

Project

November 21, 2019

```
In [2]: import pandas as pd
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import precision_score, recall_score, confusion_matrix, classification_report

        # ML Libraries
        from sklearn.ensemble import RandomForestClassifier, VotingClassifier
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.neural_network import MLPClassifier
        from sklearn.svm import SVC
        import xgboost as xgb

        # Evaluation

        from sklearn import metrics

        # Visualization Libraries
        import matplotlib
        import matplotlib.pyplot as plt
        import seaborn as sns

In [3]: df = pd.read_csv('Chicago_Crimes_2012_to_2017.csv')
        df.head()
```

```
Out[3]:
```

	Unnamed: 0	ID	Case Number	Date	\
0	3	10508693	HZ250496	05/03/2016 11:40:00 PM	
1	89	10508695	HZ250409	05/03/2016 09:40:00 PM	
2	197	10508697	HZ250503	05/03/2016 11:31:00 PM	
3	673	10508698	HZ250424	05/03/2016 10:10:00 PM	
4	911	10508699	HZ250455	05/03/2016 10:00:00 PM	

	Block	IUCR	Primary Type	Description	\
0	013XX S SAWYER AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	
1	061XX S DREXEL AVE	0486	BATTERY	DOMESTIC BATTERY SIMPLE	
2	053XX W CHICAGO AVE	0470	PUBLIC PEACE VIOLATION	RECKLESS CONDUCT	
3	049XX W FULTON ST	0460	BATTERY	SIMPLE	
4	003XX N LOTUS AVE	0820	THEFT	\$500 AND UNDER	

	Location Description	Arrest	...	Ward \
0	APARTMENT	True	...	24.0
1	RESIDENCE	False	...	20.0
2	STREET	False	...	37.0
3	SIDEWALK	False	...	28.0
4	RESIDENCE	False	...	28.0

	Community Area	FBI Code	X Coordinate	Y Coordinate	Year \
0	29.0	08B	1154907.0	1893681.0	2016
1	42.0	08B	1183066.0	1864330.0	2016
2	25.0	24	1140789.0	1904819.0	2016
3	25.0	08B	1143223.0	1901475.0	2016
4	25.0	06	1139890.0	1901675.0	2016

	Updated On	Latitude	Longitude	Location
0	05/10/2016 03:56:50 PM	41.864073	-87.706819	(41.864073157, -87.706818608)
1	05/10/2016 03:56:50 PM	41.782922	-87.604363	(41.782921527, -87.60436317)
2	05/10/2016 03:56:50 PM	41.894908	-87.758372	(41.894908283, -87.758371958)
3	05/10/2016 03:56:50 PM	41.885687	-87.749516	(41.885686845, -87.749515983)
4	05/10/2016 03:56:50 PM	41.886297	-87.761751	(41.886297242, -87.761750709)

[5 rows x 23 columns]

In [4]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1456714 entries, 0 to 1456713
Data columns (total 23 columns):
Unnamed: 0      1456714 non-null int64
ID              1456714 non-null int64
Case Number     1456713 non-null object
Date           1456714 non-null object
Block          1456714 non-null object
IUCR           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
Beat          1456714 non-null int64
District       1456713 non-null float64
Ward           1456700 non-null float64
Community Area 1456674 non-null float64
FBI Code       1456714 non-null object
X Coordinate   1419631 non-null float64
Y Coordinate   1419631 non-null float64
Year           1456714 non-null int64
Updated On     1456714 non-null object
```

```

Latitude          1419631 non-null float64
Longitude          1419631 non-null float64
Location           1419631 non-null object
dtypes: bool(2), float64(7), int64(4), object(10)
memory usage: 236.2+ MB

```

```

In [5]: #droppping empty cells
        df = df.dropna()

```

We will take a subset sample of the data to work upon

```

In [6]: df = df.sample(n = 100000)

```

Dropping Unnamed, ID and Case number as this can have no relation with the class of crime

```

In [7]: df = df.drop(['Unnamed: 0'], axis = 1)
        df = df.drop(['ID'], axis=1)
        df = df.drop(['Case Number'], axis=1)

        df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 100000 entries, 708596 to 1296987
Data columns (total 20 columns):
Date          100000 non-null object
Block         100000 non-null object
IUCR          100000 non-null object
Primary Type  100000 non-null object
Description    100000 non-null object
Location Description 100000 non-null object
Arrest        100000 non-null bool
Domestic      100000 non-null bool
Beat          100000 non-null int64
District      100000 non-null float64
Ward          100000 non-null float64
Community Area 100000 non-null float64
FBI Code      100000 non-null object
X Coordinate   100000 non-null float64
Y Coordinate   100000 non-null float64
Year          100000 non-null int64
Updated On    100000 non-null object
Latitude      100000 non-null float64
Longitude     100000 non-null float64
Location      100000 non-null object
dtypes: bool(2), float64(7), int64(2), object(9)
memory usage: 14.7+ MB

```

In []:

Converting dates to numerical values for correlation

```
In [8]: df['date_new'] = pd.to_datetime(df['Date'])
df['Hr'] = df['date_new'].dt.hour
df['Min'] = df['date_new'].dt.minute
df['Sec'] = df['date_new'].dt.second
df['YY'] = df['date_new'].dt.year
df['MM'] = df['date_new'].dt.month
df['DD'] = df['date_new'].dt.day
```

```
df = df.drop(['Date'], axis=1)
df = df.drop(['date_new'], axis=1)
df = df.drop(['Updated On'], axis=1)
df.head()
```

```
Out [8]:
```

		Block	IUCR	Primary Type	\
708596		028XX N LONG AVE	0841	THEFT	
26540		006XX N UNION AVE	0460	BATTERY	
370153		124XX S STATE ST	0460	BATTERY	
1103299	0000X W CHECKPOINT 6 ST		5007	OTHER OFFENSE	
1010405	044XX N MAGNOLIA AVE	1350		CRIMINAL TRESPASS	

	Description	\
708596	FINANCIAL ID THEFT:\$300 &UNDER	
26540	SIMPLE	
370153	SIMPLE	
1103299	OTHER WEAPONS VIOLATION	
1010405	TO STATE SUP LAND	

	Location Description	Arrest	Domestic	Beat	\
708596	SMALL RETAIL STORE	False	True	2514	
26540	OTHER	False	False	1214	
370153	SCHOOL, PUBLIC, GROUNDS	False	False	523	
1103299	AIRPORT TERMINAL UPPER LEVEL - SECURE AREA	False	False	1653	
1010405	CHA PARKING LOT/GROUNDS	True	False	1913	

	District	Ward ...	Year	Latitude	Longitude	\
708596	25.0	31.0 ...	2013	41.931564	-87.761343	
26540	12.0	27.0 ...	2014	41.892896	-87.645888	
370153	5.0	9.0 ...	2012	41.667504	-87.622283	
1103299	16.0	41.0 ...	2016	41.975869	-87.902593	
1010405	19.0	46.0 ...	2015	41.962581	-87.660979	

Location	Hr	Min	Sec	YY	MM	DD
----------	----	-----	-----	----	----	----

708596	(41.931564146, -87.761343076)	15	30	0	2013	12	26
26540	(41.892895925, -87.645887668)	8	8	0	2014	8	14
370153	(41.667503644, -87.622282981)	10	40	0	2012	11	16
1103299	(41.97586893, -87.902593203)	5	0	0	2016	4	10
1010405	(41.962581499, -87.660978843)	21	30	0	2015	4	23

[5 rows x 24 columns]

Converting Categorical Features to Numerical

```
In [9]: df['Block'] = pd.factorize(df["Block"])[0]
df['FBI Code'] = pd.factorize(df["FBI Code"])[0]

df['Location Description'] = pd.factorize(df["Location Description"])[0]

df['Location'] = pd.factorize(df["Location"])[0]

df['IUCR'] = pd.factorize(df["IUCR"])[0]
df['Description'] = pd.factorize(df["Description"])[0]
```

```
In [10]: df.head()
```

```
Out[10]:
```

	Block	IUCR	Primary Type	Description	Location Description \
708596	0	0	THEFT	0	0
26540	1	1	BATTERY	1	1
370153	2	1	BATTERY	1	2
1103299	3	2	OTHER OFFENSE	2	3
1010405	4	3	CRIMINAL TRESPASS	3	4

	Arrest	Domestic	Beat	District	Ward ...	Year	Latitude \
708596	False	True	2514	25.0	31.0 ...	2013	41.931564
26540	False	False	1214	12.0	27.0 ...	2014	41.892896
370153	False	False	523	5.0	9.0 ...	2012	41.667504
1103299	False	False	1653	16.0	41.0 ...	2016	41.975869
1010405	True	False	1913	19.0	46.0 ...	2015	41.962581

	Longitude	Location	Hr	Min	Sec	YY	MM	DD
708596	-87.761343	0	15	30	0	2013	12	26
26540	-87.645888	1	8	8	0	2014	8	14
370153	-87.622283	2	10	40	0	2012	11	16
1103299	-87.902593	3	5	0	0	2016	4	10
1010405	-87.660979	4	21	30	0	2015	4	23

[5 rows x 24 columns]

Now we have all the features with numerical values and we can plot the graphs

```
In [12]: # Plot Bar Chart visualize Primary Types
plt.figure(figsize=(20,10))
```

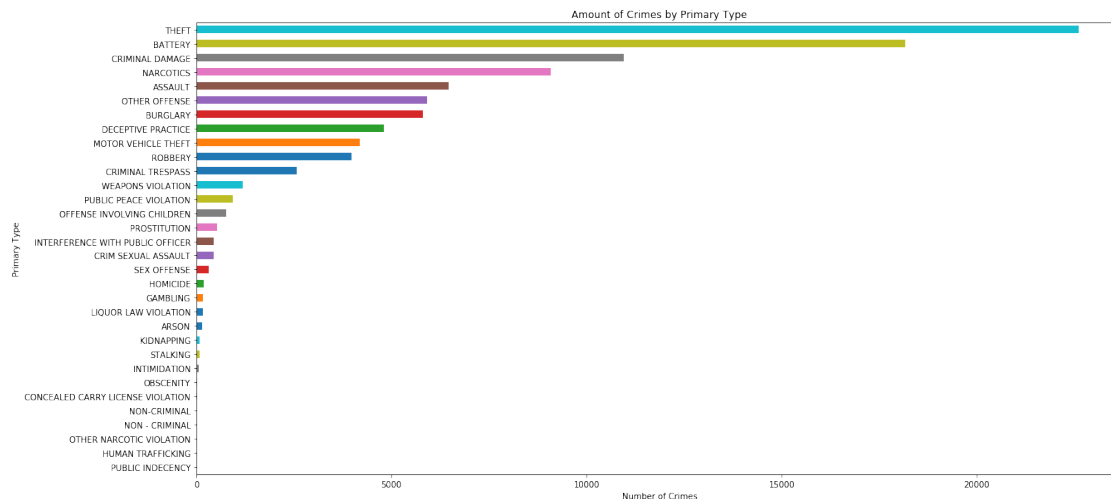
```

plt.title('Amount of Crimes by Primary Type')

plt.xlabel('Number of Crimes')
plt.ylabel('Type of Crime')
graph = df.groupby([df['Primary Type']]).size().sort_values(ascending=True)
graph.plot(kind='barh')

plt.show()

```



We can see that some crimes have very less frequency and we can club them as others

```

In [13]: # we sum up the amount of Crime Type happened and select the last 10 classes
crime_classes = df.groupby(['Primary Type'])['IUCR'].size().reset_index()
#print(all_classes.head())
crime_classes.rename(columns={"IUCR": "Size"}, inplace=True)
crime_classes = crime_classes.sort_values(['Size'], ascending=False)

other_classes = crime_classes.tail(10)
other_classes

```

```

Out[13]:

```

	Primary Type	Size
14	KIDNAPPING	75
29	STALKING	73
13	INTIMIDATION	50
20	OBSCENITY	10
4	CONCEALED CARRY LICENSE VIOLATION	7
19	NON-CRIMINAL	6
18	NON - CRIMINAL	3
22	OTHER NARCOTIC VIOLATION	3
11	HUMAN TRAFFICKING	2
25	PUBLIC INDECENCY	1

```
In [ ]:
```

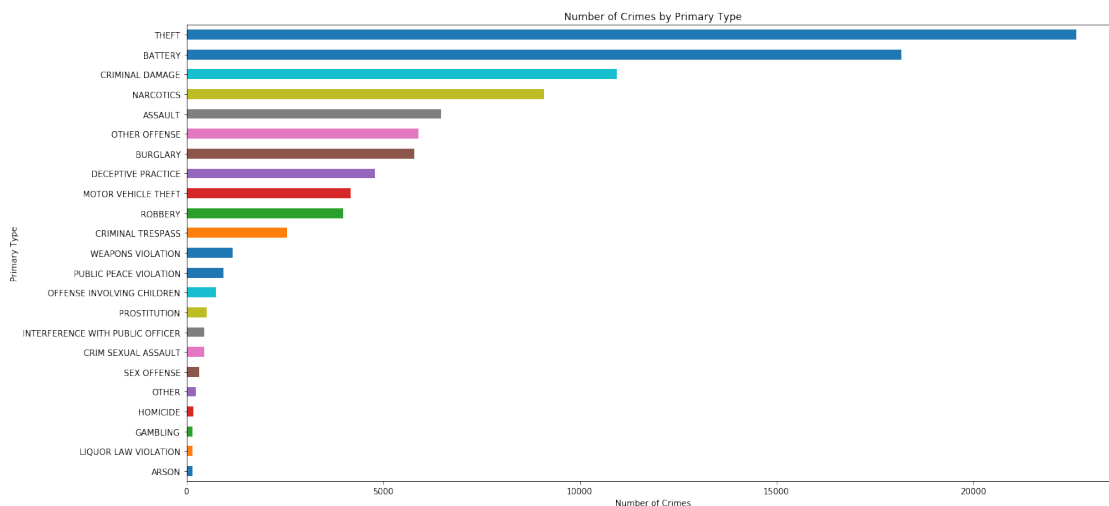
```
In [14]: name_dic = {"KIDNAPPING":"OTHER",
                    "STALKING":"OTHER",
                    "INTIMIDATION":"OTHER",
                    "OBSCENITY":"OTHER",
                    "PUBLIC INDECENCY":"OTHER",
                    "CONCEALED CARRY LICENSE VIOLATION":"OTHER",
                    "NON-CRIMINAL":"OTHER",
                    "NON - CRIMINAL":"OTHER",
                    "HUMAN TRAFFICKING":"OTHER",
                    "OTHER NARCOTIC VIOLATION":"OTHER"}
# After that, we replaced it with label 'OTHERS'

df.replace({"Primary Type":name_dic},inplace=True)
#df.loc[df['Primary Type'].isin(unwanted_classes['Primary Type']), 'Primary Type'] =

# Plot Bar Chart visualize Primary Types
plt.figure(figsize=(20,10))
plt.title('Number of Crimes by Primary Type')
plt.ylabel('Type of Crime')
plt.xlabel('Number of Crimes')

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

plt.show()
```



```
In [15]: #Now we have 23 classes to predict
Classes = df['Primary Type'].unique()
len(Classes)
```



```
In [22]: #Split dataset to Training Set & Test Set
x, y = train_test_split(df,
                        test_size = 0.2,
                        train_size = 0.8,
                        random_state= 3)
```

```
x1 = x[Features]    #Features to train
x2 = x[Target]      #Target Class to train
y1 = y[Features]    #Features to test
y2 = y[Target]      #Target Class to test
```

```
print('Features : ', Features)
print('Target Class : ', Target)
print('Training Set : ', x.shape)
print('Test Set : ', y.shape)
```

```
Features : ['IUCR', 'Description', 'Arrest', 'Location Description', 'Domestic']
Target Class : Primary Type
Training Set : (80000, 24)
Test Set : (20000, 24)
```

```
In [23]: # Random Forest
# Create Model with configuration
rf_model = RandomForestClassifier()
```

```
# Model Training
rf_model.fit(X=x1,
            y=y2)
```

```
# Prediction
result = rf_model.predict(y[Features])
```

C:\Users\tanma\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The number of samples per tree in the bootstrap cannot be less than 10 in version 0.20 to 100 in 0.22.", FutureWarning)

```
In [24]: print("Random Forest Results")
print("Accuracy : ", accuracy_score(y2, result))
print("Recall : ", recall_score(y2, result, average="weighted"))
print("Precision : ", precision_score(y2, result, average="weighted"))
print("F1 Score : ", f1_score(y2, result, average='micro'))
```

```
Random Forest Results
Accuracy : 0.992
Recall : 0.992
Precision : 0.9919089395908662
F1 Score : 0.992
```

```

In [25]: rf_model = RandomForestClassifier(n_estimators=20, # Number of trees
                                         min_samples_split = 30,
                                         bootstrap = True,
                                         max_depth = 20,
                                         min_samples_leaf = 25)

rf_model.fit(X=x1,
             y=x2)

# Prediction
result = rf_model.predict(y[Features])

In [26]: print("Random Forest Results (Tuned)")
print("Accuracy      : ", accuracy_score(y2, result))
print("Recall        : ", recall_score(y2, result, average="weighted"))
print("Precision     : ", precision_score(y2, result, average="weighted"))
print("F1 Score      : ", f1_score(y2, result, average='micro'))

Random Forest Results (Tuned)
Accuracy      : 0.9694
Recall        : 0.9694
Precision     : 0.9693551768577167
F1 Score      : 0.9694

In [27]: knn_model = KNeighborsClassifier()
knn_model.fit(X=x1,y=x2)
result = knn_model.predict(y[Features])

In [28]: print("KNN Results")
print("Accuracy      : ", accuracy_score(y2, result))
print("Recall        : ", recall_score(y2, result, average="weighted"))
print("Precision     : ", precision_score(y2, result, average="weighted"))
print("F1 Score      : ", f1_score(y2, result, average='micro'))

KNN Results
Accuracy      : 0.98365
Recall        : 0.98365
Precision     : 0.98359532945818
F1 Score      : 0.98365

In [29]: knn_model = KNeighborsClassifier(n_neighbors=7,weights='distance')
knn_model.fit(X=x1,y=x2)
result = knn_model.predict(y[Features])

In [30]: print("KNN Results(Tuned)")
print("Accuracy      : ", accuracy_score(y2, result))
print("Recall        : ", recall_score(y2, result, average="weighted"))
print("Precision     : ", precision_score(y2, result, average="weighted"))
print("F1 Score      : ", f1_score(y2, result, average='micro'))

```

KNN Results(Tuned)

```
Accuracy    : 0.9884
Recall      : 0.9884
Precision   : 0.9884235088414384
F1 Score    : 0.9884
```

```
In [31]: xg_model = xgb.XGBClassifier()
         xg_model.fit(X=x1,y=x2)
         result = xg_model.predict(y[Features])
```

```
In [32]: print("XGB Results")
         print("Accuracy    : ", accuracy_score(y2, result))
         print("Recall      : ", recall_score(y2, result, average="weighted"))
         print("Precision   : ", precision_score(y2, result, average="weighted"))
         print("F1 Score    : ", f1_score(y2, result, average='micro'))
```

XGB Results

```
Accuracy    : 0.984
Recall      : 0.984
Precision   : 0.9848091467665612
F1 Score    : 0.984
```

```
In [33]: xg_model = xgb.XGBClassifier(max_depth=5,learning_rate=0.1,n_estimator=150)
         xg_model.fit(X=x1,y=x2)
         result = xg_model.predict(y[Features])
```

```
In [34]: print("XGB Results")
         print("Accuracy    : ", accuracy_score(y2, result))
         print("Recall      : ", recall_score(y2, result, average="weighted"))
         print("Precision   : ", precision_score(y2, result, average="weighted"))
         print("F1 Score    : ", f1_score(y2, result, average='micro'))
```

XGB Results

```
Accuracy    : 0.99665
Recall      : 0.99665
Precision   : 0.9966657653162163
F1 Score    : 0.99665
```

```
In [35]: MLP_model = MLPClassifier()
         MLP_model.fit(X=x1,y=x2)
         result = MLP_model.predict(y[Features])
```

```
In [65]: print("MLPClassifier Results")
         print("Accuracy    : ", accuracy_score(y2, result))
         print("Recall      : ", recall_score(y2, result, average="weighted"))
         print("Precision   : ", precision_score(y2, result, average="weighted"))
         print("F1 Score    : ", f1_score(y2, result, average='micro'))
```

MLPClassifier Results

Accuracy : 0.9968
Recall : 0.9968
Precision : 0.9968296360098488
F1 Score : 0.9968

```
In [66]: MLP_model = MLPClassifier(hidden_layer_sizes=(150,2))  
         xg_model.fit(X=x1,y=x2)  
         result = xg_model.predict(y[Features])
```

```
In [67]: print("MLPClassifier Results")  
         print("Accuracy : ", accuracy_score(y2, result))  
         print("Recall : ", recall_score(y2, result, average="weighted"))  
         print("Precision : ", precision_score(y2, result, average="weighted"))  
         print("F1 Score : ", f1_score(y2, result, average='micro'))
```

MLPClassifier Results

Accuracy : 0.9968
Recall : 0.9968
Precision : 0.9968296360098488
F1 Score : 0.9968

```
In [ ]:
```