

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

#Preprocessing Libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_score, recall_score, confusion_matrix, classification_report, accuracy_score, f1_score

# ML Libraries
from sklearn.ensemble import RandomForestClassifier,VotingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier

# Evaluation Metrics1
from yellowbrick.classifier import ClassificationReport
from sklearn import metrics
from sklearn.svm import SVC

from google.colab import files
uploaded = files.upload()
```

No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving data1.csv to data1.csv  
Saving data2.csv to data2.csv  
Saving data3.csv to data3.csv  
Saving data4.csv to data4.csv

```
df = pd.concat([pd.read_csv('data1.csv', error_bad_lines=False)],ignore_index=True)
df = pd.concat([pd.read_csv('data2.csv', error_bad_lines=False)], ignore_index=True)
df = pd.concat([df, pd.read_csv('data3.csv', error_bad_lines=False)], ignore_index=True)
df = pd.concat([df, pd.read_csv('data4.csv', error_bad_lines=False)], ignore_index=True)
df.head()
```

```
<ipython-input-3-130af21cb0c5>:1: FutureWarning: The error_bad_lines argument has been deprecated and will be removed in a future version. Use on_bad_lines
```

```
df = pd.concat([pd.read_csv('data1.csv', error_bad_lines=False)], ignore_index=True)
```

```
<ipython-input-3-130af21cb0c5>:2: FutureWarning: The error_bad_lines argument has been deprecated and will be removed in a future version. Use on_bad_lines
```

```
df = pd.concat([pd.read_csv('data2.csv', error_bad_lines=False)], ignore_index=True)
```

```
<ipython-input-3-130af21cb0c5>:3: FutureWarning: The error_bad_lines argument has been deprecated and will be removed in a future version. Use on_bad_lines
```

```
df = pd.concat([df, pd.read_csv('data3.csv', error_bad_lines=False)], ignore_index=True)
```

```
<ipython-input-3-130af21cb0c5>:4: FutureWarning: The error_bad_lines argument has been deprecated and will be removed in a future version. Use on_bad_lines
```

```
df = pd.concat([df, pd.read_csv('data4.csv', error_bad_lines=False)], ignore_index=True)
```

	Unnamed: 0	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arrest	...	Ward	Community Area	FBI Code	Coordinates
0	0	4673626	HM274058	04-02-2006 13:00	055XX N MANGO AVE	2825	OTHER OFFENSE	HARASSMENT BY TELEPHONE	RESIDENCE	False	...	45.0	11.0	26	1136872.1
1	1	4673627	HM202199	02/26/2006 01:40:48 PM	065XX S RHODES AVE	2017	NARCOTICS	MANU/DELIVER:CRACK	SIDEWALK	True	...	20.0	42.0	18	1181027.1
2	2	4673628	HM113861	01-08-2006 23:16	013XX E 69TH ST	051A	ASSAULT	AGGRAVATED: HANDGUN	OTHER	False	...	5.0	69.0	04A	1186023.1
3	4	4673629	HM274049	04-05-2006 18:45	061XX W NEWPORT AVF	460	BATTERY	SIMPLE	RESIDENCE	False	...	38.0	17.0	08B	1134772.1

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 175975 entries, 0 to 175974
```

```
Data columns (total 23 columns):
```

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	175975 non-null	int64
1	ID	175975 non-null	int64
2	Case Number	175975 non-null	object
3	Date	175975 non-null	object
4	Block	175975 non-null	object
5	IUCR	175975 non-null	object
6	Primary Type	175975 non-null	object

```

7  Description      175975 non-null object
8  Location Description 175877 non-null object
9  Arrest          175975 non-null bool
10 Domestic        175975 non-null bool
11 Beat            175975 non-null int64
12 District         175974 non-null float64
13 Ward             175973 non-null float64
14 Community Area   175866 non-null float64
15 FBI Code         175975 non-null object
16 X Coordinate     155141 non-null float64
17 Y Coordinate     155141 non-null float64
18 Year             175975 non-null int64
19 Updated On       175975 non-null object
20 Latitude         155141 non-null float64
21 Longitude        155141 non-null float64
22 Location         155141 non-null object
dtypes: bool(2), float64(7), int64(4), object(10)
memory usage: 28.5+ MB

```

```
# Preprocessing
```

```
# Remove NaN Value (As Dataset is huge, the NaN row could be neglectable)
```

```
df = df.dropna()
```

```
# As the dataset is too huge is size, we would just subsampled a dataset for modelling as proof of concept
```

```
df = df.sample(n=100000)
```

```
# Remove irrelevant/not meaningfull attributes
```

```
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, 4739 to 167319
Data columns (total 20 columns):
#   Column              Non-Null Count  Dtype
---  -
0   Date                100000 non-null object
1   Block               100000 non-null object
2   IUCR                100000 non-null object
3   Primary Type        100000 non-null object
4   Description          100000 non-null object
5   Location Description 100000 non-null object
6   Arrest              100000 non-null bool

```

```
7 Domestic      100000 non-null bool
8 Beat          100000 non-null int64
9 District      100000 non-null float64
10 Ward         100000 non-null float64
11 Community Area 100000 non-null float64
12 FBI Code     100000 non-null object
13 X Coordinate  100000 non-null float64
14 Y Coordinate  100000 non-null float64
15 Year         100000 non-null int64
16 Updated On   100000 non-null object
17 Latitude     100000 non-null float64
18 Longitude    100000 non-null float64
19 Location     100000 non-null object
dtypes: bool(2), float64(7), int64(2), object(9)
memory usage: 14.7+ MB
```

```
# Splitting the Date to Day, Month, Year, Hour, Minute, Second
df['date2'] = pd.to_datetime(df['Date'])
df['Year'] = df['date2'].dt.year
df['Month'] = df['date2'].dt.month
df['Day'] = df['date2'].dt.day
df['Hour'] = df['date2'].dt.hour
df['Minute'] = df['date2'].dt.minute
df['Second'] = df['date2'].dt.second
df = df.drop(['Date'], axis=1)
df = df.drop(['date2'], axis=1)
df = df.drop(['Updated On'], axis=1)
df.head()
```

	Block	IUCR	Primary Type	Description	Location Description	Arrest	Domestic	Beat	District	Ward	...	Coordinate	Year	Latitu
<b>4739</b>	063XX N HOYNE AVE	810	THEFT	OVER \$500	PARKING LOT/GARAGE(NON.RESID.)	False	False	2413	24.0	50.0	...	1942168.0	2006	41.9969
<b>14717</b>	017XX W JUNEWAY TER	1350	CRIMINAL TRESPASS	TO STATE SUP LAND	CHA HALLWAY/STAIRWELL/ELEVATOR	True	False	2422	24.0	49.0	...	1951493.0	2006	42.0225
	026XX S													

```

# Convert Categorical Attributes to Numerical
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]

424024 WASHINGTON 1152 DECEPTIVE IDENTITY RESIDENCE False False 1122 11.0 28.0 1000106.0 2015 41.8927

Target = 'Primary Type'
print('Target: ', Target)

Target: Primary Type

```

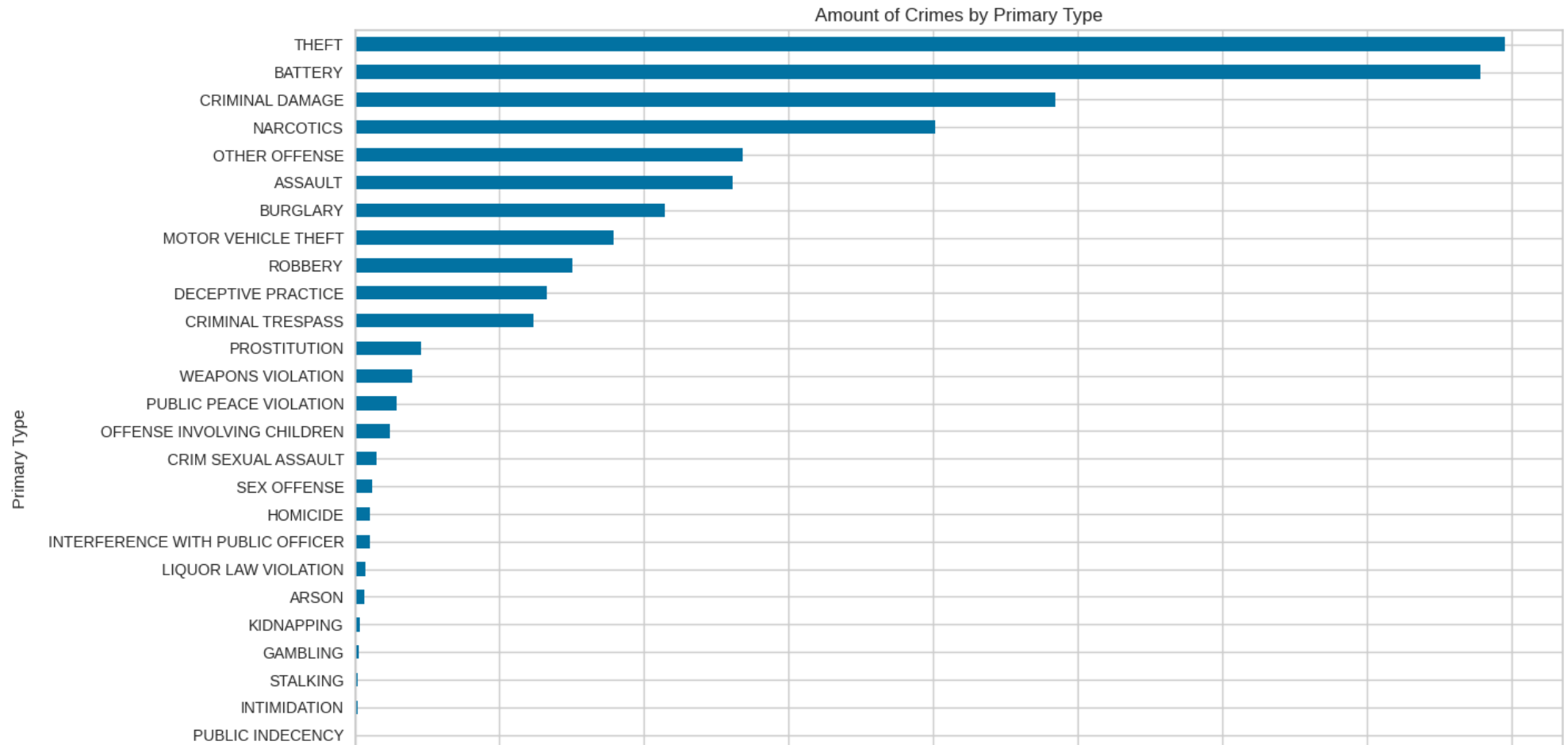
```

# Plot Bar Chart visualize Primary Types
plt.figure(figsize=(14,10))
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()

```



# At previous plot, we could see that the classes is quite imbalance

# Therefore, we are going to group several less occurred Crime Type into 'Others' to reduce the Target Class amount

# First, we sum up the amount of Crime Type happened and select the last 13 classes

```
all_classes = df.groupby(['Primary Type'])['Block'].size().reset_index()
```

```
all_classes['Amt'] = all_classes['Block']
```

```
all_classes = all_classes.drop(['Block'], axis=1)
```

```
all_classes = all_classes.sort_values(['Amt'], ascending=[False])
```

```
unwanted_classes = all_classes.tail(13)
```

```
unwanted_classes
```

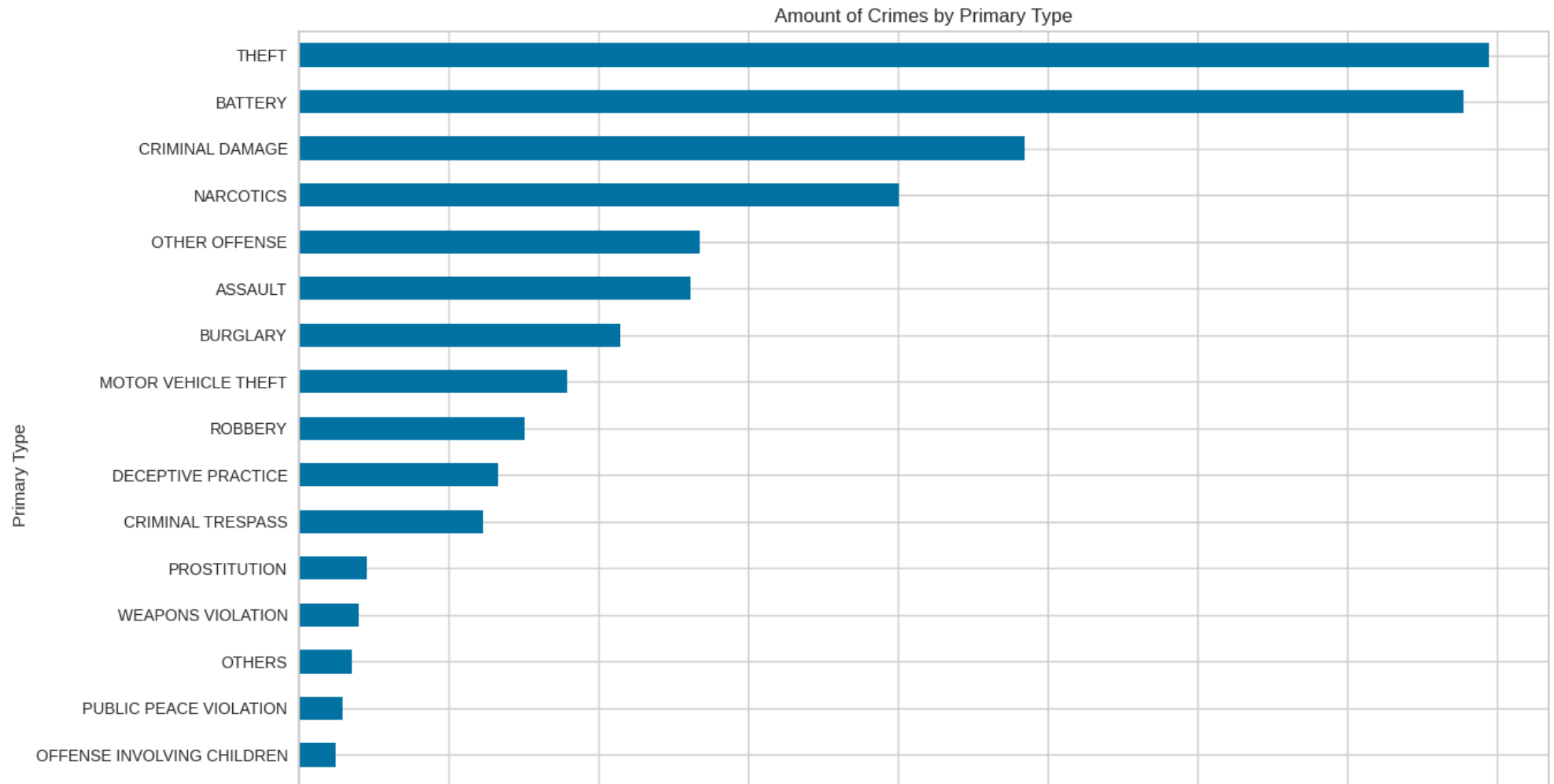
	Primary Type	Amt
12	INTERFERENCE WITH PUBLIC OFFICER	254
15	LIQUOR LAW VIOLATION	187
0	ARSON	163
14	KIDNAPPING	95
9	GAMBLING	70
28	STALKING	48
13	INTIMIDATION	46
24	PUBLIC INDECENCY	5
20	OBSCENITY	4
19	NON-CRIMINAL	2
18	NON - CRIMINAL	1
11	HUMAN TRAFFICKING	1

```
# After that, we replaced it with label 'OTHERS'
df.loc[df['Primary Type'].isin(unwanted_classes['Primary Type']), 'Primary Type'] = 'OTHERS'
```

```
# Plot Bar Chart visualize Primary Types
plt.figure(figsize=(14,10))
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()
```



# Now we are left with 14 Class as our predictive class

```
Classes = df['Primary Type'].unique()
```

```
Classes
```

```
array(['THEFT', 'CRIMINAL TRESPASS', 'NARCOTICS', 'DECEPTIVE PRACTICE',
      'BATTERY', 'BURGLARY', 'PUBLIC PEACE VIOLATION', 'ROBBERY',
      'OTHER OFFENSE', 'CRIMINAL DAMAGE', 'SEX OFFENSE', 'ASSAULT',
      'CRIM SEXUAL ASSAULT', 'MOTOR VEHICLE THEFT', 'OTHERS',
      'OFFENSE INVOLVING CHILDREN', 'WEAPONS VIOLATION', 'PROSTITUTION',
      'HOMICIDE'], dtype=object)
```



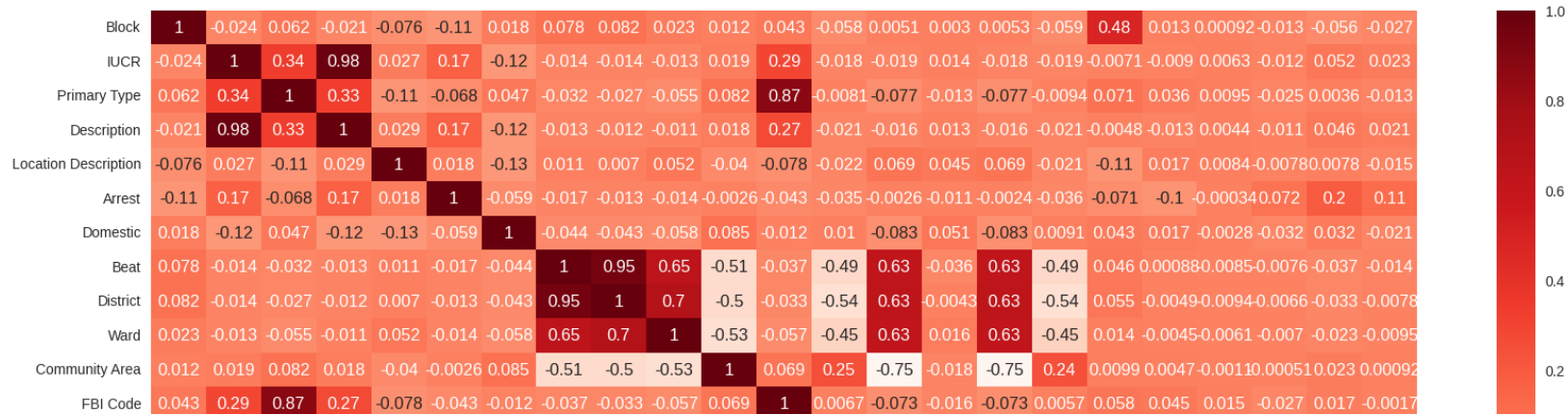
```
#Encode target labels into categorical variables:
df['Primary Type'] = pd.factorize(df["Primary Type"])[0]
df['Primary Type'].unique()

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

# Feature Selection using Filter Method
# Split Dataframe to target class and features
X_fs = df.drop(['Primary Type'], axis=1)
Y_fs = df['Primary Type']

#Using Pearson Correlation
plt.figure(figsize=(20,10))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Red)
plt.show()
```





### Further Elaboration of Correlation

The correlation coefficient has values between -1 to 1

- A value closer to 0 implies weaker correlation (exact 0 implying no correlation)
- A value closer to 1 implies stronger positive correlation
- A value closer to -1 implies stronger negative correlation

#Correlation with output variable

```
cor_target = abs(cor['Primary Type'])
```

#Selecting highly correlated features

```
relevant_features = cor_target[cor_target>0.2]
```

```
relevant_features
```

```
IUCR          0.340309
Primary Type   1.000000
Description    0.333508
FBI Code       0.873328
Name: Primary Type, dtype: float64
```

# At Current Point, the attributes is select manually based on Feature Selection Part.

```
Features = ["IUCR", "Description", "FBI Code"]
```

```
print('Full Features: ', Features)
```

```
Full Features:  ['IUCR', 'Description', 'FBI Code']
```

#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('Feature Set Used    : ', Features)
print('Target Class       : ', Target)
print('Training Set Size   : ', x.shape)
print('Test Set Size      : ', y.shape)

    Feature Set Used    :  ['IUCR', 'Description', 'FBI Code']
    Target Class       :  Primary Type
    Training Set Size   :  (80000, 23)
    Test Set Size      :  (20000, 23)

```

## Machine Learning Modelling

```

from sklearn.svm import SVC
from sklearn import metrics
svc=SVC() #Default hyperparameters
#svc.fit(X_train,y_train)
# Create Model with configuration
rf_model = RandomForestClassifier(n_estimators=70, # Number of trees
                                min_samples_split = 30,
                                bootstrap = True,
                                max_depth = 50,
                                min_samples_leaf = 25)

# Model Training
rf_model.fit(X=x1,
             y=x2)

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

# Model Evaluation
ac_sc = accuracy_score(y2, result)
rc_sc = recall_score(y2, result, average="weighted")
pr_sc = precision_score(y2, result, average="weighted")

```

```
f1_sc = f1_score(y2, result, average='micro')
confusion_m = confusion_matrix(y2, result)
```

```
print("=====  
print("Accuracy    : ", ac_sc)  
print("Recall       : ", rc_sc)  
print("Precision     : ", pr_sc)  
print("F1 Score      : ", f1_sc)  
print("Confusion Matrix: ")  
print(confusion_m)
```

```
=====  
Accuracy    : 0.99485  
Recall      : 0.99485  
Precision   : 0.9949102531584498  
F1 Score    : 0.99485  
Confusion Matrix:
```

```
[[3914  0  0  0  0  0  0  0  0  0  0  0  0  0  
  0  0  0  0  0]  
[  0 594  0  0  0  0  0  0  3  0  0  0  0  0  
  0  0  0  0  0]  
[  0  0 2001  0  0  0  0  0  0  0  0  0  0  0  
  0  4  0  0  0]  
[  0  0  0 701  0  0  0  0  0  0  0  0  0  0  
  5  0  0  0  0]  
[  0  0  0  1 3913  0  0  0  0  0  0  0  0  0  
  0  0  0  0  0]  
[  0  0  0  0  0 1026  0  0  0  0  0  0  0  0  
  0  0  0  0  0]  
[  0  0  0  0  0  0 159  0  6  0  0  0  0  0  
  1  0  0  0  0]  
[  0  0  0  0  0  0  0 762  0  0  0  0  0  0  
  0  0  0  0  0]  
[  0  0  0  0  0  0 11  9 1339  0  2  0  0  0  
  3  0  0  0  0]  
[  0  0  0  0  0  0  0  0  0 2429  0  0  0  0  
  0  0  0  0  0]  
[  0  0  0  0  0  0  0  0  0  0 59  0  0  0  
  0  0  0  0  0]  
[  0  0  0  0  0  0  0  0  0  0  0 1251  0  0  
  0  0  0  0  0]  
[  0  0  0  0  2  0  0  0  0  0  0  6  73  0  
  0  0  0  0  0]  
[  0  0  0  0  0  0  0  0  0  0  0  0  0 947  
  0  0  0  0  0]  
[  0  2  3  0  0  0 12  0  0  0  4  7  0  0  
130 11  0  0  0]  
[  0  0  0  0  0  0  0  0  0  0  2  0  0  0
```

```

      6   95   3   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0
  0   0 205   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0
  0   0   0 238   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0
  0   0   0   0 61]]

```

```

# Classification Report
# Instantiate the classification model and visualizer
target_names = Classes
visualizer = ClassificationReport(rf_model, classes=target_names)
visualizer.fit(X=x1, y=x2)      # Fit the training data to the visualizer
visualizer.score(y1, y2)       # Evaluate the model on the test data

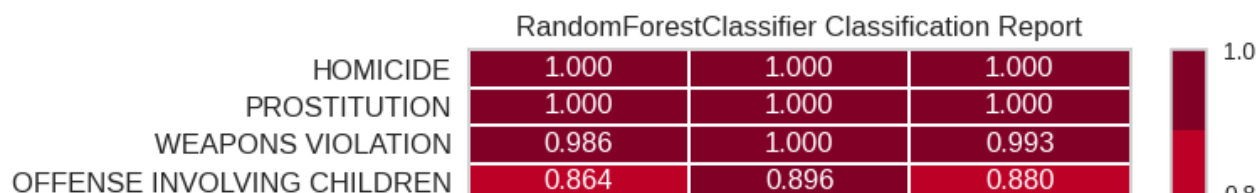
print('===== Classification Report =====')
print('')
print(classification_report(y2, result, target_names=target_names))

g = visualizer.poof()          # Draw/show/poof the data

```

```
===== Classification Report =====
```

	precision	recall	f1-score	support
THEFT	1.00	1.00	1.00	3914
CRIMINAL TRESPASS	1.00	0.99	1.00	597
NARCOTICS	1.00	1.00	1.00	2005
DECEPTIVE PRACTICE	1.00	0.99	1.00	706
BATTERY	1.00	1.00	1.00	3914
BURGLARY	1.00	1.00	1.00	1026
PUBLIC PEACE VIOLATION	0.87	0.96	0.91	166
ROBBERY	0.99	1.00	0.99	762
OTHER OFFENSE	0.99	0.98	0.99	1364
CRIMINAL DAMAGE	1.00	1.00	1.00	2429
SEX OFFENSE	0.88	1.00	0.94	59
ASSAULT	0.99	1.00	0.99	1251
CRIM SEXUAL ASSAULT	1.00	0.90	0.95	81
MOTOR VEHICLE THEFT	1.00	1.00	1.00	947
OTHERS	0.90	0.77	0.83	169
OFFENSE INVOLVING CHILDREN	0.86	0.90	0.88	106
WEAPONS VIOLATION	0.99	1.00	0.99	205
PROSTITUTION	1.00	1.00	1.00	238
HOMICIDE	1.00	1.00	1.00	61
accuracy			0.99	20000
macro avg	0.97	0.97	0.97	20000
weighted avg	0.99	0.99	0.99	20000



## # Model Training

```
nn_model.fit(X=x1,
             y=x2)
```

```
# Prediction
```

```
result = nn_model.predict(y[Features])
```

```
Train Loss: 1.000 1.000 1.000
```

```
# Model Evaluation
```

```
ac_sc = accuracy_score(y2, result)
```

```
rc_sc = recall_score(y2, result, average="weighted")
```

```
pr_sc = precision_score(y2, result, average="weighted")
```

```
f1_sc = f1_score(y2, result, average='micro')
```

```
confusion_m = confusion_matrix(y2, result)
```

```
print("===== RCNN Neural Network Results =====")
```

```
print("Accuracy : ", ac_sc)
```

```
print("Recall : ", rc_sc)
```

```
print("Precision : ", pr_sc)
```

```
print("F1 Score : ", f1_sc)
```

```
print("Confusion Matrix: ")
```

```
print(confusion_m)
```

```
===== RCNN Neural Network Results =====
```

```
Accuracy : 0.96945
```

```
Recall : 0.96945
```

```
Precision : 0.9715802635814953
```

```
F1 Score : 0.96945
```

```
Confusion Matrix:
```

```
[[3914  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0]
 [  0 523  0  0  0  0  0  0  0 74  0  0  0  0
  0  0  0  0  0  0]
 [  0  0 1895  0  0  0  0  0  0 107  0  0  0  0
  3  0  0  0  0  0]
 [  0  0  0 679  0  0  0  0  0  0  0  0  0 18
  0  0  4  5  0  0]
 [  0  0  0  0 3885  0  0 26  0  0  0  0  0  0
  3  0  0  0  0  0]
 [  0  0  0  0  0 1026  0  0  0  0  0  0  0  0
  0  0  0  0  0  0]
 [  0  0  0  0  2  0 103  0 43  0  0  0  0  0
 18  0  0  0  0  0]
 [  0  0  0  0 14  0  0 748  0  0  0  0  0  0
  0  0  0  0  0  0]
 [  0  0  0  0  0  0  0  0 1355  0  0  0  0  0
  1  8  0  0  0  0]
 [  0  0  0  0  0  0  0  0  0 2427  0  2  0  0
```

```

      0  0  0  0  0]
[  0  0  0  0  0  0  0  0  0  0  0  39  0  0  0
 20  0  0  0  0]
[  0  0  0  3  0  0  0  0  0  0  0  1219  0  11
 12  0  6  0  0]
[  0  0  0  0  0  0  0  0  0  0  0  8  51  0
 22  0  0  0  0]
[  0  0  0  0  0  0  0  0  0  0  0  0  0  944
 3  0  0  0  0]
[  0  0  0  0  18  10  0  0  11  8  0  0  0  11
 63 48  0  0  0]
[  0  0  0  0  0  0  0  0  29  0  0  1  0  0
 24 37 15  0  0]
[  0  0  0  0  0  0  0  0  0  0  0  0  0  7
 0  9 189  0  0]
[  0  0  0  5  0  0  0  0  0  0  0  0  0  0
 0  0  2 231  0]
[  0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0 61]]

```

```
# Classification Report
```

```
# Instantiate the classification model and visualizer
```

```
target_names = Classes
```

```
visualizer = ClassificationReport(nn_model, classes=target_names)
```

```
visualizer.fit(X=x1, y=x2)      # Fit the training data to the visualizer
```

```
visualizer.score(y1, y2)       # Evaluate the model on the test data
```

```
print('===== Classification Report =====')
```

```
print('')
```

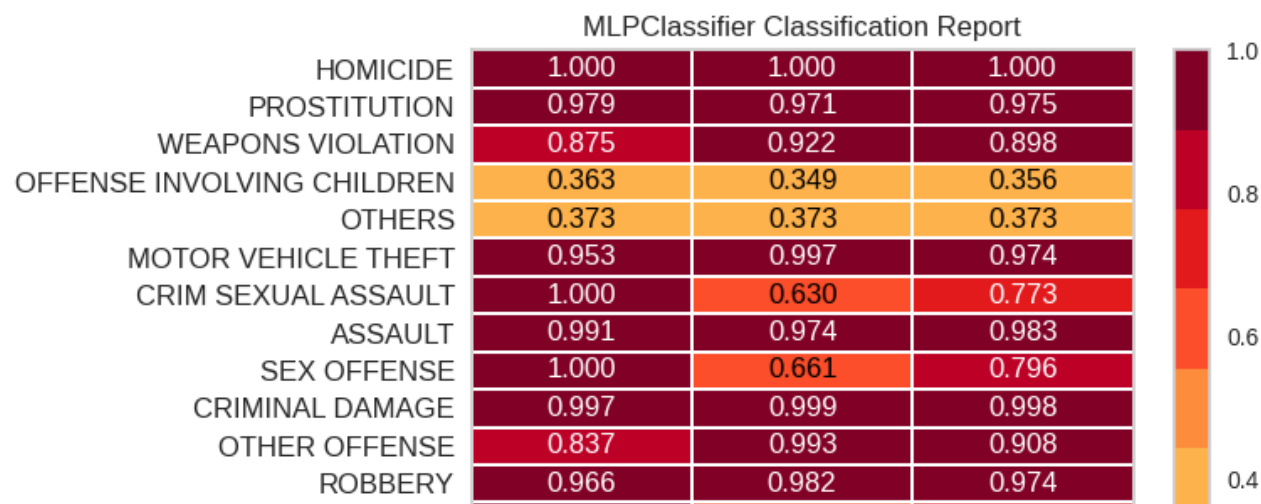
```
print(classification_report(y2, result, target_names=target_names))
```

```
g = visualizer.poof()          # Draw/show/poof the data
```



```
=====  
===== Classification Report =====  
=====
```

	precision	recall	f1-score	support
THEFT	1.00	1.00	1.00	3914
CRIMINAL TRESPASS	1.00	0.88	0.93	597
NARCOTICS	1.00	0.95	0.97	2005
DECEPTIVE PRACTICE	0.99	0.96	0.97	706
BATTERY	0.99	0.99	0.99	3914
BURGLARY	0.99	1.00	1.00	1026
PUBLIC PEACE VIOLATION	1.00	0.62	0.77	166
ROBBERY	0.97	0.98	0.97	762
OTHER OFFENSE	0.84	0.99	0.91	1364
CRIMINAL DAMAGE	1.00	1.00	1.00	2429
SEX OFFENSE	1.00	0.66	0.80	59
ASSAULT	0.99	0.97	0.98	1251
CRIM SEXUAL ASSAULT	1.00	0.63	0.77	81
MOTOR VEHICLE THEFT	0.95	1.00	0.97	947
OTHERS	0.37	0.37	0.37	169
OFFENSE INVOLVING CHILDREN	0.36	0.35	0.36	106
WEAPONS VIOLATION	0.88	0.92	0.90	205
PROSTITUTION	0.98	0.97	0.97	238
HOMICIDE	1.00	1.00	1.00	61
accuracy			0.97	20000
macro avg	0.91	0.86	0.88	20000
weighted avg	0.97	0.97	0.97	20000



```
# K-Nearest Neighbors
# Create Model with configuration
knn_model = KNeighborsClassifier(n_neighbors=3)

# Model Training
knn_model.fit(X=x1,
              y=x2)

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

# Model Evaluation
ac_sc = accuracy_score(y2, result)
rc_sc = recall_score(y2, result, average="weighted")
pr_sc = precision_score(y2, result, average="weighted")
f1_sc = f1_score(y2, result, average='micro')
confusion_m = confusion_matrix(y2, result)

print("===== K-Nearest Neighbors Results =====")
print("Accuracy    : ", ac_sc)
print("Recall      : ", rc_sc)
print("Precision    : ", pr_sc)
print("F1 Score     : ", f1_sc)
print("Confusion Matrix: ")
print(confusion_m)
```

```
===== K-Nearest Neighbors Results =====
Accuracy    :  0.9992
Recall      :  0.9992
Precision    :  0.9992021914153906
F1 Score     :  0.9992
Confusion Matrix:
[[3914   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0]
 [   0 597   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0]
 [   0   0 2003   0   0   0   0   0   1   0   0   0   0   0
   1   0   0   0   0]
 [   0   0   0 705   0   0   0   0   1   0   0   0   0   0
   0   0   0   0   0]
 [   0   0   0   0 3913   0   0   0   0   1   0   0   0   0
   0   0   0   0   0]
 [   0   0   0   0   0 1026   0   0   0   0   0   0   0   0
   0   0   0   0   0]
 [   0   0   0   0   0   0 166   0   0   0   0   0   0   0
   0   0   0   0   0]
```

```
[ 0 0 0 0 0 0 0 762 0 0 0 0 0 0
 0 0 0 0 0]
[ 1 0 1 0 0 0 0 0 1361 0 0 0 0 0
 1 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0 2429 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 1 0 0 0 0 0 58 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0 0 1251 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0 0 0 81 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0 0 0 0 947
 0 0 0 0 0]
[ 0 0 2 0 0 0 0 0 0 0 0 0 0
 165 0 2 0 0]
[ 0 0 0 0 0 0 2 0 0 0 0 0 0
 0 104 0 0 0]
[ 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 205 0 0]
[ 0 0 0 0 0 0 0 0 0 0 0 0 0
 2 0 0 236 0]
[ 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 61]]
```

```
# Classification Report
```

```
# Instantiate the classification model and visualizer
```

```
target_names = Classes
```

```
visualizer = ClassificationReport(knn_model, classes=target_names)
```

```
visualizer.fit(X=x1, y=x2)      # Fit the training data to the visualizer
```

```
visualizer.score(y1, y2)       # Evaluate the model on the test data
```

```
print('===== Classification Report =====')
```

```
print('')
```

```
print(classification_report(y2, result, target_names=target_names))
```

```
g = visualizer.poof()          # Draw/show/poof the data
```

```
=====  
===== Classification Report =====  
=====
```

	precision	recall	f1-score	support
THEFT	1.00	1.00	1.00	3914
CRIMINAL TRESPASS	1.00	1.00	1.00	597
NARCOTICS	1.00	1.00	1.00	2005
DECEPTIVE PRACTICE	1.00	1.00	1.00	706
BATTERY	1.00	1.00	1.00	3914
BURGLARY	1.00	1.00	1.00	1026
PUBLIC PEACE VIOLATION	0.99	1.00	0.99	166
ROBBERY	1.00	1.00	1.00	762
OTHER OFFENSE	1.00	1.00	1.00	1364
CRIMINAL DAMAGE	1.00	1.00	1.00	2429
SEX OFFENSE	1.00	0.98	0.99	59
ASSAULT	1.00	1.00	1.00	1251
CRIM SEXUAL ASSAULT	1.00	1.00	1.00	81
MOTOR VEHICLE THEFT	1.00	1.00	1.00	947
OTHERS	0.98	0.98	0.98	169
OFFENSE INVOLVING CHILDREN	1.00	0.98	0.99	106
WEAPONS VIOLATION	0.99	1.00	1.00	205
PROSTITUTION	1.00	0.99	1.00	238
HOMICIDE	1.00	1.00	1.00	61
accuracy			1.00	20000
macro avg	1.00	1.00	1.00	20000
weighted avg	1.00	1.00	1.00	20000



BURGLARY	1.000	1.000	1.000
BATTERY	1.000	1.000	1.000
DECEPTIVE PRACTICE	1.000	0.999	0.999
NARCOTICS	0.999	0.999	0.999

0.2

```
# Ensemble LSTM Model
import tensorflow as tf
from keras.layers import Dense, BatchNormalization, Dropout, LSTM, Bidirectional
from keras.models import Sequential
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
from sklearn.metrics import precision_score, recall_score, confusion_matrix, classification_report, accuracy_score, f1_score
from keras import callbacks
from tensorflow.keras.callbacks import EarlyStopping
# Combine 3 Models to create an Ensemble Model
```

```
# Define and compile model
from tensorflow import keras
model = keras.Sequential()
model.add(Dense(28 , input_shape=(56,) , activation="relu" , name="Hidden_Layer_1"))
model.add(Dense(10 , activation="relu" , name="Hidden_Layer_2"))
model.add(Dense(1 , activation="sigmoid" , name="Output_Layer"))
opt = keras.optimizers.Adam(learning_rate=0.01)
model.compile( optimizer=opt, loss="binary_crossentropy", metrics=['accuracy'])
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
Hidden_Layer_1 (Dense)	(None, 28)	1596
Hidden_Layer_2 (Dense)	(None, 10)	290
Output_Layer (Dense)	(None, 1)	11

```
=====
Total params: 1,897
Trainable params: 1,897
Non-trainable params: 0
```

```
# Create Model with configuration
ecclf1 = VotingClassifier(estimators=[('knn', knn_model), ('rf', rf_model), ('nn', nn_model)],
                        weights=[1,1,1],
                        flatten_transform=True)
ecclf1 = ecclf1.fit(X=x1, y=x2)

# Prediction
result = ecclf1.predict(y[Features])

# Model Evaluation
ac_sc = accuracy_score(y2, result)
rc_sc = recall_score(y2, result, average="weighted")
pr_sc = precision_score(y2, result, average="weighted")
f1_sc = f1_score(y2, result, average='micro')
confusion_m = confusion_matrix(y2, result)

print("===== LSTM Results =====")
print("Accuracy      : ", ac_sc)
print("Recall        : ", rc_sc)
print("Precision       : ", pr_sc)
print("F1 Score        : ", f1_sc)
print("Confusion Matrix: ")
print(confusion_m)
```

```
===== LSTM Results =====
```

```
Accuracy      : 0.9971
Recall        : 0.9971
Precision      : 0.9970885706244451
F1 Score      : 0.9971
```

```
Confusion Matrix:
```

```
[[3914  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [  0  0  0  0  0]
 [  0 594  0  0  0  0  0  0  3  0  0  0  0  0]
 [  0  0  0  0  0]
 [  0  0 2004  0  0  0  0  0  0  0  0  0  0  0]
 [  1  0  0  0  0]
 [  0  0  0 706  0  0  0  0  0  0  0  0  0  0]
 [  0  0  0  0  0]
 [  0  0  0  0 3914  0  0  0  0  0  0  0  0  0]
 [  0  0  0  0  0]
 [  0  0  0  0  0 1026  0  0  0  0  0  0  0  0]
 [  0  0  0  0  0]
 [  0  0  0  0  0  0 160  0  6  0  0  0  0  0]
 [  0  0  0  0  0]
 [  0  0  0  0  0  0  0 762  0  0  0  0  0  0]
 [  0  0  0  0  0]
```

```
[ 1  0  1  0  0  0  0  0  0 1360  0  0  0  0  0
 2  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0 2429  0  0  0  0
 0  0  0  0  0  0]
[ 0  0  0  0  1  0  0  0  0  0  0 58  0  0  0
 0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0 1251  0  0
 0  0  0  0  0  0]
[ 0  0  0  0  2  0  0  0  0  0  0  0  5 74  0
 0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0 947
 0  0  0  0  0  0]
[ 0  0  5  0  0 10  0  0  0  0  0  0  0  0 2
141 11  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  2  1  0  0
 2 98  3  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0 205  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0 238  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0 61]]
```

```
# Classification Report
```

```
# Instantiate the classification model and visualizer
```

```
target_names = Classes
```

```
visualizer = ClassificationReport(eclf1, classes=target_names)
```

```
visualizer.fit(X=x1, y=x2)      # Fit the training data to the visualizer
```

```
visualizer.score(y1, y2)       # Evaluate the model on the test data
```

```
print('===== Classification Report =====')
```

```
print('')
```

```
print(classification_report(y2, result, target_names=target_names))
```

```
g = visualizer.poof()          # Draw/show/poof the data
```

```

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but KNeighborsClassifier was fitted with fe
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but MLPClassifier was fitted with feature r
warnings.warn(

```

=====  
 ===== Classification Report =====

	precision	recall	f1-score	support
THEFT	1.00	1.00	1.00	3914
CRIMINAL TRESPASS	1.00	0.99	1.00	597
NARCOTICS	1.00	1.00	1.00	2005
DECEPTIVE PRACTICE	1.00	1.00	1.00	706
BATTERY	1.00	1.00	1.00	3914
BURGLARY	0.99	1.00	1.00	1026
PUBLIC PEACE VIOLATION	1.00	0.96	0.98	166
ROBBERY	1.00	1.00	1.00	762
OTHER OFFENSE	0.99	1.00	1.00	1364
CRIMINAL DAMAGE	1.00	1.00	1.00	2429
SEX OFFENSE	0.97	0.98	0.97	59
ASSAULT	1.00	1.00	1.00	1251
CRIM SEXUAL ASSAULT	1.00	0.91	0.95	81
MOTOR VEHICLE THEFT	1.00	1.00	1.00	947
OTHERS	0.97	0.83	0.90	169
OFFENSE INVOLVING CHILDREN	0.90	0.92	0.91	106
WEAPONS VIOLATION	0.99	1.00	0.99	205
PROSTITUTION	1.00	1.00	1.00	238
HOMICIDE	1.00	1.00	1.00	61
accuracy			1.00	20000
macro avg	0.99	0.98	0.98	20000
weighted avg	1.00	1.00	1.00	20000

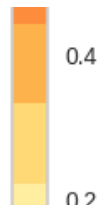
VotingClassifier Classification Report

HOMICIDE	1.000	1.000	1.000
PROSTITUTION	1.000	1.000	1.000
WEAPONS VIOLATION	0.986	1.000	0.993
OFFENSE INVOLVING CHILDREN	0.899	0.925	0.912
OTHERS	0.966	0.834	0.895
MOTOR VEHICLE THEFT	0.998	1.000	0.999
CRIM SEXUAL ASSAULT	1.000	0.914	0.955
ASSAULT	0.995	1.000	0.998
SEX OFFENSE	0.967	0.983	0.975
CRIMINAL DAMAGE	1.000	1.000	1.000





OTHER OFFENSE	0.993	0.997	0.995
ROBBERY	1.000	1.000	1.000
PUBLIC PEACE VIOLATION	1.000	0.964	0.982
BURGLARY	0.990	1.000	0.995
BATTERY	0.999	1.000	1.000
DESTRUCTIVE PRACTICE	1.000	1.000	1.000



```
from google.colab import files
uploaded = files.upload()
```

No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving District\_wise\_crimes2022.csv to District\_wise\_crimes2022.csv

Saving District2001\_2020.csv to District2001\_2020.csv



```
import numpy as np
crimes_total_women1 = pd.read_csv('District2001_2020.csv')
crimes_total_women2= pd.read_csv('District_wise_crimes2022.csv')

crimes_total_women = pd.concat([crimes_total_women1,crimes_total_women2], ignore_index=False, axis=0)
crimes_total_women.rename(columns={'STATE/UT':'STATE'}, inplace=True)

del crimes_total_women1
del crimes_total_women2

# calculating total crimes of all kinds in each state from 2001 to 2013
crimes_total_women = crimes_total_women[crimes_total_women['DISTRICT'] == 'TOTAL']
crimes_total_women.drop('DISTRICT', axis=1, inplace=True)

crimes_total_women['Total Crimes']= crimes_total_women.iloc[:, -9:-1].sum(axis=1)

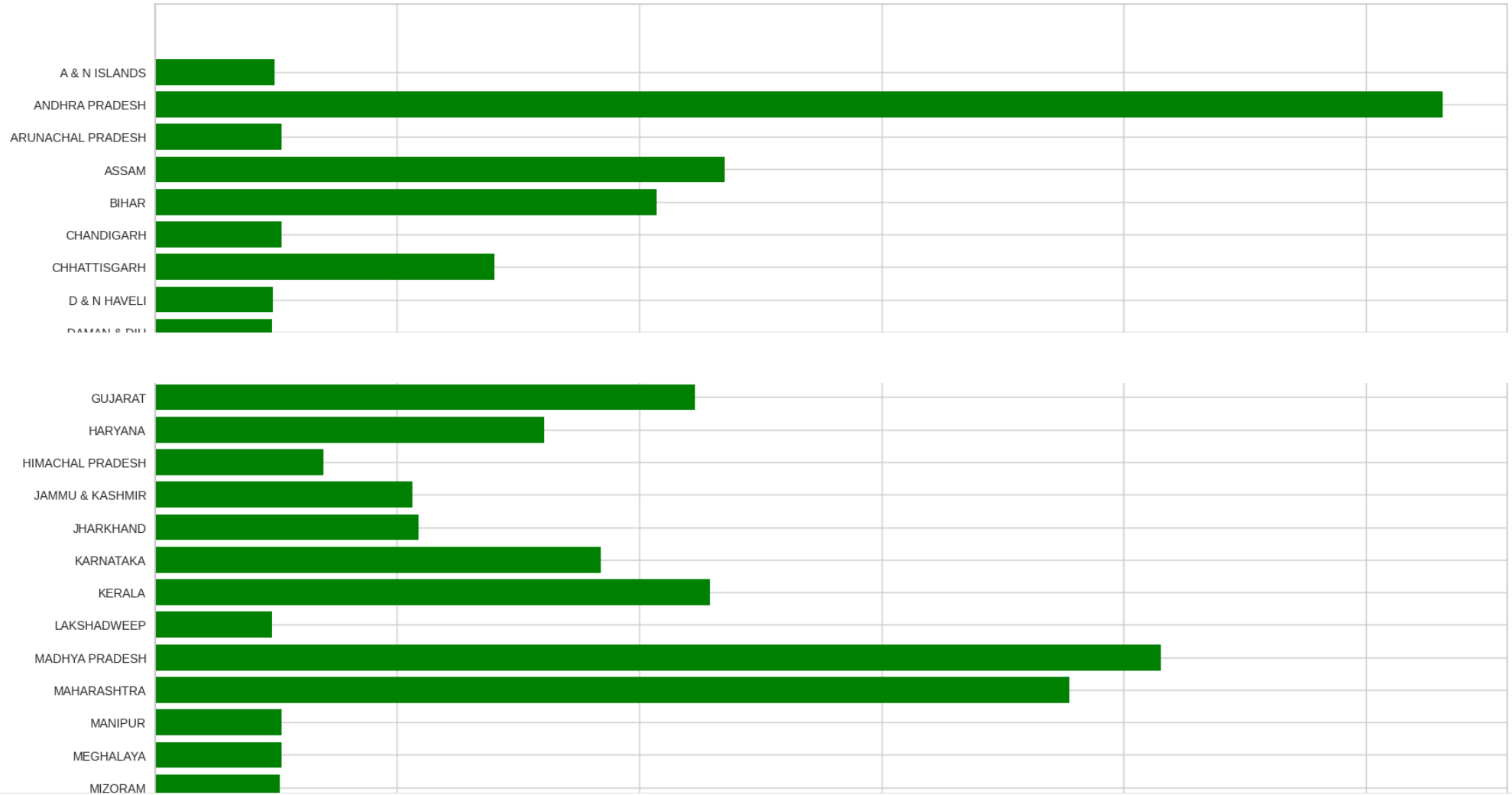
crimes_total_women = crimes_total_women.groupby(['STATE'])['Total Crimes'].sum()

# plot graph of crimes committed on women since 2001-2013 in each state/ UT
fig1, ax1 = plt.subplots()
states = crimes_total_women.index.tolist()
y_pos = np.arange(len(states))
performance = crimes_total_women.tolist()
ax1.barh(y_pos, performance, align='center',color='green', ecolor='black')
ax1.set_yticks(y_pos)
ax1.set_yticklabels(states)
ax1.invert_yaxis() # labels read top-to-bottom
ax1.set_xlabel('Overall districtwise Crimerate')
ax1.set_title('Crime VS STATE')
```

```
fig1.set_size_inches(20, 18, forward=True)  
plt.show()
```

```
<ipython-input-35-c1f36bf0c25e>:15: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version, only the non-naught values of DataFrame dtype will be considered. (one to match 'numeric_only=True')\n  crimes_total_women['Total Crimes']= crimes_total_women.iloc[:, -9:-1].sum(axis=1)
```

Crime VS STATE



✓ 0s completed at 1:15 PM

● ✕