Group3_NYPD_Arrests_Data (Ankit, Kristin, Sai, Surakshya, Tenzin)

December 14, 2022

[1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from plotnine import *
%matplotlib inline

from sklearn import preprocessing
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve,␣
↪roc_auc_score, precision_score, recall_score, f1_score, auc
from sklearn.metrics import precision_recall_curve,␣
↪plot_precision_recall_curve, average_precision_score
from sklearn.model_selection import cross_val_score, cross_val_predict
```

1 Data Preprocessing

[2]:
```
# Load dataset
df = pd.read_csv('2015data.csv')
df.drop(axis=1, columns=['Unnamed: 0'], inplace=True)
df = df[df['ARREST_DATE'] > '2019-01-01'] # change dataset size to be more␣
↪managable
```

[3]:
```
df.head()
```

[3]:
```
   ARREST_KEY ARREST_DATE  PD_CD                      PD_DESC  KY_CD  \
0   236791704  2021-11-22  581.0                          NaN    NaN
1   237354740  2021-12-04  153.0                       RAPE 3  104.0
2   236081433  2021-11-09  681.0  CHILD, ENDANGERING WELFARE  233.0
3   192799737  2019-01-26  177.0                SEXUAL ABUSE  116.0
4   193260691  2019-02-06    NaN                          NaN    NaN

    OFNS_DESC    LAW_CODE LAW_CAT_CD ARREST_BORO  ARREST_PRECINCT  \
0         NaN  PL 2225001          M           M               28
1        RAPE  PL 1302502          F           B               41
2  SEX CRIMES  PL 2601001          M           Q              113
3  SEX CRIMES  PL 1306503          F           M               25
4         NaN  PL 2203400          F           M               14

   JURISDICTION_CODE AGE_GROUP PERP_SEX       PERP_RACE  X_COORD_CD  \
0                0.0     45-64        M           BLACK    997427.0
1                0.0     25-44        M  WHITE HISPANIC   1013232.0
2                0.0     25-44        M           BLACK   1046367.0
3                0.0     45-64        M           BLACK   1000555.0
4                0.0     25-44        M         UNKNOWN    986685.0

   Y_COORD_CD   Latitude  Longitude  \
0    230378.0  40.799009 -73.952409
1    236725.0  40.816392 -73.895296
2    186986.0  40.679700 -73.776047
3    230994.0  40.800694 -73.941109
4    215375.0  40.757839 -73.991212

                                      Lon_Lat
0  POINT (-73.95240854099995 40.799008797000056)
1  POINT (-73.89529641399997 40.816391847000034)
2   POINT (-73.77604736799998 40.67970040800003)
3  POINT (-73.94110928599997 40.800694331000045)
4   POINT (-73.99121211099998 40.75783900300007)
```

[4]:
```python
# reduce repeated variables
df.drop(axis=1, columns=['X_COORD_CD', 'Y_COORD_CD', 'Lon_Lat'], inplace=True)
df.shape
```

[4]:
```
(509989, 16)
```

[5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 509989 entries, 0 to 511440
Data columns (total 16 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
```

```
 0   ARREST_KEY         509989 non-null  int64
 1   ARREST_DATE        509989 non-null  object
 2   PD_CD              509896 non-null  float64
 3   PD_DESC            509690 non-null  object
 4   KY_CD              509690 non-null  float64
 5   OFNS_DESC          509690 non-null  object
 6   LAW_CODE           509989 non-null  object
 7   LAW_CAT_CD         505839 non-null  object
 8   ARREST_BORO        509989 non-null  object
 9   ARREST_PRECINCT    509989 non-null  int64
 10  JURISDICTION_CODE  509989 non-null  float64
 11  AGE_GROUP          509989 non-null  object
 12  PERP_SEX           509989 non-null  object
 13  PERP_RACE          509989 non-null  object
 14  Latitude           509989 non-null  float64
 15  Longitude          509989 non-null  float64
dtypes: float64(5), int64(2), object(9)
memory usage: 66.1+ MB
```

[6]:
```python
# check for duplicates
df.duplicated().sum()
```

[6]:
```
0
```

[7]:
```python
# Check percentage of null values compared
# to total number of dataset observatuions
(df.isnull().sum() /df.shape[0] ) * 100
```

[7]:
```
ARREST_KEY           0.000000
ARREST_DATE          0.000000
PD_CD                0.018236
PD_DESC              0.058629
KY_CD                0.058629
OFNS_DESC            0.058629
LAW_CODE             0.000000
LAW_CAT_CD           0.813743
ARREST_BORO          0.000000
ARREST_PRECINCT      0.000000
JURISDICTION_CODE    0.000000
AGE_GROUP            0.000000
PERP_SEX             0.000000
PERP_RACE            0.000000
Latitude             0.000000
Longitude            0.000000
dtype: float64
```

As seen above, rows with missing values for some columns compromise very low percentages. For example, for LAW_CAT_CD, only 0.9% of the total observations have missng values. Because the number of missing values are so low compared to our data size, it would be appropriate to drop rows containing missing values.

We will remove the rows with missing values using the LAW_CAT_CD and OFNS_DESC columns. Choosing these columns will lead to getting rid of all missing value observations.

[8]:
```
# drop nan rows
df = df.dropna(subset=['LAW_CAT_CD', 'OFNS_DESC'])
df.shape
```

[8]:
```
(505540, 16)
```

[9]:
```
# Change data type to date
df['ARREST_DATE']  = pd.to_datetime(df['ARREST_DATE'])

# columns to be changed to category data type
col = ['PD_CD', 'PD_DESC', 'KY_CD', 'OFNS_DESC','LAW_CODE', 'LAW_CAT_CD',
       'ARREST_BORO', 'ARREST_PRECINCT','JURISDICTION_CODE',
       'AGE_GROUP', 'PERP_SEX', 'PERP_RACE']

# PD_CD, KY_CD, JURISDICTION_CODE do not require decimals
# the following should show that all categories within these varibles have .0␣
 ↪as decimal values that are meaningless
# print(df['PD_CD'].value_counts())
# print(df['KY_CD'].value_counts())
# print(df['JURISDICTION_CODE'].value_counts())

# before changing to category for PD_CD, KY_CD, JURISDICTION_CODE,
# change to int to format the classification codes properly withoud decimals
df['PD_CD'] = df['PD_CD'].astype("int")
df['KY_CD'] = df['KY_CD'].astype("int")
df['JURISDICTION_CODE'] = df['JURISDICTION_CODE'].astype("int")
#  correct data types for the categorical variables
for c in col:
    df[c]  = df[c].astype("category")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 505540 entries, 1 to 511440
Data columns (total 16 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   ARREST_KEY         505540 non-null  int64
 1   ARREST_DATE        505540 non-null  datetime64[ns]
 2   PD_CD              505540 non-null  category
 3   PD_DESC            505540 non-null  category
 4   KY_CD              505540 non-null  category
 5   OFNS_DESC          505540 non-null  category
 6   LAW_CODE           505540 non-null  category
```

```
 7   LAW_CAT_CD         505540 non-null  category
 8   ARREST_BORO        505540 non-null  category
 9   ARREST_PRECINCT    505540 non-null  category
 10  JURISDICTION_CODE  505540 non-null  category
 11  AGE_GROUP          505540 non-null  category
 12  PERP_SEX           505540 non-null  category
 13  PERP_RACE          505540 non-null  category
 14  Latitude           505540 non-null  float64
 15  Longitude          505540 non-null  float64
dtypes: category(12), datetime64[ns](1), float64(2), int64(1)
memory usage: 26.6 MB
```

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

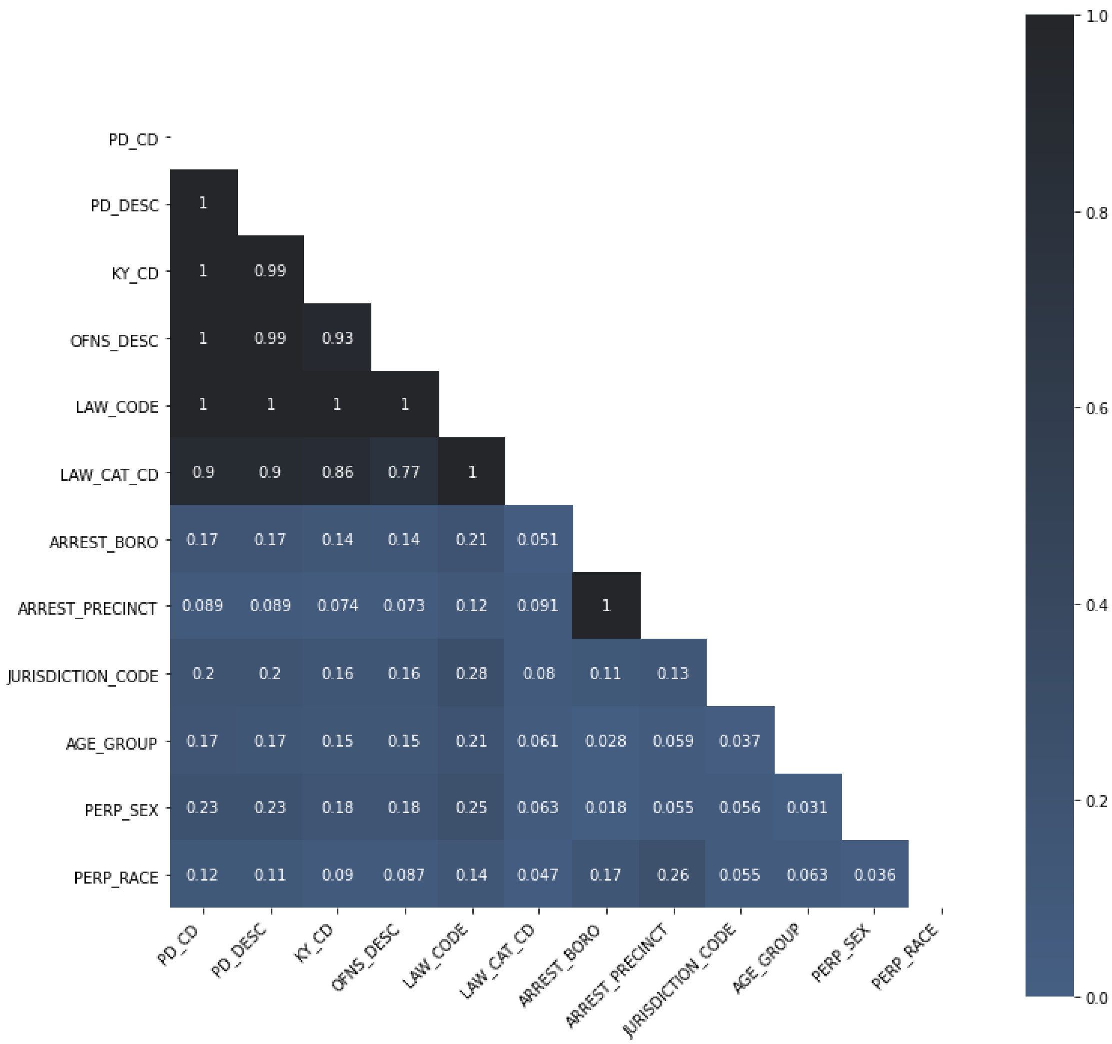
[10]:
```
   ARREST_KEY ARREST_DATE PD_CD                         PD_DESC KY_CD  \
1   237354740  2021-12-04   153                          RAPE 3   104
2   236081433  2021-11-09   681      CHILD, ENDANGERING WELFARE   233
3   192799737  2019-01-26   177                   SEXUAL ABUSE   116
6   236106641  2021-11-10   263                    ARSON 2,3,4   114
7   238383628  2021-12-28   729  FORGERY,ETC.,UNCLASSIFIED-FELO   113

     OFNS_DESC    LAW_CODE LAW_CAT_CD ARREST_BORO ARREST_PRECINCT  \
1         RAPE  PL 1302502          F           B              41
2  SEX CRIMES  PL 2601001          M           Q             113
3  SEX CRIMES  PL 1306503          F           M              25
6        ARSON  PL 1501001          F           B              41
7      FORGERY  PL 1702500          F           Q             113

  JURISDICTION_CODE AGE_GROUP PERP_SEX       PERP_RACE  Latitude  Longitude
1                 0     25-44        M  WHITE HISPANIC  40.816392 -73.895296
2                 0     25-44        M           BLACK  40.679700 -73.776047
3                 0     45-64        M           BLACK  40.800694 -73.941109
6                72     25-44        M  WHITE HISPANIC  40.804013 -73.878332
7                 0     18-24        M           BLACK  40.691660 -73.779199
```

We want to explore if some variables are correlated with each other. For insatnce, the variables PD_CD and KY_CD are likely to be associated since they both hold classification hold with the only difference being that PD_CD is more granular than KY_CD. We want to look at such associations throughout the database features. Since all our variables are categorical, we will apply the CramersV function which is more suitable than trying to compute correlation matrix. Note: CramersV will produce numbers ranging from 0 to 1 and is symmetrical.

[11]:
```
# pip install association-metrics
```

[12]:
```
# Import association_metrics
import association_metrics as am

# Initialize a CamresV object using you pandas.DataFrame
```

```
cramersv = am.CramersV(df)
# will return a pairwise matrix filled with Cramer's V, where columns and index␣
↪are
# the categorical variables of the passed DataFrame
assoc = cramersv.fit()
matrix = np.triu(assoc)  # retrieve only tiangular bottom of the symmetrical␣
↪matrix

# Heatmap to visualize associations between features
plt.subplots(figsize=(12,12))
ax = sns.heatmap(assoc, mask=matrix, cmap=sns.dark_palette("#69d",␣
↪reverse=True, as_cmap=True), annot=True,
    vmin=0, vmax=1, center=0, square=True)
ax.set_xticklabels(ax.get_xticklabels(),rotation=45,horizontalalignment='right')
plt.savefig('Association.png')
```



We see that some of the categorical variables ('PD_CD', 'KY_CD', 'PD_DESC','LAW_CODE', 'ARREST_PRECINCT', 'LAW_CAT_CD') are highly associated with other variables like 'OFNS_DESC', 'ARREST_PRECINCT'. Therefore, we can drop them to reduce the dimensions of our dataset.

[13]:
```
# remove associated variables
df.drop(axis=1, columns=['PD_CD', 'KY_CD', 'PD_DESC','LAW_CODE',␣
 ↪'ARREST_PRECINCT'], inplace=True)
```

[14]:
```
from scipy.stats import chi2_contingency

# Chi-squared tests to look at associations
chisqt = pd.crosstab(df.AGE_GROUP, df.LAW_CAT_CD, margins=True)
value = np.array([chisqt.iloc[0][0:5].values,
                  chisqt.iloc[1][0:5].values])
print(chi2_contingency(value)[0:3])
```

```
(771.4174624772288, 1.1918192039544272e-165, 4)
```

[15]:
```
chisqt2 = pd.crosstab(df.AGE_GROUP, df.PERP_RACE, margins=True)
print(chisqt2)
```

```
PERP_RACE  AMERICAN INDIAN/ALASKAN NATIVE  ASIAN / PACIFIC ISLANDER   BLACK  \
AGE_GROUP
18-24                                 324                      5243   51962
25-44                                 769                     15084  130327
45-64                                 260                      6162   48920
65+                                    17                       653    2815
<18                                    38                       724   12899
All                                  1408                     27866  246923

PERP_RACE  BLACK HISPANIC  UNKNOWN  WHITE  WHITE HISPANIC     All
AGE_GROUP
18-24               10337      523   6876           24790  100055
25-44               24491     1516  33318           71833  277338
45-64                6461      470  15101           22881  100255
65+                   436       30   1602            1456    7009
<18                  2114       64    822            4222   20883
All                 43839     2603  57719          125182  505540
```

[16]:
```
chisqt2 = pd.crosstab(df.AGE_GROUP, df.PERP_SEX, margins=True)
value = np.array([chisqt2.iloc[0][0:5].values,
                  chisqt2.iloc[1][0:5].values])
print(chi2_contingency(value)[0:3])
```

```
(54.25203780217128, 1.6569891904275434e-12, 2)
```

[17]:
```python
chisqt3 = pd.crosstab(df.ARREST_BORO, df.PERP_SEX, margins=True)
print(chisqt)
```

```
LAW_CAT_CD       F    I       M     V     All
AGE_GROUP
18-24        47059  151   52064   781  100055
25-44       116483  507  158302  2046  277338
45-64        39533  155   59794   773  100255
65+           2506   28    4355   120    7009
<18          13542    4    7306    31   20883
All         219123  845  281821  3751  505540
```

[18]:
```python
chisqt3 = pd.crosstab(df.ARREST_BORO, df.PERP_SEX, margins=True)
value = np.array([chisqt3.iloc[0][0:5].values,
                  chisqt3.iloc[1][0:5].values])
print(chi2_contingency(value)[0:3])
```

```
(95.42696862221496, 1.8980036851219296e-21, 2)
```

[19]:
```python
CrosstabResult=pd.crosstab(index=df['AGE_GROUP'],columns=df['PERP_RACE'])
print(CrosstabResult)

ChiSqResult = chi2_contingency(CrosstabResult)
print('The P-Value of the ChiSq Test is:', ChiSqResult[1])
```

```
PERP_RACE  AMERICAN INDIAN/ALASKAN NATIVE  ASIAN / PACIFIC ISLANDER   BLACK  \
AGE_GROUP
18-24                                 324                      5243   51962
25-44                                 769                     15084  130327
45-64                                 260                      6162   48920
65+                                    17                       653    2815
<18                                    38                       724   12899

PERP_RACE  BLACK HISPANIC  UNKNOWN  WHITE  WHITE HISPANIC
AGE_GROUP
18-24               10337      523   6876           24790
25-44               24491     1516  33318           71833
45-64                6461      470  15101           22881
65+                   436       30   1602            1456
<18                  2114       64    822            4222
The P-Value of the ChiSq Test is: 0.0
```

[20]:
```python
CrosstabResult2=pd.crosstab(index=df['ARREST_BORO'],columns=df['PERP_SEX'])
print(CrosstabResult2)

ChiSqResult1 = chi2_contingency(CrosstabResult2)
print('The P-Value of the ChiSq Test is:', ChiSqResult1[1])
```

```
PERP_SEX         F       M
```

```
ARREST_BORO
B           20896   93505
K           23037  114242
M           21967  102707
Q           18539   88319
S            4385   17943
The P-Value of the ChiSq Test is: 4.5933077496993295e-35
```

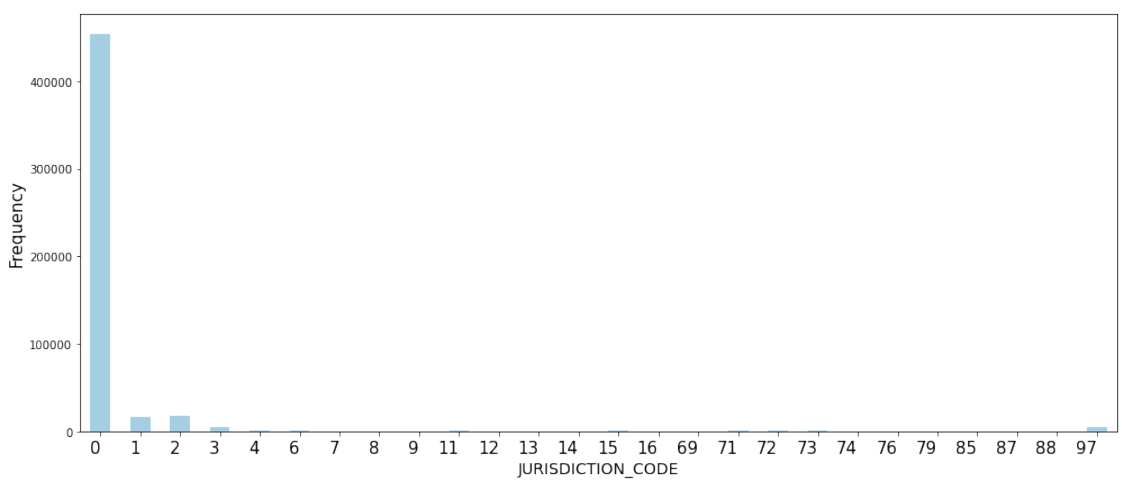
[ ]:

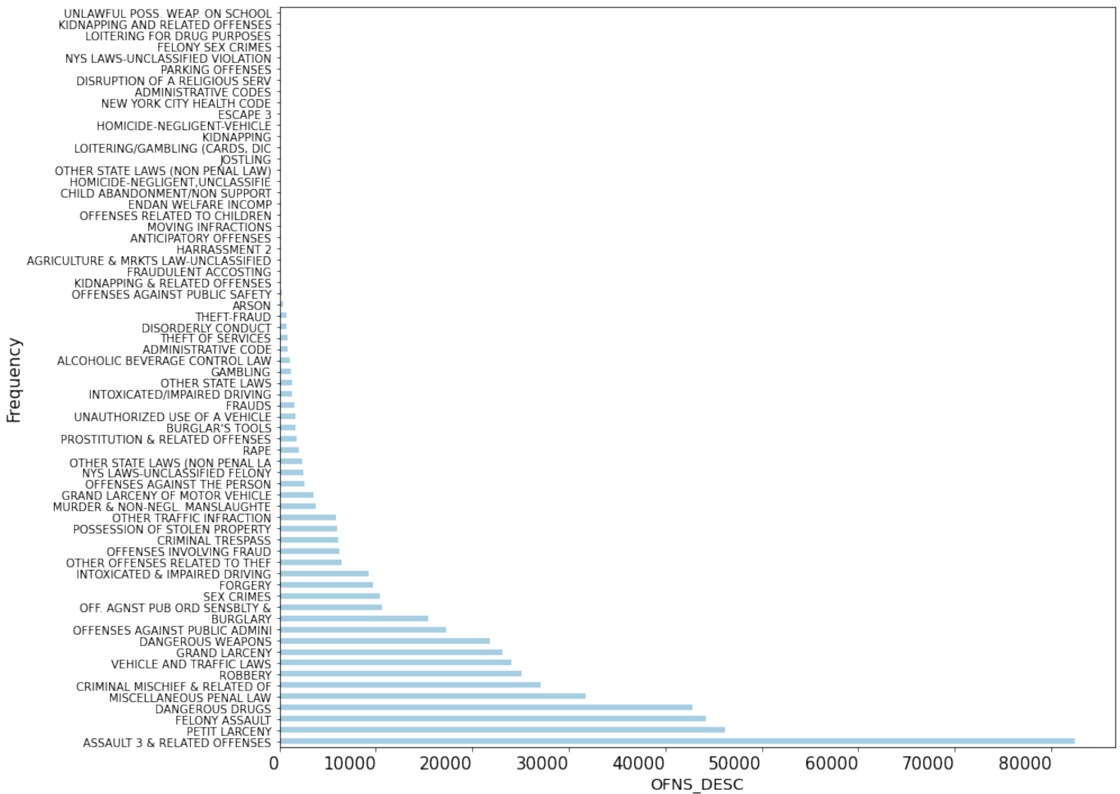
```

```

2 Visualization

[21]:

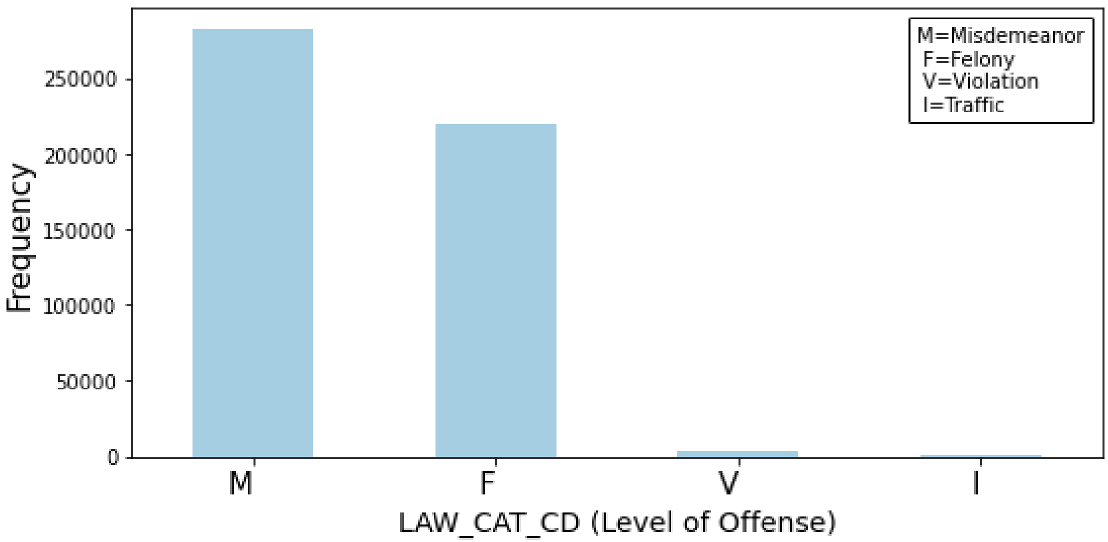
```python
from matplotlib.offsetbox import AnchoredText

def plot_bar(c, x, y, annot=False, text='', rot=None, kind='bar', sort=False,␣
↪name=None):   #function to plot bar graphs
    ax = df[c].value_counts(sort=sort).plot(kind=kind, figsize=(x,y),␣
↪colormap='Paired')
    ax.set_xlabel(name, size=14)
    ax.set_ylabel("Frequency",size=15)
    plt.xticks(rotation=rot, ha='right', size=15)
    plt.xticks(size=15)
    if annot is True:
        at = AnchoredText(
                text, prop=dict(size=10), frameon=True, loc='upper right')
        at.patch.set_boxstyle("round,pad=0.,rounding_size=0.1")
        ax.add_artist(at)
    plt.tight_layout()
    plt.savefig(c, facecolor='white')
    plt.show()

plot_bar('JURISDICTION_CODE', 14, 6, 90, name='JURISDICTION_CODE')
plot_bar('OFNS_DESC', 14, 10, 90, kind='barh', sort=True, name='OFNS_DESC')
```

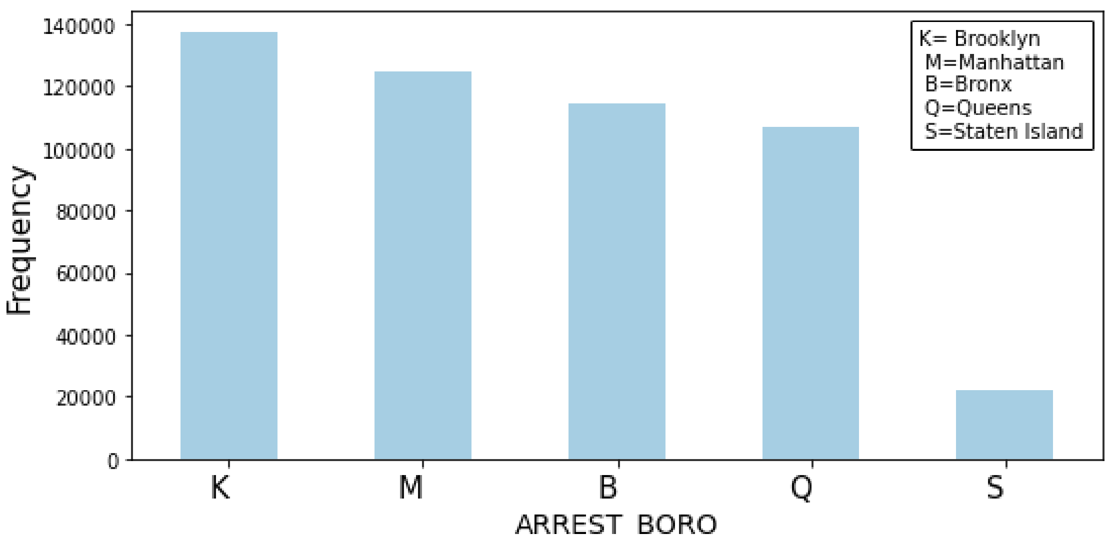


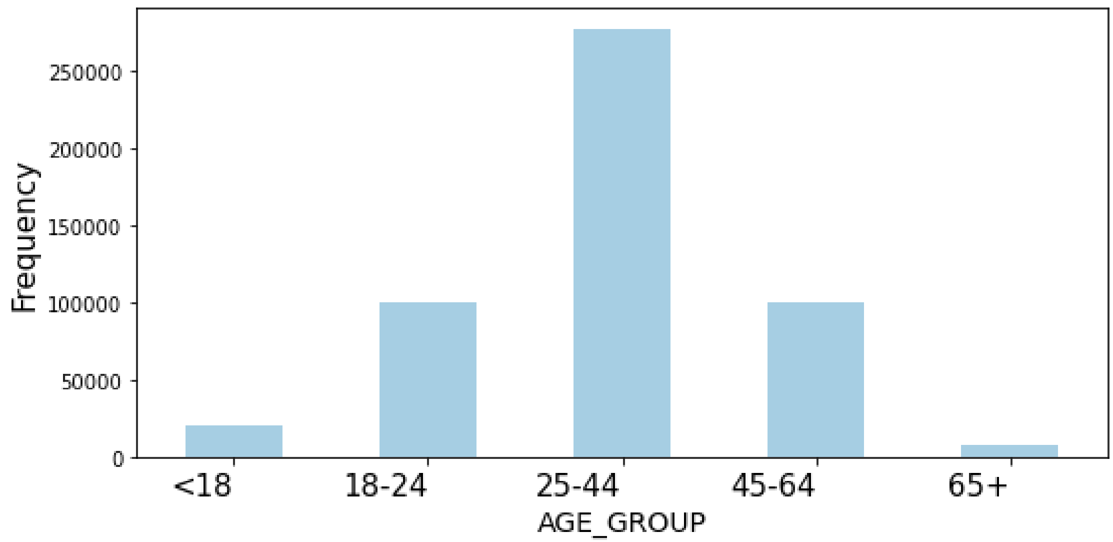


[22]:

```python
label = "M=Misdemeanor\n F=Felony\n V=Violation\n I=Traffic"
plot_bar('LAW_CAT_CD', 8, 4, text=label, annot=True, sort=True, name='LAW_CAT_CD (Level of Offense)')

label = "K= Brooklyn\n M=Manhattan\n B=Bronx\n Q=Queens\n S=Staten Island"
plot_bar('ARREST_BORO', 8, 4,  text=label, annot=True, sort=True, name='ARREST_BORO')

# Make age ordered categorical variable
age_labels = ['<18', '18-24', '25-44', '45-64', '65+']
df['AGE_GROUP'] = pd.Categorical(df['AGE_GROUP'], categories = age_labels, ordered = True)
plot_bar('AGE_GROUP', 8, 4,  name='AGE_GROUP')
```


M=Misdemeanor
F=Felony
V=Violation
I=Traffic
Frequency
250000
200000
150000
100000
50000
0
M
F
V
I
LAW_CAT_CD (Level of Offense)


K= Brooklyn
M=Manhattan
B=Bronx
Q=Queens
S=Staten Island
Frequency
140000
120000
100000
80000
60000
40000
20000
0
K
M
B
Q
S
ARREST_BORO



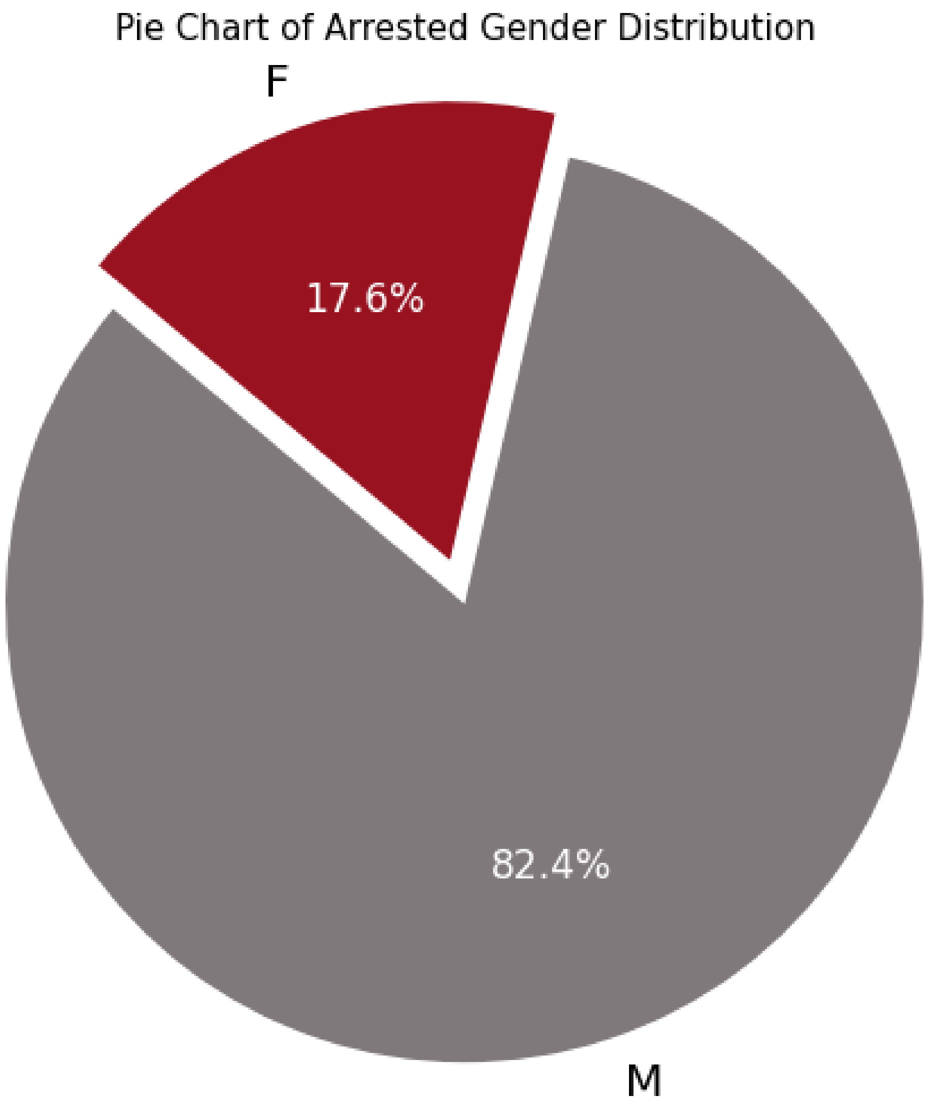
[23]:
```
df_gender = pd.DataFrame(df['PERP_SEX'].value_counts()).reset_index()
df_gender['Percentage'] = (df_gender['PERP_SEX'] / len(df))*100
df_gender.rename(columns = {'index':'Gender', 'PERP_SEX':'Total'}, inplace =␣
↪True)
df_gender = df_gender.sort_values('Total', ascending = False).reset_index(drop␣
↪= True)

# Show the data
df_gender
```

[23]:

	Gender	Total	Percentage
0	M	416716	82.429877
1	F	88824	17.570123

[24]:
```
# Customize colors and other settings
plt.subplots(figsize=(7,7))
colors = ['#80797c', '#981220']
explode = (0.1,0) # Explode 1st slice
# Create a pie chart
_, _, autotexts = plt.pie(df_gender['Total'], explode = explode, labels =␣
↪df_gender['Gender'],
                          textprops={'fontsize': 20}, colors = colors,
                          autopct = '%1.1f%%', shadow = False, startangle = 140)
for autotext in autotexts:
    autotext.set_color('white')
    autotext.set_size(17)

\
```

```
# Add title
plt.title('Pie Chart of Arrested Gender Distribution', size=15)
plt.axis('equal')
plt.tight_layout()
plt.savefig('Gender.png')
plt.show()
```



[25]:
```
# The composition of PERP_RACE
df_ethnicity = pd.DataFrame(df['PERP_RACE'].value_counts()).reset_index()
mapper = {'UNKNOWN':'OTHERS', 'AMERICAN INDIAN/ALASKAN NATIVE': 'OTHERS'}
df_ethnicity['index'] = df_ethnicity['index'].replace(mapper)
df_ethnicity.loc[len(df_ethnicity.index)] =(df_ethnicity.loc[[5,6]].sum())
```

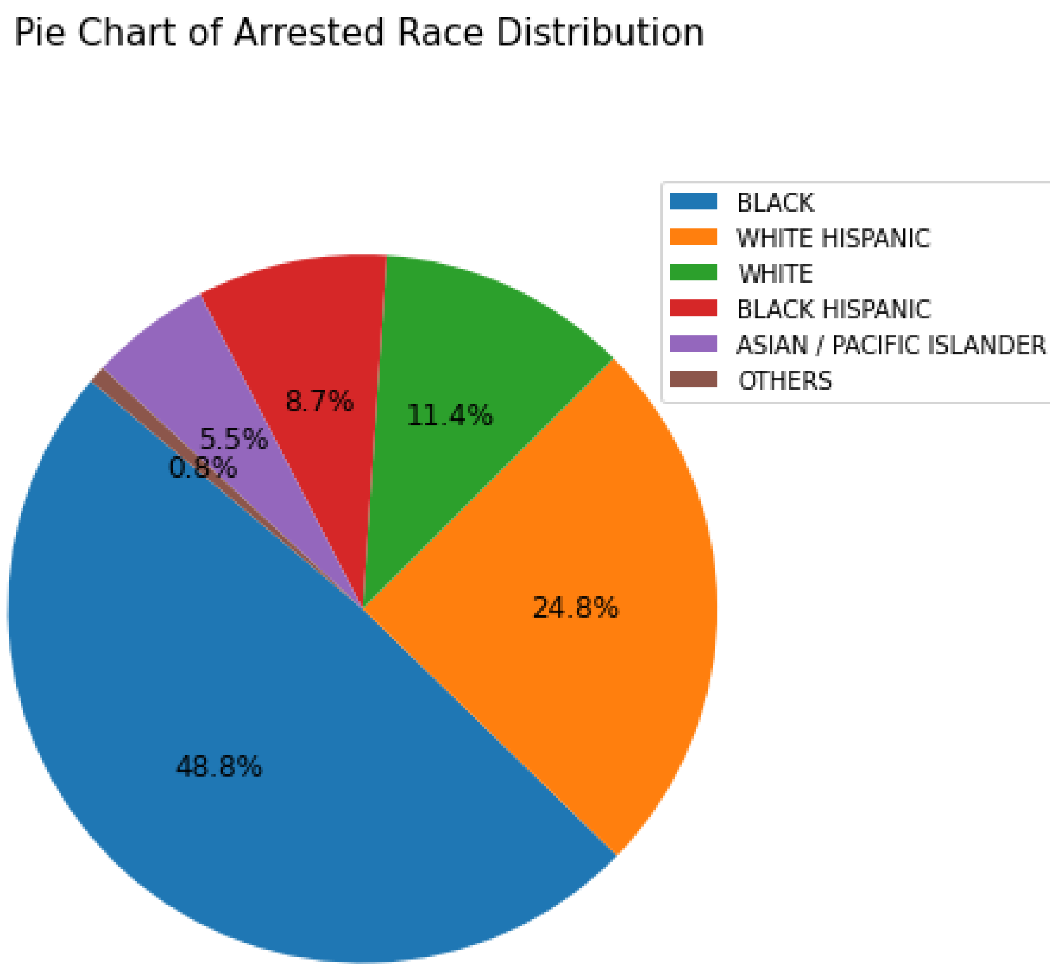
```python
df_ethnicity.drop([5, 6], inplace=True)
remap = {'OTHERSOTHERS':'OTHERS'}
df_ethnicity['index'] = df_ethnicity['index'].replace(remap)

df_ethnicity['Percentage'] = (df_ethnicity['PERP_RACE'] / len(df) )*100
df_ethnicity.rename(columns = {'index':'Ethnicity', 'PERP_RACE':'Total'},␣
 ↪inplace = True)
df_ethnicity = df_ethnicity.sort_values('Total', ascending = False).
 ↪reset_index(drop = True)

# Show the data
df_ethnicity
```

[25]:

	Ethnicity	Total	Percentage
0	BLACK	246923	48.843415
1	WHITE HISPANIC	125182	24.762037
2	WHITE	57719	11.417296
3	BLACK HISPANIC	43839	8.671717
4	ASIAN / PACIFIC ISLANDER	27866	5.512126
5	OTHERS	4011	0.793409

[26]:

```python
# Create a pie chart
plt.subplots(figsize=(7,7))
_, _, autotexts = plt.pie(df_ethnicity['Total'], autopct = '%1.1f%%', shadow =␣
 ↪False, startangle = 140)
for autotext in autotexts:
    autotext.set_size(12)
# Add title
plt.title('Pie Chart of Arrested Race Distribution', size=15)
plt.legend(labels = df_ethnicity['Ethnicity'], bbox_to_anchor=(1.4, 0.9),␣
 ↪loc="upper right")
plt.axis('equal')
plt.tight_layout()
plt.savefig('race.png')
plt.show()
```



[27]:
```
locate = df.groupby(['Latitude','Longitude']).size()
locate[0:5]
```

[27]:
```
Latitude   Longitude
40.498905  -74.241537    1
40.498957  -74.244367    1
40.499401  -74.242175    1
40.499850  -74.239918    2
40.499948  -74.238006    1
dtype: int64
```

[28]:
```
import plotly.express as px
fig = px.density_mapbox(locate, lat=locate.index.get_level_values(0),␣
↪lon=locate.index.get_level_values(1), z=locate.values,
                        mapbox_style="stamen-terrain")

fig
```

3 Heirarchical clustering (Unsupervised)

[29]:
```
df_hclust = df.head(1000) # selecting only a few rows since the dataset is too␣
↪large
df_hclust.columns
```

[29]:
```
Index(['ARREST_KEY', 'ARREST_DATE', 'OFNS_DESC', 'LAW_CAT_CD', 'ARREST_BORO',
       'JURISDICTION_CODE', 'AGE_GROUP', 'PERP_SEX', 'PERP_RACE', 'Latitude',
       'Longitude'],
      dtype='object')
```

[30]:
```
obj_df = df_hclust.drop(axis=1, columns=['ARREST_KEY', 'ARREST_DATE',
                                          ␣
↪'JURISDICTION_CODE','Latitude','Longitude'])
obj_df.head()
```

[30]:

	OFNS_DESC	LAW_CAT_CD	ARREST_BORO	AGE_GROUP	PERP_SEX	PERP_RACE
1	RAPE	F	B	25-44	M	WHITE HISPANIC
2	SEX CRIMES	M	Q	25-44	M	BLACK
3	SEX CRIMES	F	M	45-64	M	BLACK
6	ARSON	F	B	25-44	M	WHITE HISPANIC
7	FORGERY	F	Q	18-24	M	BLACK

[31]:
```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()

label_encoded_df = obj_df.copy()

for col in label_encoded_df.drop(axis=1, columns=['AGE_GROUP']).columns:
    if col != 'AGE_GROUP':
        label_encoded_df[col]=le.fit_transform(label_encoded_df[col])

label_encoded_df.replace({'AGE_GROUP': {'<18':0, '18-24':1, '25-44':2, '45-64':
↪3, '65+':4 }}, inplace=True)
label_encoded_df
```

[31]:

	OFNS_DESC	LAW_CAT_CD	ARREST_BORO	AGE_GROUP	PERP_SEX	PERP_RACE
1	34	0	0	2	1	6
2	36	2	3	2	1	2

```
3           36    0    2    3    1    2
6            2    0    0    2    1    6
7           13    0    3    1    1    2
…           …     …    …    …    …    …
1180        10    0    1    1    1    2
1181        32    0    2    2    1    6
1182         3    2    3    2    0    6
1183         8    2    1    1    0    2
1184        16    0    2    2    1    5

[1000 rows x 6 columns]
```

[32]:

```
#Standardizing OFNS_DESC Code so that it doesnot create undue clustering␣
↪because the other variales are in single digit number but offense␣
↪description has 50 hence, we standardize. So there is no added weightage.
label_encoded_df['OFNS_DESC'] = (label_encoded_df['OFNS_DESC'] -␣
↪label_encoded_df['OFNS_DESC'].mean()) / label_encoded_df['OFNS_DESC'].std()
df_std = label_encoded_df
df_std
```

[32]:

	OFNS_DESC	LAW_CAT_CD	ARREST_BORO	AGE_GROUP	PERP_SEX	PERP_RACE
1	1.077943	0	0	2	1	6
2	1.234020	2	3	2	1	2
3	1.234020	0	2	3	1	2
6	-1.419283	0	0	2	1	6
7	-0.560861	0	3	1	1	2
…	…	…	…	…	…	…
1180	-0.794976	0	1	1	1	2
1181	0.921866	0	2	2	1	6
1182	-1.341244	2	3	2	0	6
1183	-0.951053	2	1	1	0	2
1184	-0.326746	0	2	2	1	5

[1000 rows x 6 columns]

[33]:

```
g_matrix = df_std.to_numpy()
g_matrix
```

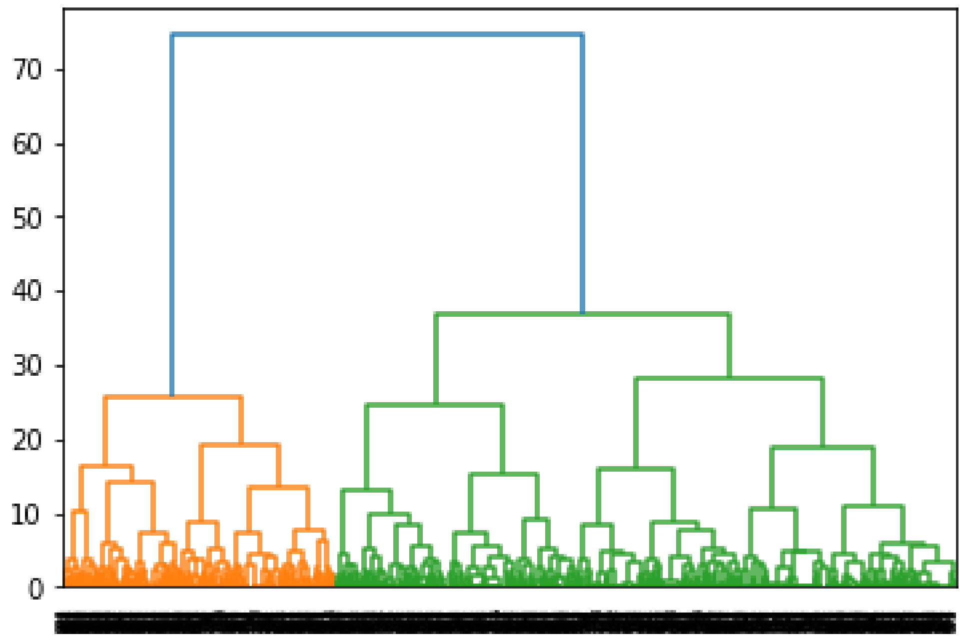
[33]:

```
array([[ 1.07794309,  0.        ,  0.        ,  2.        ,  1.        ,
         6.        ],
       [ 1.2340197 ,  2.        ,  3.        ,  2.        ,  1.        ,
         2.        ],
       [ 1.2340197 ,  0.        ,  2.        ,  3.        ,  1.        ,
         2.        ],
       …,
       [-1.34124433,  2.        ,  3.        ,  2.        ,  0.        ,
         6.        ],
```

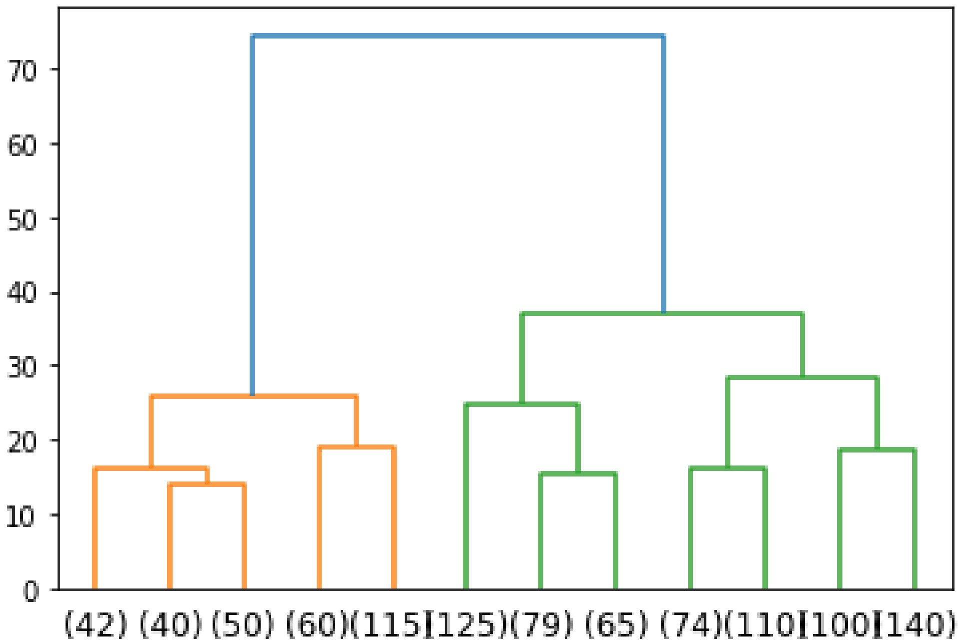
```
       [-0.95105281,  2.        ,  1.        ,  1.        ,  0.        ,
         2.        ],
       [-0.32674638,  0.        ,  2.        ,  2.        ,  1.        ,
         5.        ]])
```

[34]:
```python
from collections import defaultdict
from scipy.spatial.distance import pdist, squareform
from scipy.cluster.hierarchy import linkage, dendrogram
from matplotlib.colors import rgb2hex, colorConverter
from scipy.cluster.hierarchy import set_link_color_palette
```

[35]:
```python
import scipy.cluster.hierarchy as sch
from sklearn.cluster import AgglomerativeClustering
dendrogram = sch.dendrogram(sch.linkage(g_matrix, method = 'ward'))
```



[36]:
```python
# Unable to read above dendogram. See hierarchial clustering for last 12␣
↪clusters
dendrogram1 = sch.dendrogram(sch.linkage(g_matrix, method = 'ward'),␣
↪truncate_mode = 'lastp', p=12)
```



[37]:
```
from sklearn.cluster import AgglomerativeClustering
cluster_model = AgglomerativeClustering(n_clusters = 3, affinity = 'euclidean',␣
 ↪linkage = 'ward')
```

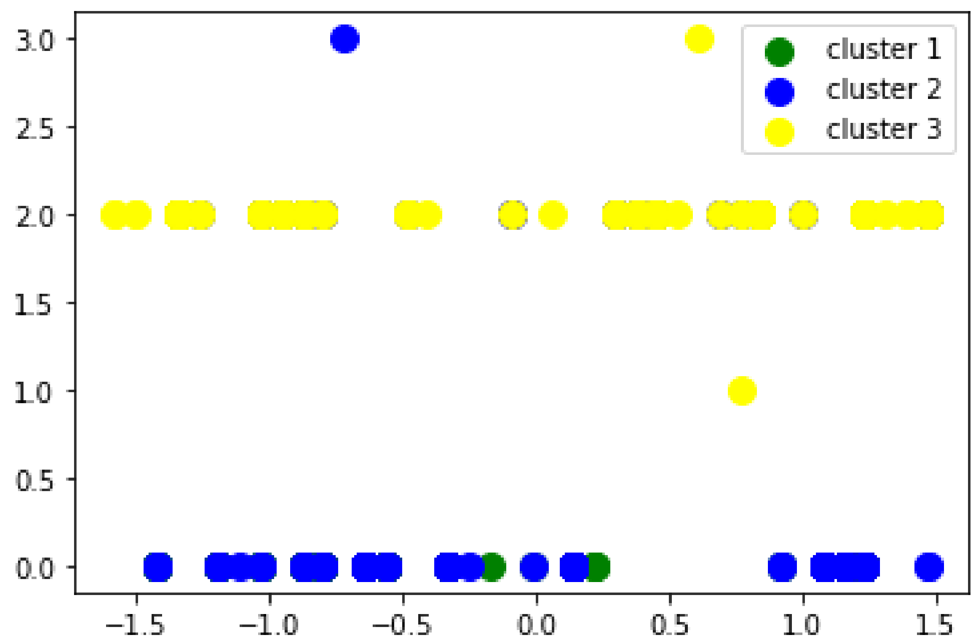
[38]:
```
y_hc = cluster_model.fit_predict(g_matrix)
y_hc
```

[38]:
```
array([1, 2, 0, 1, 0, 2, 0, 2, 0, 1, 2, 0, 0, 0, 2, 2, 2, 2, 0, 2, 0, 1,
       1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 2, 1, 1, 0, 0, 0,
       1, 0, 0, 1, 1, 0, 0, 0, 2, 1, 1, 0, 0, 0, 1, 1, 2, 0, 1, 0, 1, 1,
       0, 0, 2, 0, 0, 0, 0, 2, 0, 0, 2, 0, 0, 1, 1, 2, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 0, 1, 2, 0, 2, 0, 0, 2, 0, 1, 1, 0, 0, 0, 1, 2, 0, 1, 0,
       2, 0, 1, 0, 0, 1, 2, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 2, 0, 0,
       0, 1, 2, 0, 2, 2, 1, 2, 0, 1, 0, 0, 1, 0, 0, 0, 2, 1, 1, 1, 0, 0,
       1, 2, 1, 1, 0, 2, 2, 2, 0, 2, 2, 1, 0, 1, 1, 0, 1, 0, 0, 1, 2, 0,
       0, 0, 0, 0, 0, 0, 1, 2, 0, 1, 2, 0, 2, 0, 0, 0, 0, 0, 2, 0, 1, 0,
       0, 2, 0, 1, 0, 0, 1, 0, 2, 0, 2, 0, 0, 0, 0, 1, 2, 1, 2, 0, 1, 0,
       2, 0, 0, 1, 1, 0, 1, 1, 0, 2, 2, 0, 0, 0, 0, 0, 0, 0, 1, 0, 2, 0,
       2, 2, 1, 2, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 2, 2, 0, 2, 0, 1, 0,
       0, 0, 0, 0, 0, 2, 0, 0, 1, 1, 0, 0, 0, 1, 2, 0, 0, 2, 0, 1, 2, 1,
       0, 1, 1, 2, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 2, 0, 0,
       0, 0, 1, 0, 0, 1, 2, 1, 0, 0, 0, 0, 1, 2, 0, 2, 1, 0, 1, 2, 0, 0,
       0, 0, 2, 0, 2, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       2, 1, 1, 0, 1, 0, 2, 0, 0, 2, 2, 1, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0,
       0, 2, 2, 2, 0, 2, 2, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 2, 0, 0, 1, 1,
```

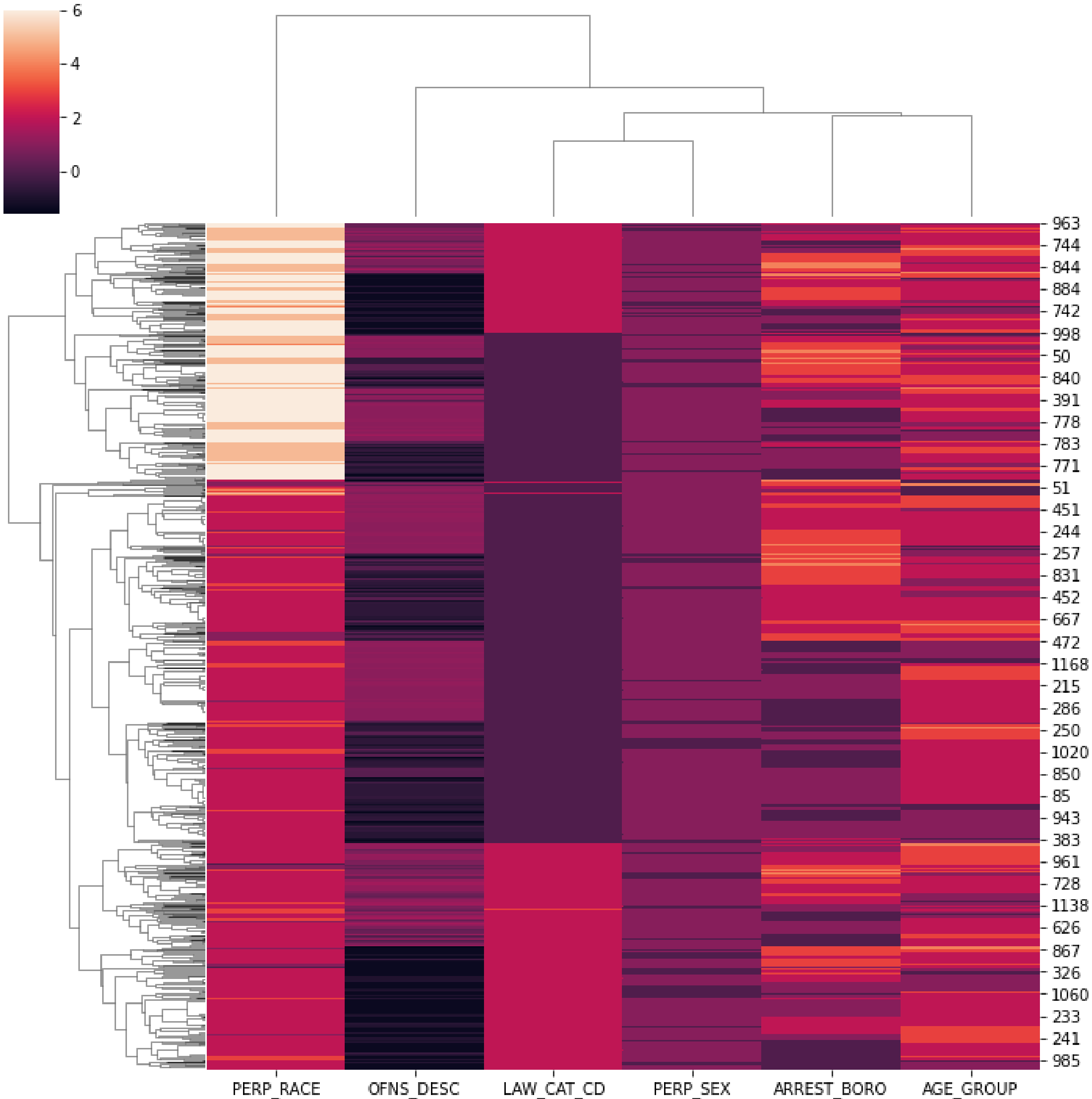
```
       0, 2, 1, 0, 0, 1, 1, 0, 2, 2, 0, 0, 1, 2, 1, 0, 1, 1, 0, 2, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1,
       1, 0, 1, 0, 0, 2, 2, 0, 2, 2, 1, 0, 2, 0, 0, 2, 1, 0, 0, 2, 1, 2,
       0, 2, 2, 2, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 2, 1, 2, 2, 1, 1,
       1, 0, 2, 2, 0, 0, 1, 1, 2, 2, 2, 1, 0, 2, 1, 2, 2, 1, 0, 0, 0, 0,
       2, 0, 2, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 2, 2, 2, 2, 1, 2, 0, 1, 2,
       2, 0, 0, 0, 2, 2, 2, 0, 1, 0, 2, 0, 0, 2, 1, 0, 0, 1, 0, 1, 2, 2,
       0, 2, 2, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 2, 0, 1, 1, 2, 1,
       0, 0, 2, 0, 1, 1, 1, 1, 2, 0, 0, 0, 2, 1, 2, 0, 2, 2, 1, 2, 2, 1,
       2, 2, 0, 1, 1, 2, 2, 1, 1, 2, 1, 2, 1, 1, 0, 1, 0, 1, 0, 1, 1, 2,
       0, 1, 2, 1, 1, 0, 0, 2, 2, 0, 0, 0, 2, 0, 2, 2, 0, 1, 2, 2, 2, 2,
       0, 0, 0, 1, 2, 2, 0, 2, 0, 0, 1, 0, 2, 0, 0, 0, 0, 1, 0, 1, 1, 1,
       0, 0, 1, 1, 2, 0, 0, 1, 0, 2, 2, 2, 2, 0, 0, 1, 2, 0, 1, 0, 1, 0,
       1, 0, 1, 2, 1, 1, 0, 0, 0, 0, 1, 2, 2, 2, 0, 1, 1, 0, 2, 0, 1, 0,
       0, 2, 0, 0, 1, 0, 1, 0, 0, 2, 0, 2, 2, 1, 1, 2, 0, 2, 0, 2, 1, 1,
       2, 2, 2, 0, 0, 0, 0, 1, 2, 0, 0, 2, 1, 1, 1, 2, 0, 0, 0, 1, 1, 1,
       2, 1, 1, 2, 1, 1, 0, 1, 0, 1, 2, 0, 1, 0, 2, 0, 0, 2, 0, 2, 0, 2,
       1, 0, 2, 2, 1, 2, 1, 1, 0, 2, 2, 1, 0, 2, 0, 0, 2, 0, 1, 2, 2, 2,
       1, 2, 1, 2, 0, 0, 2, 2, 1, 2, 2, 2, 1, 2, 2, 1, 1, 1, 2, 2, 2, 1,
       1, 1, 1, 2, 0, 2, 2, 2, 1, 1, 1, 0, 2, 2, 0, 2, 2, 0, 0, 2, 1, 2,
       1, 0, 0, 2, 2, 0, 1, 2, 0, 1, 1, 1, 2, 1, 2, 2, 1, 0, 1, 2, 0, 1,
       1, 2, 2, 2, 1, 1, 0, 2, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 2, 0,
       2, 1, 2, 2, 1, 0, 1, 2, 0, 1, 0, 2, 2, 0, 0, 0, 1, 2, 0, 1, 2, 2,
       2, 0, 0, 2, 1, 2, 0, 2, 2, 0, 1, 2, 1, 1, 1, 2, 1, 0, 1, 0, 1, 1,
       1, 0, 1, 0, 0, 0, 2, 2, 1, 2, 1, 1, 0, 2, 0, 1, 1, 2, 2, 0, 2, 1,
       2, 2, 2, 1, 1, 1, 2, 2, 2, 2, 1, 0, 1, 0, 0, 1, 1, 1, 1, 2, 2, 2,
       0, 0, 1, 1, 0, 1, 0, 0, 2, 1, 2, 1, 0, 0, 0, 0, 0, 0, 1, 2, 2, 1,
       1, 2, 2, 1, 0, 0, 1, 1, 2, 1], dtype=int64)
```

Visualize Clustering

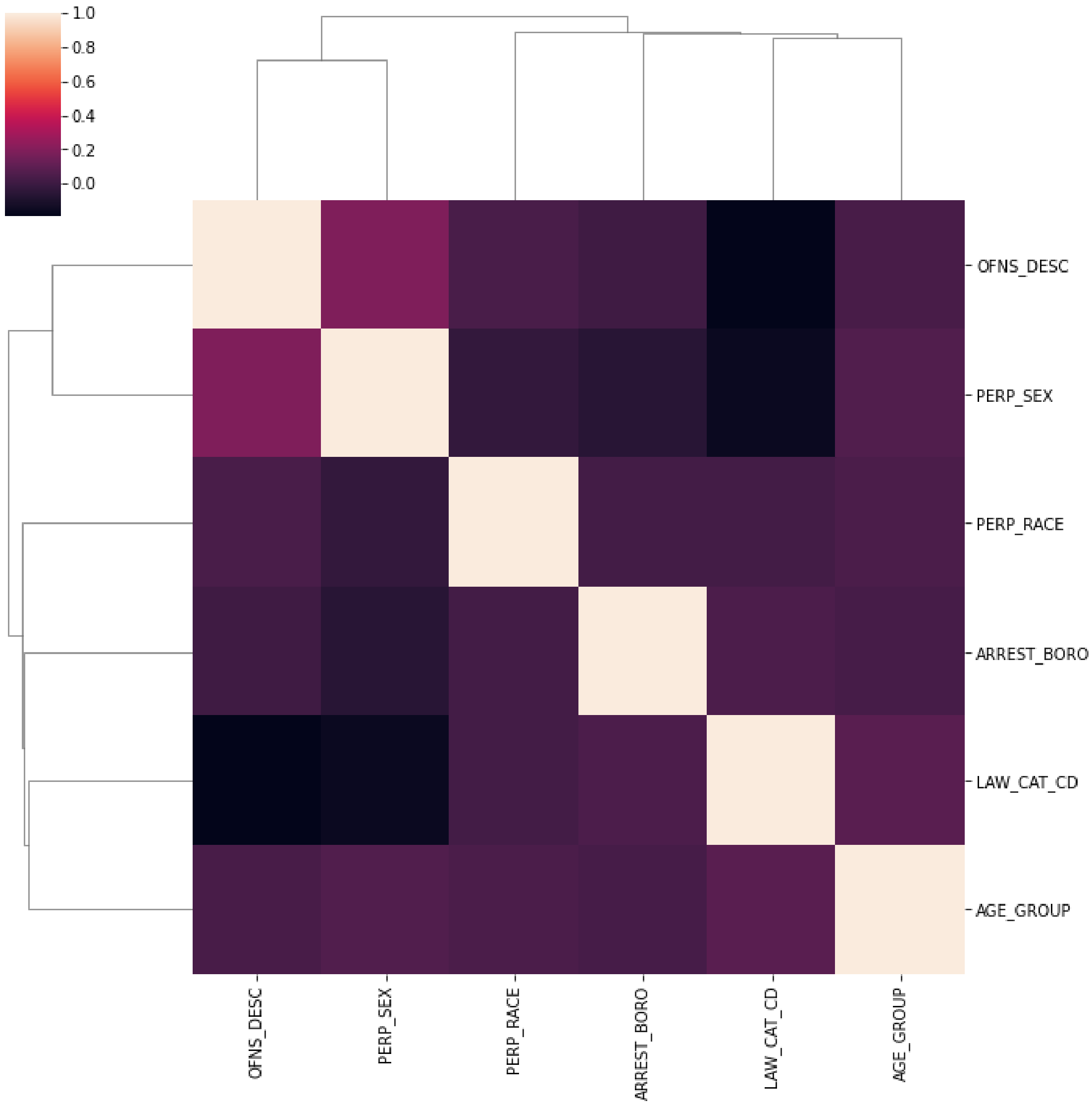
[39]:
```
plt.scatter(g_matrix[y_hc == 0,0], g_matrix[y_hc == 0,1], s = 100, c = 'green',␣
 ↪label = "cluster 1")
plt.scatter(g_matrix[y_hc == 1,0], g_matrix[y_hc == 1,1], s = 100, c = 'blue',␣
 ↪label = 'cluster 2')
plt.scatter(g_matrix[y_hc == 2,0], g_matrix[y_hc == 2,1], s = 100, c =␣
 ↪'yellow', label = 'cluster 3')
plt.legend()
plt.show()
```



[40]:
```
cg = sns.clustermap(df_std)
plt.show()
```



[41]:
```
cg = sns.clustermap(df_std.corr())
plt.show()
```



[42]:
```
df_std['pred'] = y_hc
df_std
```

[42]:

	OFNS_DESC	LAW_CAT_CD	ARREST_BORO	AGE_GROUP	PERP_SEX	PERP_RACE	pred
1	1.077943	0	0	2	1	6	1
2	1.234020	2	3	2	1	2	2
3	1.234020	0	2	3	1	2	0
6	-1.419283	0	0	2	1	6	1
7	-0.560861	0	3	1	1	2	0
…	…	…	…	…	…	…	…
1180	-0.794976	0	1	1	1	2	0
1181	0.921866	0	2	2	1	6	1
1182	-1.341244	2	3	2	0	6	1

```
1183  -0.951053          2            1          1          0          2      2
1184  -0.326746          0            2          2          1          5      1

[1000 rows x 7 columns]
```

[43]:
```python
df_hclust['pred'] = y_hc
df_hclust.drop(axis=1,  columns=['ARREST_KEY', 'ARREST_DATE',
                                'JURISDICTION_CODE','Latitude','Longitude'])
```

[43]:
```
                          OFNS_DESC LAW_CAT_CD ARREST_BORO AGE_GROUP PERP_SEX  \
1                              RAPE          F           B     25-44        M
2                        SEX CRIMES          M           Q     25-44        M
3                        SEX CRIMES          F           M     45-64        M
6                             ARSON          F           B     25-44        M
7                           FORGERY          F           Q     18-24        M
…                                 …        …          …         …       …
1180              DANGEROUS WEAPONS          F           K     18-24        M
1181  POSSESSION OF STOLEN PROPERTY          F           M     25-44        M
1182   ASSAULT 3 & RELATED OFFENSES          M           Q     25-44        F
1183              CRIMINAL TRESPASS          M           K     18-24        F
1184                  GRAND LARCENY          F           M     25-44        M

            PERP_RACE  pred
1      WHITE HISPANIC     1
2               BLACK     2
3               BLACK     0
6      WHITE HISPANIC     1
7               BLACK     0
…                   …   …
1180            BLACK     0
1181   WHITE HISPANIC     1
1182   WHITE HISPANIC     1
1183            BLACK     2
1184            WHITE     1

[1000 rows x 7 columns]
```

4 K-modes clustering (unsupervised)

[44]:
```python
#!pip install kmodes
from kmodes.kmodes import KModes #KModes Clustering Algorithm for Categorical␣
↪data similar
```

[45]:
```python
#!pip install plotnine
# Import module for data visualization
# Use the theme of ggplot
```

```
plt.style.use('ggplot')
```

[46]:
```
# Selecting only the categorical data columns
cols = df.select_dtypes('category').columns
df_cat = df[cols]

df_cat.head()
```

[46]:
```
     OFNS_DESC LAW_CAT_CD ARREST_BORO JURISDICTION_CODE AGE_GROUP PERP_SEX  \
1         RAPE          F           B                 0     25-44        M
2   SEX CRIMES          M           Q                 0     25-44        M
3   SEX CRIMES          F           M                 0     45-64        M
6        ARSON          F           B                72     25-44        M
7      FORGERY          F           Q                 0     18-24        M

         PERP_RACE
1   WHITE HISPANIC
2            BLACK
3            BLACK
6   WHITE HISPANIC
7            BLACK
```

[47]:
```
#more cleaning for kmode clustering
clean_df_cat2=df_cat.drop(["JURISDICTION_CODE"], axis = 1)
clean_df_cat2.head()
```

[47]:
```
     OFNS_DESC LAW_CAT_CD ARREST_BORO AGE_GROUP PERP_SEX       PERP_RACE
1         RAPE          F           B     25-44        M  WHITE HISPANIC
2   SEX CRIMES          M           Q     25-44        M           BLACK
3   SEX CRIMES          F           M     45-64        M           BLACK
6        ARSON          F           B     25-44        M  WHITE HISPANIC
7      FORGERY          F           Q     18-24        M           BLACK
```

[48]:
```
#converting dataframe to matrix
dfMatrix = clean_df_cat2.loc[:, clean_df_cat2.columns].to_numpy()
dfMatrix
```

[48]:
```
array([['RAPE', 'F', 'B', '25-44', 'M', 'WHITE HISPANIC'],
       ['SEX CRIMES', 'M', 'Q', '25-44', 'M', 'BLACK'],
       ['SEX CRIMES', 'F', 'M', '45-64', 'M', 'BLACK'],
       …,
       ['MISCELLANEOUS PENAL LAW', 'F', 'M', '25-44', 'M',
        'BLACK HISPANIC'],
       ['FELONY ASSAULT', 'F', 'B', '25-44', 'M', 'BLACK HISPANIC'],
       ['OFFENSES INVOLVING FRAUD', 'M', 'K', '25-44', 'M', 'BLACK']],
      dtype=object)
```

[49]:
```python
#choosing optimal K
cost = []
for cluster in range(1, 10):
    try:
        kmodes = KModes(n_jobs = -1, n_clusters = cluster, init = 'Huang',␣
↪random_state = 0, verbose=1)
        kmodes.fit_predict(dfMatrix)
        cost.append(kmodes.cost_)
        print('iteration #: {}'.format(cluster))
    except:
        break
```

```
Best run was number 1
iteration #: 1
Best run was number 1
iteration #: 2
Best run was number 4
iteration #: 3
Best run was number 2
iteration #: 4
Best run was number 4
iteration #: 5
Best run was number 4
iteration #: 6
Best run was number 2
iteration #: 7
Best run was number 5
iteration #: 8
Best run was number 8
iteration #: 9
```

[50]:
```python
#converting the results into a dataframe
df_cost = pd.DataFrame({'Cluster': range(1, 10), 'Cost': cost})
df_cost
```

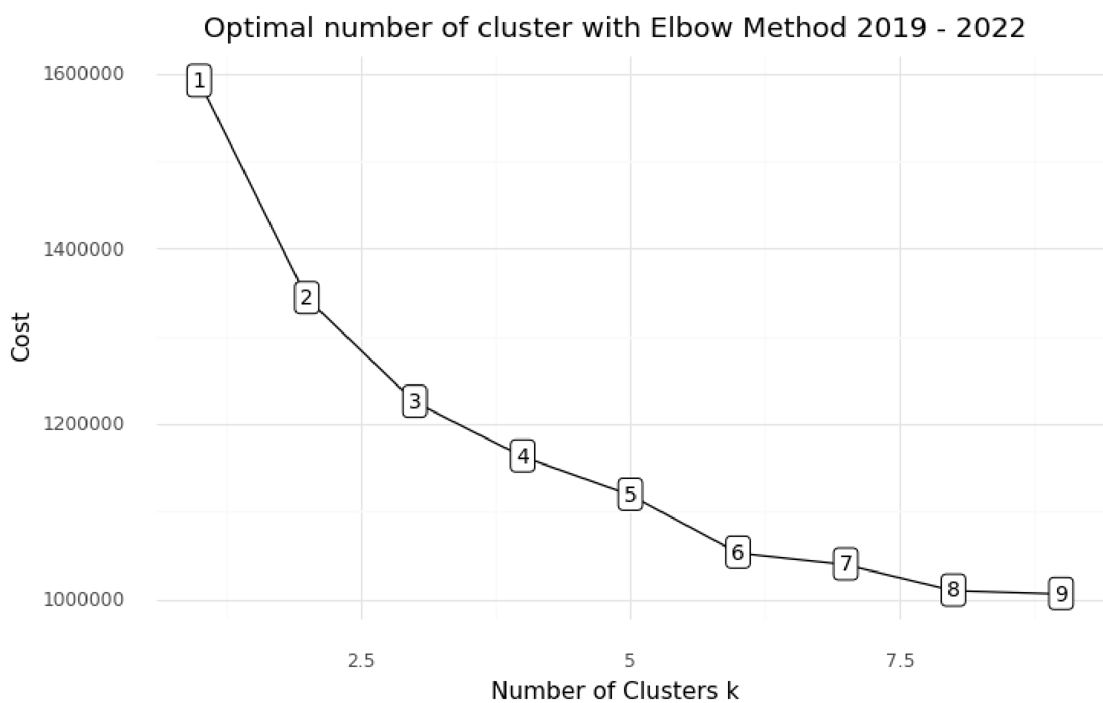
[50]:

	Cluster	Cost
0	1	1590700.0
1	2	1343437.0
2	3	1225104.0
3	4	1162981.0
4	5	1119123.0
5	6	1053027.0
6	7	1039768.0
7	8	1009956.0
8	9	1006103.0

[52]:
```python
import plotnine
```

[53]:

```
#plotting the cost versus the number of cluster or in this case iterations to␣
↪find the optimal k
#where the elbow like bend takes place is the optimal number of clusters
plotnine.options.figure_size = (8, 4.8)
(
    ggplot(data = df_cost)+
    geom_line(aes(x = 'Cluster',
                  y = 'Cost'))+
    geom_point(aes(x = 'Cluster',
                   y = 'Cost'))+
    geom_label(aes(x = 'Cluster',
                   y = 'Cost',
                   label = 'Cluster'),
               size = 10,
               nudge_y = 1000) +
    labs(title = 'Optimal number of cluster with Elbow Method 2019 - 2022')+
    xlab('Number of Clusters k')+
    ylab('Cost')+
    theme_minimal()
)
```



[53]: <ggplot: (154554695696)>

[54]:
```
#fiting the clusters
kmodes = KModes(n_jobs = -1, n_clusters = 3, init = 'Huang', random_state = 0)
kmodes.fit_predict(dfMatrix)
```

[54]:
```
array([0, 1, 0, …, 0, 0, 0], dtype=uint16)
```

[55]:
```
#clusters centroids
kmodes.cluster_centroids_
```

[55]:
```
array([['FELONY ASSAULT', 'F', 'K', '25-44', 'M', 'BLACK'],
       ['ASSAULT 3 & RELATED OFFENSES', 'M', 'M', '25-44', 'M', 'BLACK'],
       ['ASSAULT 3 & RELATED OFFENSES', 'M', 'B', '45-64', 'M',
        'WHITE HISPANIC']], dtype='<U28')
```

[56]:
```
#cost
kmodes.cost_
```

[56]:
```
1225104.0
```

[57]:
```
#adding the clusters to the dataframe
clean_df_cat2['Cluster Labels'] = kmodes.labels_
clean_df_cat2['Segment'] = clean_df_cat2['Cluster Labels'].map({0:'First', 1:
 ↪'Second', 2:'Third'})
clean_df_cat2.head()
```

[57]:
```
    OFNS_DESC LAW_CAT_CD ARREST_BORO AGE_GROUP PERP_SEX       PERP_RACE  \
1        RAPE          F           B     25-44        M  WHITE HISPANIC
2  SEX CRIMES          M           Q     25-44        M           BLACK
3  SEX CRIMES          F           M     45-64        M           BLACK
6       ARSON          F           B     25-44        M  WHITE HISPANIC
7     FORGERY          F           Q     18-24        M           BLACK

   Cluster Labels Segment
1               0   First
2               1  Second
3               0   First
6               0   First
7               0   First
```

[58]:
```
clean_df_cat2['Segment'] = clean_df_cat2['Segment'].astype('category')
clean_df_cat2['Segment'] = clean_df_cat2['Segment'].cat.
 ↪reorder_categories(['First', 'Second', 'Third'])
clean_df_cat2.head()
```

[58]:
```
    OFNS_DESC LAW_CAT_CD ARREST_BORO AGE_GROUP PERP_SEX       PERP_RACE  \
1        RAPE          F           B     25-44        M  WHITE HISPANIC
2  SEX CRIMES          M           Q     25-44        M           BLACK
3  SEX CRIMES          F           M     45-64        M           BLACK
```

```
6        ARSON            F            B     25-44          M  WHITE HISPANIC
7      FORGERY            F            Q     18-24          M           BLACK

   Cluster Labels Segment
1               0   First
2               1  Second
3               0   First
6               0   First
7               0   First
```

[59]:
```python
#columns for centroids
list_col = ['Cluster Labels', 'Segment']
cols = [col for col in clean_df_cat2 if col not in list_col]
cols
```

[59]:
```
['OFNS_DESC',
 'LAW_CAT_CD',
 'ARREST_BORO',
 'AGE_GROUP',
 'PERP_SEX',
 'PERP_RACE']
```

[60]:
```python
index = ['First Cluster', 'Second Cluster', 'Third Cluster']
pd.DataFrame(kmodes.cluster_centroids_, columns = cols, index = index)
```

[60]:
```
                                   OFNS_DESC LAW_CAT_CD ARREST_BORO AGE_GROUP  \
First Cluster                 FELONY ASSAULT          F           K     25-44
Second Cluster  ASSAULT 3 & RELATED OFFENSES          M           M     25-44
Third Cluster   ASSAULT 3 & RELATED OFFENSES          M           B     45-64

               PERP_SEX       PERP_RACE
First Cluster         M           BLACK
Second Cluster        M           BLACK
Third Cluster         M  WHITE HISPANIC
```

5 Supervised classification

Response variable is : LAW_CAT_CD

[14]:
```python
data = df.copy()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 505540 entries, 1 to 511440
Data columns (total 11 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   ARREST_KEY        505540 non-null  int64
```

```
 1   ARREST_DATE        505540 non-null  datetime64[ns]
 2   OFNS_DESC          505540 non-null  category
 3   LAW_CAT_CD         505540 non-null  category
 4   ARREST_BORO        505540 non-null  category
 5   JURISDICTION_CODE  505540 non-null  category
 6   AGE_GROUP          505540 non-null  category
 7   PERP_SEX           505540 non-null  category
 8   PERP_RACE          505540 non-null  category
 9   Latitude           505540 non-null  float64
 10  Longitude          505540 non-null  float64
dtypes: category(7), datetime64[ns](1), float64(2), int64(1)
memory usage: 22.7 MB
```

[15]:
```
data.drop(axis=1,
          columns=['ARREST_KEY', 'ARREST_DATE', 'JURISDICTION_CODE',␣
 ↪'OFNS_DESC'],
          inplace=True)
data.head()
```

[15]:
```
  LAW_CAT_CD ARREST_BORO AGE_GROUP PERP_SEX       PERP_RACE   Latitude  \
1          F           B     25-44        M  WHITE HISPANIC  40.816392
2          M           Q     25-44        M           BLACK  40.679700
3          F           M     45-64        M           BLACK  40.800694
6          F           B     25-44        M  WHITE HISPANIC  40.804013
7          F           Q     18-24        M           BLACK  40.691660

   Longitude
1 -73.895296
2 -73.776047
3 -73.941109
6 -73.878332
7 -73.779199
```

[16]:
```
mapper = {'25-44':2, '18-24':1, '45-64':3, '<18':0, '65+':4}
data['AGE_GROUP'] = data['AGE_GROUP'].replace(mapper)
df_encod = pd.get_dummies(data, columns=['ARREST_BORO', 'PERP_SEX',␣
 ↪'PERP_RACE'])
df_encod
```

[16]:
```
       LAW_CAT_CD  AGE_GROUP   Latitude  Longitude  ARREST_BORO_B  \
1               F          2  40.816392 -73.895296              1
2               M          2  40.679700 -73.776047              0
3               F          3  40.800694 -73.941109              0
6               F          2  40.804013 -73.878332              1
7               F          1  40.691660 -73.779199              0
…             …        …        …        …            …
511436          F          2  40.664416 -73.891022              0
```

```
511437         F         2  40.656619 -73.930903             0
511438         F         2  40.765397 -73.985702             0
511439         F         2  40.823387 -73.870170             1
511440         M         2  40.681443 -73.961427             0

        ARREST_BORO_K  ARREST_BORO_M  ARREST_BORO_Q  ARREST_BORO_S  \
1                   0              0              0              0
2                   0              0              1              0
3                   0              1              0              0
6                   0              0              0              0
7                   0              0              1              0
…                …            …            …            …
511436              1              0              0              0
511437              1              0              0              0
511438              0              1              0              0
511439              0              0              0              0
511440              1              0              0              0

        PERP_SEX_F  PERP_SEX_M  PERP_RACE_AMERICAN INDIAN/ALASKAN NATIVE  \
1                0           1                                         0
2                0           1                                         0
3                0           1                                         0
6                0           1                                         0
7                0           1                                         0
…             …         …                                       …
511436           0           1                                         0
511437           0           1                                         0
511438           0           1                                         0
511439           0           1                                         0
511440           0           1                                         0

        PERP_RACE_ASIAN / PACIFIC ISLANDER  PERP_RACE_BLACK  \
1                                        0                0
2                                        0                1
3                                        0                1
6                                        0                0
7                                        0                1
…                                     …             …
511436                                   0                0
511437                                   0                1
511438                                   0                0
511439                                   0                0
511440                                   0                1

        PERP_RACE_BLACK HISPANIC  PERP_RACE_UNKNOWN  PERP_RACE_WHITE  \
1                              0                  0                0
2                              0                  0                0
```

```
3                                0                  0                0
6                                0                  0                0
7                                0                  0                0
…                            …                …              …
511436                           0                  0                0
511437                           0                  0                0
511438                           1                  0                0
511439                           1                  0                0
511440                           0                  0                0

        PERP_RACE_WHITE HISPANIC
1                              1
2                              0
3                              0
6                              1
7                              0
…                            …
511436                         1
511437                         0
511438                         0
511439                         0
511440                         0

[505540 rows x 18 columns]
```

[17]:

```python
x = df_encod.drop(axis=1, columns=['LAW_CAT_CD'])
y = df_encod['LAW_CAT_CD']
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state =␣
 ↪42,test_size=0.20)

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(404432, 17)
(404432,)
(101108, 17)
(101108,)
```

[18]:

```python
x_train.head()
```

[18]:

```
        AGE_GROUP   Latitude  Longitude  ARREST_BORO_B  ARREST_BORO_K  \
132050          1  40.681065 -74.008554              0              1
373728          3  40.784507 -73.975483              0              0
359826          1  40.821805 -73.943457              0              0
298942          0  40.875530 -73.829056              1              0
10760           1  40.819886 -73.901227              1              0
```

```
        ARREST_BORO_M  ARREST_BORO_Q  ARREST_BORO_S  PERP_SEX_F  PERP_SEX_M  \
132050              0              0              0           0           1
373728              1              0              0           0           1
359826              1              0              0           0           1
298942              0              0              0           1           0
10760               0              0              0           0           1

        PERP_RACE_AMERICAN INDIAN/ALASKAN NATIVE  \
132050                                         0
373728                                         0
359826                                         0
298942                                         0
10760                                          0

        PERP_RACE_ASIAN / PACIFIC ISLANDER  PERP_RACE_BLACK  \
132050                                   0                1
373728                                   0                1
359826                                   0                1
298942                                   0                1
10760                                    0                0

        PERP_RACE_BLACK HISPANIC  PERP_RACE_UNKNOWN  PERP_RACE_WHITE  \
132050                         0                  0                0
373728                         0                  0                0
359826                         0                  0                0
298942                         0                  0                0
10760                          0                  0                0

        PERP_RACE_WHITE HISPANIC
132050                         0
373728                         0
359826                         0
298942                         0
10760                          1
```

[19]:
```
y_train.head()
```

[19]:
```
132050    M
373728    F
359826    M
298942    M
10760     M
Name: LAW_CAT_CD, dtype: category
Categories (4, object): ['F', 'I', 'M', 'V']
```

5.0.1 Logistic Regression

[20]:
```
lr = LogisticRegression(random_state = 42, max_iter=1000,␣
↪class_weight='balanced',multi_class='multinomial')
lr.fit(x_train, y_train)
y_pred = lr.predict(x_test)
y_pred
```

[20]:
```
array(['I', 'V', 'F', …, 'F', 'M', 'I'], dtype=object)
```

[21]:
```
print('classes: ',lr.classes_)
print('intercept :', lr.intercept_)
print('coefficient: ',lr.coef_)
```

```
classes:  ['F' 'I' 'M' 'V']
intercept : [ 0.01370863  0.01183857 -0.00787345 -0.01767375]
coefficient:  [[-0.18950425  1.13524135  0.62011192  0.03455245 -0.17210813
-0.28353393
  -0.21798852  0.65276355  0.01967705 -0.00599163  0.07743348  0.15978197
   0.30094706  0.19180631 -0.63236944 -0.14010704  0.05619308]
 [ 0.1298038   0.39183264  0.21842995 -0.44644961  0.11287673 -0.09474347
   0.29239881  0.14773132 -0.12095339  0.13276716 -0.18235701  0.1809181
  -0.34716991 -0.02819598  0.56474127 -0.15518496 -0.02093774]
 [ 0.03157321  0.9078124   0.49584804  0.2141628  -0.39260007 -0.22329104
  -0.20051133  0.5943852   0.16303121 -0.17088566  0.34974287  0.09334546
  -0.0178849  -0.0358473  -0.14668906 -0.19128461 -0.05923692]
 [ 0.02812723 -2.43488639 -1.3343899   0.19773436  0.45183148  0.60156844
   0.12610105 -1.39488006 -0.06175486  0.04411013 -0.24481933 -0.43404553
   0.06410775 -0.12776303  0.21431723  0.48657661  0.02398157]]
```

[22]:
```
cm =confusion_matrix(y_test,y_pred)
cm
```

[22]:
```
array([[10373, 10163,  9899, 13343],
       [   17,    63,    25,    69],
       [ 9714, 13773, 16392, 16537],
       [  103,   148,    64,   425]], dtype=int64)
```

[23]:
```
# Compute logistic regression model scores
lr_precision = precision_score(y_test,y_pred,average='weighted')
lr_recall = recall_score(y_test,y_pred,average='weighted')
lr_f1 = f1_score(y_test,y_pred,average='weighted')
```

[24]:
```
print("Logistic regression Scores")
print('----------------------------------')
print('Recall: {:.2f} '.format(lr_recall))
print('Precision: {:.2f}'.format(lr_precision))
print('F1 Score: {:.2f}'.format(lr_f1))
```

```python
print('Accuracy Score: {:.2f}'.format(accuracy_score(y_pred, y_test)))
```

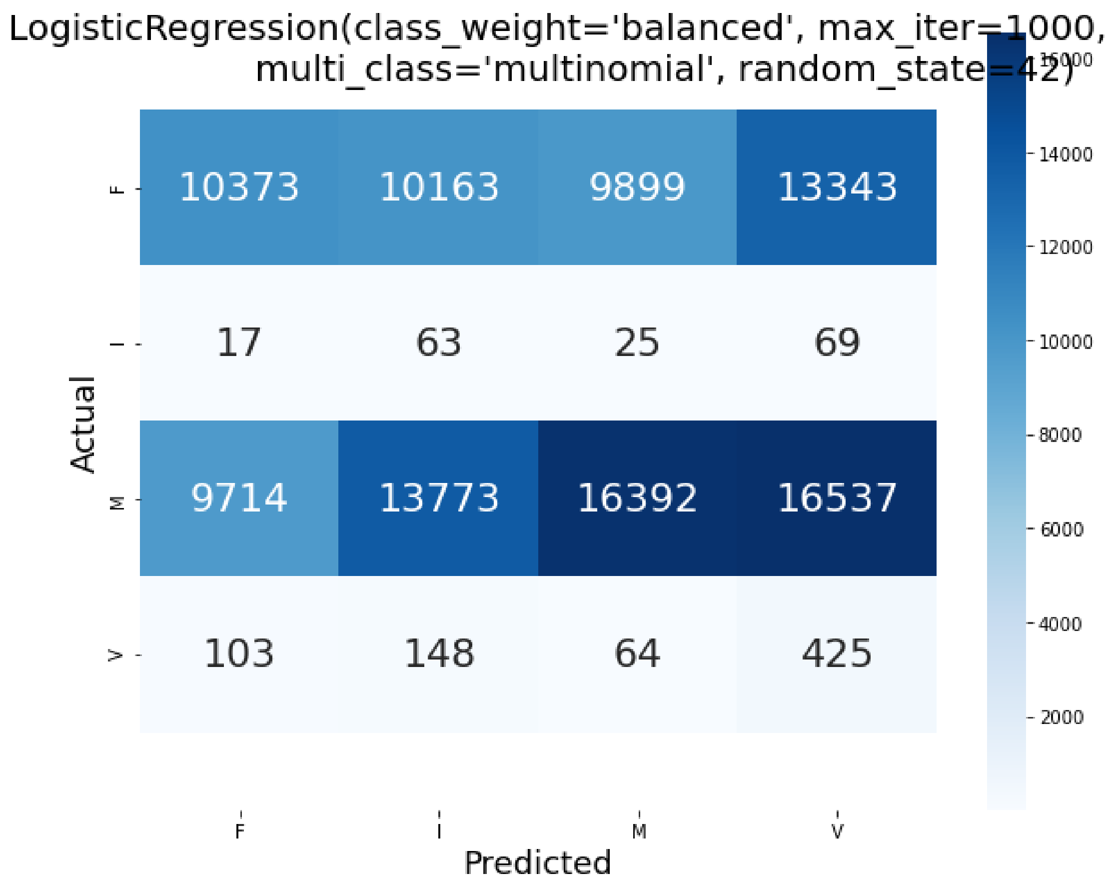
```
Logistic regression Scores
---------------------------------
Recall: 0.27
Precision: 0.57
F1 Score: 0.36
Accuracy Score: 0.27
```

[25]:

```python
#  Confusion Matrix
def plot_confusionmatrix(y_true, y_pred, cm, model_name):
    fig, ax = plt.subplots(figsize=(10, 8))
    ax = sns.heatmap(
      cm,
      annot=True,
      fmt="d",
      cmap="Blues",
      ax=ax,
      annot_kws={"size":22}
    )
    plt.ylabel('Actual', fontsize=18)
    plt.xlabel('Predicted', fontsize=18)
    ax.set_xticklabels(['F', 'I', 'M', 'V'])
    ax.set_yticklabels(['F', 'I', 'M', 'V'])
    plt.suptitle(model_name, fontsize=20, y=0.9, x=0.45)
    b, t = plt.ylim()
    b += 0.5
    t -= 0.5
    plt.ylim(b, t)
    plt.show()
```

[26]:

```python
plot_confusionmatrix(y_test, y_pred, cm, lr)
```

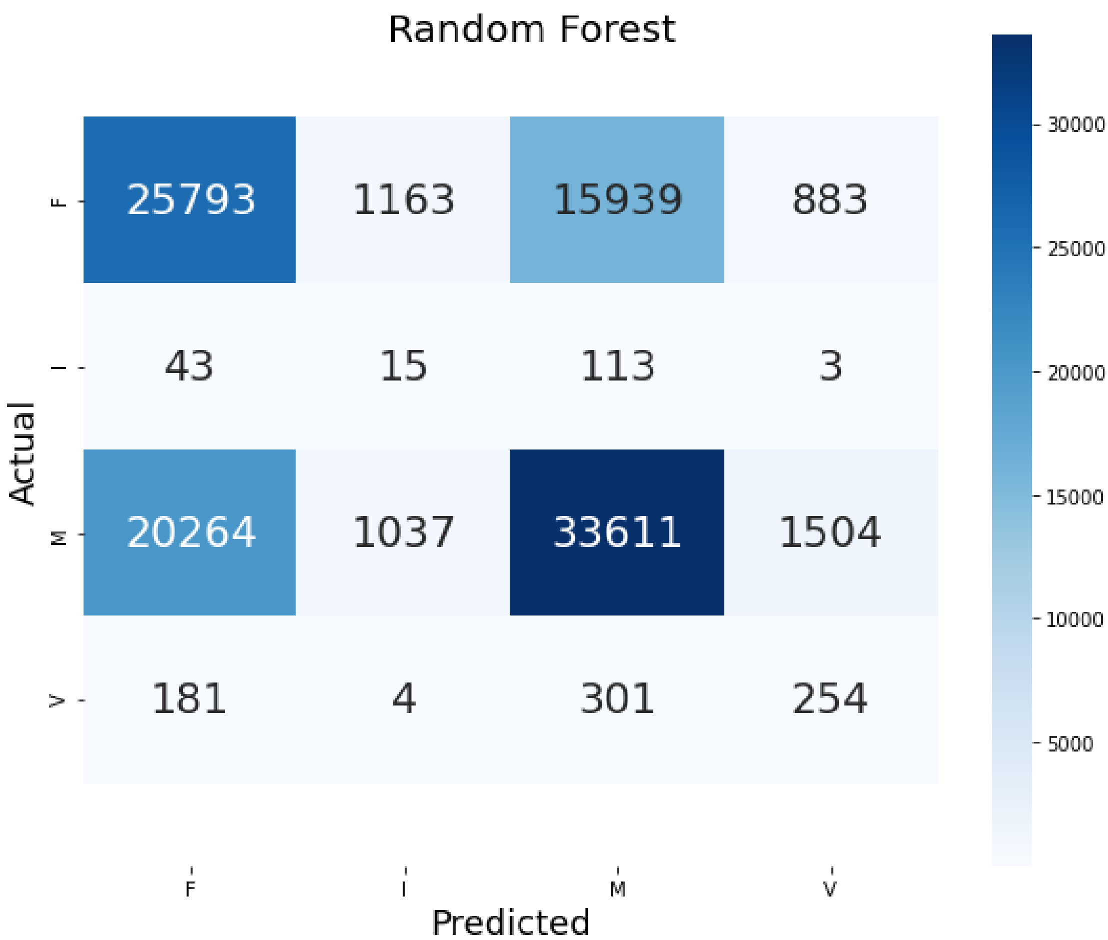


5.0.2 Random Forest

[27]:
```python
# The following code trains a DecisionTreeClassifier on the dataset
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

randomF_clf = RandomForestClassifier(n_estimators=100, random_state=42,␣
↪class_weight='balanced')
randomF_clf.fit(x_train, y_train)
```

[27]:
```
RandomForestClassifier(class_weight='balanced', random_state=42)
```

[28]:
```python
# Predicting classes
randomF_pred = randomF_clf.predict(x_test)
cm2 =confusion_matrix(y_test,randomF_pred)
plot_confusionmatrix(y_test, randomF_pred, cm2, "Random Forest")
```



[29]:
```
rf_precision = precision_score(y_test,randomF_pred,average='weighted')
rf_recall = recall_score(y_test,randomF_pred,average='weighted')
rf_f1 = f1_score(y_test, randomF_pred,average='weighted')
```

[30]:
```
print("Random Forest Scores")
print('---------------------------------')
print('Recall: {:.2f}'.format(rf_recall))
print('Precision: {:.2f} '.format(rf_precision))
print('F1 Score: {:.2f} '.format(rf_f1))
print('Accuracy Score: {:.2f}'.format(accuracy_score(randomF_pred, y_test)))
```

```
Random Forest Scores
---------------------------------
Recall: 0.59
Precision: 0.62
F1 Score: 0.60
Accuracy Score: 0.59
```

5.0.3 Bagging

[31]:
```
#Bagging
# Bagging
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from imblearn.ensemble import BalancedBaggingClassifier

bag_clf = BalancedBaggingClassifier(
    DecisionTreeClassifier(random_state=42, class_weight='balanced'),␣
 ↪n_estimators=500,
    max_samples=100, bootstrap=True, random_state=42 )
bag_clf.fit(x_train, y_train)
```

[31]:
```
BalancedBaggingClassifier(base_estimator=DecisionTreeClassifier(class_weight='ba
lanced',
random_state=42),
                          max_samples=100, n_estimators=500, random_state=42)
```

[32]:
```
bag_pred = bag_clf.predict(x_test)
```

[33]:
```
bag_precision = precision_score(y_test,bag_pred,average='weighted')
bag_recall = recall_score(y_test,bag_pred,average='weighted')
bag_f1 = f1_score(y_test,bag_pred,average='weighted')
```

[34]:
```
print("Bagging Scores")
print('----------------------------------')
print('Recall: {:.2f}'.format(bag_recall))
print('Precision: {:.2f} '.format(bag_precision))
print('F1 Score: {:.2f} '.format(bag_f1))
print('Accuracy Score: {:.2f}'.format(accuracy_score(bag_pred, y_test)))
```

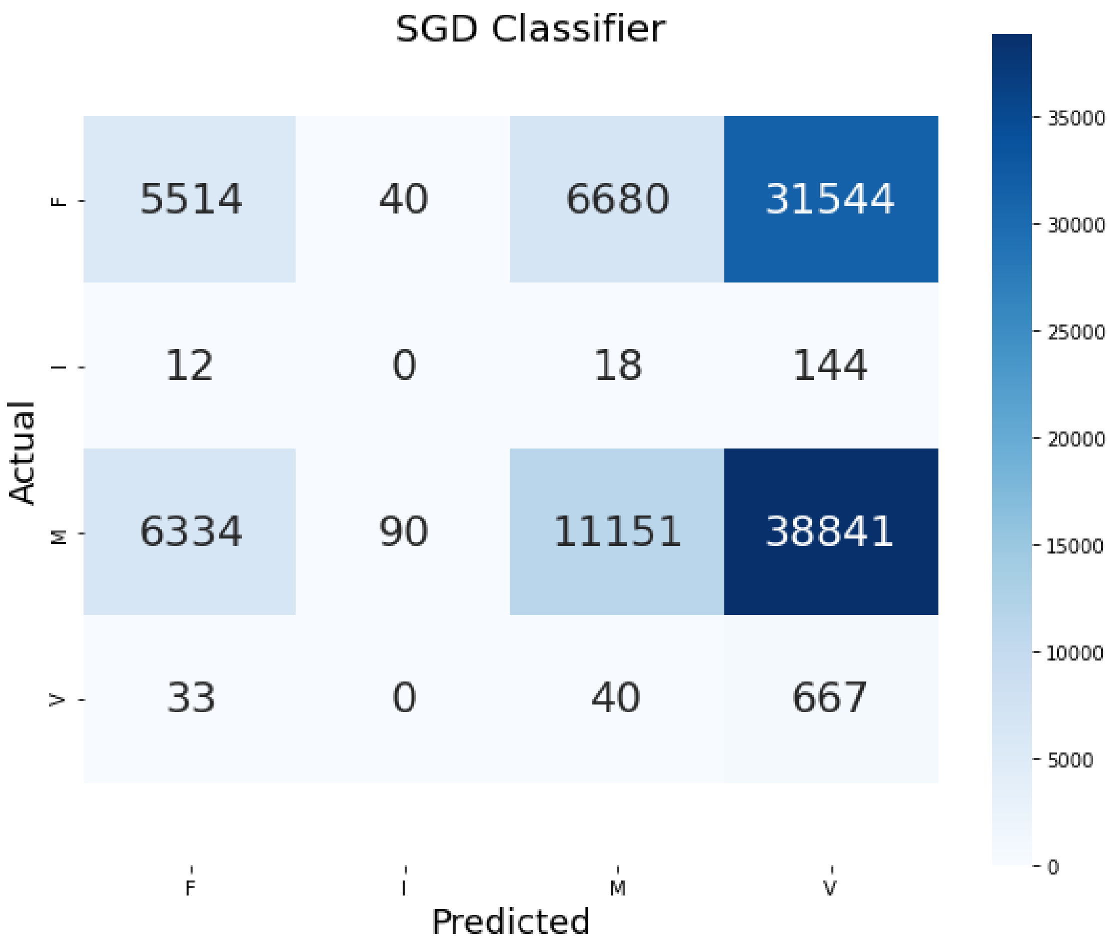
```
Bagging Scores
---------------------------------
Recall: 0.56
Precision: 0.56
F1 Score: 0.56
Accuracy Score: 0.56
```

5.0.4 SGD

[35]:
```
sgd_clf = SGDClassifier(max_iter=1000, random_state=42,class_weight='balanced')
sgd_clf.fit(x_train,y_train)
sgd_pred = sgd_clf.predict(x_test)
```

[36]:
```
sgd_precision = precision_score(y_test,sgd_pred,average='weighted')
sgd_recall = recall_score(y_test,sgd_pred,average='weighted')
sgd_f1 = f1_score(y_test,sgd_pred,average='weighted')
```

[37]:
```
cm4 =confusion_matrix(y_test,sgd_pred)
plot_confusionmatrix(y_test, sgd_pred, cm4, "SGD Classifier")
```



[38]:
```
print("SGD Scores")
print('---------------------------------')
print('Recall: {:.2f}'.format(sgd_recall))
print('Precision: {:.2f} '.format(sgd_precision))
print('F1 Score: {:.2f} '.format(sgd_f1))
print('Accuracy Score: {:.2f}'.format(accuracy_score(sgd_pred, y_test)))
```

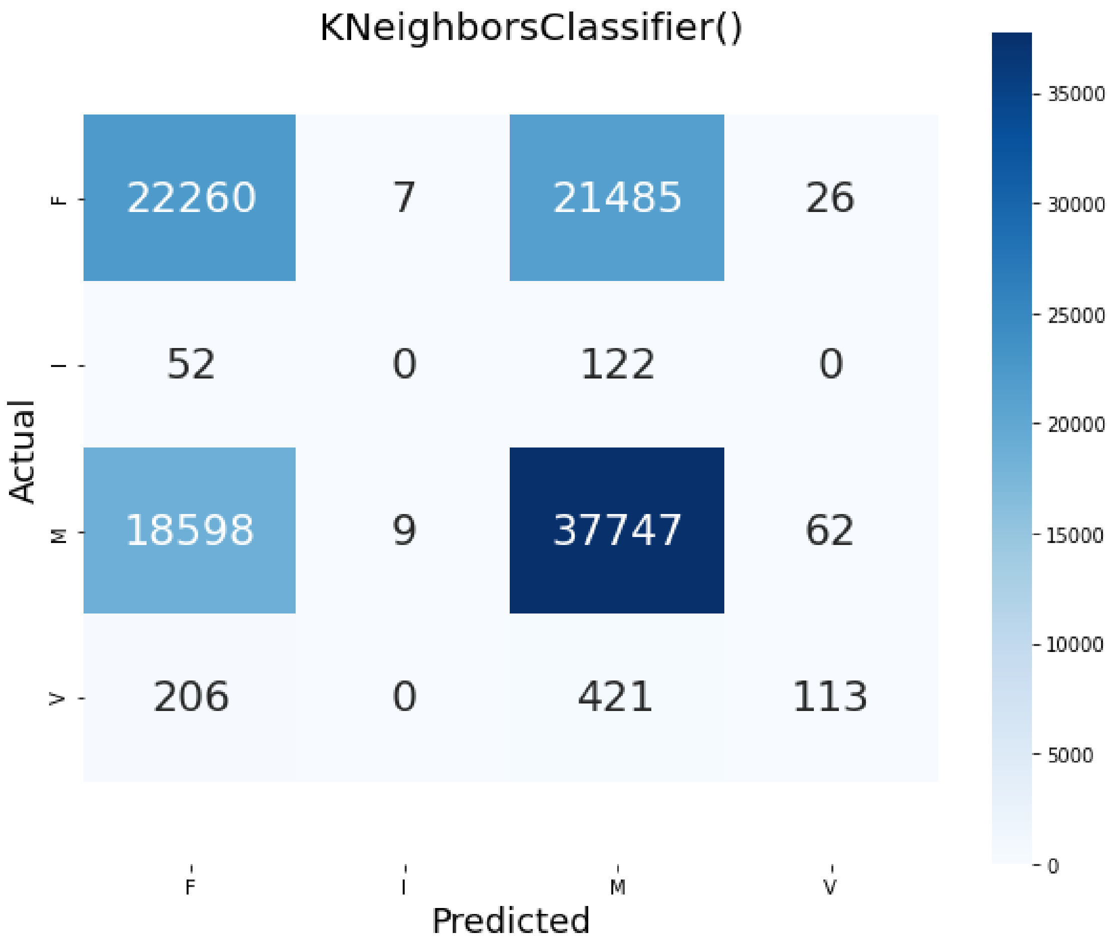
```
SGD Scores
---------------------------------
Recall: 0.17
Precision: 0.55
F1 Score: 0.25
Accuracy Score: 0.17
```

5.0.5 KNeighbors

[39]:
```
# pip install threadpoolctl==3.1.0
```

[40]:
```
kn_clf = KNeighborsClassifier()
kn_clf.fit(x_train,y_train)
kn_pred = kn_clf.predict(x_test)
```

[41]:
```
cm5 = confusion_matrix(y_test,kn_pred)
plot_confusionmatrix(y_test, kn_pred, cm5, kn_clf)
```



[42]:
```
kn_precision = precision_score(y_test,kn_pred,average='weighted')
kn_recall = recall_score(y_test,kn_pred,average='weighted')
kn_f1 = f1_score(y_test,kn_pred,average='weighted')
```

[43]:
```
print("KNeighbors Scores")
print('--------------------------------')
print('Recall: {:.2f}'.format(kn_recall))
```

```python
print('Precision: {:.2f} '.format(kn_precision))
print('F1 Score: {:.2f} '.format(kn_f1))
print('Accuracy Score: {:.2f}'.format(accuracy_score(kn_pred, y_test)))
```

```
KNeighbors Scores
---------------------------------
Recall: 0.59
Precision: 0.59
F1 Score: 0.59
Accuracy Score: 0.59
```

5.0.6 Soft Voting

[88]:
```python
voting_clf = VotingClassifier(
    estimators=[('lr', lr), ('rf', randomF_clf)],
    voting='soft') # Soft voting
voting_clf.fit(x_train, y_train)
```

[88]:
```
VotingClassifier(estimators=[('lr',
                              LogisticRegression(class_weight='balanced',
                                                 max_iter=1000,
                                                 multi_class='multinomial',
                                                 random_state=42)),
                             ('rf',
                              RandomForestClassifier(class_weight='balanced',
                                                     random_state=42))],
                 voting='soft')
```

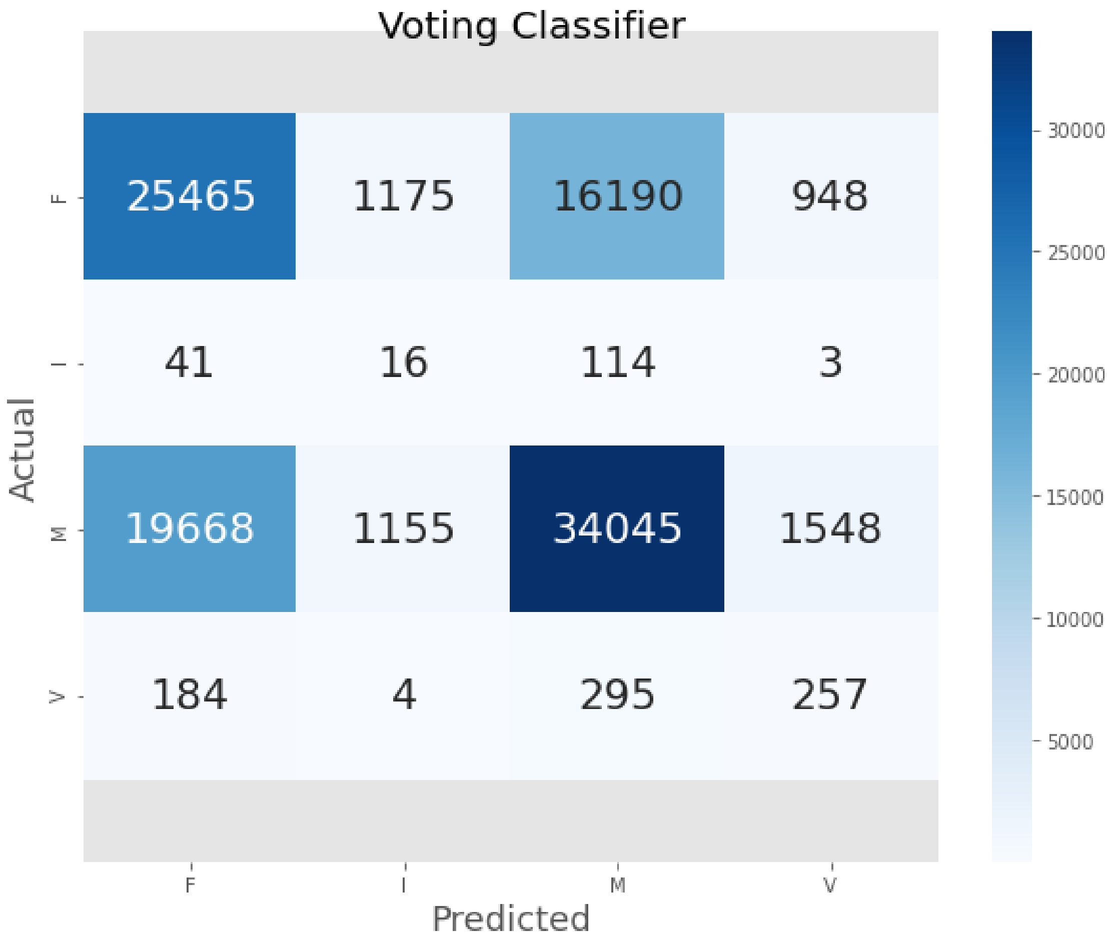
[89]:
```python
voting_pred = voting_clf.predict(x_test)
```

[90]:
```python
voting_precision = precision_score(y_test,voting_pred,average='weighted')
voting_recall = recall_score(y_test,voting_pred,average='weighted')
voting_f1 = f1_score(y_test,voting_pred,average='weighted')
```

[91]:
```python
print("Soft Voting Scores")
print('---------------------------------')
print('Recall: {:.2f}'.format(voting_recall))
print('Precision: {:.2f} '.format(voting_precision))
print('F1 Score: {:.2f} '.format(voting_f1))
print('Accuracy Score: {:.2f}'.format(accuracy_score(voting_pred, y_test)))
```

```
Soft Voting Scores
---------------------------------
Recall: 0.59
Precision: 0.62
F1 Score: 0.60
Accuracy Score: 0.59
```

[92]:
```
cm6 = confusion_matrix(y_test,voting_pred)
plot_confusionmatrix(y_test, voting_pred, cm6, "Voting Classifier")
```



5.0.7 Hard Voting

[96]:
```
hard_voting_clf = VotingClassifier(
    estimators=[('lr', lr), ('rf', randomF_clf)],
    voting='hard') # Soft voting
hard_voting_clf.fit(x_train, y_train)
```

[96]:
```
VotingClassifier(estimators=[('lr',
                              LogisticRegression(class_weight='balanced',
                                                 max_iter=1000,
                                                 multi_class='multinomial',
                                                 random_state=42)),
                             ('rf',
                              RandomForestClassifier(class_weight='balanced',
```

```
                                        random_state=42))])
```

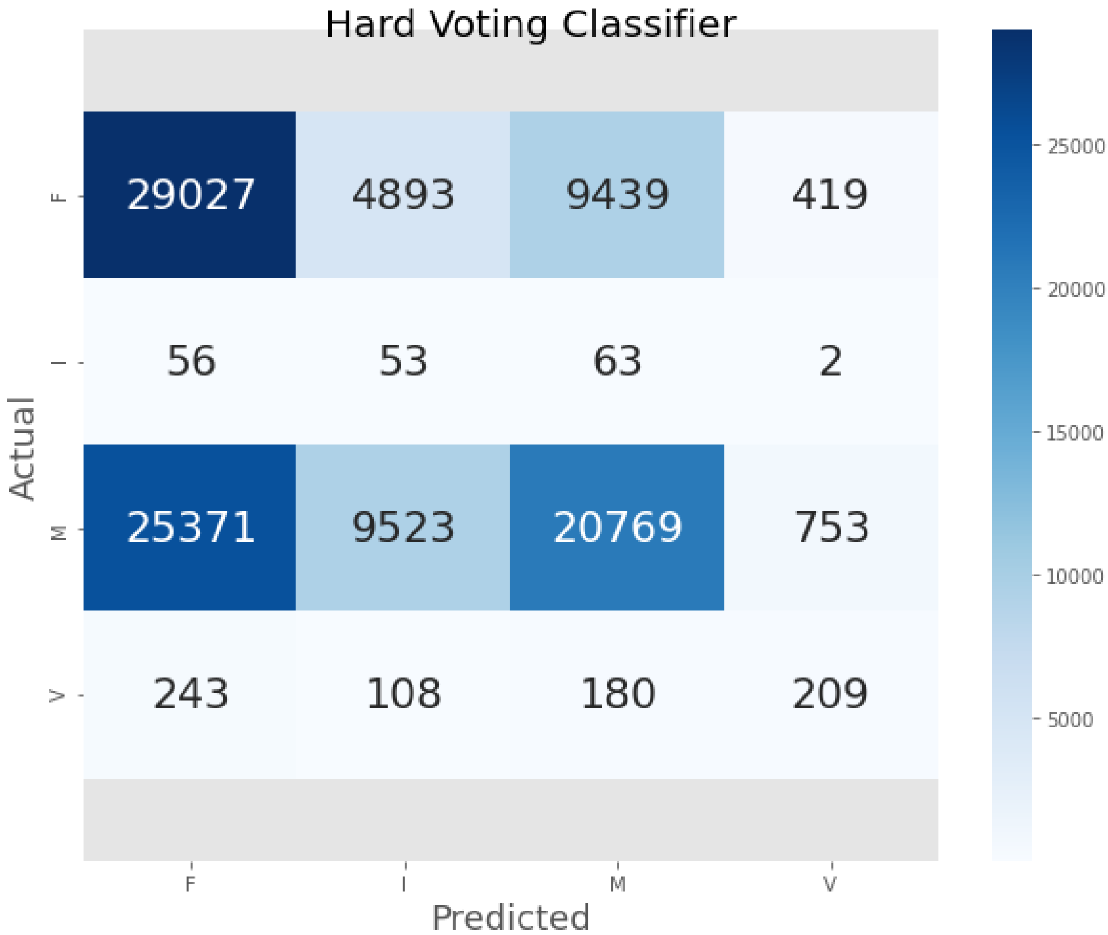
[97]:
```python
hard_voting_pred = hard_voting_clf.predict(x_test)
```

[98]:
```python
hard_voting_precision =␣
 ↪precision_score(y_test,hard_voting_pred,average='weighted')
hard_voting_recall = recall_score(y_test,hard_voting_pred,average='weighted')
hard_voting_f1 = f1_score(y_test,hard_voting_pred,average='weighted')
```

[99]:
```python
print("Hard Voting Scores")
print('---------------------------------')
print('Recall: {:.2f}'.format(hard_voting_recall))
print('Precision: {:.2f} '.format(hard_voting_precision))
print('F1 Score: {:.2f} '.format(hard_voting_f1))
print('Accuracy Score: {:.2f}'.format(accuracy_score(hard_voting_pred, y_test)))
```

```
Hard Voting Scores
---------------------------------
Recall: 0.50
Precision: 0.61
F1 Score: 0.52
Accuracy Score: 0.50
```

[100]:
```python
cm7 = confusion_matrix(y_test,hard_voting_pred)
plot_confusionmatrix(y_test, hard_voting_pred, cm7, "Hard Voting Classifier")
```



Hard Voting Classifier
29027
4893
9439
419
56
53
63
2
25371
9523
20769
753
243
108
180
209
F
I
M
V
Actual
Predicted
25000
20000
15000
10000
5000


```
[ ]:
```