Modeling

This notebook combines the three cleaned datasets into one central location and aggregates them before conducting data engineering and running a wide array of models to determine the final top performer and understand the relationships between the features.

Data Imports

In [1]:

```
# Basics
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sys
import pickle

# Importing databases using SQL
from sqlalchemy import create_engine

# Model preprocessing and processing
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import make_column_selector, make_column_transformer
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
from imblearn.pipeline import Pipeline
from sklearn.base import clone

# Models
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier

# Performance evaluation
from sklearn.metrics import f1_score,precision_score,accuracy_score,recall_score
from sklearn.metrics import confusion_matrix, plot_confusion_matrix
from sklearn.inspection import permutation_importance

# Data visualization
import shap

# Options
#pd.options.display.max_rows = 200
pd.options.display.max_columns = 200
%matplotlib inline

# Convenience for working with external src code files
%load_ext autoreload
%autoreload 2
sys.path.insert(1, '../src')
```

```
# Custom functions
from create_target import *
from remove_missing_data import *
from evaluate_model_performance import *
from custom_plots import *
from identify_collinearity import *

# Global constants
RANDOM_STATE = 2021
```

Import "Protests" dataset

In [2]:

```
engine = create_engine('sqlite:///../data/processed/protests.db')
with engine.begin() as connection:
    df_protests = pd.read_sql('SELECT * FROM protests', con=connection)

# Type casting
df_protests.startdate = pd.to_datetime(df_protests.startdate)
```

Import "Governments" dataset

In [3]:

```
engine = create_engine('sqlite:///../data/processed/governments.db')
with engine.begin() as connection:
    df_govts = pd.read_sql('SELECT * FROM governments', con=connection)

# Set index to be used on Join later
df_govts.index = df_govts.year_scode

# Remove unused features
df_govts.drop('year_scode', axis=1, inplace=True)
```

Join "Protests" and "Governments" datasets

In [4]:

```
# Join both dataframes
df = df_protests.join(df_govts, how='left', on='year_scode')

# Remove entries that don't have corresponding 'government' data
df.dropna(inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15064 entries, 0 to 15207
Data columns (total 76 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   country                            15064 non-null  object
 1   scode                              15064 non-null  object
 2   region                             15064 non-null  object
 3   protestnumber                      15064 non-null  int64
 4   protesterviolence                  15064 non-null  int64
 5   startdate                          15064 non-null  datetime64[ns]
 6   duration_days                      15064 non-null  int64
 7   participants                       15064 non-null  int64
 8   participants_category              15064 non-null  object
 9   demand_labor-wage-dispute          15064 non-null  int64
 10  demand_land-farm-issue             15064 non-null  int64
 11  demand_police-brutality            15064 non-null  int64
```

```
12  demand_political-behavior/process  15064 non-null  int64
13  demand_price-increases/tax-policy  15064 non-null  int64
14  demand_removal-of-politician       15064 non-null  int64
15  demand_social-restrictions         15064 non-null  int64
16  year_scode                         15064 non-null  object
17  participants_log                   15064 non-null  float64
18  duration_days_log                  15064 non-null  float64
19  protestnumber_log                  15064 non-null  float64
20  system                             15064 non-null  object
21  yrsoffc                            15064 non-null  float64
22  finittrm                           15064 non-null  float64
23  yrcurnt                            15064 non-null  float64
24  termlimit                          15064 non-null  float64
25  reelect                            15064 non-null  float64
26  multpl                             15064 non-null  float64
27  military                           15064 non-null  float64
28  defmin                             15064 non-null  float64
29  prtyin                             15064 non-null  float64
30  execrlc                            15064 non-null  object
31  execnat                            15064 non-null  float64
32  execrel                            15064 non-null  object
33  execage                            15064 non-null  float64
34  allhouse                           15064 non-null  float64
35  totalseats                         15064 non-null  float64
36  oppmajh                            15064 non-null  float64
37  oppmajs                            15064 non-null  float64
38  legelec                            15064 non-null  float64
39  exelec                             15064 non-null  float64
40  liec                               15064 non-null  float64
41  eiec                               15064 non-null  float64
42  mdmh                               15064 non-null  float64
43  mdms                               15064 non-null  float64
44  ssh                                15064 non-null  float64
45  pluralty                           15064 non-null  float64
46  pr                                 15064 non-null  float64
47  housesys                           15064 non-null  object
48  sensys                             15064 non-null  object
49  thresh                             15064 non-null  float64
50  cl                                 15064 non-null  float64
51  gq                                 15064 non-null  float64
52  gqi                                15064 non-null  float64
53  fraud                              15064 non-null  object
54  auton                              15064 non-null  float64
55  muni                               15064 non-null  float64
56  state                              15064 non-null  float64
57  author                             15064 non-null  float64
58  numvote                            15064 non-null  float64
59  oppvote                            15064 non-null  float64
60  maj                                15064 non-null  float64
61  partyage                           15064 non-null  float64
62  herfgov                            15064 non-null  float64
63  herfopp                            15064 non-null  float64
64  frac                               15064 non-null  float64
65  oppfrac                            15064 non-null  float64
66  govfrac                            15064 non-null  float64
67  tensys_strict                      15064 non-null  float64
68  checks                             15064 non-null  float64
69  stabs_strict                       15064 non-null  float64
70  tenlong_strict                     15064 non-null  float64
71  tenshort_strict                    15064 non-null  float64
72  polariz                            15064 non-null  float64
73  country_govt                       15064 non-null  object
74  scode_govt                         15064 non-null  object
75  percent                            15064 non-null  float64
```

```
dtypes: datetime64[ns](1), float64(51), int64(11), object(13)
memory usage: 8.8+ MB
```

Import "Regime Changes" dataset

In [5]:

```
# IMPORT REGIME CHANGE DATASET
engine = create_engine('sqlite:///../data/processed/regime_changes.db')
with engine.begin() as connection:
    df_regimes = pd.read_sql('SELECT * FROM regime_changes', con=connection)

# Type conversions
df_regimes.startdate = pd.to_datetime(df_regimes.startdate)
df_regimes.enddate = pd.to_datetime(df_regimes.enddate)
df_regimes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296 entries, 0 to 1295
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   country        1296 non-null   object
 1   scode          1296 non-null   object
 2   startdate      1296 non-null   datetime64[ns]
 3   enddate        1296 non-null   datetime64[ns]
 4   duration_yrs   1296 non-null   float64
 5   xconst         1296 non-null   int64
 6   present        1296 non-null   int64
dtypes: datetime64[ns](2), float64(1), int64(2), object(2)
memory usage: 71.0+ KB
```

QC that country names and country IDs match

In [6]:

```
cols = ['scode', 'scode_govt', 'country', 'country_govt']
missing_countries = df.loc[(df.country != df.country_govt)][cols]
missing_countries = missing_countries.drop_duplicates()
display(missing_countries.sort_values(by='scode'))
```

scode	scode_govt	country	country_govt

Remove countries that do not contain government data

In [7]:

```
scodes_to_remove = missing_countries.scode.unique()
scodes_to_remove_ind = [x in scodes_to_remove for x in df.scode]
df.drop(df.loc[scodes_to_remove_ind].index, axis=0, inplace=True)
```

Identify countries that are missing from "Regime Changes" dataset

In [8]:

```
# All countries in union of Protests and Governments
all_countries = df.scode.unique()

# All countries in Regimes
regime_countries = df_regimes.scode.unique()


# Loop over all_countries
missing = []
for country in all_countries:
    # Make note of any countries not in Regimes
```

```
    if country not in regime_countries:
        missing.append(country)

print('Countries missing from "Regimes" dataset:', missing)

# Remove these countries from dataset
scodes_to_remove_ind = [x in missing for x in df.scode]
df.drop(df.loc[scodes_to_remove_ind].index, axis=0, inplace=True)
```

```
Countries missing from "Regimes" dataset: ['LUX']
```

Create "Target" column and add to dataframe

In [9]:

```
target = create_target(df, df_regimes)
df = pd.concat([df, target], axis=1)
```

Basic cleaning

Start by running custom function that removes all features that don't have a minimum threshold of non-null values.

In [10]:

```
# Remove entries with limited "government" data
df = remove_missing_data(df, MAX_MISSING_VALUES=1000)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11840 entries, 0 to 15060
Data columns (total 54 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   index                                11840 non-null  float64
 1   country                              11840 non-null  object
 2   scode                                11840 non-null  object
 3   region                               11840 non-null  object
 4   protestnumber                        11840 non-null  float64
 5   protesterviolence                    11840 non-null  float64
 6   startdate                            11840 non-null  datetime64[ns]
 7   duration_days                        11840 non-null  float64
 8   participants                         11840 non-null  float64
 9   participants_category                11840 non-null  object
 10  demand_labor-wage-dispute            11840 non-null  float64
 11  demand_land-farm-issue               11840 non-null  float64
 12  demand_police-brutality              11840 non-null  float64
 13  demand_political-behavior/process    11840 non-null  float64
 14  demand_price-increases/tax-policy    11840 non-null  float64
 15  demand_removal-of-politician         11840 non-null  float64
 16  demand_social-restrictions           11840 non-null  float64
 17  year_scode                           11840 non-null  object
 18  participants_log                     11840 non-null  float64
 19  duration_days_log                    11840 non-null  float64
 20  protestnumber_log                    11840 non-null  float64
 21  system                               11840 non-null  object
 22  yrsoffc                              11840 non-null  float64
 23  finittrm                             11840 non-null  float64
 24  termlimit                            11840 non-null  float64
 25  military                             11840 non-null  float64
 26  defmin                               11840 non-null  float64
```

```
 27  execnat                         11840 non-null  float64
 28  execrel                         11840 non-null  object
 29  totalseats                      11840 non-null  float64
 30  oppmajh                         11840 non-null  float64
 31  legelec                         11840 non-null  float64
 32  exelec                          11840 non-null  float64
 33  liec                            11840 non-null  float64
 34  eiec                            11840 non-null  float64
 35  gq                              11840 non-null  float64
 36  gqi                             11840 non-null  float64
 37  auton                           11840 non-null  float64
 38  numvote                         11840 non-null  float64
 39  oppvote                         11840 non-null  float64
 40  maj                             11840 non-null  float64
 41  herfgov                         11840 non-null  float64
 42  govfrac                         11840 non-null  float64
 43  tensys_strict                   11840 non-null  float64
 44  checks                          11840 non-null  float64
 45  stabs_strict                    11840 non-null  float64
 46  tenlong_strict                  11840 non-null  float64
 47  tenshort_strict                 11840 non-null  float64
 48  country_govt                    11840 non-null  object
 49  scode_govt                      11840 non-null  object
 50  xconst                          11840 non-null  float64
 51  present                         11840 non-null  float64
 52  next_regime_chg_date            11840 non-null  datetime64[ns]
 53  days_until_next_regime_chg      11840 non-null  float64
dtypes: datetime64[ns](2), float64(43), object(9)
memory usage: 5.0+ MB
```

In [11]:

```python
# Convert startdate to a float instead of datetime since datetime
# cannot be handled by models but fractional years can
df['startdate'] = df.startdate.dt.year + \
                  df.startdate.dt.month/12 + \
                  df.startdate.dt.day/365
```

In [12]:

```python
# Convert to Categorical datatypes
df['region'] = df.region.astype('category')
df['system'] = df.system.astype('category')
df['country'] = df.country.astype('category')
```

Adjust encoding of *xconst*

The *xconst* ("Executive Constraints") ranges from 1 ("Unlimited Authority") to 7 ("Executive Parity"). However, there are also three different placeholder values to represent a period of instability. An "interruption period" is coded as -66. An "interregnum period" is coded as -77. A "transition period" is coded as -88. Clearly, these outliers need to be addressed. They cannot be removed because they are inherently valuable when studying regime changes. There is also no conventional way to "normalize" these values. Lastly, given the strong impact this feature has on the model, it has been determined that a one-hot encoding scheme is not the most valuable. Instead, I created my own encoding after meticulous review of the data dictionary (see page 19).

Instead of these periods being represented by -66, -77, and -88, they are instead represented as -1, -2, and 0, respectively. Keeping in mind how this metric will be interpreted as continuous by the model, I have chosen to rank these time periods on a scale of "less stable" to "more stable", where the least stable is the farthest away from achieving "Executive Parity" (7). In summary:

1. Transition periods, previously encoded as -88, are now encoded as 0.
2. Interruption periods, previously encoded as -66, are now encoded as -1.
3. Interregnum periods, previously encoded as -77, are now encoded as -2.

In [13]:

```
print('Before:\n', df.xconst.value_counts())
df.xconst.replace(-66.0, -1, inplace=True) # 'Interruption periods'
df.xconst.replace(-77.0, -2, inplace=True) # 'Interregnum periods'
df.xconst.replace(-88.0, 0, inplace=True) # 'Transition periods'
print('\nAfter:\n', df.xconst.value_counts())
```

```
Before:
  7.0     4796
 6.0     1994
 3.0     1592
 5.0     1511
 2.0      674
 4.0      510
 1.0      426
-88.0     161
-77.0     114
-66.0      62
Name: xconst, dtype: int64

After:
  7.0    4796
 6.0    1994
 3.0    1592
 5.0    1511
 2.0     674
 4.0     510
 1.0     426
 0.0     161
-2.0     114
-1.0      62
Name: xconst, dtype: int64
```

Define target

This allows the user to define the target in terms of the amount of time before which a regime transition will occur. For this analysis, it uses 1 year, but other values have also been explored with similar results. The shorter the time period, the lower the model performance - as would be expected.

In [14]:

```
DAYS_UNTIL_CHG = 365

target = pd.DataFrame(df['days_until_next_regime_chg'] < DAYS_UNTIL_CHG)
target = target.astype('int')
target.columns = ['target']
```

Drop unused columns

In [15]:

```
drop_cols = ['year_scode', 'scode_govt', 'country_govt', 'startdate',
             'days_until_next_regime_chg', 'scode', 'participants_category',
             'participants','next_regime_chg_date', 'index', 'duration_days',
             'present', 'protestnumber']
```

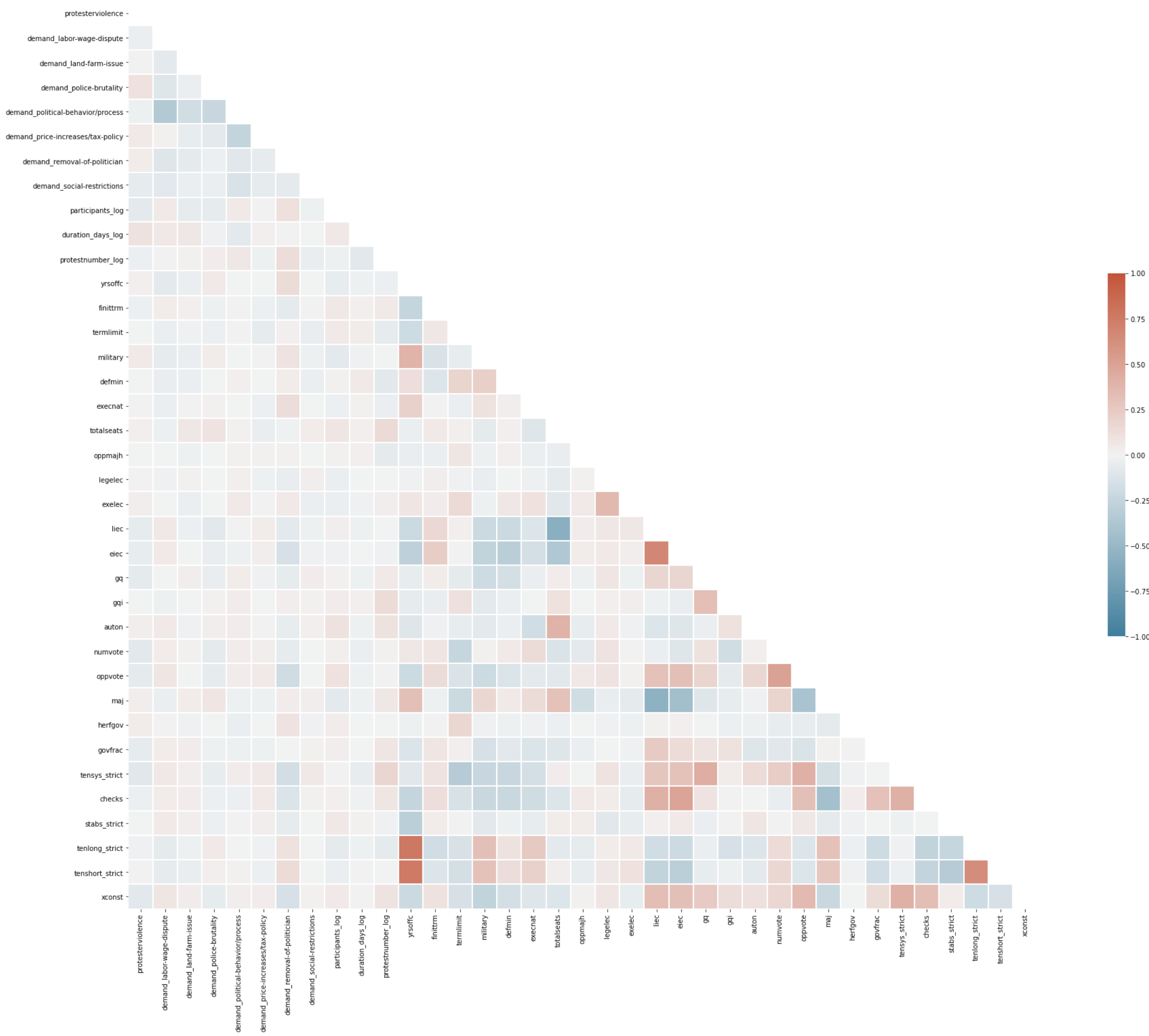
```
model_inputs = df.drop(drop_cols, axis=1)
model_inputs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11840 entries, 0 to 15060
Data columns (total 41 columns):
 #   Column                               Non-Null Count  Dtype   
---  ------                               --------------  -----   
 0   country                              11840 non-null  category
 1   region                               11840 non-null  category
 2   protesterviolence                    11840 non-null  float64 
 3   demand_labor-wage-dispute            11840 non-null  float64 
 4   demand_land-farm-issue               11840 non-null  float64 
 5   demand_police-brutality              11840 non-null  float64 
 6   demand_political-behavior/process    11840 non-null  float64 
 7   demand_price-increases/tax-policy    11840 non-null  float64 
 8   demand_removal-of-politician         11840 non-null  float64 
 9   demand_social-restrictions           11840 non-null  float64 
 10  participants_log                     11840 non-null  float64 
 11  duration_days_log                    11840 non-null  float64 
 12  protestnumber_log                    11840 non-null  float64 
 13  system                               11840 non-null  category
 14  yrsoffc                              11840 non-null  float64 
 15  finittrm                             11840 non-null  float64 
 16  termlimit                            11840 non-null  float64 
 17  military                             11840 non-null  float64 
 18  defmin                               11840 non-null  float64 
 19  execnat                              11840 non-null  float64 
 20  execrel                              11840 non-null  object  
 21  totalseats                           11840 non-null  float64 
 22  oppmajh                              11840 non-null  float64 
 23  legelec                              11840 non-null  float64 
 24  exelec                               11840 non-null  float64 
 25  liec                                 11840 non-null  float64 
 26  eiec                                 11840 non-null  float64 
 27  gq                                   11840 non-null  float64 
 28  gqi                                  11840 non-null  float64 
 29  auton                                11840 non-null  float64 
 30  numvote                              11840 non-null  float64 
 31  oppvote                              11840 non-null  float64 
 32  maj                                  11840 non-null  float64 
 33  herfgov                              11840 non-null  float64 
 34  govfrac                              11840 non-null  float64 
 35  tensys_strict                        11840 non-null  float64 
 36  checks                               11840 non-null  float64 
 37  stabs_strict                         11840 non-null  float64 
 38  tenlong_strict                       11840 non-null  float64 
 39  tenshort_strict                      11840 non-null  float64 
 40  xconst                               11840 non-null  float64 
dtypes: category(3), float64(37), object(1)
memory usage: 3.6+ MB
```

Identify and resolve multi-collinearity

In [16]:

```
calculate_collinearity(model_inputs, min_threshold=0.5)
```



```
Features with correlation higher than 0.5:
```

pairs	cc
(protesterviolence, protesterviolence)	1.000000
(yrsoffc, tenlong_strict)	0.780163
(tenshort_strict, yrsoffc)	0.765382
(liec, eiec)	0.674035
(tenlong_strict, tenshort_strict)	0.633976
(liec, totalseats)	0.573247
(liec, maj)	0.553506
(oppvote, numvote)	0.504882

Check for high Variance Inflation Factors (VIFs), indicating problematic collinearity

Note the correlation between *liec* and *eiec* in the above heat map is the highest on the plot. Investigate this relationship alongside other features using VIF analysis.

Note that the VIF threshold of 10 is higher than usual. This is because high multi-collinearity is less of an issue for tree-based models, as this notebook deems the most appropriate. A threshold of 10 ensures that extreme collinearity is addressed while also ensuring that features are not unnecessarily dropped, losing valuable predictive information.

In [17]:

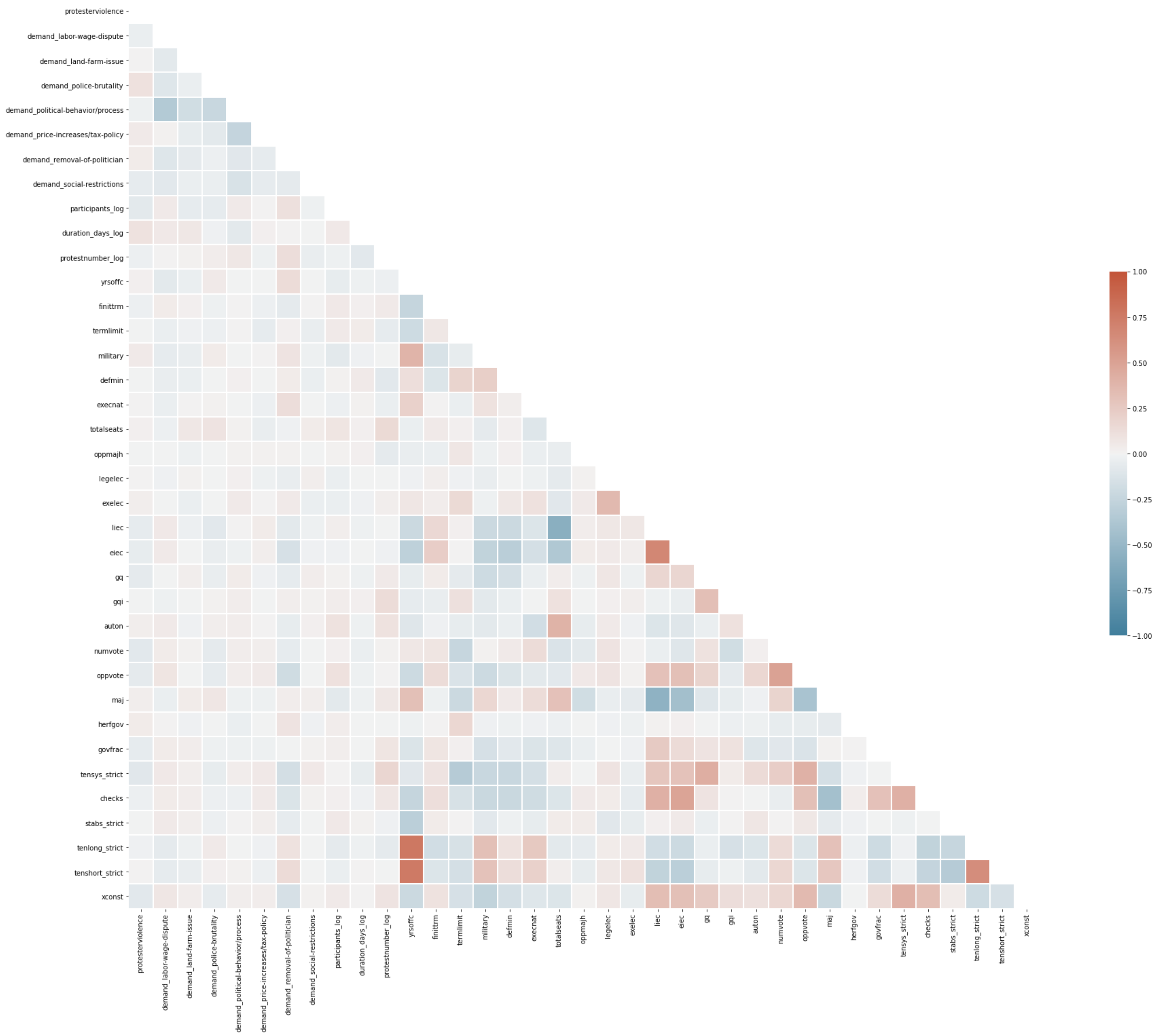
```
# Calculate Variance Inflation Factor for input DataFrame
def calc_vif(df_input):
    # Source: Flatiron School course material
    # https://github.com/learn-co-curriculum/dsc-modeling-your-data

    vif = [variance_inflation_factor(df_input.values, i) for i in range(df_input.shape[
    return list(zip(df_input.columns, vif))
```

In [18]:

```
# Ignore categoricals for VIF
vif_droppers = ['country', 'region', 'system', 'execrel'] # Categoricals
collinearity_df = model_inputs.drop(vif_droppers, axis=1)

display(calc_vif(collinearity_df))
calculate_collinearity(collinearity_df, min_threshold=0.2, plot=True)
```

```
[('protesterviolence', 1.44868299774804),
 ('demand_labor-wage-dispute', 1.6204214619562236),
 ('demand_land-farm-issue', 1.208810302966097),
 ('demand_police-brutality', 1.3395906398870971),
 ('demand_political-behavior/process', 5.513852371701452),
 ('demand_price-increases/tax-policy', 1.3168762166422847),
 ('demand_removal-of-politician', 1.425511446325062),
 ('demand_social-restrictions', 1.1676559446483674),
 ('participants_log', 9.263351416533459),
 ('duration_days_log', 1.1461953736415431),
 ('protestnumber_log', 3.410186100779725),
 ('yrsoffc', 8.37284616777815),
 ('finittrm', 54.41943320661126),
 ('termlimit', 4.873827265679371),
 ('military', 1.5299962092037278),
 ('defmin', 1.474407369303405),
 ('execnat', 1.3426018999607543),
 ('totalseats', 3.771894688181355),
 ('oppmajh', 1.0624530491055708),
 ('legelec', 1.5828221998186602),
 ('exelec', 1.4835143009886813),
 ('liec', 99.23294309707873),
 ('eiec', 64.8298165175228),
 ('gq', 3.084535900311382),
 ('gqi', 1.8876143244248036),
 ('auton', 1.861315081362755),
 ('numvote', 5.697092005756747),
 ('oppvote', 5.929034892174823),
 ('maj', 23.87346082448925),
 ('herfgov', 1.0692269050561742),
 ('govfrac', 2.3605737922563983),
 ('tensys_strict', 5.422521995236603),
 ('checks', 9.594313096599041),
 ('stabs_strict', 1.4338279978327284),
 ('tenlong_strict', 6.652744071314912),
```

```
('tenshort_strict', 5.777808363310377),
('xconst', 10.436065434582105)]
```




```
Features with correlation higher than 0.2:
```

pairs	cc
(protesterviolence, protesterviolence)	1.000000
(yrsoffc, tenlong_strict)	0.780163
(tenshort_strict, yrsoffc)	0.765382
(liec, eiec)	0.674035
(tenlong_strict, tenshort_strict)	0.633976
...	...
(yrsoffc, execnat)	0.209019
(eiec, tenlong_strict)	0.206541
(oppvote, yrsoffc)	0.204862
(military, oppvote)	0.203807

	cc
pairs	
(military, gq)	0.202514

78 rows × 1 columns

Remove *liec*

Reminder of definitions:

- *liec:* legislative index of electoral competitiveness
- *eiec:* executive index of electoral competitiveness

Given the similar nature of these features, collinearity is not surprising. Given the downstream analysis of past models, it was determined that *eiec* has a stronger impact on model performance than *liec*. Drop the latter.

In [19]:

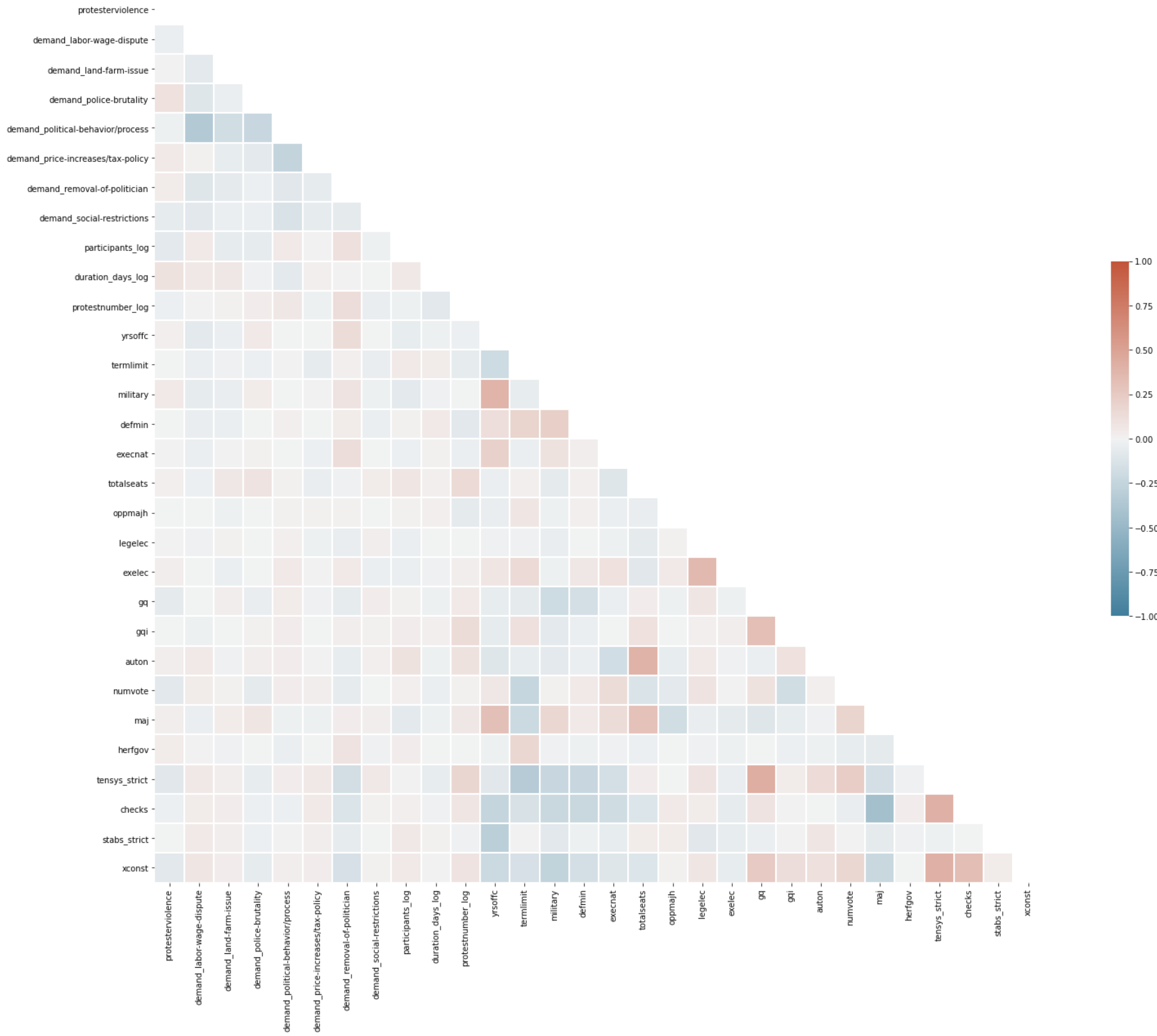
```
model_inputs.drop(['liec', 'eiec', 'tenlong_strict', 'tenshort_strict',
                   'finittrm', 'govfrac', 'oppvote'], axis=1, inplace=True)
```

In [20]:

```
# Ignore categoricals for VIF
vif_droppers = ['country', 'region', 'system', 'execrel'] # Categoricals
collinearity_df = model_inputs.drop(vif_droppers, axis=1)

display(calc_vif(collinearity_df))
calculate_collinearity(collinearity_df, min_threshold=0.2, plot=True)
```

```
[('protesterviolence', 1.4284165923417442),
 ('demand_labor-wage-dispute', 1.5775585041959777),
 ('demand_land-farm-issue', 1.198318309118901),
 ('demand_police-brutality', 1.3113263252488623),
 ('demand_political-behavior/process', 5.182846671644404),
 ('demand_price-increases/tax-policy', 1.29445052765119),
 ('demand_removal-of-politician', 1.3739765526630505),
 ('demand_social-restrictions', 1.1555870540176596),
 ('participants_log', 8.347742330546884),
 ('duration_days_log', 1.1440221138508397),
 ('protestnumber_log', 3.3552785319353164),
 ('yrsoffc', 2.80425614997517),
 ('termlimit', 3.7274704558416283),
 ('military', 1.498776804304648),
 ('defmin', 1.433254004090043),
 ('execnat', 1.2781958948352632),
 ('totalseats', 2.588238035302926),
 ('oppmajh', 1.0557336248410882),
 ('legelec', 1.5578114828080951),
 ('exelec', 1.4671253709952061),
 ('gq', 2.905367989418863),
 ('gqi', 1.8010361525378558),
 ('auton', 1.7968805145686535),
 ('numvote', 3.225797973005871),
 ('maj', 11.970029851031912),
 ('herfgov', 1.0596117867189228),
 ('tensys_strict', 4.957215632157678),
 ('checks', 5.870319376019616),
```

```
('stabs_strict', 1.3645299784376301),
('xconst', 9.271719398976682)]
```




```
Features with correlation higher than 0.2:
```

pairs	cc
(protesterviolence, protesterviolence)	1.000000
(maj, checks)	0.436117
(gq, tensys_strict)	0.432867
(checks, tensys_strict)	0.420018
(tensys_strict, xconst)	0.416724
(auton, totalseats)	0.402273
(yrsoffc, military)	0.398234
(exelec, legelec)	0.364723
(demand_political-behavior/process, demand_labor-wage-dispute)	0.344554
(termlimit, tensys_strict)	0.330994

	cc
pairs	
(checks, xconst)	0.329545
(gq, gqi)	0.327936
(yrsoffc, maj)	0.316189
(totalseats, maj)	0.310318
(yrsoffc, stabs_strict)	0.302692
(military, xconst)	0.271173
(xconst, gq)	0.255725
(demand_price-increases/tax-policy, demand_political-behavior/process)	0.250856
(yrsoffc, checks)	0.244412
(termlimit, numvote)	0.235820
(numvote, tensys_strict)	0.234276
(demand_political-behavior/process, demand_police-brutality)	0.233095
(military, tensys_strict)	0.232767
(defmin, tensys_strict)	0.229613
(military, defmin)	0.224279
(military, checks)	0.224193
(checks, defmin)	0.222042
(maj, xconst)	0.221840
(termlimit, maj)	0.217684
(xconst, yrsoffc)	0.211793
(execnat, yrsoffc)	0.209019
(military, gq)	0.202514

Modeling

Given the cleaned and aggregated dataset above, the next section moves into the Modeling phase. Each model type is constructed using elements of encoding, scaling, resampling and hyperparameter optimization.

- One hot encoding was essential given the categorical type of some features
- Standard scaling was essential given the vast array of different numerical feature distributions and ranges. Min-max scaling was considered but proved less effective.

- SMOTE was determined to be essential given the imbalanced nature of the dataset. Only 11% of the target feature values were 1, leaving the other 89% as 0. This is a prime example of the need for resampling, and SMOTE proved highly effective.
- Hyperparameter grid searches are inherently valuable when optimizing a model. Appropriate hyperparameter searches were used for each model type.

The output of each model is provided in terms of four core statistical measures (f1 score, accuracy, precision, and recall), in addition to displaying a confusion matrix for the test data. F1 was selected before the modeling process as the most relevant metric given that it encompasses all possible outcomes, as opposed to the other three metrics which leave out at least one possible outcome from their evaluation.

Train-test split

In [21]:

```
x_train, x_test, y_train, y_test = train_test_split(model_inputs, target,
                                                    random_state=RANDOM_STATE,
                                                    test_size=0.3)
```

Define models and parameter grids

Define all models and grids in one place. A pipeline structure is created such that each of these models can be run with the below-defined hyperparameter tuning grids alongside their resampling, scaling and encoding. This allows for minimal repetition in code and a consistent structure.

In [22]:

```
# Set parameter grid to search across
grid_bay = {'model__var_smoothing': [1e-9]}

grid_log = {'model__C': np.logspace(-1, 5, 10)}

grid_dt = {
    'model__max_depth': [3, 5, 7],
    'model__criterion': ['gini', 'entropy'],
    'model__min_samples_split': [5, 10],
    'model__min_samples_leaf': [5, 10]}

grid_rf = {
    'model__n_estimators': [25, 75, 150],
    'model__criterion': ['gini', 'entropy'],
    'model__max_depth': [3, 6, 10],
    'model__min_samples_split': [5, 10],
    'model__min_samples_leaf': [3, 6]}

grid_knn = {
    'model__leaf_size': [25, 50, 75],
    'model__n_neighbors': [3, 5, 7, 9],
    'model__weights': ['uniform', 'distance']}

grid_ada = {
    'model__n_estimators': [50, 200],
    'model__learning_rate': [1, 0.5, 0.25]}

grid_xgb = {
    'model__learning_rate': [0.1, 0.25, 0.5], #0.25
```

```
    'model__max_depth': [6, 8, 10], #8
    'model__n_estimators': [50, 100, 150, 200]} #100


np.random.seed(RANDOM_STATE)
model_bay = GaussianNB()
model_log = LogisticRegression(max_iter=5000)
model_dt = DecisionTreeClassifier()
model_rf = RandomForestClassifier()
model_knn = KNeighborsClassifier()
model_ada = AdaBoostClassifier(random_state=RANDOM_STATE)
model_xgb = XGBClassifier(eval_metric='logloss', use_label_encoder=False,
                          random_state=RANDOM_STATE)

grids = [grid_bay, grid_log, grid_dt, grid_rf, grid_knn, grid_ada, grid_xgb]
models = [model_bay, model_log, model_dt, model_rf, model_knn, model_ada, model_xgb]
```

Pipeline function

This high-level function wraps all the different components of the model pipeline into one location, applying one-hot encoding, standard scaling, smote resampling, and grid searches to the input model. It also outputs performance in the form of standard metrics and a confusion matrix.

In [23]:

```
def create_pipeline_and_run(model, grid, metric='accuracy'):
    np.random.seed(RANDOM_STATE)
    ohe = OneHotEncoder(handle_unknown='ignore', sparse=False)
    scaler = StandardScaler()
    smote = SMOTE(random_state=RANDOM_STATE)

    selector_object = make_column_selector(dtype_exclude='number')
    selector_numeric = make_column_selector(dtype_include='number')
    transformer = make_column_transformer((ohe, selector_object),
                                          (scaler, selector_numeric))


    pipe = Pipeline([('transformer', transformer),
                     ('smote', smote),
                     ('model', model)])

    # Instantiate and fit grid search object
    grid = GridSearchCV(pipe, grid, scoring='f1', cv=10)
    grid.fit(x_train, y_train.values.ravel())
    pred = grid.best_estimator_.predict(x_test)


    print(f'{model}:')
    print_scores(pred, y_test)

    # Confusion matrix
    plt.figure()
    plot_confusion_matrix(grid.best_estimator_, x_test, y_test)
    plt.show();

    return grid.best_estimator_
```

Dummy classifier as performance baseline

In [24]:

```
for strategy in ["stratified", "uniform", "most_frequent"]:
    dummy_clf = DummyClassifier(strategy=strategy)
    dummy_clf.fit(x_train, y_train)

    print(f'DUMMY SCORE ({strategy}):')
    pred = dummy_clf.predict(x_test)
    print_scores(pred, y_test)
```

```
DUMMY SCORE (stratified):
- f1: 0.11267605633802816
- accuracy: 0.8226351351351351
- precision: 0.11299435028248588
- recall: 0.11235955056179775
DUMMY SCORE (uniform):
- f1: 0.17419060647514822
- accuracy: 0.4901463963963964
- precision: 0.10397387044093631
- recall: 0.5365168539325843
DUMMY SCORE (most_frequent):
- f1: 0.0
- accuracy: 0.8997747747747747
- precision: 0.0
- recall: 0.0
```

```
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_div
ision` parameter to control this behavior.
```

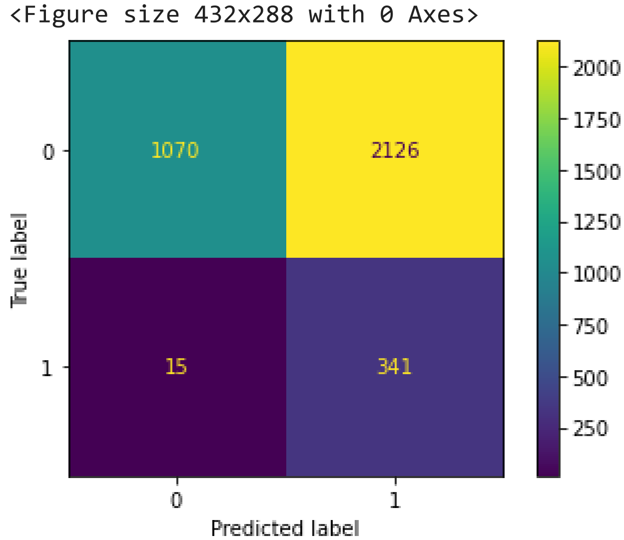
Run *all models* defined above

Run this cell to output the performance of all above-defined models in one place for a side-by-side comparison

In [25]:

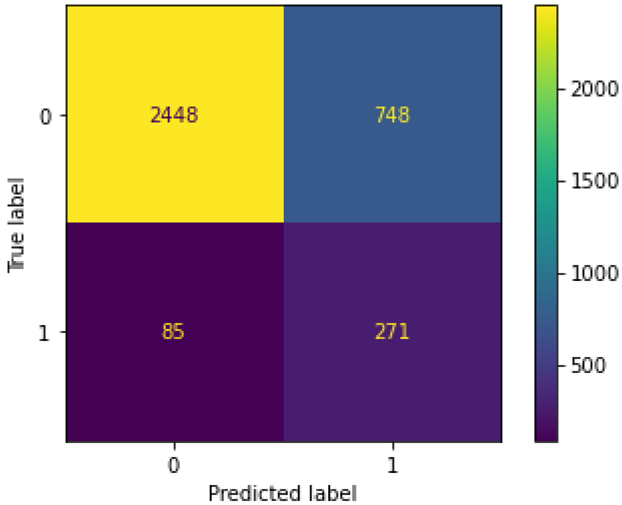
```
pipes = []
for grid, model in zip(grids, models):
    pipe = create_pipeline_and_run(model, grid)
    pipes.append(pipe)
```

```
GaussianNB():
- f1: 0.24158696422245837
- accuracy: 0.3972409909909097
- precision: 0.13822456424807458
- recall: 0.9578651685393258
<Figure size 432x288 with 0 Axes>
```

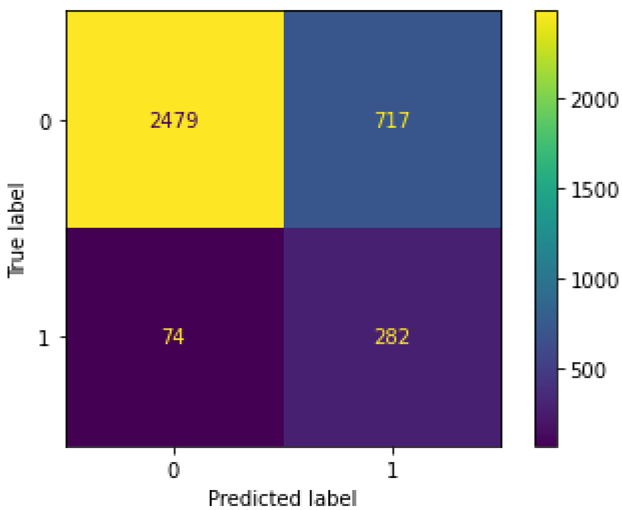



```
LogisticRegression(max_iter=5000):
```

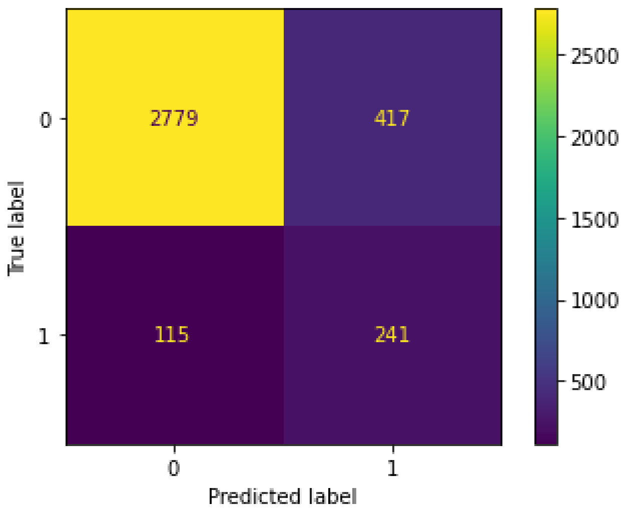
```
- f1: 0.3941818181818182
- accuracy: 0.7654842342342343
- precision: 0.26594700686947986
- recall: 0.7612359550561798
&lt;Figure size 432x288 with 0 Axes&gt;
```



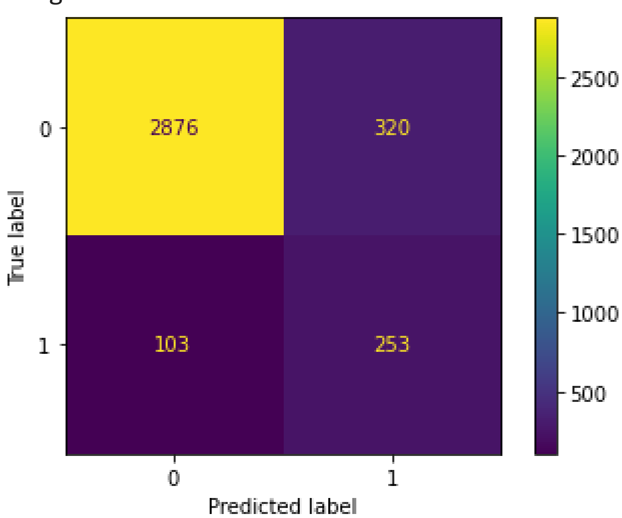

```
DecisionTreeClassifier():
- f1: 0.4162361623616236
- accuracy: 0.7773085585585585
- precision: 0.2822822822822823
- recall: 0.7921348314606742
&lt;Figure size 432x288 with 0 Axes&gt;
```



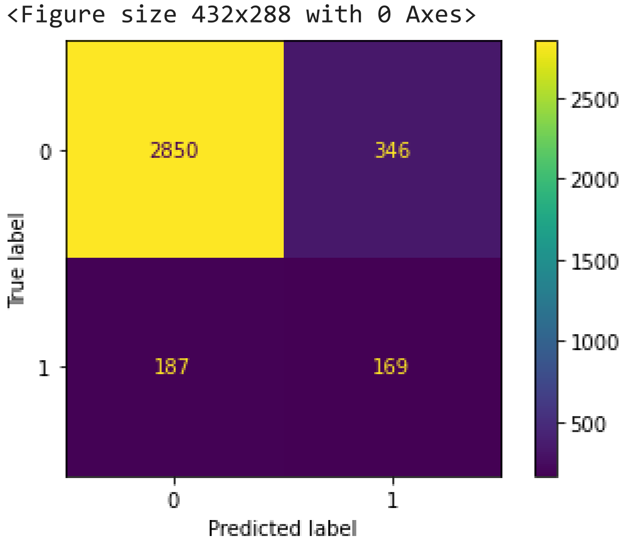

```
RandomForestClassifier():
- f1: 0.47534516765286
- accuracy: 0.8502252252252253
- precision: 0.3662613981762918
- recall: 0.6769662921348315
&lt;Figure size 432x288 with 0 Axes&gt;
```



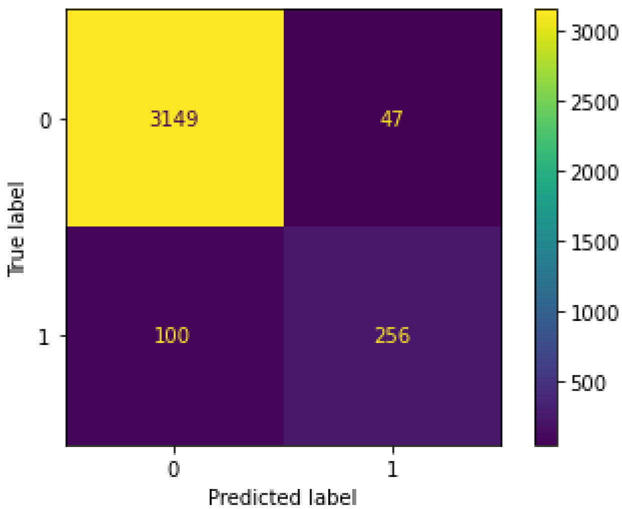

```
KNeighborsClassifier():
- f1: 0.5446716899892357
- accuracy: 0.8809121621621622
- precision: 0.44153577661431065
- recall: 0.7106741573033708
<Figure size 432x288 with 0 Axes>
```




```
AdaBoostClassifier(random_state=2021):
- f1: 0.3880597014925373
- accuracy: 0.8499436936936937
- precision: 0.32815533980582523
- recall: 0.4747191011235955
<Figure size 432x288 with 0 Axes>
```



```
XGBClassifier(base_score=None, booster=None, colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None,
              eval_metric='logloss', gamma=None, gpu_id=None,
              importance_type='gain', interaction_constraints=None,
              learning_rate=None, max_delta_step=None, max_depth=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              random_state=2021, reg_alpha=None, reg_lambda=None,
              scale_pos_weight=None, subsample=None, tree_method=None,
              use_label_encoder=False, validate_parameters=None,
              verbosity=None):
- f1: 0.7769347496206372
- accuracy: 0.9586148648648649
- precision: 0.8448844884488449
- recall: 0.7191011235955056
<Figure size 432x288 with 0 Axes>
```



Run *only one* model

Choose which model to run in the below cell (this cell is only used for iterative testing and investigating model specifics without running all models)

In [26]:

```
# Uncomment and run to look at one model separately
#xgb = create_pipeline_and_run(model_xgb, grid_xgb);
```

Print optimal model hyperparameters

In [27]:

```
xgb = pipes[-1] # Since it is the last model in pipes
print(xgb.steps[2])
```

```
('model', XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='logloss',
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.5, max_delta_step=0,
              max_depth=10, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=200, n_jobs=8,
              num_parallel_tree=1, random_state=2021, reg_alpha=0, reg_lambda=1,
              scale_pos_weight=1, subsample=1, tree_method='exact',
              use_label_encoder=False, validate_parameters=1, verbosity=None))
```

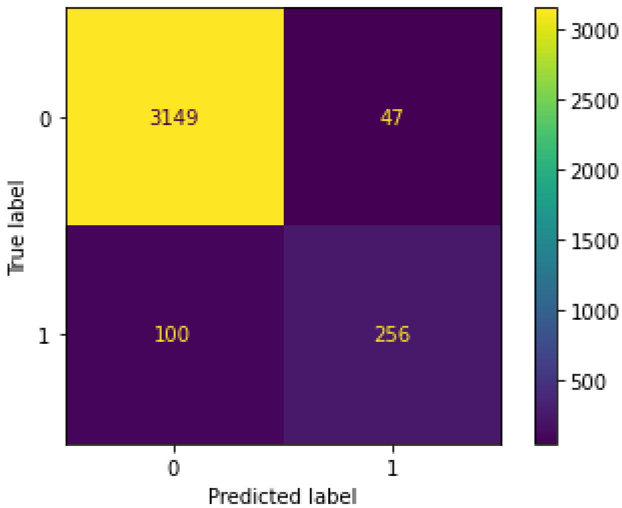
Test model on test dataset

XG boost proves to be the highest performing model. Test its performance on the test dataset.

In [28]:

```
# Predict output
pred = xgb.predict(x_test)

# Show performance
print_scores(pred, y_test)
plot_confusion_matrix(xgb, x_test, y_test);
```

```
- f1: 0.7769347496206372
- accuracy: 0.9586148648648649
- precision: 0.8448844884488449
- recall: 0.7191011235955056
```



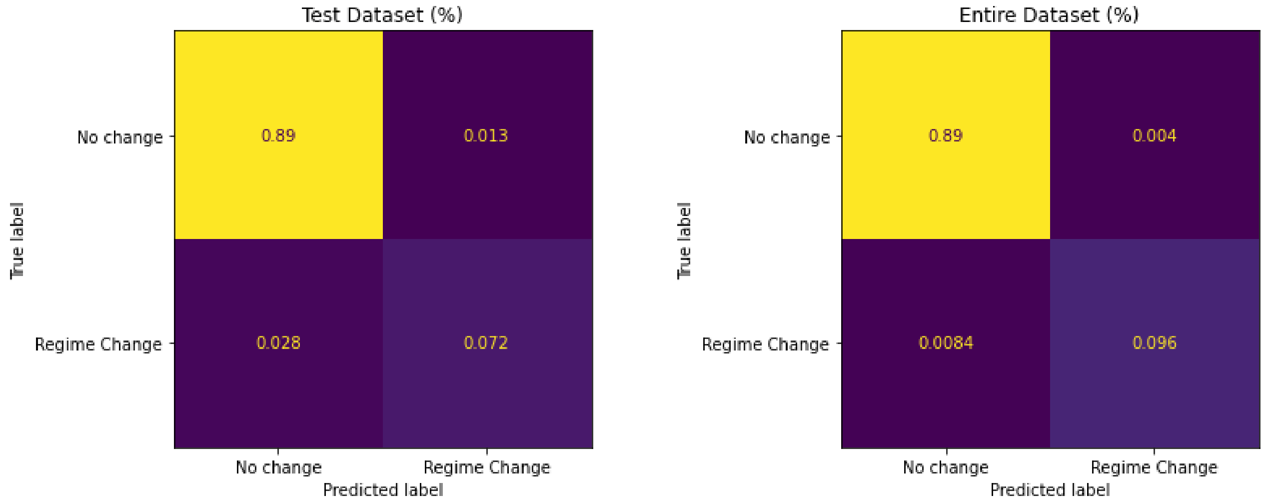
Plot confusion matrices

In [29]:

```
# Predict output
pred = xgb.predict(x_test)

# Show performance
print_scores(pred, y_test)

# Plot test data and full data performance
labels = ['No change', 'Regime Change']
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,8))
plt.subplots_adjust(wspace=0.6, hspace=None)
axes[0].set_title('Test Dataset (%)')
axes[1].set_title('Entire Dataset (%)')

plot_confusion_matrix(xgb, x_test, y_test,
                      ax=axes[0],
                      display_labels=labels,
                      colorbar=False,
                      normalize='all')

plot_confusion_matrix(xgb, model_inputs, target,
                      ax=axes[1],
                      display_labels=labels,
                      colorbar=False,
                      normalize='all');

plt.savefig('../images/confusion_matrices.png')
```

```
- f1: 0.7769347496206372
```

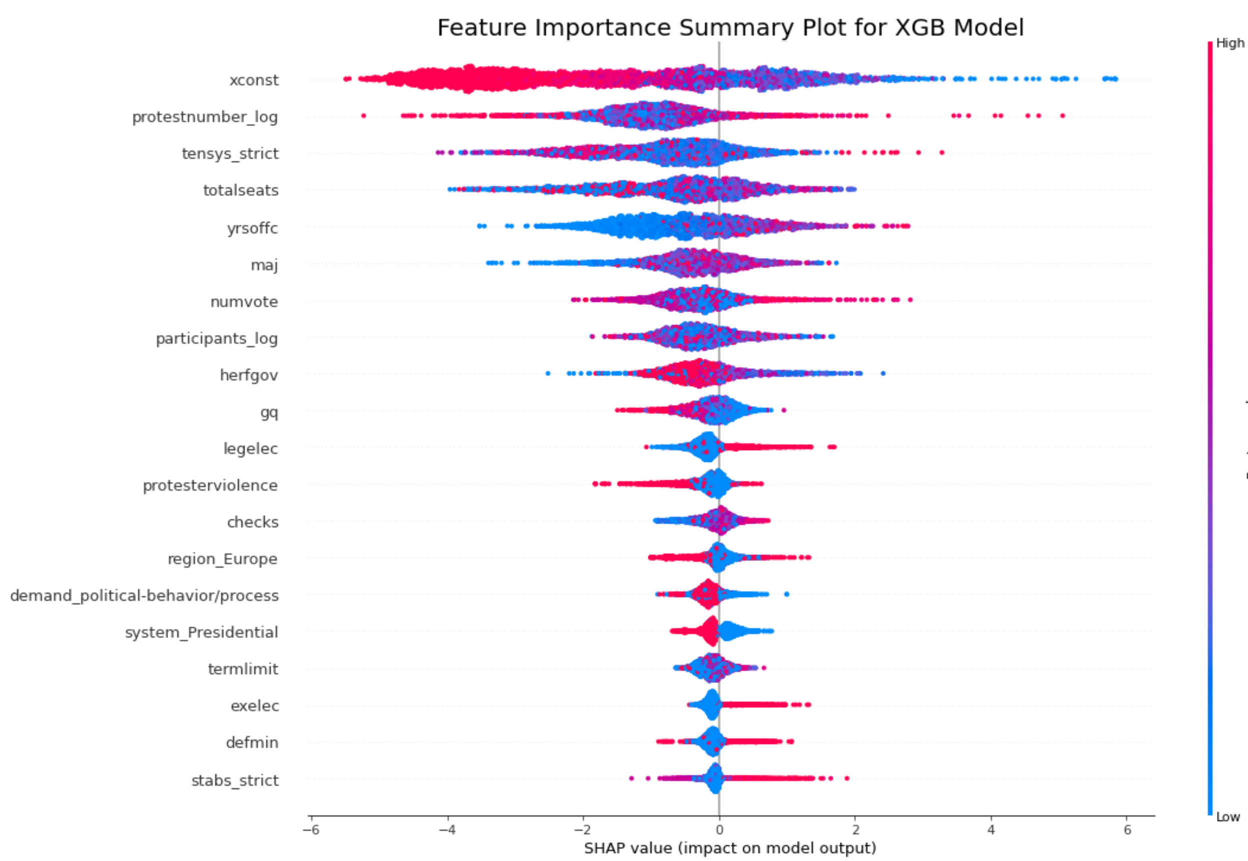
```
- accuracy: 0.9586148648648649
- precision: 0.8448844884488449
- recall: 0.7191011235955056
```



Feature importance

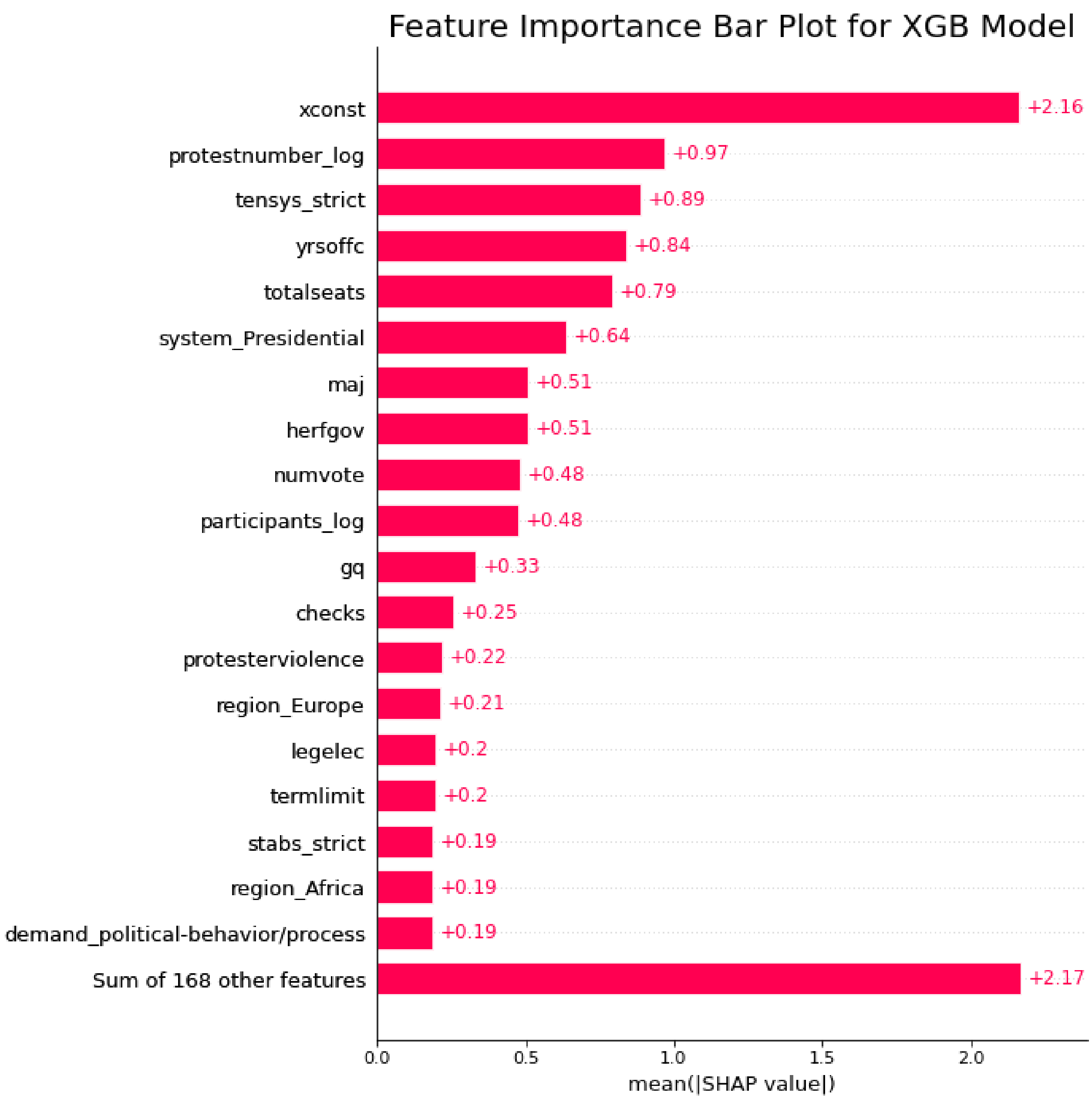
Evaluate the feature importance in the top-performing model.

In [30]:
```
# SHAP summary plot for XGB
produce_shap_plot(x_train, y_train, x_test, y_test, clone(xgb),
                  title='Feature Importance Summary Plot for XGB Model',
                  savepath = '../images/shap_summary_plot.png');
```



In [31]:
```
# SHAP bar plot for XGB model
x_tr_manual, y_tr_manual, x_te_manual = get_shap_df(x_train, y_train, x_test)
```

```
model = xgb.steps[2][1]

# Calculate SHAP values
explainer = shap.Explainer(model)
shap_values = explainer(x_te_manual)

# SHAP bar plot for XGB model
plt.figure()
plt.title('Feature Importance Bar Plot for XGB Model', fontsize=20)
shap.plots.bar(shap_values, max_display=20, show=False)
plt.savefig('../images/shap_bar_plot.png');
```



Permutation Feature Importance

Source: https://scikit-learn.org/stable/modules/permutation_importance.html

In [32]:
```
# Subsequent functions can't handle categoricals so
# fit dataframe outside pipeline
```

```
model = xgb.steps[2][1]
x_tr, y_tr, x_te = get_shap_df(x_train, y_train, x_test)
model.fit(x_tr, y_tr);



r = permutation_importance(model, x_te, y_test,
                           n_repeats=30,
                           random_state=RANDOM_STATE)

for i in r.importances_mean.argsort()[::-1]:
    if r.importances_mean[i] - 3 * r.importances_std[i] > 0:
        #print(f"{df_train.feature_names[i]:<8}"
        print(f"{x_tr.columns[i]} "
              f"{r.importances_mean[i]:.3f}")
```

```
xconst 0.065
tensys_strict 0.023
yrsoffc 0.020
totalseats 0.018
protestnumber_log 0.016
maj 0.013
herfgov 0.007
numvote 0.006
gq 0.004
region_Europe 0.003
military 0.002
country_Ethiopia 0.001
region_MENA 0.001
country_Niger 0.001
country_Guyana 0.001
execrel_Islamic 0.001
execrel_OTHER 0.001
country_Haiti 0.000
country_Guinea 0.000
country_Venezuela 0.000
country_Paraguay 0.000
country_Comoros 0.000
country_Turkey 0.000
country_Sierra Leone 0.000
country_Senegal 0.000
```

Export final datasets and models for use in other notebooks

The final, cleaned dataframe with features selected and engineered is exported via SQL to be used in the EDA notebook. Three selected final, fitted models are stored as Pickle files for use in the Final Presentation notebook.

Export data via SQL

In [33]:

```
engine = create_engine('sqlite:///../data/processed/all_data.db')

model_data = pd.concat([model_inputs, target], axis=1)

with engine.begin() as connection:
    model_data.to_sql(name='all_modeled_data',
                      con=connection,
```

```
                        if_exists='replace',
                        index=False)
```

Export models via Pickle

In [34]:

```
# Save fitted Logistic Regression
with open('../data/processed/model_logreg.pickle', 'wb') as f:
    pickle.dump(pipes[1], f)

# Save fitted Random Forest
with open('../data/processed/model_rf.pickle', 'wb') as f:
    pickle.dump(pipes[3], f)

# # Save fitted XG Boost
with open('../data/processed/model_xgb.pickle', 'wb') as f:
    pickle.dump(pipes[-1], f)
```