Project : Kaggle project CrimeCast: Forecasting Crime Categories

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Kaggle Completitions : [https://www.kaggle.com/competitions/crime-cast-forecasting-crime-categories/overview]

Overview

This dataset offers a comprehensive snapshot of criminal activities within the city. It encompasses various aspects of each incident, including date, time, location, victim demographics, and more.

By leveraging machine learning techniques, participants can analyze this rich dataset to predict crime categories, enhance law enforcement strategies, and bolster public safety measures.

Your task is straightforward: Develop models capable of accurately predicting the crime categories based on this information.

Step up and demonstrate your prowess in anticipating crime categories – it's your chance to transform this data into actionable insights!

Dataset Description In this competition, you'll analyze a dataset filled with information about crime incidents. You'll look at where the incidents happened, details about the victims, and other important factors.

Your goal is to use this data to predict the type of crime that occurred.

Dataset Overview:

Welcome to the Crime Category Prediction Challenge! Our dataset serves as your gateway to exploring the world of crime incidents. Each entry encapsulates a unique narrative, featuring details such as incident locations, victim demographics, and other key attributes. Your task is to explore this comprehensive dataset and construct predictive models that can forecast the category of crime for each incident. Unleash your creativity and analytical skills to uncover the underlying patterns.

Data Files:

The dataset consists of the following files:

train.csv: The training set, inclusive of the target variable 'crime_category' and relevant feature attributes. test.csv: The test set, containing similar feature attributes but excluding the target variable 'crime_category', as it is the variable to be predicted. sample_submission.csv: A sample submission file provided in the correct format for competition submissions.

Columns Description:

Location: Street address of the crime incident.

- Cross_Street: Cross street of the rounded address.
- Latitude: Latitude coordinates of the crime incident.
- Longitude: Longitude coordinates of the crime incident.
- Date_Reported: Date the incident was reported.
- Date_Occurred: Date the incident occurred.
- Time_Occurred: Time the incident occurred in 24-hour military time.
- Area_ID: LAPD's Geographic Area number.
- Area_Name: Name designation of the LAPD Geographic Area.
- Reporting_District_no: Reporting district number.
- Part 1-2: Crime classification.
- Modus_Operandi: Activities associated with the suspect.
- Victim_Age: Age of the victim.
- Victim_Sex: Gender of the victim.
- Victim_Descent: Descent code of the victim.
- Premise_Code: Premise code indicating the location of the crime.
- Premise_Description: Description of the premise code.
- Weapon_Used_Code: Weapon code indicating the type of weapon used.
- Weapon_Description: Description of the weapon code.
- Status: Status of the case.
- Status_Description: Description of the status code.
- Crime_Category: The category of the crime (Target Variable)

In [ ]:
```
# @title
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/)
# that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/crime-cast-forecasting-crime-categories/sample.csv
/kaggle/input/crime-cast-forecasting-crime-categories/train.csv
/kaggle/input/crime-cast-forecasting-crime-categories/test.csv
```

Importing Required Libraries

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.preprocessing import MinMaxScaler,LabelEncoder,OneHotEncoder, StandardScaler,OrdinalEncoder
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline,FeatureUnion
from sklearn.compose import ColumnTransformer

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import TruncatedSVD

from sklearn.linear_model import LogisticRegression
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from imblearn.over_sampling import SMOTE
import xgboost as xgb
import lightgbm as lgb
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV, cross_val_score,
                                    learning_curve,KFold, StratifiedKFold
from sklearn.metrics import accuracy_score, classification_report,confusion_matrix, log_loss, ConfusionMatrixDisplay
```

Display and warning setting

In [ ]:
```
pd.set_option('display.max_categories',200)
pd.set_option('display.max_columns',50)
import warnings
warnings.filterwarnings("ignore")
```

Loading Datasets

In [ ]:
```
# Loading the csv file
data_train = pd.read_csv("/kaggle/input/crime-cast-forecasting-crime-categories/train.csv")
data_test = pd.read_csv("/kaggle/input/crime-cast-forecasting-crime-categories/test.csv")

df_train = data_train.copy()
df_test = data_test.copy()
```

EDA (Exploratory Data Analysis)

- The shape of training dataset is 20,000 rows(samples) and 22 columns(features =21 + Target =1)

Features

- Numerical:
    1. **Latitude** : no null values, diferent decimal length, 0.0 values, outliers present

2. **Longitude** :no null values, diferent decimal length,0.0 values,outliers present. can we concate lat and long for clustering using k-means cluster.
3. **Time_Occurred** : Needs formatting, Its in 2400 hours format.
   - Think about binning indaystime (morning,afternoon, evening,night)
   - investigate on 1,2,3 digit number samples.need to convert.
   - can use only Hours for analysis
4. **Area_ID** : It is linked with 'Area_Name' Feature. Data is clean.convert to int or cat
5. **Reporting_District_no**
6. **Part 1-2** : Type of cases. 1 - voilent 2- moderate
7. **Victim_Age** : some -ve numbers and many 0 values. Need preprocessing. or make binary category classification
8. **Premise_Code** : This is linked with 'Premise_Description' feature
9. **Weapon_Used_Code** : This is linked with 'Weapon_Description' feature

- Categorical:

1. **Location** : it is text data with many spaces between words.
2. **Cross_Street** : high number of missing values.make binary category classification
3. **Date_Reported** : need to convert in to dattime and extract day, month, year, weekday, month day.
4. **Date_Occurred** :need to convert in to dattime and extract day, month, year, weekday, month day.
5. **Area_Name** : highly correlated with Area ID. Area ID description.
6. **Modus_Operandi** : Modus operandi codes. multiple code for each record and missing values.Modus Operandi Code details
7. **Victim_Sex** :
8. **Victim_Descent**
9. **Premise_Description** description for Premised ID
10. **Weapon_Description** Description for Weapon_used_code
11. **Status** : 5 types of status. arrest done or not for juvenile and adult.
12. **Status_Description** : Description of status.
13. **Crime_Category** : This is Target vector

In [ ]:
```
df_train.shape
```

Out[ ]:
```
(20000, 22)
```

In [ ]:

```python
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 22 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Location               20000 non-null  object 
 1   Cross_Street           3448 non-null   object 
 2   Latitude               20000 non-null  float64
 3   Longitude              20000 non-null  float64
 4   Date_Reported          20000 non-null  object 
 5   Date_Occurred          20000 non-null  object 
 6   Time_Occurred          20000 non-null  float64
 7   Area_ID                20000 non-null  float64
 8   Area_Name              20000 non-null  object 
 9   Reporting_District_no  20000 non-null  float64
 10  Part 1-2               20000 non-null  float64
 11  Modus_Operandi         17259 non-null  object 
 12  Victim_Age             20000 non-null  float64
 13  Victim_Sex             17376 non-null  object 
 14  Victim_Descent         17376 non-null  object 
 15  Premise_Code           20000 non-null  float64
 16  Premise_Description    19995 non-null  object 
 17  Weapon_Used_Code       7335 non-null   float64
 18  Weapon_Description     7335 non-null   object 
 19  Status                 20000 non-null  object 
 20  Status_Description     20000 non-null  object 
 21  Crime_Category         20000 non-null  object 
dtypes: float64(9), object(13)
memory usage: 3.4+ MB
```

In [ ]:

```python
df_train.head()
```

Out[ ]:

	Location	Cross_Street	Latitude	Longitude	Date_Reported	Date_Occurred	Time_Occurred	Area_ID	Area_Name	Reporting_District_no	P
0	4500 CARPENTER AV	0	34.1522	-118.3910	03/09/2020 12:00:00 AM	03/06/2020 12:00:00 AM	1800.0	15.0	N Hollywood	1563	
1	45TH ST	ALAMEDA ST	34.0028	-118.2391	02/27/2020 12:00:00 AM	02/27/2020 12:00:00 AM	1345.0	13.0	Newton	1367	
2	600 E MARTIN	0	34.0111	-118.2653	08/21/2020 12:00:00 AM	08/21/2020 12:00:00 AM	605.0	13.0	Newton	1343	

	Location	Cross_Street	Latitude	Longitude	Date_Reported	Date_Occurred	Time_Occurred	Area_ID	Area_Name	Reporting_District_no	P
	LUTHER KING JR BL										
3	14900 ORO GRANDE ST	0	34.2953	-118.4590	11/08/2020 12:00:00 AM	11/06/2020 12:00:00 AM	1800.0	19.0	Mission	1924	
4	7100 S VERMONT AV	0	33.9787	-118.2918	02/25/2020 12:00:00 AM	02/25/2020 12:00:00 AM	1130.0	12.0	77th Street	1245	

In [ ]:

```
df_train.isna().sum()
```

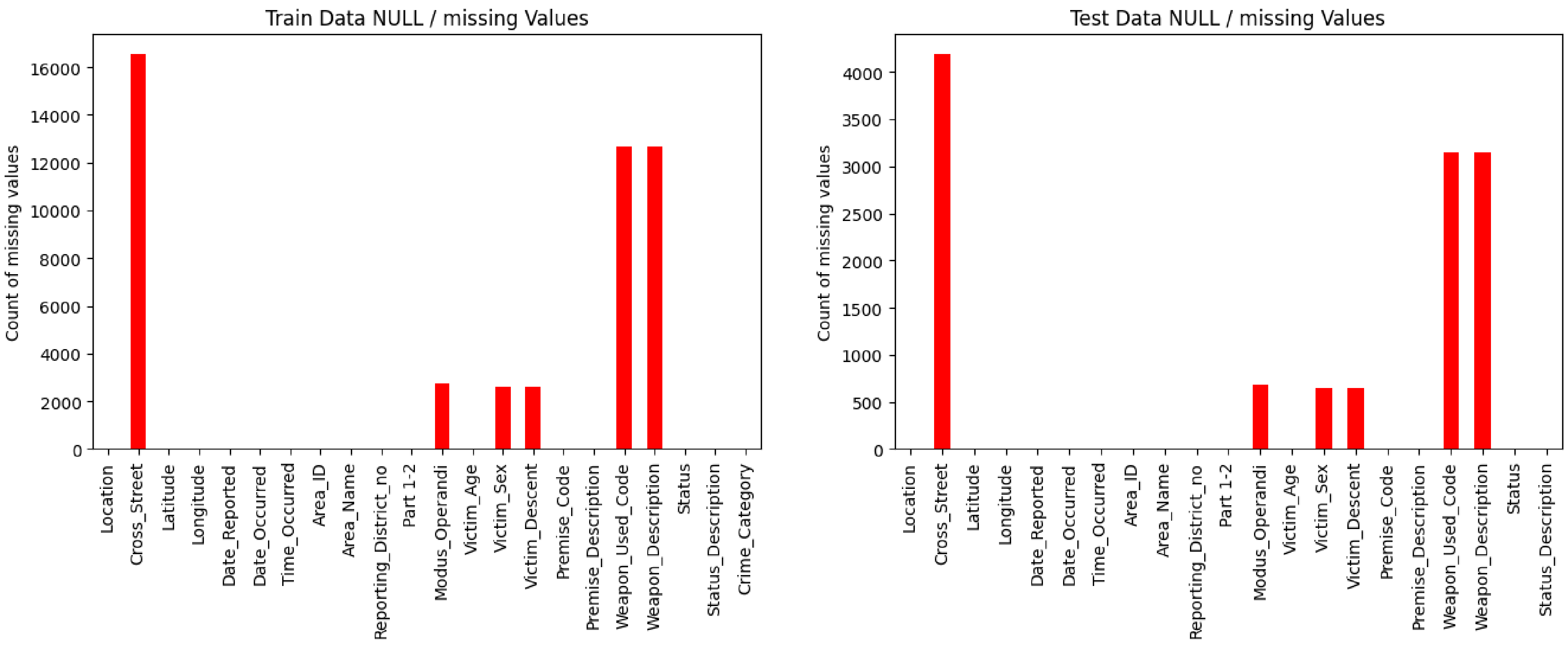
Out[ ]:

```
Location                      0
Cross_Street              16552
Latitude                      0
Longitude                     0
Date_Reported                 0
Date_Occurred                 0
Time_Occurred                 0
Area_ID                       0
Area_Name                     0
Reporting_District_no         0
Part 1-2                      0
Modus_Operandi             2741
Victim_Age                    0
Victim_Sex                 2624
Victim_Descent             2624
Premise_Code                  0
Premise_Description           5
Weapon_Used_Code          12665
Weapon_Description        12665
Status                        0
Status_Description            0
Crime_Category                0
dtype: int64
```

In [ ]:

```
plt.figure(figsize=(16, 10))
plt.subplot(2, 2, 1)
df_train.isnull().sum().plot(kind='bar',title='Train Data NULL / missing Values',
                             ylabel='Count of missing values',color='red')
plt.subplot(2, 2, 2)
df_test.isnull().sum().plot(kind='bar',title='Test Data NULL / missing Values',
```

```
                             ylabel='Count of missing values',color='red')
plt.show()
```



In [ ]:

```
print("Duplicate records in train dataset: ", df_train.duplicated().sum())
print("Duplicate records in test dataset: ", df_test.duplicated().sum())

#13 records are found duplicated, We may keep them as we may assume that similar crimes occure multiple times,
# as we can't differentiate as crime_ID unique nubers are not provided.
```

```
Duplicate records in train dataset:  13
Duplicate records in test dataset:  3
```

In [ ]:

```
# Numnerical statistical Analysis
df_train.describe()
```

Out[ ]:

	Latitude	Longitude	Time_Occurred	Area_ID	Reporting_District_no	Part 1-2	Victim_Age	Premise_Code	Weapon_
count	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	7
mean	33.940704	-117.893072	1352.380350	10.834250	1129.599200	1.418150	30.135000	297.176950	

	Latitude	Longitude	Time_Occurred	Area_ID	Reporting_District_no	Part 1-2	Victim_Age	Premise_Code	Weapon_
std	2.126810	7.377726	646.100291	6.033166	603.330519	0.493267	21.863645	212.007298	
min	0.000000	-118.663400	1.000000	1.000000	101.000000	1.000000	-2.000000	101.000000	
25%	34.009200	-118.429700	930.000000	6.000000	632.000000	1.000000	12.000000	101.000000	
50%	34.058700	-118.323000	1430.000000	11.000000	1162.000000	1.000000	31.000000	203.000000	
75%	34.165025	-118.274400	1900.000000	16.000000	1622.000000	2.000000	46.000000	501.000000	
max	34.328100	0.000000	2359.000000	21.000000	2197.000000	2.000000	99.000000	969.000000	

- Longitude and Latitude contains 0 values (missing) and also having outliers.
- Victim_Age having -ve (missing) values.std is high, 4828 values are Zero. last quantile indicate outliers.

In [ ]:

```
corr = df_train.select_dtypes(include =['float64','int32']).corr()
corr
```

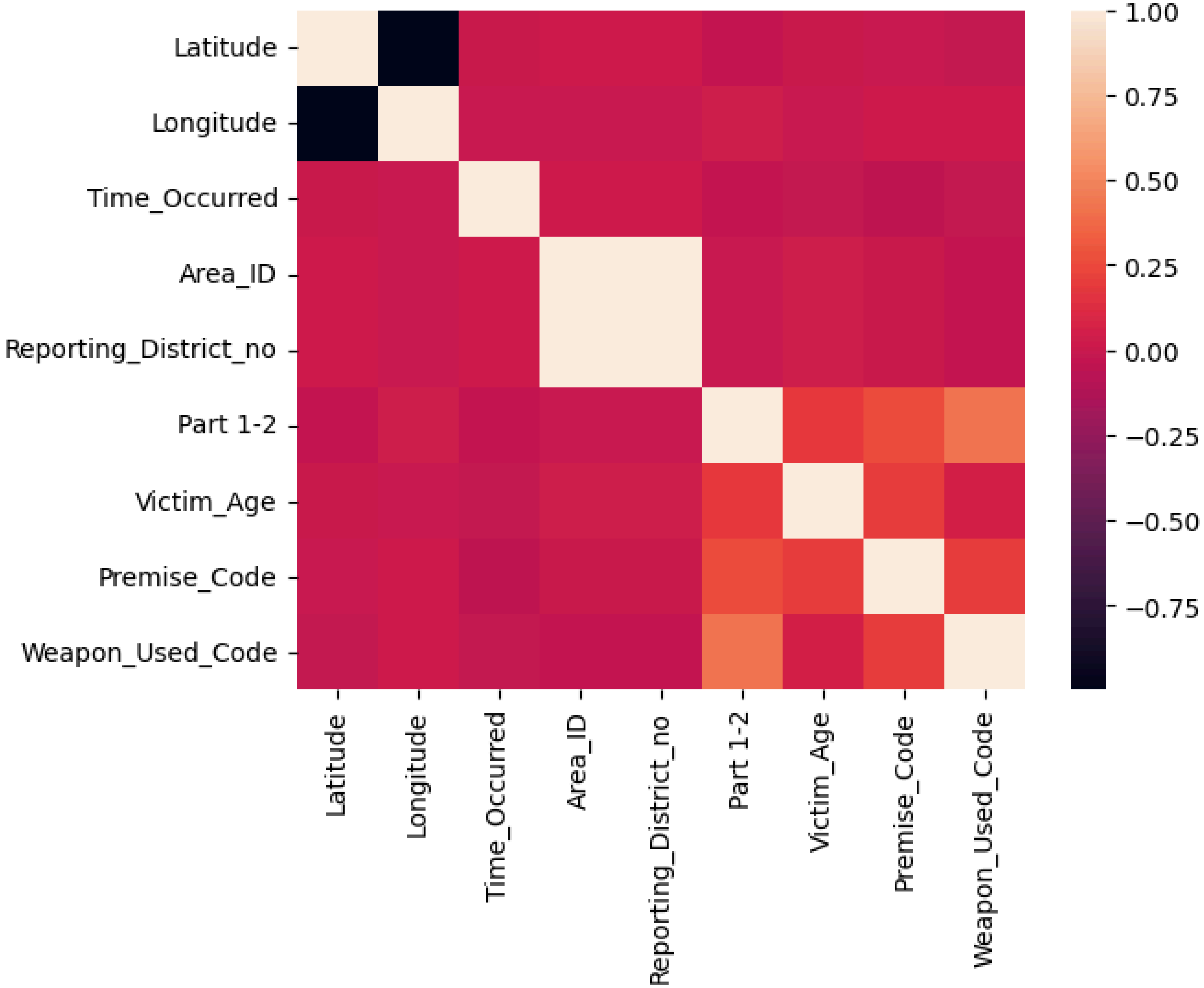
Out[ ]:

	Latitude	Longitude	Time_Occurred	Area_ID	Reporting_District_no	Part 1-2	Victim_Age	Premise_Code	Weapon_U
Latitude	1.000000	-0.998910	0.005952	0.018411	0.017928	-0.036357	0.003195	-0.011293	
Longitude	-0.998910	1.000000	-0.005361	-0.006480	-0.006139	0.036373	-0.002252	0.011205	
Time_Occurred	0.005952	-0.005361	1.000000	0.012346	0.012127	-0.028881	-0.017798	-0.057534	
Area_ID	0.018411	-0.006480	0.012346	1.000000	0.999024	-0.002518	0.028966	0.004045	-
Reporting_District_no	0.017928	-0.006139	0.012127	0.999024	1.000000	-0.002108	0.028721	0.004121	
Part 1-2	-0.036357	0.036373	-0.028881	-0.002518	-0.002108	1.000000	0.186780	0.254579	
Victim_Age	0.003195	-0.002252	-0.017798	0.028966	0.028721	0.186780	1.000000	0.191313	
Premise_Code	-0.011293	0.011205	-0.057534	0.004045	0.004121	0.254579	0.191313	1.000000	
Weapon_Used_Code	-0.017656	0.019185	-0.016911	-0.027243	-0.027117	0.419642	0.056768	0.196771	

In [ ]:

```
sns.heatmap(corr)
```

Out[ ]: <Axes: >



- Insight from correlation heat map is there is very strong positive corelation in Reporting_District_no and Area_ID.
- correlation beween Reported_Month and Occured_Month are higly related . Correlation-> 0.903226 .So we can Drop Reported month column.

In [ ]:
```
# Categorical statistical Analysis
df_train.select_dtypes(include = 'object').describe()
```

Out[ ]:

	Location	Cross_Street	Date_Reported	Date_Occurred	Area_Name	Modus_Operandi	Victim_Sex	Victim_Descent	Premise_Description
count	20000	3448	20000	20000	20000	17259	17376	17376	19995
unique	12399	1495	811	366	21	10489	4	17	216
top	6TH	BROADWAY	07/13/2020 12:00:00 AM	01/01/2020 12:00:00 AM	77th Street	0344	M	H	STREET
freq	33	56	87	137	1345	826	8538	6143	5033

- Hispanian are most in Vistim_descent with 6143 occurances.
- 5033 crimes are on street (Premise_Description)
- 11666 are from Property Crimes category.

In [ ]:

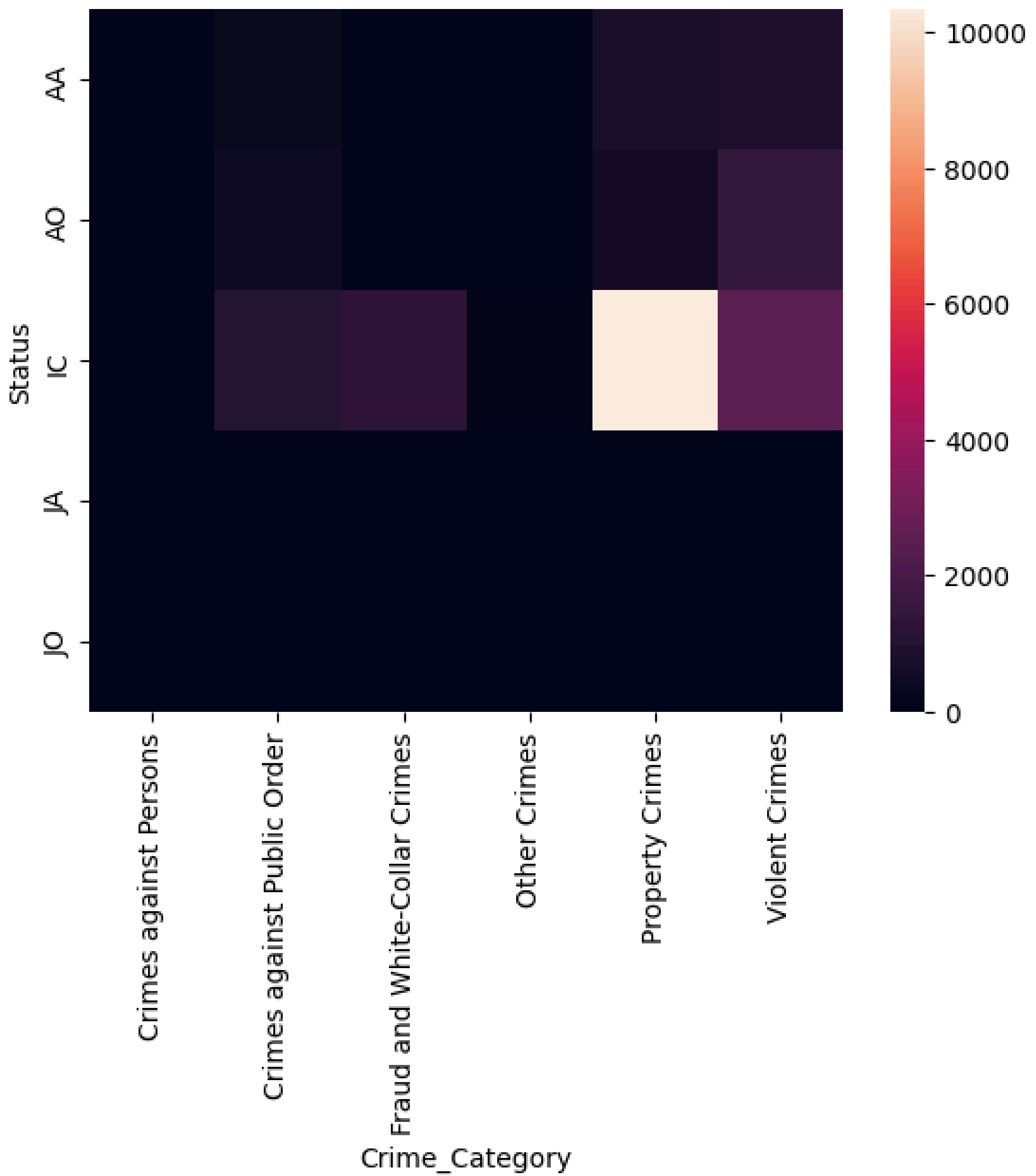
```
var1 ='Status'
contingency_table1 = pd.crosstab(df_train[var1], df_train['Crime_Category'],)
contingency_table1
```

Out[ ]:

Crime_Category Status	Crimes against Persons	Crimes against Public Order	Fraud and White-Collar Crimes	Other Crimes	Property Crimes	Violent Crimes
AA	69	323	38	33	753	838
AO	80	465	37	28	550	1437
IC	74	1011	1279	117	10320	2435
JA	1	6	0	1	35	27
JO	1	3	1	0	8	30

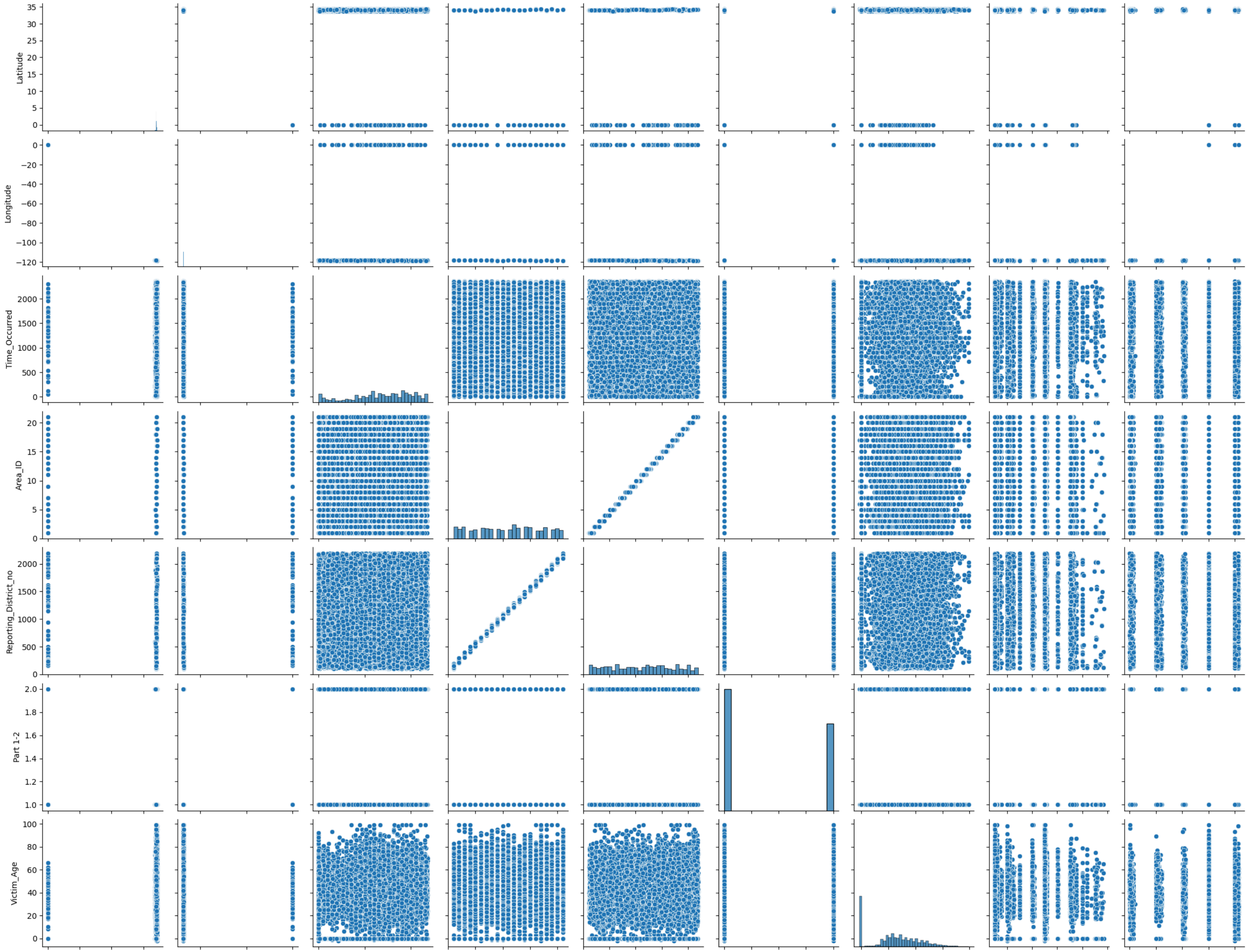
In [ ]:

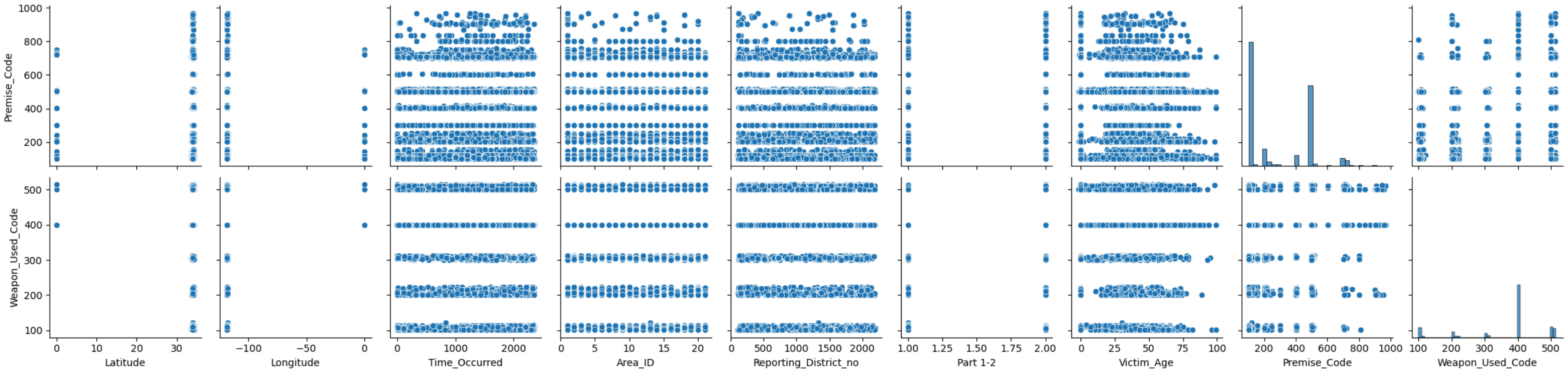
```
sns.heatmap(contingency_table1)
plt.show()
```



In [ ]:

```
sns.pairplot(df_train,diag_kind='hist')
plt.show()
```


Latitude
35
30
25
20
15
10
5
0
Longitude
0
−20
−40
−60
−80
−100
−120
Time_Occurred
2000
1500
1000
500
0
Area_ID
20
15
10
5
0
Reporting_District_no
2000
1500
1000
500
0
Part 1-2
2.0
1.8
1.6
1.4
1.2
1.0
Victim_Age
100
80
60
40
20
0



Preprocessing Train Data

In [ ]:
```
lat_long_missing = df_train[(df_train['Latitude'] == 0) & (df_train['Longitude']==0)].index
df_train.drop(lat_long_missing, inplace=True)
df_train.shape
# Do not drop records from test data as it will give error because for submission.csv we have to provide 5000 rows.
```

Out[ ]:
```
(19922, 22)
```

Interesting findings:

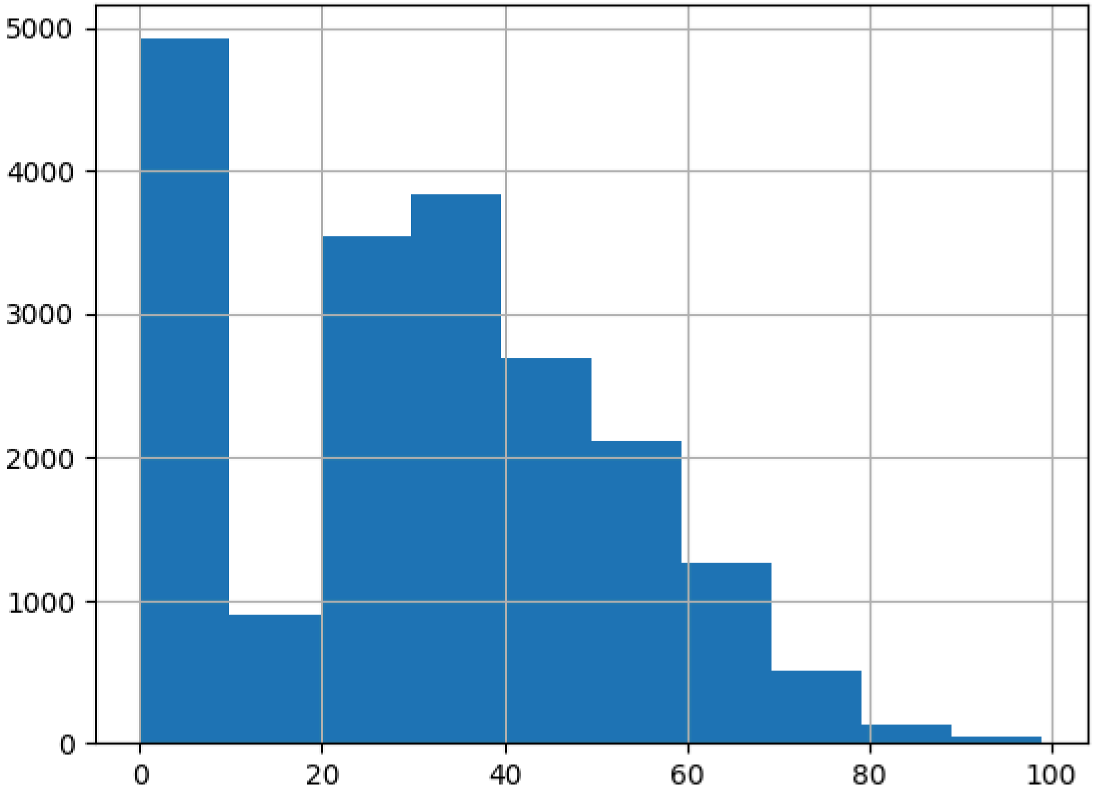
- in Modus operandi codes, we carefully study it is 4 digit code and first 2 digit has certain meanings and based on that next 2 digits have list of categoris. details in below linked pdf Modus Operandi Code details

Processing Outliers and invalid values

In [ ]:
```
#Removing -ve values and assigning 0.
df_train['Victim_Age'] = df_train['Victim_Age'].apply(lambda x: 0 if x < 0 else x)
```

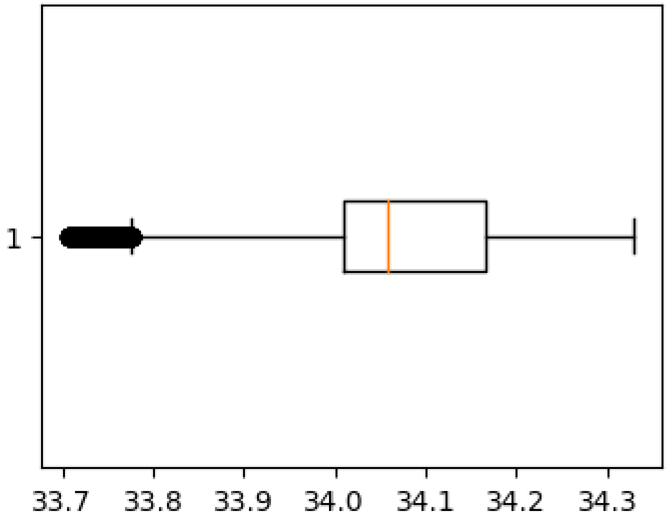
In [ ]:
```
df_train['Victim_Age'].hist()
```

Out[ ]:
```
<Axes: >
```



In [ ]:

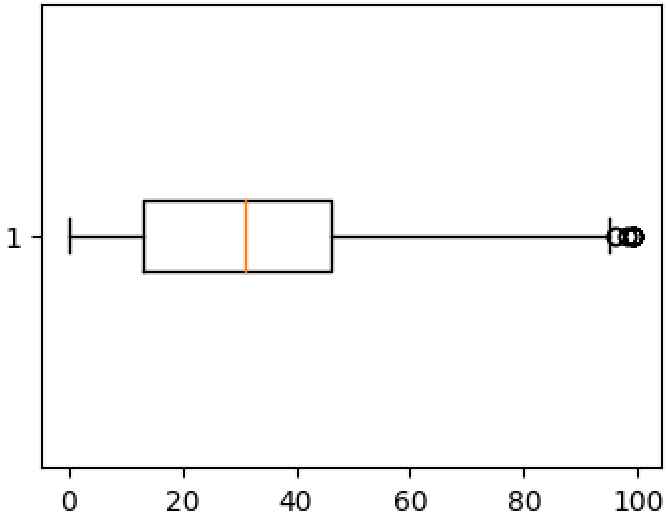
```
# box plot for finding outliers ( lattitude, longitude and victim_age)
data =[df_train['Latitude']]
fig, ax = plt.subplots(figsize = (4,3))
ax.boxplot(data, vert =False)
plt.show()
```



In [ ]:
```
var = 'Latitude'
Q1 = df_train[var].quantile(0.25)
Q3 = df_train[var].quantile(0.75)
IQR = Q3 - Q1
low_bound = Q1 - 1.5 * IQR
upper_bound = Q3 +  1.5 * IQR
df_train = df_train[(df_train[var] > low_bound) & (df_train[var] < upper_bound)]
df_train.shape
```

Out[ ]:
```
(19462, 22)
```

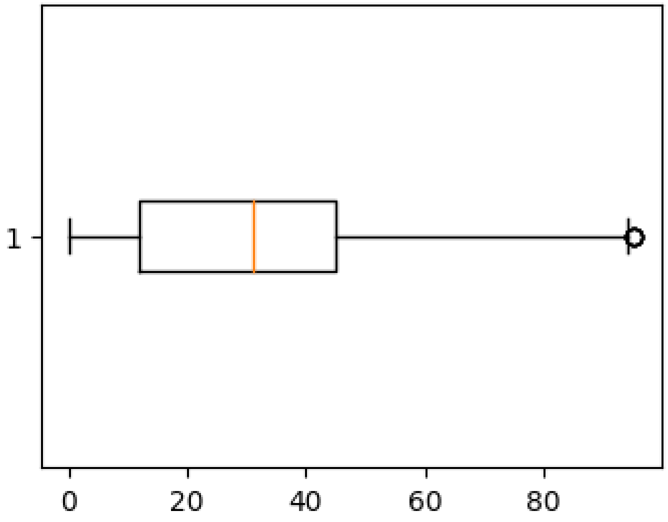
In [ ]:
```
# box plot for finding outliers ( lattitude, longitude and victim_age)
data =[df_train['Victim_Age']]
fig, ax = plt.subplots(figsize = (4,3))
ax.boxplot(data, vert =False)
plt.show()
```



In [ ]:
```
var = 'Victim_Age'
Q1 = df_train[var].quantile(0.25)
Q3 = df_train[var].quantile(0.75)
IQR = Q3 - Q1
low_bound = Q1 - 1.5 * IQR
upper_bound = Q3 +  1.5 * IQR
df_train = df_train[(df_train[var] > low_bound) & (df_train[var] < upper_bound)]
df_train.shape
```

Out[ ]: (19447, 22)

In [ ]:
```
# box plot After removing outliers from victim_age)
data =[df_train['Victim_Age']]
fig, ax = plt.subplots(figsize = (4,3))
ax.boxplot(data, vert =False)
plt.show()
```



In [ ]:

```
#train data
df_train.fillna(value =0, inplace =True)
df_train['Is_CrossStreet'] = df_train['Cross_Street'].apply(lambda x : 0 if x == 0 else 1)
df_train['Victim_Present'] = df_train['Victim_Age'].apply(lambda x : 0 if x <= 0 else 1)

df_train['Reporting_District_no'] = df_train['Reporting_District_no'].astype(int)
df_train['Rep_Dist_no'] = df_train['Reporting_District_no'].apply(lambda x: str(x)[-2:])
# extracted last 2 characters from District_no, first 2 are same as Area_ID
df_train['Rep_Dist_no'] = df_train['Rep_Dist_no'].astype(int)

df_train['Part 1-2'] = df_train['Part 1-2'].astype(int)
df_train['Part 1-2'] = df_train['Part 1-2'].apply(lambda x: 0 if x == 1 else 1)

df_train['PCode'] = df_train['Premise_Code'].apply(lambda x: int(x/100))

df_train['Arrest_done'] = df_train['Status'].map({'IC':0,'AO':0, 'AA':1, 'JA':1, 'JO':0})
```

In [ ]:

```
#train data
# Converting Date_Reported into year, month, weekday. in train data
df_train['Reported_Year'] = pd.to_datetime(df_train.Date_Reported).dt.year
df_train['Reported_Month'] = pd.to_datetime(df_train.Date_Reported).dt.month
df_train['Reported_day'] = pd.to_datetime(df_train.Date_Reported).dt.day
df_train['Reported_Weekday'] = pd.to_datetime(df_train.Date_Reported).dt.weekday

# Converting Date_Occurred into year, month, weekday in train data
```

```
df_train['Occured_Year'] = pd.to_datetime(df_train.Date_Occurred).dt.year
df_train['Occured_Month'] = pd.to_datetime(df_train.Date_Occurred).dt.month
df_train['Occured_day'] = pd.to_datetime(df_train.Date_Occurred).dt.day
df_train['Occured_Weekday'] = pd.to_datetime(df_train.Date_Occurred).dt.weekday
df_train['DayOfYear'] = (pd.to_datetime(df_train['Date_Occurred'])).dt.dayofyear

# converting df_test ['Time_Occurred'] column to %h%M format as done for train column
df_train['Time_Occurred_Hour'] = pd.to_datetime(df_train['Time_Occurred'].
                                      astype(int).astype(str).str.zfill(4),format ='%H%M').dt.hour
df_train['Days_Lapsed'] = (pd.to_datetime(df_train['Date_Reported'])
                           - pd.to_datetime(df_train['Date_Occurred'])).dt.days
```

Encoding of Label vector ('Crime_Category)

In [ ]:
```
le = LabelEncoder()
df_train['Crime_Category'] = le.fit_transform(df_train['Crime_Category'])
df_train['Crime_Category'].shape
```

Out[ ]:
```
(19447,)
```

Crime_Category Encoded as below**

- 'Property Crimes' = 4
- 'Violent Crimes'= 5
- 'Other Crimes' = 1
- 'Crimes against Public Order' = 2
- 'Fraud and White-Collar Crimes' = 0
- 'Crimes against Persons' = 3

In [ ]:
```
#  Remember to  Drop columns Crime_Category from list of Test data as this is Target label

columns_train = ['Latitude', 'Longitude','Area_ID','Reporting_District_no', 'Part 1-2', 'Modus_Operandi', 'Victim_Age',
       'Victim_Sex', 'Victim_Descent', 'Premise_Code','Weapon_Used_Code', 'Status','Crime_Category',
         'Is_CrossStreet','Victim_Present','Days_Lapsed','Occured_day','Occured_Weekday', 'Occured_Month',
 'Reported_day','DayOfYear', 'Rep_Dist_no','Time_Occurred_Hour','PCode', 'Arrest_done']
```

In [ ]:
```
df_train_processed = pd.DataFrame(df_train, columns = columns_train)
df_train_processed.shape
```

Out[ ]: (19447, 25)

In [ ]:
```
# from sklearn.feature_extraction.text import TfidfVectorizer
# mo_op = df_train_processed['Modus_Operandi'].replace(0,'')
# mo_op = mo_op.astype(str)
# tfidf = TfidfVectorizer()
# tfidf_matrix = tfidf.fit_transform(mo_op)
# tfidf_df = pd.DataFrame(tfidf_matrix.toarray(),columns=[f'tfidf_{col}' for col in tfidf.get_feature_names_out()])
# tfidf_df.shape
```

In [ ]:
```
# num_cols = ['Area_ID','Latitude', 'Longitude','Victim_Age', 'DayOfYear','Days_Lapsed','Reporting_District_no',
#                  'Premise_Code','Weapon_Used_Code','Occured_day','Reported_day', 'PCode','Rep_Dist_no','Occured_Weekday
#                       'Time_Occurred_Hour','Occured_Month']
```

In [ ]:
```
# from sklearn.preprocessing import MinMaxScaler
# scaler = MinMaxScaler()
# df_train_processed[num_cols] = scaler.fit_transform(df_train_processed[num_cols])
# df_train_processed.shape
```

In [ ]:
```
# df_train_transform_1 = pd.concat([df_train_processed.reset_index(drop=True), tfidf_df.reset_index(drop=True)], axis=1
# df_train_transform_1.shape
```

In [ ]:
```
# df_train_transform_1['Victim_Sex'] = df_train_transform_1['Victim_Sex'].astype('str')
# df_train_transform_1['Victim_Descent'] = df_train_transform_1['Victim_Descent'].astype('str')
# df_train_transform_1['Status'] = df_train_transform_1['Status'].astype('str')

# cat_cols = ['Victim_Sex', 'Victim_Descent','Status']
# ohe = OneHotEncoder(handle_unknown='ignore')
# df_train_transform_1_ohe= ohe.fit_transform(df_train_transform_1[cat_cols])
# df_train_transform_1_ohe_df = pd.DataFrame(df_train_transform_1_ohe.toarray(), columns=[f'ohe_{col}'
#                                for col in ohe.get_feature_names_out(cat_cols)])
# df_train_transform_1_ohe_df.shape
```

In [ ]:
```
# df_train_transform_2 = pd.concat([df_train_transform_1.reset_index(drop=True),
#                           df_train_transform_1_ohe_df.reset_index(drop=True)], axis=1)
# df_train_transform_2.shape
```

In [ ]:
```
# df_train_transform_3 = df_train_transform_2.drop(columns = cat_cols)
# df_train_transform_3.shape
```

In [ ]:
```
# df_train_transform_4 = df_train_transform_3.drop(columns ='Modus_Operandi')
# df_train_transform_4.shape
```

Pipeline and ColumnTransformer for train data

In [ ]:
```
num_cols = ['Area_ID','Latitude', 'Longitude','Victim_Age', 'DayOfYear','Days_Lapsed','Reporting_District_no',
               'Premise_Code','Weapon_Used_Code','Occured_day','Reported_day', 'PCode','Rep_Dist_no','Occured_Weekday',
            'Time_Occurred_Hour','Occured_Month']
cat_cols = ['Victim_Sex', 'Victim_Descent','Status']
```

In [ ]:
```
df_train_processed['Modus_Operandi'] = df_train_processed['Modus_Operandi'].replace(0,'').astype(str)
df_train_processed['Victim_Sex'] = df_train_processed['Victim_Sex'].astype('str')
df_train_processed['Victim_Descent'] = df_train_processed['Victim_Descent'].astype('str')
df_train_processed['Status'] = df_train_processed['Status'].astype('str')
```

In [ ]:
```
# Define preprocessing for text features
text_transformer = Pipeline(steps=[
    ('tfidf', TfidfVectorizer())
])

# Define preprocessing for numerical features
numerical_transformer = Pipeline(steps=[
    ('scaler', MinMaxScaler())
])

# Define preprocessing for categorical features
categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# label_transformer = Pipeline(steps=[
#     ('le', LabelEncoder())
# ])


# Combine all transformers into a single ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('text', text_transformer, 'Modus_Operandi'),
        ('num', numerical_transformer, num_cols),
        ('cat', categorical_transformer,['Victim_Sex', 'Victim_Descent','Status']),
```

```
        ('passthrough', 'passthrough', ['Part 1-2','Is_CrossStreet','Arrest_done'])
    ]
)
```

In [ ]:
```
preprocessor
```

Out[ ]:

ColumnTransformer

text	num	cat	passthrough
TfidfVectorizer	MinMaxScaler	OneHotEncoder	passthrough

In [ ]:
```
df_train_transform_4 = preprocessor.fit_transform(df_train_processed)
```

In [ ]:
```
df_train_transform_4.shape
```

Out[ ]:
```
(19447, 527)
```

Preprocessing on Test data

In [ ]:
```
df_test.shape
```

Out[ ]:
```
(5000, 21)
```

In [ ]:
```
# test data
# Converting Date_Reported into year, month, weekday. in
df_test['Reported_Year'] = pd.to_datetime(df_test.Date_Reported).dt.year
df_test['Reported_Month'] = pd.to_datetime(df_test.Date_Reported).dt.month
df_test['Reported_day'] = pd.to_datetime(df_train.Date_Reported).dt.day
df_test['Reported_Weekday'] = pd.to_datetime(df_train.Date_Reported).dt.weekday

# Converting Date_Occurred into year, month, weekday in test data
df_test['Occured_Year'] = pd.to_datetime(df_test.Date_Occurred).dt.year
df_test['Occured_Month'] = pd.to_datetime(df_test.Date_Occurred).dt.month
df_test['Occured_day'] = pd.to_datetime(df_test.Date_Occurred).dt.day
df_test['Occured_Weekday'] = pd.to_datetime(df_test.Date_Occurred).dt.weekday
df_test['DayOfYear'] = (pd.to_datetime(df_test['Date_Occurred'])).dt.dayofyear

# converting df_test ['Time_Occurred'] column to %h%M format as done for test column
```

```
df_test['Time_Occurred_Hour'] = pd.to_datetime(df_test['Time_Occurred'].astype(int).astype(str)
                                              .str.zfill(4),format ='%H%M').dt.hour
df_test['Days_Lapsed'] = (pd.to_datetime(df_test['Date_Reported'])
                          - pd.to_datetime(df_test['Date_Occurred'])).dt.days
```

In [ ]:
```
#Test data
df_test.fillna(value =0, inplace =True)
df_test['Is_CrossStreet'] = df_test['Cross_Street'].apply(lambda x : 0 if x == 0 else 1)
df_test['Victim_Age'] = df_test['Victim_Age'].apply(lambda x: 0 if x < 0 else x)
df_test['Victim_Present'] = df_test['Victim_Age'].apply(lambda x : 0 if x <= 0 else 1)

df_test['Reporting_District_no'] = df_test['Reporting_District_no'].astype(int)
df_test['Rep_Dist_no'] = df_test['Reporting_District_no'].apply(lambda x: str(x)[-2:])
df_test['Rep_Dist_no'] = df_test['Rep_Dist_no'].astype(int)

df_test['Part 1-2'] = df_test['Part 1-2'].astype(int)
df_test['Part 1-2'] = df_test['Part 1-2'].apply(lambda x: 0 if x == 1 else 1)

df_test['PCode'] = df_test['Premise_Code'].apply(lambda x: int(x/100))
df_test['Arrest_done'] = df_test['Status'].map({'IC':0,'AO':0, 'AA':1, 'JA':1, 'JO':0})
df_test.shape
```

Out[ ]: (5000, 37)

In [ ]:
```
# Required columns
columns_test = ['Latitude', 'Longitude','Area_ID','Reporting_District_no', 'Part 1-2', 'Modus_Operandi', 'Victim_Age',
       'Victim_Sex', 'Victim_Descent', 'Premise_Code','Weapon_Used_Code', 'Status',
         'Is_CrossStreet','Victim_Present','Days_Lapsed','Occured_day','Occured_Weekday', 'Occured_Month',
 'Reported_day','DayOfYear', 'Rep_Dist_no','Time_Occurred_Hour','PCode', 'Arrest_done']
```

In [ ]:
```
df_test_processed = pd.DataFrame(df_test, columns = columns_test)
df_test_processed.shape
```

Out[ ]: (5000, 24)

In [ ]:
```
# mo_op_test = df_test_processed['Modus_Operandi'].replace(0,'')
# mo_op_test = mo_op_test.astype(str)
# tfidf_matrix_test = tfidf.transform(mo_op_test)
# tfidf_df_test = pd.DataFrame(tfidf_matrix_test.toarray(), columns=[f'tfidf_{col}'
# for col in tfidf.get_feature_names_out()])
# tfidf_df_test.shape
```

In [ ]:
```
# df_test_processed[num_cols] = scaler.transform(df_test_processed[num_cols])
# df_test_processed.shape
```

In [ ]:
```
# df_test_transform_1 = pd.concat([df_test_processed.reset_index(drop=True),
#                            tfidf_df_test.reset_index(drop=True)], axis=1)
# df_test_transform_1.shape
```

In [ ]:
```
# df_test_transform_1['Victim_Sex'] = df_test_transform_1['Victim_Sex'].astype('str')
# df_test_transform_1['Victim_Descent'] = df_test_transform_1['Victim_Descent'].astype('str')
# df_test_transform_1['Status'] = df_test_transform_1['Status'].astype('str')

# cat_cols = ['Victim_Sex', 'Victim_Descent','Status']
# df_test_transform_1_ohe= ohe.transform(df_test_transform_1[cat_cols])
# df_test_transform_1_ohe_df = pd.DataFrame(df_test_transform_1_ohe.toarray(), columns=[f'ohe_{col}'
#                                  for col in ohe.get_feature_names_out(cat_cols)])
```

In [ ]:
```
# df_test_transform_2 = pd.concat([df_test_transform_1.reset_index(drop=True),
#                          df_test_transform_1_ohe_df.reset_index(drop=True)], axis=1)
# df_test_transform_2.shape
```

In [ ]:
```
# df_test_transform_3 = df_test_transform_2.drop(columns = cat_cols)
# df_test_transform_3.shape
```

In [ ]:
```
# df_test_transform_4 = df_test_transform_3.drop(columns ='Modus_Operandi')
# df_test_transform_4.shape
```

Pipeline and ColumnTransformer for Test data

In [ ]:
```
df_test_processed['Modus_Operandi'] = df_test_processed['Modus_Operandi'].replace(0,'').astype(str)
df_test_processed['Victim_Sex'] = df_test_processed['Victim_Sex'].astype('str')
df_test_processed['Victim_Descent'] = df_test_processed['Victim_Descent'].astype('str')
df_test_processed['Status'] = df_test_processed['Status'].astype('str')
```

In [ ]:
```
df_test_transform_4 = preprocessor.transform(df_test_processed)
```

In [ ]:
```
df_test_transform_4.shape
```

Out[ ]:
```
(5000, 527)
```

Final Train and Test Data

```
In [ ]: df_train_final = df_train_transform_4
        df_test_final = df_test_transform_4
        print("shape of final train data and test data :",df_train_final.shape,df_test_final.shape)
```

```
shape of final train data and test data : (19447, 527) (5000, 527)
```

Train_Test_Split

For Pipeline

```
In [ ]: X = df_train_final
        y = df_train['Crime_Category']
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Without Pipeline

```
In [ ]: # X = df_train_final.drop(columns='Crime_Category')
        # y = df_train_final['Crime_Category']
        # X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
In [ ]: # Display the shapes of the resulting datasets
        print("X_train shape:", X_train.shape)
        print("X_test shape:", X_test.shape)
        print("y_train shape:", y_train.shape)
        print("y_test shape:", y_test.shape)
```

```
X_train shape: (15557, 527)
X_test shape: (3890, 527)
y_train shape: (15557,)
y_test shape: (3890,)
```

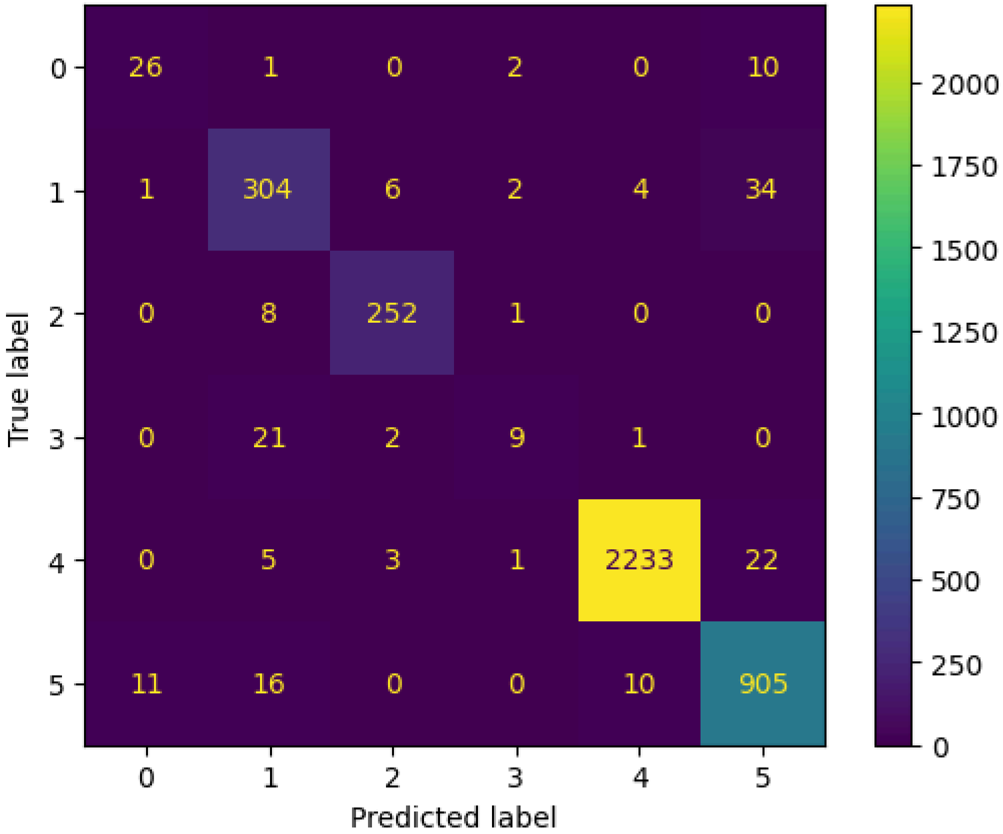
Model Building

3. xgBoost Classifier

In [ ]:
```
# from xgboost import XGBClassifier
model_3 = xgb.XGBClassifier()

# Train the model
model_3.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_3.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print("\nClassification Report:\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred, labels=model_3.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_3.classes_)
disp.plot()
```

```
Accuracy: 0.9586118251928021

Classification Report:
               precision    recall  f1-score   support

           0       0.68      0.67      0.68        39
           1       0.86      0.87      0.86       351
           2       0.96      0.97      0.96       261
           3       0.60      0.27      0.37        33
           4       0.99      0.99      0.99      2264
           5       0.93      0.96      0.95       942

    accuracy                           0.96      3890
   macro avg       0.84      0.79      0.80      3890
weighted avg       0.96      0.96      0.96      3890
```

Out[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7b49db703790>
```



Result for xgBoost Classifier¶ (kaggle score 0.95520 , with_pipeline 0.95400 V29)

Accuracy: 0.9580976863753213

Classification Report: precision recall f1-score support

0	0.73	0.69	0.71	39
1	0.86	0.87	0.87	351
2	0.95	0.96	0.96	261
3	0.54	0.21	0.30	33
4	0.99	0.98	0.99	2264
5	0.93	0.96	0.95	942
accuracy			0.96	3890

macro avg 0.83 0.78 0.80 3890 weighted avg 0.96 0.96 0.96 3890

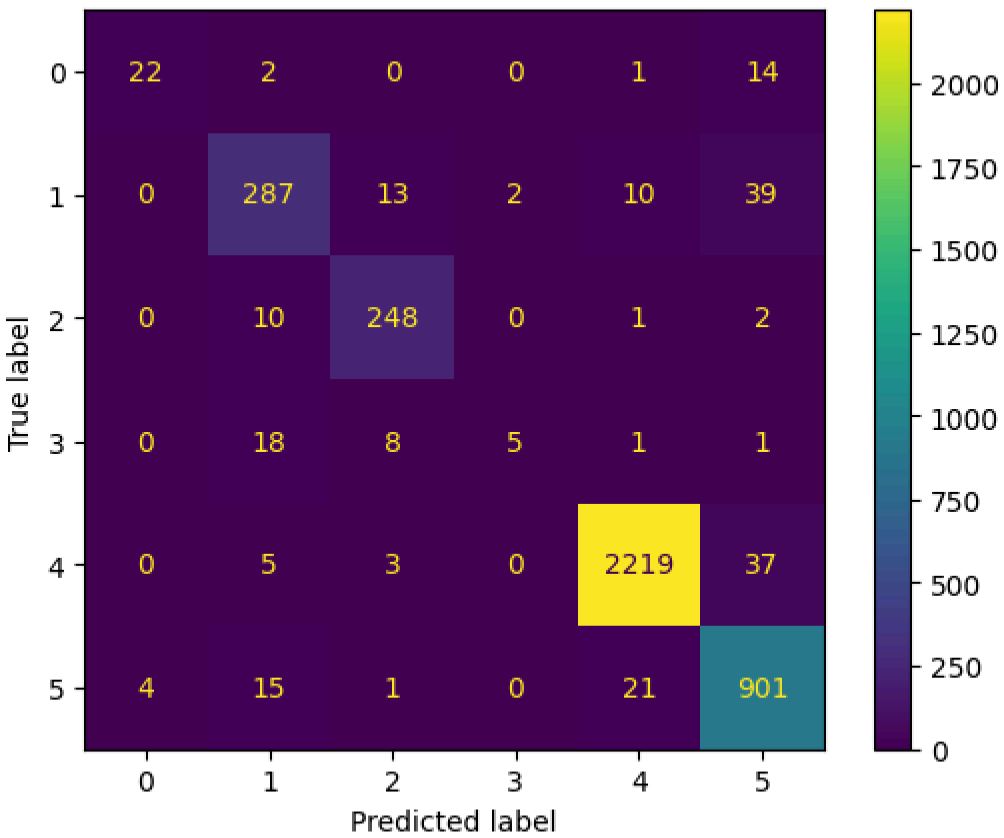
Confusion Matrix: [[27 0 0 1 0 11] [2 306 7 1 5 30] [0 7 250 2 1 1] [0 22 3 7 1 0] [0 6 2 2 2229 25] [8 14 0 0 12 908]]

1. Logistic regression

In [ ]:
```
model_1 = LogisticRegression(random_state = 42, max_iter = 1000)

# Train the model
model_1.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_1.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print("\nClassification Report:\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred, labels=model_1.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_1.classes_)
disp.plot()
```

```
Accuracy: 0.9465295629820052

Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.56      0.68        39
           1       0.85      0.82      0.83       351
           2       0.91      0.95      0.93       261
           3       0.71      0.15      0.25        33
           4       0.98      0.98      0.98      2264
           5       0.91      0.96      0.93       942

    accuracy                           0.95      3890
   macro avg       0.87      0.74      0.77      3890
weighted avg       0.95      0.95      0.94      3890
```

Out[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7b49a40ba4d0>
```



Result for Logistic regression (kaggle score = 0.93920 v24)

Accuracy: 0.9467866323907455

Classification Report: precision recall f1-score support

0	0.85	0.56	0.68	39
1	0.85	0.82	0.83	351
2	0.91	0.95	0.93	261
3	0.71	0.15	0.25	33
4	0.98	0.98	0.98	2264
5	0.91	0.95	0.93	942
accuracy			0.95	3890

macro avg 0.87 0.74 0.77 3890 weighted avg 0.95 0.95 0.94 3890

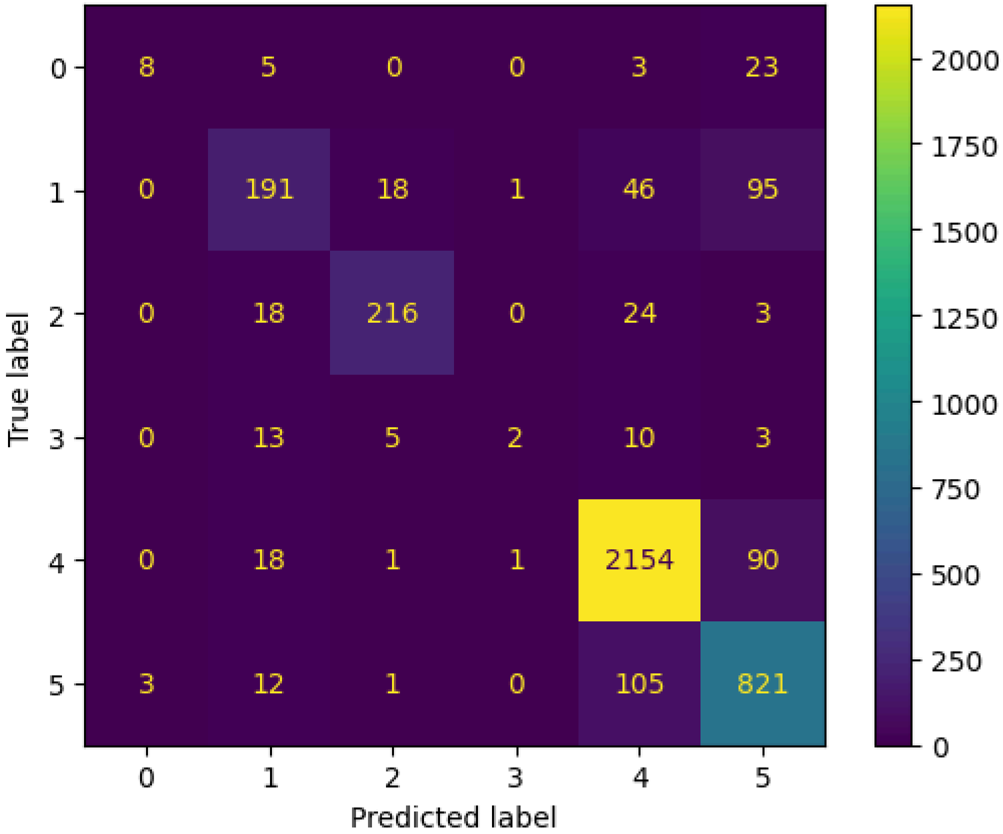
Confusion Matrix: [[22 2 0 0 1 14] [0 287 13 2 11 38] [0 10 248 0 1 2] [0 19 7 5 1 1] [0 5 3 0 2222 34] [4 15 1 0 23 899]]

2. KNeighborsClassifier

In [ ]:
```
model_2 = KNeighborsClassifier(n_neighbors=7)

# Train the model
model_2.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_2.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print("\nClassification Report:\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred, labels=model_2.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_2.classes_)
disp.plot()
```

```
Accuracy: 0.8719794344473007

Classification Report:
               precision    recall  f1-score   support

           0       0.73      0.21      0.32        39
           1       0.74      0.54      0.63       351
           2       0.90      0.83      0.86       261
           3       0.50      0.06      0.11        33
           4       0.92      0.95      0.94      2264
           5       0.79      0.87      0.83       942

    accuracy                           0.87      3890
   macro avg       0.76      0.58      0.61      3890
weighted avg       0.87      0.87      0.86      3890
```

Out[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7b499d6a09a0>
```



Result for KNeighborsClassifier

Accuracy: 0.8717223650385604

Classification Report: precision recall f1-score support

0	0.64	0.18	0.28	39
1	0.75	0.52	0.62	351
2	0.89	0.85	0.87	261
3	0.25	0.03	0.05	33
4	0.92	0.95	0.94	2264
5	0.79	0.87	0.83	942
accuracy			0.87	3890

macro avg 0.71 0.57 0.60 3890 weighted avg 0.86 0.87 0.86 3890

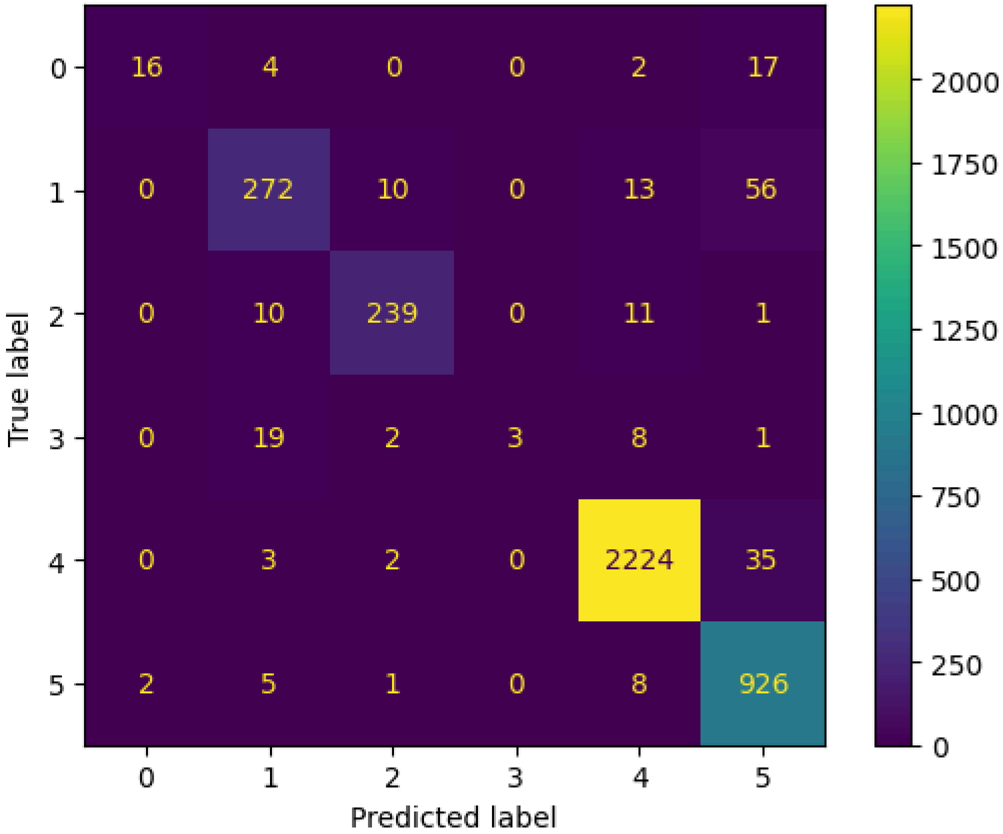
Confusion Matrix: [[7 4 0 0 4 24] [0 183 19 2 50 97] [0 13 221 0 24 3] [1 14 5 1 9 3] [0 18 2 1 2156 87] [3 12 1 0 103 823]]

4. Random Forest classifier

In [ ]:
```
model_4 = RandomForestClassifier(random_state=42)

# Train the model
model_4.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_4.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print("\nClassification Report:\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred, labels=model_4.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_4.classes_)
disp.plot()
```

```
Accuracy: 0.9460154241645244

Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.41      0.56        39
           1       0.87      0.77      0.82       351
           2       0.94      0.92      0.93       261
           3       1.00      0.09      0.17        33
           4       0.98      0.98      0.98      2264
           5       0.89      0.98      0.94       942

    accuracy                           0.95      3890
   macro avg       0.93      0.69      0.73      3890
weighted avg       0.95      0.95      0.94      3890
```

Out[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7b49a40548e0>
```



Result for Random Forest classifier (Kaggle score 0.94280 V25)

Accuracy: 0.9460154241645244

Classification Report: precision recall f1-score support

```
           0       0.84      0.41      0.55        39
           1       0.87      0.79      0.83       351
           2       0.95      0.91      0.93       261
           3       1.00      0.09      0.17        33
           4       0.98      0.98      0.98      2264
           5       0.90      0.98      0.94       942

    accuracy                           0.95      3890
```

macro avg 0.92 0.69 0.73 3890 weighted avg 0.95 0.95 0.94 3890

Confusion Matrix: [[16 4 0 0 2 17] [0 277 9 0 16 49] [0 10 238 0 13 0] [0 19 1 3 10 0] [0 3 1 0 2222 38] [3 5 1 0 9 924]]

5. Decision Tree classifier

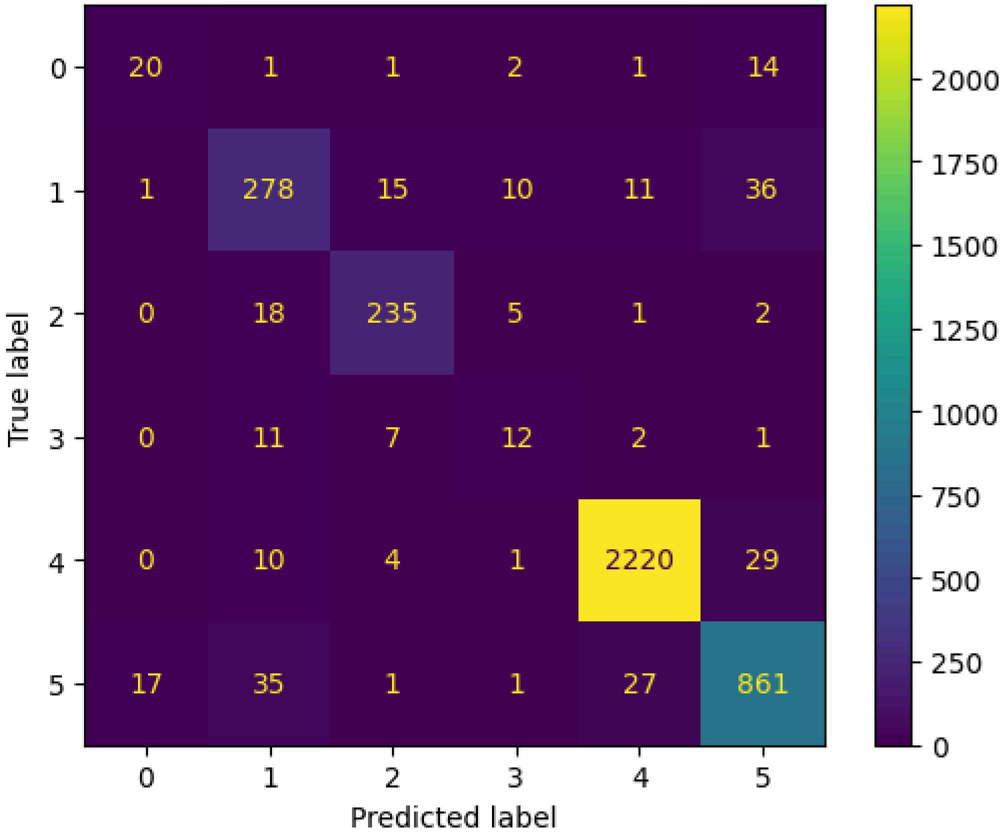
In [ ]:

```
# from sklearn.tree import DecisionTreeClassifier
model_5 = DecisionTreeClassifier()

# Train the model
model_5.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_5.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print("\nClassification Report:\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred, labels=model_5.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_5.classes_)
disp.plot()
```

```
Accuracy: 0.9321336760925449

Classification Report:
               precision    recall  f1-score   support

           0       0.53      0.51      0.52        39
           1       0.79      0.79      0.79       351
           2       0.89      0.90      0.90       261
           3       0.39      0.36      0.38        33
           4       0.98      0.98      0.98      2264
           5       0.91      0.91      0.91       942

    accuracy                           0.93      3890
   macro avg       0.75      0.74      0.75      3890
weighted avg       0.93      0.93      0.93      3890
```

Out[ ]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7b49a40545b0>
```



Result for DecisionTreeClassifier

Accuracy: 0.9339331619537276

Classification Report: precision recall f1-score support

0	0.47	0.44	0.45	39
1	0.80	0.79	0.79	351
2	0.90	0.90	0.90	261
3	0.39	0.39	0.39	33
4	0.98	0.98	0.98	2264
5	0.91	0.92	0.92	942
accuracy			0.93	3890

macro avg 0.74 0.74 0.74 3890 weighted avg 0.93 0.93 0.93 3890

Confusion Matrix: [[17 2 1 1 1 17] [1 277 13 11 14 35] [0 16 236 5 1 3] [1 10 7 13 1 1] [0 9 4 3 2222 26] [17 34 2 0 21 868]]

Hyper Parameter Tuning

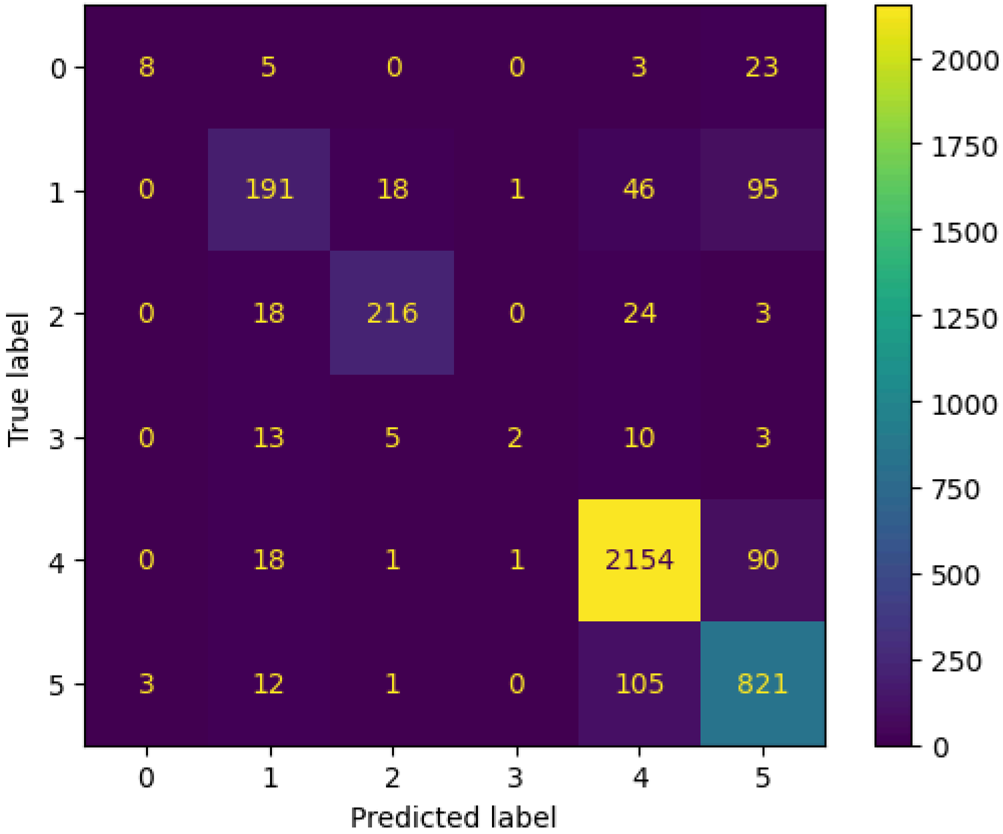
In [ ]:

```
knn = KNeighborsClassifier()
# lg = LogisticRegression()
# rfc = RandomForestClassifier(random_state=42)
param_grid = {'n_neighbors': [3, 5, 7, 9, 11]
#     'metric': ['euclidean', 'minkowski'], #'manhattan'
#     'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute']
}
model_hpt = GridSearchCV(estimator=knn, param_grid=param_grid, cv=2, n_jobs=-1, verbose=2)

# # taking too much time for execution. not able to pass through the time.
# taking more 30 sec for each run specially for manhattan taking more time.
# #try  for randomizedsearchcv
model_hpt.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model_hpt.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print("\nClassification Report:\n", classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred, labels=model_hpt.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=model_hpt.classes_)
disp.plot()
```

```
Fitting 2 folds for each of 5 candidates, totalling 10 fits
[CV] END ......................................n_neighbors=3; total time=  43.8s
[CV] END ......................................n_neighbors=3; total time=  43.6s
[CV] END ......................................n_neighbors=5; total time=  43.5s
[CV] END ......................................n_neighbors=5; total time=  43.7s
[CV] END ......................................n_neighbors=7; total time=  43.7s
[CV] END ......................................n_neighbors=7; total time=  43.5s
[CV] END ......................................n_neighbors=9; total time=  43.6s
[CV] END ......................................n_neighbors=9; total time=  43.6s
[CV] END .....................................n_neighbors=11; total time=  43.7s
```

```
[CV] END .....................................n_neighbors=11; total time=  43.5s
Accuracy: 0.8719794344473007

Classification Report:
               precision    recall  f1-score   support

           0       0.73      0.21      0.32        39
           1       0.74      0.54      0.63       351
           2       0.90      0.83      0.86       261
           3       0.50      0.06      0.11        33
           4       0.92      0.95      0.94      2264
           5       0.79      0.87      0.83       942

    accuracy                           0.87      3890
   macro avg       0.76      0.58      0.61      3890
weighted avg       0.87      0.87      0.86      3890
```

Out[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7b499ef4bdc0>
```



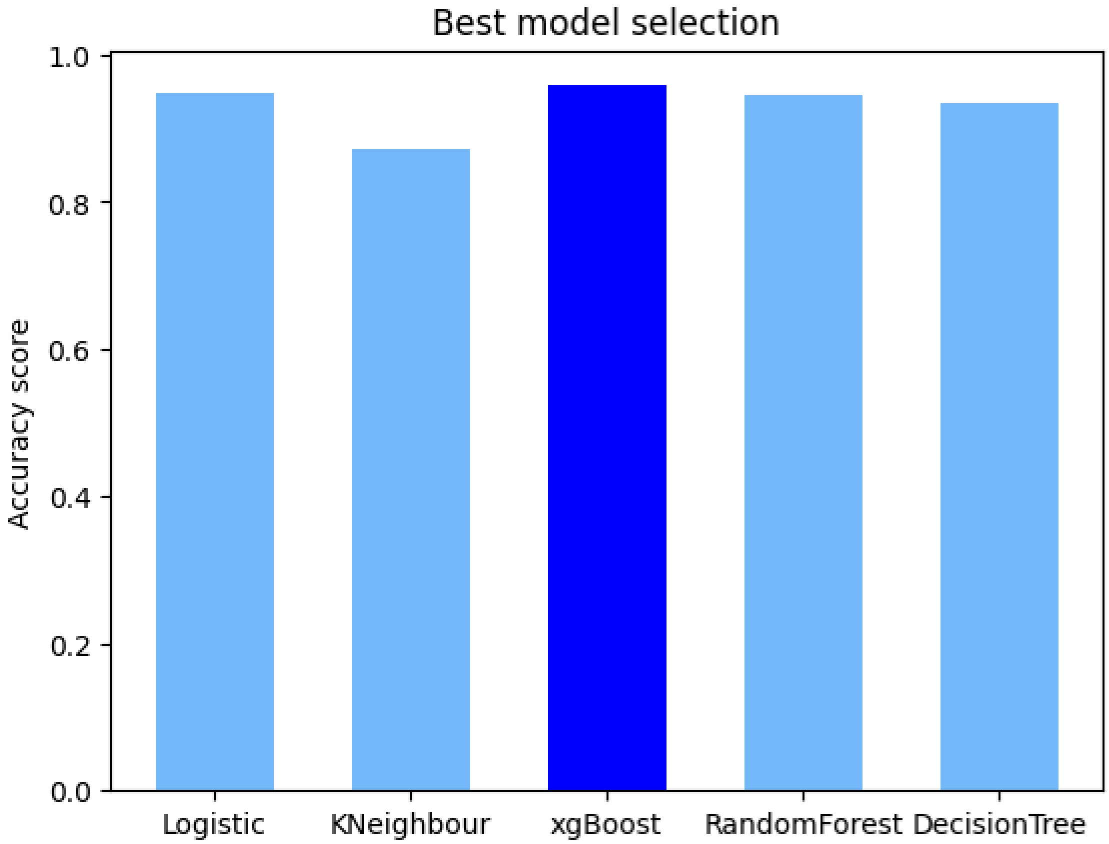

```
In [ ]: model_hpt.best_params_
```

```
Out[ ]: {'n_neighbors': 5}
```

Best Model selection based on accuracy score

```
In [ ]: fig, ax = plt.subplots()

models = ['Logistic', 'KNeighbour', 'xgBoost', 'RandomForest','DecisionTree']
accuracy = [0.9467866323907455, 0.8717223650385604,0.9580976863753213,0.9460154241645244,0.9339331619537276]
bar_colors = ['xkcd:sky blue', 'xkcd:sky blue', 'b', 'xkcd:sky blue','xkcd:sky blue']

ax.bar(models, accuracy,color=bar_colors, width = 0.6)
ax.set_ylabel('Accuracy score')
```

```python
ax.set_title('Best model selection')
plt.show()
```



Final Model Training and output

In [ ]:

```python
# Choose final model for submission
model = model_3

# Train the model
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
```

```
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
```

```
Accuracy: 0.9546984209163862
```

In [ ]:
```
y_pred_final = model.predict(df_test_final)
print(y_pred_final)
```

```
[5 4 2 ... 5 5 4]
```

In [ ]:
```
decoded_y_pred_final = le.inverse_transform(y_pred_final)
decoded_y_pred_final = pd.DataFrame(decoded_y_pred_final, columns =['Crime_Category'])
print(decoded_y_pred_final)
```

```
                  Crime_Category
0                 Violent Crimes
1                Property Crimes
2     Fraud and White-Collar Crimes
3                Property Crimes
4       Crimes against Public Order
...                          ...
4995             Property Crimes
4996             Property Crimes
4997              Violent Crimes
4998              Violent Crimes
4999             Property Crimes

[5000 rows x 1 columns]
```

Submission

In [ ]:
```
submission = pd.DataFrame({"ID": np.arange(1,5001),
                           "Crime_Category": decoded_y_pred_final['Crime_Category'],
                          }
                         )

submission.to_csv('submission.csv',index=False)
```

In [ ]:
```
submission.head()
```

Out[ ]:

	ID	Crime_Category
0	1	Violent Crimes

	ID	Crime_Category
1	2	Property Crimes
2	3	Fraud and White-Collar Crimes
3	4	Property Crimes
4	5	Crimes against Public Order

-------------------------------- End of Code --