roscoe Village  -----------


***Highest***

STREET       20.497945
APARTMENT    16.569049
RESIDENCE    13.263048
Name: Location Description, dtype: float64

***Lowest***

FEDERAL BUILDING    0.001859
PORCH               0.001859
RETAIL STORE        0.001859
Name: Location Description, dtype: float64

-----------  Roseland   -----------


***Highest***

RESIDENCE    30.274698
STREET       22.573170
SIDEWALK      5.675757
Name: Location Description, dtype: float64

***Lowest***

DRIVEWAY                    0.001998
PARKING LOT                 0.001998
JAIL / LOCK-UP FACILITY     0.001998
Name: Location Description, dtype: float64

-----------  South Chicago   -----------


***Highest***

STREET       27.296987
RESIDENCE    24.913654
SIDEWALK     13.447889
Name: Location Description, dtype: float64

***Lowest***

HIGHWAY/EXPRESSWAY          0.000613
BARBER SHOP/BEAUTY SALON    0.000613
TAXI CAB                    0.000613
Name: Location Description, dtype: float64

-----------  South Deering   -----------


***Highest***

RESIDENCE    28.658291
```

```
STREET       22.703518
OTHER         5.125628
Name: Location Description, dtype: float64

***Lowest***

RETAIL STORE                        0.005025
FACTORY/MANUFACTURING BUILDING    0.005025
PORCH                               0.005025
Name: Location Description, dtype: float64

-----------  South Lawndale   -----------


***Highest***

STREET                              19.799607
CHA HALLWAY/STAIRWELL/ELEVATOR    11.362002
OTHER                                7.977372
Name: Location Description, dtype: float64

***Lowest***

FIRE STATION    0.002397
HOTEL           0.002397
LIBRARY         0.002397
Name: Location Description, dtype: float64

-----------  South Shore   -----------


***Highest***

STREET              26.637157
RESIDENCE           19.500499
RESIDENCE-GARAGE     6.194940
Name: Location Description, dtype: float64

***Lowest***

NEWSSTAND                       0.00217
PARKING LOT                     0.00217
COLLEGE/UNIVERSITY GROUNDS    0.00217
Name: Location Description, dtype: float64

-----------  Uptown   -----------


***Highest***

STREET       27.534997
RESIDENCE    15.714559
APARTMENT    15.171056
Name: Location Description, dtype: float64

***Lowest***

VEHICLE - DELIVERY TRUCK    0.001469
```

```
VEHICLE - DELIVERY TRUCK    0.001469
PARKING LOT                 0.001469
JAIL / LOCK-UP FACILITY     0.001469
Name: Location Description, dtype: float64

-----------  Washington Heights   -----------


***Highest***

STREET              22.841200
RESIDENCE           21.269472
RESIDENCE-GARAGE     7.495931
Name: Location Description, dtype: float64

***Lowest***

AIRPORT EXTERIOR - NON-SECURE AREA           0.00465
VEHICLE - OTHER RIDE SERVICE                 0.00465
AIRPORT TERMINAL LOWER LEVEL - SECURE AREA    0.00465
Name: Location Description, dtype: float64

-----------  Washington Park   -----------


***Highest***

RESIDENCE    33.997751
STREET       28.592375
SIDEWALK      9.513152
Name: Location Description, dtype: float64

***Lowest***

BARBER SHOP/BEAUTY SALON          0.001102
CHA HALLWAY/STAIRWELL/ELEVATOR    0.001102
COLLEGE/UNIVERSITY GROUNDS        0.001102
Name: Location Description, dtype: float64

-----------  West Elsdon   -----------


***Highest***

STREET       26.644931
APARTMENT    19.796611
RESIDENCE    12.225282
Name: Location Description, dtype: float64

***Lowest***

SAVINGS AND LOAN    0.001689
PAWN SHOP           0.001689
AIRPORT/AIRCRAFT    0.001689
Name: Location Description, dtype: float64

-----------  West Englewood   -----------
```

```
***Highest***

STREET                        24.995589
RESIDENCE                     24.441543
SCHOOL, PUBLIC, BUILDING       8.127184
Name: Location Description, dtype: float64

***Lowest***

PORCH      0.003529
GANGWAY    0.003529
HALLWAY    0.003529
Name: Location Description, dtype: float64

-----------  West Garfield Park   -----------


***Highest***

STREET       24.443307
SIDEWALK     19.492838
APARTMENT    13.567305
Name: Location Description, dtype: float64

***Lowest***

AIRPORT TERMINAL UPPER LEVEL - SECURE AREA    0.000648
BARBER SHOP/BEAUTY SALON                      0.000648
HOSPITAL                                      0.000648
Name: Location Description, dtype: float64

-----------  West Lawn   -----------


***Highest***

APARTMENT    25.444853
STREET       23.700573
RESIDENCE    14.686414
Name: Location Description, dtype: float64

***Lowest***

AIRPORT VENDING ESTABLISHMENT         0.000558
BRIDGE                                0.000558
AIRPORT EXTERIOR - NON-SECURE AREA    0.000558
Name: Location Description, dtype: float64

-----------  West Pullman   -----------


***Highest***

RESIDENCE                     30.465342
STREET                        19.510422
SCHOOL, PUBLIC, BUILDING       4.386815
Name: Location Description, dtype: float64
```

```
***Lowest***

COIN OPERATED MACHINE    0.008079
SAVINGS AND LOAN         0.008079
BOAT/WATERCRAFT          0.008079
Name: Location Description, dtype: float64

-----------  West Ridge   -----------


***Highest***

STREET       23.235962
APARTMENT    18.993948
RESIDENCE    12.269501
Name: Location Description, dtype: float64

***Lowest***

ELEVATOR        0.001189
CREDIT UNION    0.001189
PORCH           0.001189
Name: Location Description, dtype: float64

-----------  West Town   -----------


***Highest***

STREET       28.113729
SIDEWALK     18.941155
RESIDENCE    11.660879
Name: Location Description, dtype: float64

***Lowest***

GARAGE                           0.000957
CREDIT UNION                     0.000957
COLLEGE/UNIVERSITY GROUNDS       0.000957
Name: Location Description, dtype: float64

-----------  Woodlawn   -----------


***Highest***

RESIDENCE    28.703390
STREET       23.449153
APARTMENT     5.737288
Name: Location Description, dtype: float64

***Lowest***

TRAILER             0.008475
CREDIT UNION        0.008475
FEDERAL BUILDING    0.008475
Name: Location Description, dtype: float64
```

```
Name: Location Description, dtype: float64
```

By the above data we can say the following:

- Considerably across all the districts crimes on the STREET have a higher percentage always ~>2
- APARTMENT/ RESIDENCE trail the STREET with similar percentages also greater than 20% in m
- There is no pattern in defining the location with lower crime percentage, so can't accurately say lowest crimes.
- AIRPORT, VEHICLES, PARKING LOT have little consistancy in appearing the lowest crimes per di

Classification Modelling/ Predicting

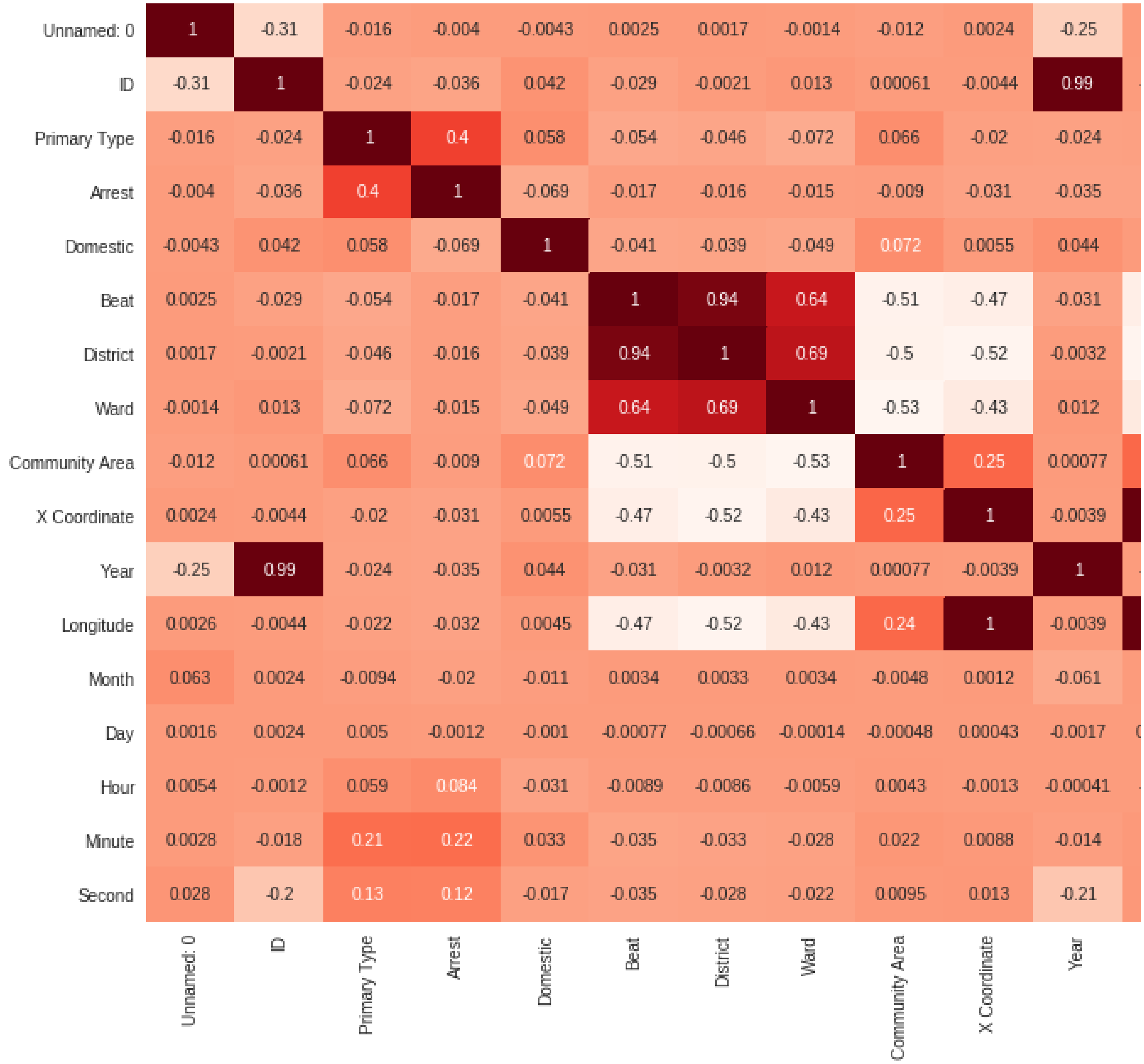
> Before directly jumping into the modelling part, first let us try to get the correlation map of the fea important features referring to our target feature.

> The Primary Type here is in Labels, let us convert into Categorical variables so that we can see th

```
df['Primary Type'] = pd.factorize(df["Primary Type"])[0]
df['Primary Type'].unique()
```

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21])
```

```
cor = df.corr()
plt.figure(figsize=(20,10))
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



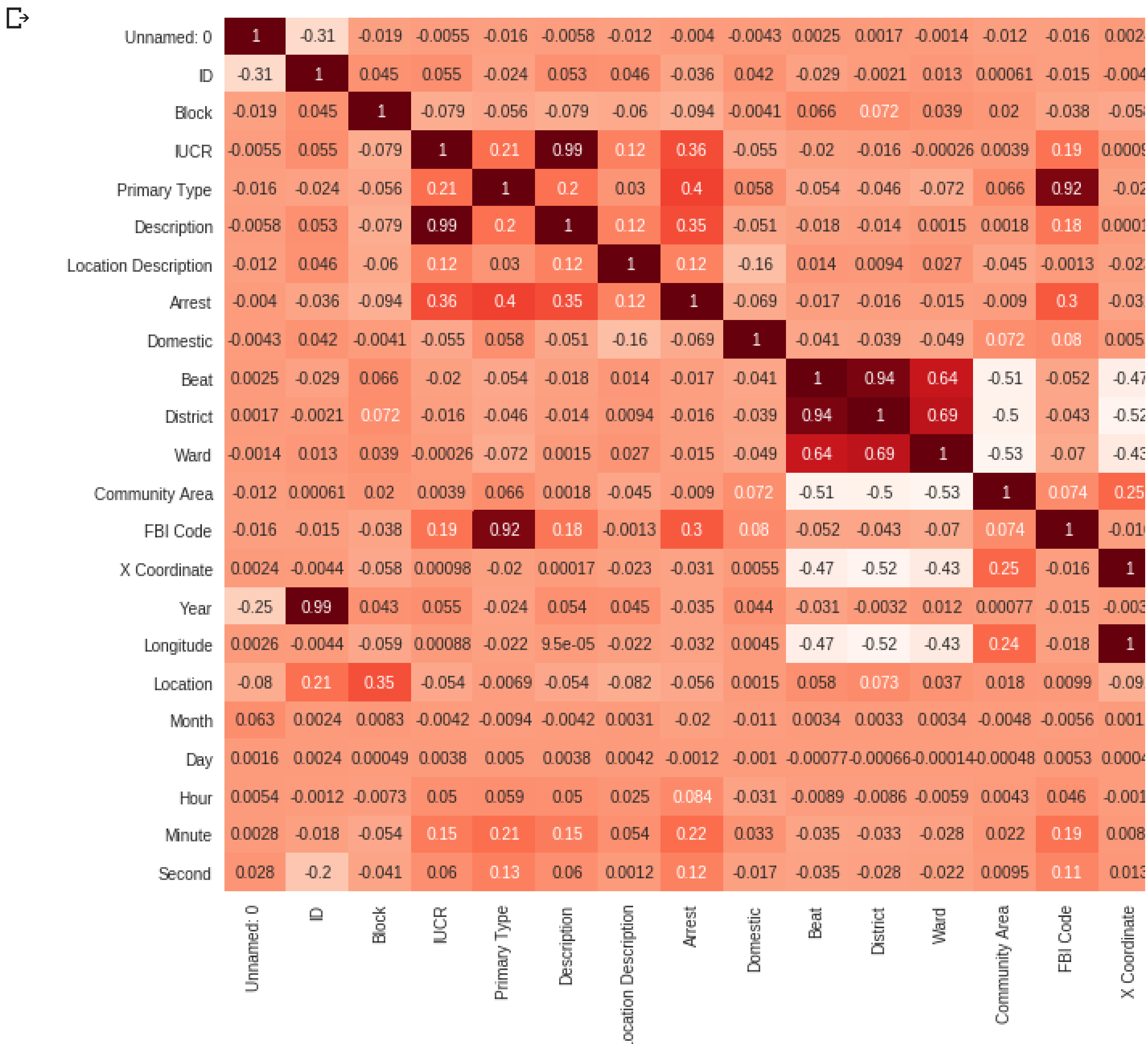
> Here we don't see all the features, so we need to convert those which are of object datatype to ca
> correlation to take effect.

```
df['Block'] = pd.factorize(df["Block"])[0]
df['IUCR'] = pd.factorize(df["IUCR"])[0]
df['Description'] = pd.factorize(df["Description"])[0]
df['Location Description'] = pd.factorize(df["Location Description"])[0]
df['FBI Code'] = pd.factorize(df["FBI Code"])[0]
df['Location'] = pd.factorize(df["Location"])[0]
```

> Correlation Facts:

- 1 - Positively Correlated
- -1 - Negatively Correlated
- 0 - No Correlation

```
cor = df.corr()
plt.figure(figsize=(20,10))
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



> Let us try to predict the Primary Type of the crime. Based on the heatmap above it is mainly corre
> Arrest, FBI Code.

> So here,

- Target Class = Primary Type
- Feature Set for training = [IUCR, Description, FBI Code, Arrest]

Let us import libaries

```
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

```
target_feature = 'Primary Type'
feature_set = ['IUCR','FBI Code', 'Description','Arrest']
# feature_set = ['IUCR','FBI Code', 'Description']
```

```
# Splitting the dataset into test and train
X, Y = train_test_split(df,
                        test_size = 0.2,
                        train_size = 0.8,
                        random_state= 3)
```

```
print("Train Sample Size : ", X.shape)
print("Test Sample Size : ", Y.shape)
```

```
Train Sample Size :  (4382663, 27)
Test Sample Size :  (1095666, 27)
```

```
train_x = X[feature_set]    #training features
train_y = X[target_feature]      #target Class to train

test_x = Y[feature_set]    #test features
test_y = Y[target_feature]      #target Class to test
```

```
from sklearn.linear_model import LinearRegression
```

```
linear_regressor = LinearRegression()
linear_regressor.fit(train_x, train_y) #training the algorithm
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
predict_linearReg = linear_regressor.predict(test_x)
```

```
predict_linearReg
```

```
array([ 1.90056719, 14.83369776, 19.33589537, ..., 10.16560144,
        1.85064689,  1.90287489])
```

```
res = []
for i, val in enumerate(predict_linearReg):
  # predict_linearReg[i] = int(round(predict_linearReg[i]))
  res.append(int(round(predict_linearReg[i])))
  # print(int(round(predict_linearReg[i])))

# predict_linearReg
```

```
res
```

```
      1,
      8,
      10,
      4,
      12,
      2,
      19,
      12,
      12,
      12,
      3,
      2,
      12,
      2,
      10,
      4,
      2,
      8,
      8,
      2,
      3,
      ...]
```

```
from sklearn.metrics import mean_squared_error
from math import sqrt

rms = sqrt(mean_squared_error(test_y, res))
```

```
rms
```

```
2.0290652879760795
```

```
test_y
```

```
Date
2015-08-18 16:45:00     1
2012-05-16 14:34:00    15
2005-08-07 21:30:00    19
2007-01-22 22:32:41    11
2007-05-25 18:12:00     0
                       ..
2005-09-21 12:18:52    14
2011-02-10 23:07:00     6
2005-08-01 12:00:00    11
2014-07-26 06:00:00     1
2004-06-01 08:55:00     1
Name: Primary Type, Length: 1095666, dtype: int64
```

```
# importing metrics
from sklearn.metrics import precision_score, recall_score, classification_report, accuracy_sc
```

```
# Model Evaluation
accuracy_linReg = accuracy_score(test_y, res)
```

```
recall_linReg = recall_score(test_y, res, average="weighted")
precision_linReg= precision_score(test_y, res, average="weighted")
f1_linReg = f1_score(test_y, res, average='micro')

print("========== Random Forest Results ==========")
print("Accuracy    : ", accuracy_linReg)
print("Recall      : ", recall_linReg)
print("Precision   : ", precision_linReg)
print("F1 Score    : ", f1_linReg)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: Undefine
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: Undefine
  _warn_prf(average, modifier, msg_start, len(result))
========== Random Forest Results ==========
Accuracy    :  0.14370255169002233
Recall      :  0.14370255169002233
Precision   :  0.19646989143851568
F1 Score    :  0.14370255169002233
```

As we can see Linear Regressor has a very low accuracy, this is due to the uneven distribution of the c value is not linear with the features and there is a varied proportion of unnormalization.

> Let's try Random Forest Classifier as this is a tree based classifier and more suitable for our case

```
from sklearn.ensemble import RandomForestClassifier


# Creating RandomForest Model with configuration
rf_model = RandomForestClassifier(n_estimators=10,
                                  min_samples_split = 30,
                                  bootstrap = True,
                                  max_depth = 50,
                                  min_samples_leaf = 15)


#Fitting the model with training data
rf_model.fit(X=train_x, y=train_y)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=50, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=15, min_samples_split=30,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

```
# Predicting for test
predict_RF = rf_model.predict(test_x)
```

```
# Model Evaluation
accuracy_RF = accuracy_score(test_y, predict_RF)
recall_RF = recall_score(test_y, predict_RF, average="weighted")
precision_RF= precision_score(test_y, predict_RF, average="weighted")
f1_RF = f1_score(test_y, predict_RF, average='micro')

print("========== Random Forest Results ==========")
print("Accuracy    : ", accuracy_RF)
print("Recall      : ", recall_RF)
print("Precision   : ", precision_RF)
print("F1 Score    : ", f1_RF)
```

```
========== Random Forest Results ==========
Accuracy    :  0.9999607544634953
Recall      :  0.9999607544634953
Precision   :  0.9999608297494788
F1 Score    :  0.9999607544634953
```

```
from sklearn.neural_network import MLPClassifier
```

```
# Create Model with configuration
nn_model = MLPClassifier(solver='adam',
                         alpha=1e-5,
                         hidden_layer_sizes=(,),
                         random_state=1,
                         max_iter=1000
                        )
```

```
nn_model.fit(X=train_x,y=train_y)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:
  warnings.warn("Training interrupted by user.")
MLPClassifier(activation='relu', alpha=1e-05, batch_size='auto', beta_1=0.9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
              hidden_layer_sizes=(40,), learning_rate='constant',
              learning_rate_init=0.001, max_fun=15000, max_iter=1000,
              momentum=0.9, n_iter_no_change=10, nesterovs_momentum=True,
              power_t=0.5, random_state=1, shuffle=True, solver='adam',
              tol=0.0001, validation_fraction=0.1, verbose=False,
              warm_start=False)
```

```
predict_nn = nn_model.predict(test_x)
```

```
# Model Evaluation
accuracy_nn = accuracy_score(test_y, predict_nn)
recall_nn = recall_score(test_y, predict_nn, average="weighted")
precision_nn= precision_score(test_y, predict_nn, average="weighted")
f1_nn = f1_score(test_y, predict_nn, average='micro')
```

```
print("========== Random Forest Results ==========")
print("Accuracy    : ", accuracy_nn)
print("Recall      : ", recall_nn)
print("Precision   : ", precision_nn)
print("F1 Score    : ", f1_nn)
```

```
========== Random Forest Results ==========
Accuracy    :  0.9920358941502246
Recall      :  0.9920358941502246
Precision   :  0.9922035979765862
F1 Score    :  0.9920358941502246
```

```
# from sklearn.neighbors import KNeighborsClassifier


# knn_model = KNeighborsClassifier(n_neighbors=3)


# knn_model.fit(X=train_x,y=train_y)


# predict_knn = knn_model.predict(test_y)


# # Model Evaluation
# accuracy_knn = accuracy_score(test_y, predict_knn)
# recall_knn = recall_score(test_y, predict_knn, average="weighted")
# precision_knn= precision_score(test_y, predict_knn, average="weighted")
# f1_knn = f1_score(test_y, predict_knn, average='micro')

# print("========== Random Forest Results ==========")
# print("Accuracy    : ", accuracy_knn)
# print("Recall      : ", recall_knn)
# print("Precision   : ", precision_knn)
# print("F1 Score    : ", f1_knn)
```

```
df.head(5)
```

	Unnamed: 0	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Lo Descr
Date									
2003-03-01 00:00:00	2544	4676906	HM278933	2003-03-01 00:00:00	0	0	0	0	
2003-05-01 01:00:00	3302	4677901	HM275615	2003-05-01 01:00:00	1	1	1	1	
2001-01-01 11:00:00	3756	4791194	HM403711	2001-01-01 11:00:00	2	2	2	2	
2003-03-15 00:00:00	4502	4679521	HM216293	2003-03-15 00:00:00	3	3	0	3	
2003-01-01 00:00:00	4904	4680124	HM282389	2003-01-01 00:00:00	4	4	1	4	

```
df['Community Area'].sort_values().unique
```

```
Date
2002-02-04 19:30:00     0.0
2010-05-12 12:00:00     0.0
2012-02-19 18:54:00     0.0
2003-01-11 08:55:00     0.0
2008-06-16 10:00:00     0.0
                       ...
2007-10-15 17:45:29    77.0
2013-08-11 19:49:00    77.0
2015-10-14 12:15:00    77.0
2002-12-02 21:30:00    77.0
2004-08-12 13:50:00    77.0
Name: Community Area, Length: 5478329, dtype: float64
```

```
community_mapping = {0.0: 'Rogers Park ', 1.0: 'West Ridge ', 2.0: 'Uptown ', 3.0: 'Lincoln S
```

```
df['Community'] = df['Community Area'].map(community_mapping)
```

```
78
```