Final_Project_Part5_State_Models

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1 File Information

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Course: DSC630 - Predictive Analytics

Assignment Number: Final Project Part 4

Purpose: Build model(s) for each state

Usage: Python 3.7.6

Developed using Jupter Notebook 6.0.3

2 Data Source

Uniform Crime Reporting Program Data: National Incident-Based Reporting System, [United States], 2016; United States Federal Bureau of Investigation; Inter-university Consortium for Political and Social Research (ICPSR), University of Michigan; https://www.icpsr.umich.edu/icpsrweb/NACJD/NIBRS/

Geodetic Data for US Cities: https://simplemaps.com/data/us-cities

3 Part 5

In Part 5, I will build separate models for the top 6 reporting states to predict the type of offenses committed, given location information.

3.1 Import required packages

[1]:
```
# Suppress Warnings
#import warnings
#warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
```

4 Prepare Data

[2]:
```
# Load data into dataframe
data_file = "Data\crime_offenses_top6.csv"    # Data from Top 6 States
df = pd.read_csv(data_file)
```

```
C:\Users\amomu\Anaconda3\lib\site-
packages\IPython\core\interactiveshell.py:3063: DtypeWarning: Columns
(7,11,14,15,16,17,18,19,41,42,44,46,51,52,53,54,56) have mixed types.Specify
dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

4.1 Eliminate features

[3]:
```
print(df.columns)
```

```
Index(['Unnamed: 0', 'X1', 'ORI', 'INC_NUM', 'VIC_INC_DATE', 'VICTIM_TYPE',
       'ACT_TYPE_OFFC', 'ASSG_TYPE_OFFC', 'AGE_OF_VICTIM', 'SEX_OF_VICTIM',
       'RACE_OF_VICTIM', 'ETHNIC_OF_VIC', 'VIC_RESIDENT', 'ASSAULT_CIRC1',
       'ASSAULT_CIRC2', 'JUST_HOM_CIRC', 'INJURY_TYPE1', 'INJURY_TYPE2',
       'INJURY_TYPE3', 'INJURY_TYPE4', 'INJURY_TYPE5', 'NUM_RECS_PER_VICTIM',
       'VIC_INC_YEAR', 'VIC_INC_MONTH', 'VIC_INC_DAY', 'VIC_INC_DOW',
       'NUM_STATE_CODE', 'CITY', 'STATE', 'POP_GROUP', 'CTRY_DIVISION',
       'CTRY_REGION', 'AGENCY_IND', 'CORE_CITY', 'FBI_OFFICE', 'JUDICIAL_DIST',
       'CURRENT_POP1', 'UCR_COUNTY_CD1', 'MSA_CD1', 'LAST_POP1',
       'FIPS_COUNTY1', 'city_ascii', 'state_name', 'county_fips',
       'county_name', 'county_fips_all', 'county_name_all', 'lat', 'lng',
       'population', 'density', 'source', 'military', 'incorporated',
       'timezone', 'ranking', 'zips', 'id', 'OFF_CODE'],
      dtype='object')
```

[4]:
```
# Remove irrelevant and redundant fields

# Drop unneeded columns
# KEEP STATE
df.drop(['X1','id', 'county_fips', 'county_fips_all', 'Unnamed: 0',
         'ORI', 'INC_NUM', 'NUM_RECS_PER_VICTIM', 'VIC_INC_DATE',␣
 ↪'VIC_INC_YEAR', 'VIC_INC_DAY',
         'ASSAULT_CIRC1', 'ASSAULT_CIRC2', 'JUST_HOM_CIRC',
         'INJURY_TYPE1', 'INJURY_TYPE2', 'INJURY_TYPE3',
         'INJURY_TYPE4', 'INJURY_TYPE5', 'NUM_RECS_PER_VICTIM', 'AGENCY_IND',
         'FBI_OFFICE', 'JUDICIAL_DIST', 'FIPS_COUNTY1',
         'LAST_POP1', 'UCR_COUNTY_CD1', 'MSA_CD1', 'city_ascii', 'CITY',
         'state_name', 'county_name', 'county_name_all', 'population', 'zips',
         'source'],
        axis=1, inplace = True)
```

```
# Also removing victim demograohics since they are not relevant to predict␣
↪offenses and locations
df.drop(['VICTIM_TYPE','RACE_OF_VICTIM', 'AGE_OF_VICTIM',
         'SEX_OF_VICTIM', 'ETHNIC_OF_VIC', 'VIC_RESIDENT'],
        axis=1, inplace = True)

# Verify Change
print(df.columns)
```

```
Index(['ACT_TYPE_OFFC', 'ASSG_TYPE_OFFC', 'VIC_INC_MONTH', 'VIC_INC_DOW',
       'NUM_STATE_CODE', 'STATE', 'POP_GROUP', 'CTRY_DIVISION', 'CTRY_REGION',
       'CORE_CITY', 'CURRENT_POP1', 'lat', 'lng', 'density', 'military',
       'incorporated', 'timezone', 'ranking', 'OFF_CODE'],
      dtype='object')
```

[5]:
```
# Replace NA values with NULL
df.replace('NA', np.nan)

# Remove Unknown Values with NULL
df.replace('U', np.nan)

# Drop columns with mostly NULL data
df.drop(['ACT_TYPE_OFFC','ASSG_TYPE_OFFC'],
        axis=1, inplace = True)

# Drop records with remaining null values
df.dropna(axis=0, inplace=True)
```

4.2 Encoding

[6]:
```
# Change DOW to numeric value
def f_dow(df):
    if df['VIC_INC_DOW'] == 'Sunday':
        val = 1
    elif df['VIC_INC_DOW'] == 'Monday':
        val = 2
    elif df['VIC_INC_DOW'] == 'Tuesday':
        val = 3
    elif df['VIC_INC_DOW'] == 'Wednesday':
        val = 4
    elif df['VIC_INC_DOW'] == 'Thursday':
        val = 5
    elif df['VIC_INC_DOW'] == 'Friday':
        val = 6
    elif df['VIC_INC_DOW'] == 'Saturday':
        val = 7
    else:
```

```
        val=0
    return val

# Change Timezone to numeric value
def f_tz(df):
    if df['timezone'] == 'America/New_York':
        val = 1
    elif df['timezone'] == 'America/Detroit':
        val = 2
    elif df['timezone'] == 'America/Chicago':
        val = 2
    elif df['timezone'] == 'America/Denver':
        val = 3
    elif df['timezone'] == 'America/Los_Angeles':
        val = 4
    else:
        val=0
    return val

def f_state(df):
    if df['STATE'] == 'TN':
        val = 1
    elif df['STATE'] == 'MI':
        val = 2
    elif df['STATE'] == 'SC':
        val = 3
    elif df['STATE'] == 'MA':
        val = 4
    elif df['STATE'] == 'OH':
        val = 5
    elif df['STATE'] == 'WA':
        val = 6
    else:
        val=0
    return val

# Convert simple categorical features to numeric to limit dummy features
df['VIC_INC_DOW'] = df.apply(f_dow, axis=1)
df['timezone'] = df.apply(f_tz, axis=1)
df['STATE'] = df.apply(f_state, axis=1)

df['CORE_CITY'] = df['CORE_CITY'].map({'Y': 1, 'N': 0})
df['military'] = df['military'].map({True: 1, False: 0})
df['incorporated'] = df['incorporated'].map({True: 1, False: 0})

# Change target feature to easily translated numeric values
def f_off(df):
```

```
    if df['OFF_CODE'] == '09A':
        val = 91
    elif df['OFF_CODE'] == '09B':
        val = 92
    elif df['OFF_CODE'] == '09C':
        val = 93
    elif df['OFF_CODE'] == '100':
        val = 100
    elif df['OFF_CODE'] == '11A':
        val = 111
    elif df['OFF_CODE'] == '11B':
        val = 112
    elif df['OFF_CODE'] == '11C':
        val = 113
    elif df['OFF_CODE'] == '11D':
        val = 114
    elif df['OFF_CODE'] == '120':
        val = 120
    elif df['OFF_CODE'] == '13A':
        val = 131
    elif df['OFF_CODE'] == '13B':
        val = 132
    elif df['OFF_CODE'] == '13C':
        val = 133
    elif df['OFF_CODE'] == '200':
        val = 200
    elif df['OFF_CODE'] == '210':
        val = 210
    elif df['OFF_CODE'] == '220':
        val = 220
    elif df['OFF_CODE'] == '23A':
        val = 231
    elif df['OFF_CODE'] == '23B':
        val = 232
    elif df['OFF_CODE'] == '23C':
        val = 233
    elif df['OFF_CODE'] == '23D':
        val = 234
    elif df['OFF_CODE'] == '23E':
        val = 235
    elif df['OFF_CODE'] == '23F':
        val = 236
    elif df['OFF_CODE'] == '23G':
        val = 237
    elif df['OFF_CODE'] == '23H':
        val = 238
    elif df['OFF_CODE'] == '240':
```

```
        val = 240
    elif df['OFF_CODE'] == '250':
        val = 250
    elif df['OFF_CODE'] == '26A':
        val = 261
    elif df['OFF_CODE'] == '26B':
        val = 262
    elif df['OFF_CODE'] == '26C':
        val = 263
    elif df['OFF_CODE'] == '26D':
        val = 264
    elif df['OFF_CODE'] == '26E':
        val = 265
    elif df['OFF_CODE'] == '26F':
        val = 266
    elif df['OFF_CODE'] == '26G':
        val = 267
    elif df['OFF_CODE'] == '270':
        val = 270
    elif df['OFF_CODE'] == '280':
        val = 280
    elif df['OFF_CODE'] == '290':
        val = 290
    elif df['OFF_CODE'] == '35A':
        val = 351
    elif df['OFF_CODE'] == '35B':
        val = 352
    elif df['OFF_CODE'] == '36A':
        val = 361
    elif df['OFF_CODE'] == '36B':
        val = 362
    elif df['OFF_CODE'] == '370':
        val = 370
    elif df['OFF_CODE'] == '39A':
        val = 391
    elif df['OFF_CODE'] == '39B':
        val = 392
    elif df['OFF_CODE'] == '39C':
        val = 393
    elif df['OFF_CODE'] == '39D':
        val = 394
    elif df['OFF_CODE'] == '40A':
        val = 401
    elif df['OFF_CODE'] == '40B':
        val = 402
    elif df['OFF_CODE'] == '40C':
        val = 403
```

```python
    elif df['OFF_CODE'] == '510':
        val = 510
    elif df['OFF_CODE'] == '520':
        val = 520
    elif df['OFF_CODE'] == '64A':
        val = 641
    elif df['OFF_CODE'] == '64B':
        val = 642
    elif df['OFF_CODE'] == '720':
        val = 720
    else:
        val=0
    return val
df['OFF_CODE'] = df.apply(f_off, axis=1)

# Convert population group to easily translated numeric values
def f_pop(df):
    if df['POP_GROUP'] == '1A':
        val = 11
    elif df['POP_GROUP'] == '1B':
        val = 12
    elif df['POP_GROUP'] == '1C':
        val = 13
    elif df['POP_GROUP'] == '8A':
        val = 81
    elif df['POP_GROUP'] == '8B':
        val = 82
    elif df['POP_GROUP'] == '8C':
        val = 83
    elif df['POP_GROUP'] == '8D':
        val = 84
    elif df['POP_GROUP'] == '8E':
        val = 85
    elif df['POP_GROUP'] == '9A':
        val = 91
    elif df['POP_GROUP'] == '9B':
        val = 92
    elif df['POP_GROUP'] == '9C':
        val = 93
    elif df['POP_GROUP'] == '9D':
        val = 94
    elif df['POP_GROUP'] == '9E':
        val = 95
    else:
        val=df['POP_GROUP']
    return val
df['POP_GROUP'] = df.apply(f_pop, axis=1)
```

4.3 Determine Target Variable

Use offense code as the target variable. The goal is to be able to predict offense code based on varying features.

4.4 Split Datasets

[7]:
```
# Separate datasets by state
tn_df = df[df['STATE'] == 1]
mi_df = df[df['STATE'] == 2]
sc_df = df[df['STATE'] == 3]
ma_df = df[df['STATE'] == 4]
oh_df = df[df['STATE'] == 5]
wa_df = df[df['STATE'] == 6]
```

[8]:
```
# Split data into two sets: Training and Testing.

# Split out target variable
tn_data_model_y = tn_df.OFF_CODE
mi_data_model_y = mi_df.OFF_CODE
sc_data_model_y = sc_df.OFF_CODE
ma_data_model_y = ma_df.OFF_CODE
oh_data_model_y = oh_df.OFF_CODE
wa_data_model_y = wa_df.OFF_CODE

# Remove target variable from feature list
tn_data_model_X = tn_df.drop(['OFF_CODE'], axis=1, inplace = False)
mi_data_model_X = mi_df.drop(['OFF_CODE'], axis=1, inplace = False)
sc_data_model_X = sc_df.drop(['OFF_CODE'], axis=1, inplace = False)
ma_data_model_X = ma_df.drop(['OFF_CODE'], axis=1, inplace = False)
oh_data_model_X = oh_df.drop(['OFF_CODE'], axis=1, inplace = False)
wa_data_model_X = wa_df.drop(['OFF_CODE'], axis=1, inplace = False)

# Split the data into training and validation datasets
# Save 30% for validation
tn_X_train, tn_X_val, tn_y_train, tn_y_val = train_test_split(tn_data_model_X, tn_data_model_y, test_size =0.3, random_state=7)
mi_X_train, mi_X_val, mi_y_train, mi_y_val = train_test_split(mi_data_model_X, mi_data_model_y, test_size =0.3, random_state=7)
sc_X_train, sc_X_val, sc_y_train, sc_y_val = train_test_split(sc_data_model_X, sc_data_model_y, test_size =0.3, random_state=7)
ma_X_train, ma_X_val, ma_y_train, ma_y_val = train_test_split(ma_data_model_X, ma_data_model_y, test_size =0.3, random_state=7)
oh_X_train, oh_X_val, oh_y_train, oh_y_val = train_test_split(oh_data_model_X, oh_data_model_y, test_size =0.3, random_state=7)
wa_X_train, wa_X_val, wa_y_train, wa_y_val = train_test_split(wa_data_model_X, wa_data_model_y, test_size =0.3, random_state=7)
```

5 Model Evaluation and Selection

5.1 Random Forest Classifer

5.1.1 Build Model

[15]:
```
# Optimized Hyperparameters for each state
#TN:  {'max_depth': 18, 'n_estimators': 445}
#MI:  {'max_depth': 16, 'n_estimators': 186}
#SC:  {'max_depth': 17, 'n_estimators': 284}
#MA:  {'max_depth': 17, 'n_estimators': 293}
#OH:  {'max_depth': 17, 'n_estimators': 284}
#WA:  {'max_depth': 18, 'n_estimators': 484}

# Create random forest classifer object
from sklearn.ensemble import RandomForestClassifier
tn_rf_model = RandomForestClassifier(random_state=0, n_estimators=445,␣
↪n_jobs=-1, max_depth=18, bootstrap=False)
mi_rf_model = RandomForestClassifier(random_state=0, n_estimators=186,␣
↪n_jobs=-1, max_depth=16, bootstrap=False)
sc_rf_model = RandomForestClassifier(random_state=0, n_estimators=284,␣
↪n_jobs=-1, max_depth=17, bootstrap=False)
ma_rf_model = RandomForestClassifier(random_state=0, n_estimators=293,␣
↪n_jobs=-1, max_depth=17, bootstrap=False)
oh_rf_model = RandomForestClassifier(random_state=0, n_estimators=284,␣
↪n_jobs=-1, max_depth=17, bootstrap=False)
wa_rf_model = RandomForestClassifier(random_state=0, n_estimators=484,␣
↪n_jobs=-1, max_depth=18, bootstrap=False)

# Train model
tn_forest = tn_rf_model.fit(tn_X_train, tn_y_train)
mi_forest = mi_rf_model.fit(mi_X_train, mi_y_train)
sc_forest = sc_rf_model.fit(sc_X_train, sc_y_train)
ma_forest = ma_rf_model.fit(ma_X_train, ma_y_train)
oh_forest = oh_rf_model.fit(oh_X_train, oh_y_train)
wa_forest = wa_rf_model.fit(wa_X_train, wa_y_train)
```

5.1.2 Model Evaluation

[16]:
```
# Predict values
tn_y_pred_forest = tn_forest.predict(tn_X_val)
mi_y_pred_forest = mi_forest.predict(mi_X_val)
sc_y_pred_forest = sc_forest.predict(sc_X_val)
ma_y_pred_forest = ma_forest.predict(ma_X_val)
oh_y_pred_forest = oh_forest.predict(oh_X_val)
wa_y_pred_forest = wa_forest.predict(wa_X_val)
```

[17]:
```python
# Create classification report
print(classification_report(tn_y_val, tn_y_pred_forest))
print(classification_report(mi_y_val, mi_y_pred_forest))
print(classification_report(sc_y_val, sc_y_pred_forest))
print(classification_report(ma_y_val, ma_y_pred_forest))
print(classification_report(oh_y_val, oh_y_pred_forest))
print(classification_report(wa_y_val, wa_y_pred_forest))
```

```
C:\Users\amomu\Anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1272: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
              precision    recall  f1-score   support

          91       0.00      0.00      0.00        52
          92       0.00      0.00      0.00         2
          93       0.00      0.00      0.00         6
         100       0.22      0.05      0.08       323
         111       0.18      0.01      0.03       267
         112       0.86      0.79      0.82       154
         113       0.00      0.00      0.00        28
         114       0.48      0.11      0.18       366
         120       0.25      0.23      0.24      2027
         131       0.31      0.38      0.34      6936
         132       0.22      0.54      0.31     14417
         133       0.22      0.31      0.26      4151
         200       0.12      0.11      0.12       151
         210       0.00      0.00      0.00        48
         220       0.23      0.21      0.22      6810
         231       0.00      0.00      0.00        46
         232       0.00      0.00      0.00        28
         233       0.17      0.17      0.17      7623
         234       0.20      0.07      0.11      4794
         235       0.00      0.00      0.00        51
         236       0.22      0.20      0.21      5673
         237       0.17      0.01      0.01      1127
         238       0.22      0.09      0.12      4622
         240       0.14      0.01      0.02      2110
         250       0.42      0.21      0.28      2744
         261       0.18      0.08      0.11      3321
         262       0.44      0.37      0.40      3904
         263       0.27      0.03      0.06      1263
         264       0.00      0.00      0.00        12
         265       0.24      0.07      0.10       120
         266       0.14      0.03      0.05       468
         267       0.00      0.00      0.00         3
```

270	0.56	0.11	0.19	575
280	0.75	0.52	0.61	827
290	0.23	0.21	0.22	9008
351	0.16	0.13	0.14	7945
352	0.10	0.04	0.05	5373
361	0.00	0.00	0.00	5
362	0.33	0.04	0.08	67
370	0.00	0.00	0.00	103
391	0.00	0.00	0.00	1
392	0.00	0.00	0.00	3
393	0.00	0.00	0.00	5
401	0.00	0.00	0.00	83
402	0.00	0.00	0.00	17
403	0.25	0.25	0.25	12
510	0.00	0.00	0.00	6
520	0.04	0.00	0.00	1504
641	0.00	0.00	0.00	1
720	0.00	0.00	0.00	38
accuracy			0.23	99220
macro avg	0.17	0.11	0.12	99220
weighted avg	0.23	0.23	0.21	99220

	precision	recall	f1-score	support
91	0.24	0.05	0.08	85
92	0.00	0.00	0.00	5
93	0.00	0.00	0.00	1
100	0.42	0.12	0.18	186
111	0.18	0.01	0.02	603
112	0.27	0.03	0.05	271
113	0.00	0.00	0.00	106
114	0.41	0.12	0.18	791
120	0.27	0.15	0.19	1813
131	0.29	0.30	0.30	6132
132	0.23	0.62	0.34	16586
133	0.20	0.12	0.15	3829
200	0.38	0.22	0.28	392
210	0.33	0.02	0.03	64
220	0.26	0.25	0.25	8057
231	0.33	0.01	0.01	159
232	0.08	0.01	0.02	100
233	0.21	0.20	0.21	5534
234	0.23	0.07	0.11	3768
235	0.08	0.06	0.07	36
236	0.42	0.31	0.36	6474
237	0.30	0.04	0.07	1135
238	0.21	0.12	0.16	8029

240	0.17	0.02	0.03	2408
250	0.22	0.03	0.05	938
261	0.28	0.12	0.17	3589
262	0.29	0.12	0.17	2235
263	0.21	0.10	0.13	1020
264	0.00	0.00	0.00	20
265	0.11	0.01	0.01	147
266	0.27	0.22	0.24	1602
267	0.31	0.26	0.29	19
270	0.44	0.04	0.08	604
280	0.49	0.35	0.40	1336
290	0.28	0.22	0.25	10833
351	0.16	0.14	0.15	7580
352	0.05	0.01	0.01	2027
361	0.00	0.00	0.00	5
362	0.00	0.00	0.00	9
370	0.00	0.00	0.00	120
391	0.00	0.00	0.00	4
392	0.00	0.00	0.00	3
401	0.00	0.00	0.00	65
402	0.00	0.00	0.00	18
403	0.00	0.00	0.00	2
510	0.00	0.00	0.00	4
520	0.05	0.00	0.00	1593
641	0.30	1.00	0.46	22
642	0.00	0.00	0.00	2
720	0.00	0.00	0.00	31
accuracy			0.25	100392
macro avg	0.18	0.11	0.11	100392
weighted avg	0.25	0.25	0.22	100392

	precision	recall	f1-score	support
91	0.09	0.05	0.06	60
92	0.00	0.00	0.00	1
93	0.00	0.00	0.00	7
100	0.34	0.13	0.19	297
111	0.10	0.01	0.01	265
112	0.27	0.10	0.15	58
113	0.00	0.00	0.00	26
114	0.27	0.07	0.11	247
120	0.29	0.23	0.26	1960
131	0.34	0.38	0.36	4840
132	0.24	0.53	0.33	11305
133	0.23	0.09	0.13	2397
200	0.49	0.24	0.32	119
210	0.05	0.11	0.07	18

220	0.31	0.29	0.30	6300
231	0.27	0.39	0.32	51
232	0.00	0.00	0.00	30
233	0.16	0.12	0.13	5925
234	0.15	0.06	0.09	1699
235	0.00	0.00	0.00	71
236	0.27	0.38	0.32	7205
237	0.37	0.05	0.09	778
238	0.22	0.19	0.20	6743
240	0.12	0.02	0.03	1847
250	0.22	0.07	0.11	1557
261	0.40	0.12	0.19	2307
262	0.29	0.12	0.17	1620
263	0.65	0.24	0.36	757
264	0.00	0.00	0.00	7
265	0.40	0.06	0.10	136
266	0.00	0.00	0.00	7
270	0.81	0.50	0.62	505
280	0.26	0.14	0.18	939
290	0.22	0.24	0.23	9068
351	0.17	0.15	0.16	6352
352	0.10	0.03	0.04	2114
361	0.00	0.00	0.00	1
362	0.38	0.15	0.21	20
370	0.00	0.00	0.00	54
391	0.00	0.00	0.00	2
392	0.00	0.00	0.00	1
393	0.00	0.00	0.00	6
401	0.00	0.00	0.00	101
402	0.00	0.00	0.00	5
403	0.00	0.00	0.00	26
510	0.00	0.00	0.00	2
520	0.06	0.01	0.01	1572
641	0.00	0.00	0.00	2
accuracy			0.25	79410
macro avg	0.18	0.11	0.12	79410
weighted avg	0.24	0.25	0.23	79410

	precision	recall	f1-score	support
91	0.50	0.03	0.05	37
92	0.00	0.00	0.00	2
100	0.30	0.08	0.13	172
111	0.50	0.01	0.01	272
112	0.59	0.15	0.24	106
113	0.00	0.00	0.00	8
114	0.14	0.02	0.04	213

120	0.20	0.09	0.13	1802
131	0.23	0.19	0.21	5144
132	0.24	0.54	0.33	10065
133	0.25	0.11	0.15	3264
200	0.49	0.47	0.48	265
210	0.00	0.00	0.00	33
220	0.23	0.26	0.24	5808
231	0.00	0.00	0.00	162
232	0.00	0.00	0.00	44
233	0.22	0.05	0.08	2431
234	0.25	0.08	0.12	1763
235	0.00	0.00	0.00	7
236	0.30	0.19	0.23	3826
237	0.05	0.00	0.00	507
238	0.36	0.38	0.37	7788
240	0.14	0.01	0.02	1458
250	0.16	0.03	0.06	587
261	0.32	0.07	0.12	1675
262	0.25	0.10	0.15	912
263	0.50	0.19	0.28	1021
264	0.00	0.00	0.00	6
265	0.00	0.00	0.00	25
266	0.00	0.00	0.00	125
267	0.00	0.00	0.00	6
270	0.50	0.26	0.34	149
280	0.30	0.18	0.23	682
290	0.31	0.42	0.36	9959
351	0.08	0.00	0.01	1973
352	0.00	0.00	0.00	32
361	0.00	0.00	0.00	3
362	0.09	0.03	0.05	98
370	0.00	0.00	0.00	77
392	0.00	0.00	0.00	5
401	0.00	0.00	0.00	96
402	0.00	0.00	0.00	14
403	0.00	0.00	0.00	2
510	0.00	0.00	0.00	1
520	0.00	0.00	0.00	996
720	0.00	0.00	0.00	1
accuracy			0.27	63622
macro avg	0.16	0.09	0.10	63622
weighted avg	0.26	0.27	0.24	63622

	precision	recall	f1-score	support
91	0.33	0.02	0.04	89
100	0.30	0.22	0.25	407

111	0.33	0.01	0.02	515
112	0.10	0.02	0.03	54
113	0.00	0.00	0.00	1
114	0.34	0.12	0.18	438
120	0.25	0.15	0.19	1886
131	0.31	0.12	0.18	2146
132	0.23	0.42	0.30	11997
133	0.25	0.37	0.30	9479
200	0.28	0.30	0.29	398
210	0.00	0.00	0.00	37
220	0.25	0.23	0.24	9740
231	0.23	0.04	0.06	170
232	0.06	0.01	0.01	164
233	0.23	0.21	0.22	5960
234	0.31	0.15	0.20	4092
235	0.33	0.06	0.10	36
236	0.33	0.24	0.28	6436
237	0.11	0.00	0.00	433
238	0.23	0.33	0.27	11224
240	0.14	0.02	0.03	1693
250	0.30	0.06	0.10	1251
261	0.19	0.02	0.04	998
262	0.23	0.03	0.05	899
263	0.30	0.16	0.21	1464
264	0.60	0.09	0.16	32
265	0.00	0.00	0.00	5
266	0.00	0.00	0.00	221
270	0.00	0.00	0.00	10
280	0.55	0.29	0.38	1897
290	0.28	0.35	0.31	12968
351	0.17	0.12	0.14	7403
352	0.12	0.04	0.06	5541
361	0.00	0.00	0.00	4
362	1.00	0.02	0.05	41
370	0.00	0.00	0.00	172
392	0.00	0.00	0.00	5
401	0.00	0.00	0.00	17
402	0.09	0.01	0.02	108
510	0.00	0.00	0.00	2
520	0.19	0.01	0.02	1324
accuracy			0.25	101757
macro avg	0.21	0.10	0.11	101757
weighted avg	0.25	0.25	0.23	101757

	precision	recall	f1-score	support
91	0.44	0.19	0.27	58

92	0.00	0.00	0.00	4
93	0.00	0.00	0.00	3
100	0.36	0.03	0.05	361
111	0.39	0.04	0.08	521
112	0.00	0.00	0.00	46
113	0.00	0.00	0.00	19
114	0.31	0.05	0.09	635
120	0.30	0.11	0.17	1998
131	0.31	0.14	0.19	3420
132	0.23	0.19	0.21	11284
133	0.60	0.34	0.44	3364
200	0.45	0.25	0.32	399
210	0.00	0.00	0.00	44
220	0.28	0.25	0.26	13304
231	0.50	0.07	0.12	103
232	0.26	0.02	0.04	258
233	0.19	0.15	0.17	7935
234	0.33	0.13	0.19	3245
235	0.00	0.00	0.00	34
236	0.46	0.50	0.48	19899
237	0.31	0.15	0.20	1414
238	0.43	0.60	0.50	25196
240	0.19	0.04	0.07	6324
250	0.49	0.23	0.32	3401
261	0.40	0.26	0.31	2083
262	0.74	0.54	0.63	2767
263	0.50	0.39	0.44	2533
264	0.00	0.00	0.00	11
265	0.78	0.10	0.18	68
266	0.26	0.10	0.14	1739
267	0.00	0.00	0.00	14
270	0.72	0.67	0.70	309
280	0.61	0.62	0.61	8519
290	0.24	0.47	0.32	20381
351	0.10	0.02	0.03	4896
352	0.09	0.03	0.05	2485
361	0.31	0.18	0.23	22
362	0.00	0.00	0.00	63
370	0.00	0.00	0.00	115
392	0.00	0.00	0.00	1
401	0.00	0.00	0.00	72
402	0.00	0.00	0.00	18
403	0.00	0.00	0.00	12
520	0.04	0.00	0.00	1358
641	0.00	0.00	0.00	9
720	0.00	0.00	0.00	16
accuracy			0.36	150760

```
   macro avg       0.25      0.15      0.17    150760
weighted avg       0.35      0.36      0.33    150760
```

[12]:
```
# Use the random grid to search for best hyperparameters
# https://jamesrledoux.com/code/randomized_parameter_search

#from sklearn.model_selection import RandomizedSearchCV
#from scipy.stats import randint

#model_params = {
#    'n_estimators': randint(10,500),
#    'max_depth': randint(1,50)
#}

# First create the base model to tune
#rf = RandomForestClassifier()

# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
#tn_rf_random = RandomizedSearchCV(rf, model_params, n_iter=100, cv=3,␣
↪random_state=3, n_jobs = -1)
#mi_rf_random = RandomizedSearchCV(rf, model_params, n_iter=100, cv=3,␣
↪random_state=3, n_jobs = -1)
#sc_rf_random = RandomizedSearchCV(rf, model_params, n_iter=100, cv=3,␣
↪random_state=3, n_jobs = -1)
#ma_rf_random = RandomizedSearchCV(rf, model_params, n_iter=100, cv=3,␣
↪random_state=3, n_jobs = -1)
#oh_rf_random = RandomizedSearchCV(rf, model_params, n_iter=100, cv=3,␣
↪random_state=3, n_jobs = -1)
#wa_rf_random = RandomizedSearchCV(rf, model_params, n_iter=100, cv=3,␣
↪random_state=3, n_jobs = -1)

#tn_rf_random.fit(tn_X_train, tn_y_train)
#mi_rf_random.fit(mi_X_train, mi_y_train)
#sc_rf_random.fit(sc_X_train, sc_y_train)
#ma_rf_random.fit(ma_X_train, ma_y_train)
#oh_rf_random.fit(oh_X_train, oh_y_train)
#wa_rf_random.fit(wa_X_train, wa_y_train)

#print('TN: ', tn_rf_random.best_params_)
#print('MI: ', mi_rf_random.best_params_)
#print('SC: ', sc_rf_random.best_params_)
#print('MA: ', ma_rf_random.best_params_)
#print('OH: ', oh_rf_random.best_params_)
#print('WA: ', wa_rf_random.best_params_)
```

```
C:\Users\amomu\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:667: UserWarning: The least populated
class in y has only 2 members, which is less than n_splits=3.
  % (min_groups, self.n_splits)), UserWarning)
C:\Users\amomu\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:667: UserWarning: The least populated
class in y has only 1 members, which is less than n_splits=3.
  % (min_groups, self.n_splits)), UserWarning)
C:\Users\amomu\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:667: UserWarning: The least populated
class in y has only 1 members, which is less than n_splits=3.
  % (min_groups, self.n_splits)), UserWarning)
C:\Users\amomu\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:667: UserWarning: The least populated
class in y has only 2 members, which is less than n_splits=3.
  % (min_groups, self.n_splits)), UserWarning)
C:\Users\amomu\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:667: UserWarning: The least populated
class in y has only 1 members, which is less than n_splits=3.
  % (min_groups, self.n_splits)), UserWarning)
```

```
TN:  {'max_depth': 18, 'n_estimators': 445}
MI:  {'max_depth': 16, 'n_estimators': 186}
SC:  {'max_depth': 17, 'n_estimators': 284}
MA:  {'max_depth': 17, 'n_estimators': 293}
OH:  {'max_depth': 17, 'n_estimators': 284}
WA:  {'max_depth': 18, 'n_estimators': 484}
```

Results of model hyperparameter assessments: TN: {'max_depth': 18, 'n_estimators': 445

MI: {'max_depth': 16, 'n_estimators': 186}

SC: {'max_depth': 17, 'n_estimators': 284}

MA: {'max_depth': 17, 'n_estimators': 293}

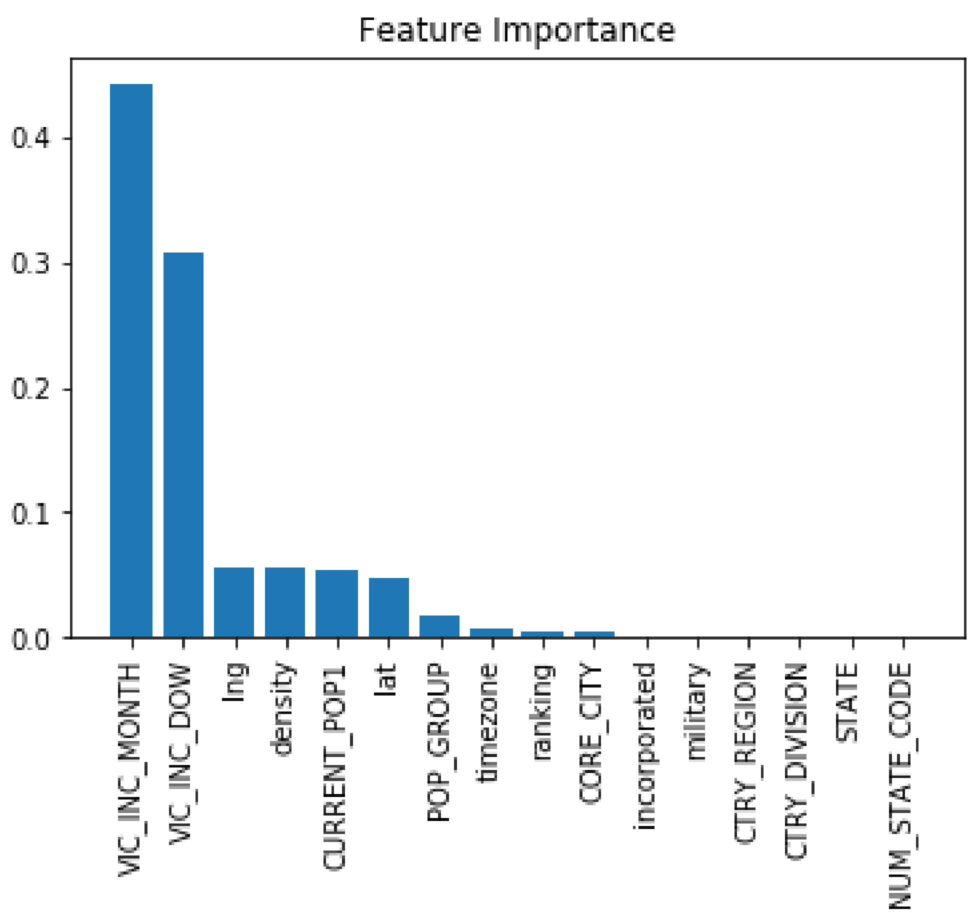
OH: {'max_depth': 17, 'n_estimators': 284}

WA: {'max_depth': 18, 'n_estimators': 484}

6 Model Visualization

[19]:
```
# Find most important features in Random Forest model
import matplotlib.pyplot as plt

# Calculate feature importances
tn_importances = tn_forest.feature_importances_

# Sort feature importances in descending order
```

```python
indices = np.argsort(tn_importances)[::-1]

# Rearrange feature names so they match the sorted feature importances
tn_names = [tn_X_train.columns[i] for i in indices]

# Create plot
plt.figure()

# Create plot title
plt.title("Feature Importance")

# Add bars
plt.bar(range(tn_X_train.shape[1]), tn_importances[indices])

# Add feature names as x-axis labels
plt.xticks(range(tn_X_train.shape[1]), tn_names, rotation=90)

# Show plot
plt.show()
```



[20]:
```
# Re-run random forest, limiting to important features

# Drop features w/ little importance
tn_data_model_X.drop(['CTRY_DIVISION', 'CTRY_REGION', 'military',␣
↪'incorporated', 'STATE', 'NUM_STATE_CODE'],
                    axis=1, inplace = True)

# Split the data into training and validation datasets
# Save 30% for validation
tn_X_train, tn_X_val, tn_y_train, tn_y_val = train_test_split(tn_data_model_X,␣
↪tn_data_model_y, test_size =0.3, random_state=7)

tn_rf_model = RandomForestClassifier(random_state=0, n_estimators=445,␣
↪n_jobs=-1, max_depth=18, bootstrap=False)
tn_forest = tn_rf_model.fit(tn_X_train, tn_y_train)
tn_y_pred_forest = tn_forest.predict(tn_X_val)
print(classification_report(tn_y_val, tn_y_pred_forest))
```

```
              precision    recall  f1-score   support

          91       0.00      0.00      0.00        52
          92       0.00      0.00      0.00         2
          93       0.00      0.00      0.00         6
         100       0.19      0.05      0.08       323
         111       0.18      0.01      0.03       267
         112       0.86      0.79      0.82       154
         113       0.00      0.00      0.00        28
         114       0.48      0.11      0.18       366
         120       0.25      0.23      0.24      2027
         131       0.31      0.38      0.34      6936
         132       0.22      0.55      0.31     14417
         133       0.22      0.31      0.26      4151
         200       0.12      0.11      0.11       151
         210       0.00      0.00      0.00        48
         220       0.23      0.21      0.22      6810
         231       0.00      0.00      0.00        46
         232       0.00      0.00      0.00        28
         233       0.17      0.17      0.17      7623
         234       0.20      0.07      0.11      4794
         235       0.00      0.00      0.00        51
         236       0.23      0.20      0.21      5673
         237       0.19      0.01      0.01      1127
         238       0.22      0.09      0.12      4622
         240       0.15      0.01      0.02      2110
         250       0.42      0.21      0.28      2744
         261       0.19      0.08      0.11      3321
```

```
         262       0.44      0.37      0.40      3904
         263       0.27      0.03      0.06      1263
         264       0.00      0.00      0.00        12
         265       0.23      0.07      0.10       120
         266       0.15      0.03      0.05       468
         267       0.00      0.00      0.00         3
         270       0.56      0.11      0.19       575
         280       0.75      0.52      0.61       827
         290       0.23      0.21      0.22      9008
         351       0.16      0.13      0.14      7945
         352       0.10      0.04      0.05      5373
         361       0.00      0.00      0.00         5
         362       0.33      0.04      0.08        67
         370       0.00      0.00      0.00       103
         391       0.00      0.00      0.00         1
         392       0.00      0.00      0.00         3
         393       0.00      0.00      0.00         5
         401       0.00      0.00      0.00        83
         402       0.00      0.00      0.00        17
         403       0.25      0.25      0.25        12
         510       0.00      0.00      0.00         6
         520       0.04      0.00      0.00      1504
         641       0.00      0.00      0.00         1
         720       0.00      0.00      0.00        38

    accuracy                           0.23     99220
   macro avg       0.17      0.11      0.12     99220
weighted avg       0.23      0.23      0.21     99220

C:\Users\amomu\Anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1272: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[ ]: