CAPSTONE 2

A machine learning analysis of coup attempts in Python using a variable threshold Random Forest Regressor model


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ZBC
PAULIE 2017·11·15

THE DATA

Problem Statement

- Companies face political risk factors every day, all around the world
  - *Assets held abroad rely heavily on the political stability of the host country*
  - *Coups can result in seizure of assets (ex. Cuba*
- Two factors govern the longevity of regimes:
  - *“selectorate” – the set of people with a say in choosing leaders and with a prospect of gaining access to special privileges doled out by leaders.*
  - *“winning coalition” – a subgroup of the selectorate who maintain incumbents in office and in exchange receive special privileges.*
- If the leader loses the loyalty of a sufficient number of members of the winning coalition, a challenger can remove and replace them in office.
- What factors contribute to coup attempts? Can we predict coup attempts?

Data Description

- Curtis Bell has assembled the Rulers, Elections, and Irregular Governance (REIGN) dataset.
- The dataset describes political conditions in every country each and every month.
- These conditions include:
  - *tenures and personal characteristics of leaders*
  - *the types of political institutions in effect*
  - *election-related outcomes and announcements*
  - *irregular events like coup attempts and other violent conflicts*

Data Wrangling Steps

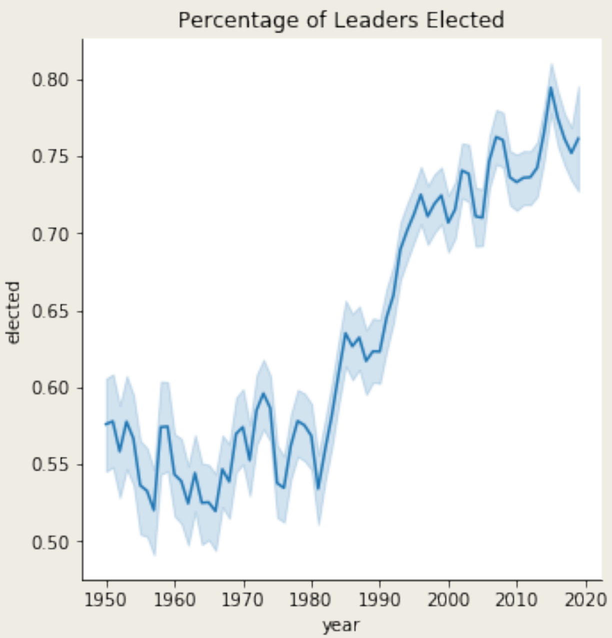
1. Remove Undefined Features
   a. *irregular*
   b. *couprisk*
   c. *pctile_risk*
2. Convert ‘government’ to Dummy Variables
   a. *Results in 16 new variables one for each of the different government regime types.*
   b. *This allows us to determine whether regime-type has a significant effect on the likelihood of coup attempts.*
3. Remove Missing Values
   a. *The original dataset contained 132,866 observations, and after removing any observations with missing values the number of observations remained the same, indicating no missing values in the dataset.*

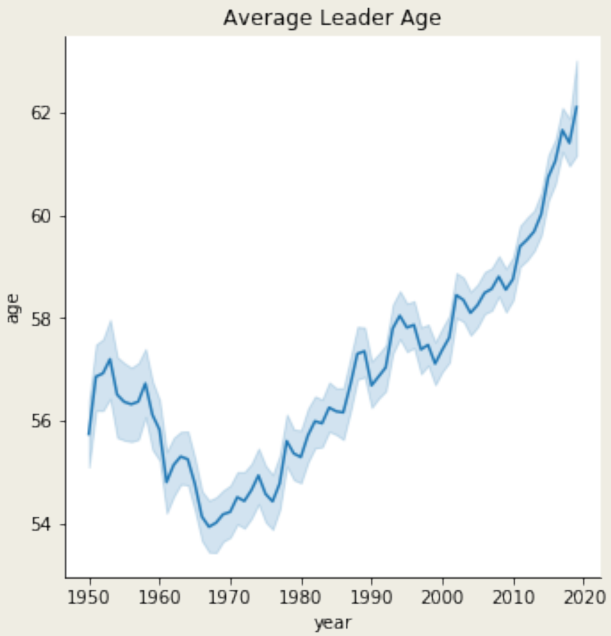
- The end results a dataset with 50 features and 132,866 observations.

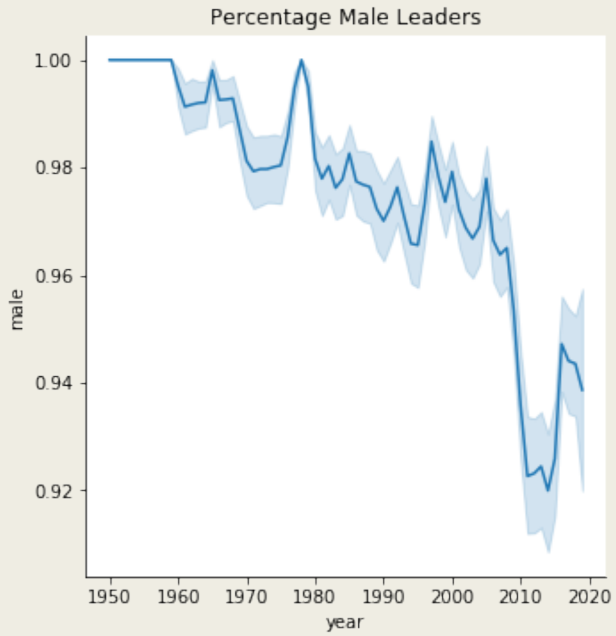
TREND ANALYSIS

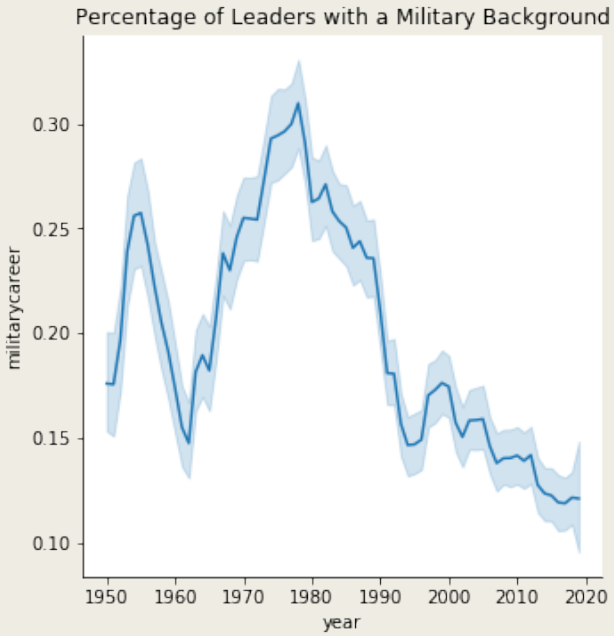
Leader Characteristics

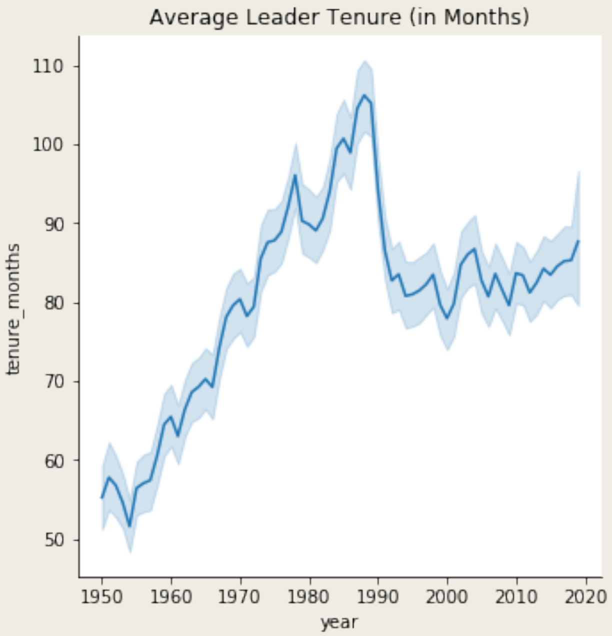
- When we look at leader characteristics we see a distinct rise in the percentage of leader elected, the average leader age, average leader tenure
- We also see a distinct decline in the percentage of male leaders and the percentage of leaders with a military background





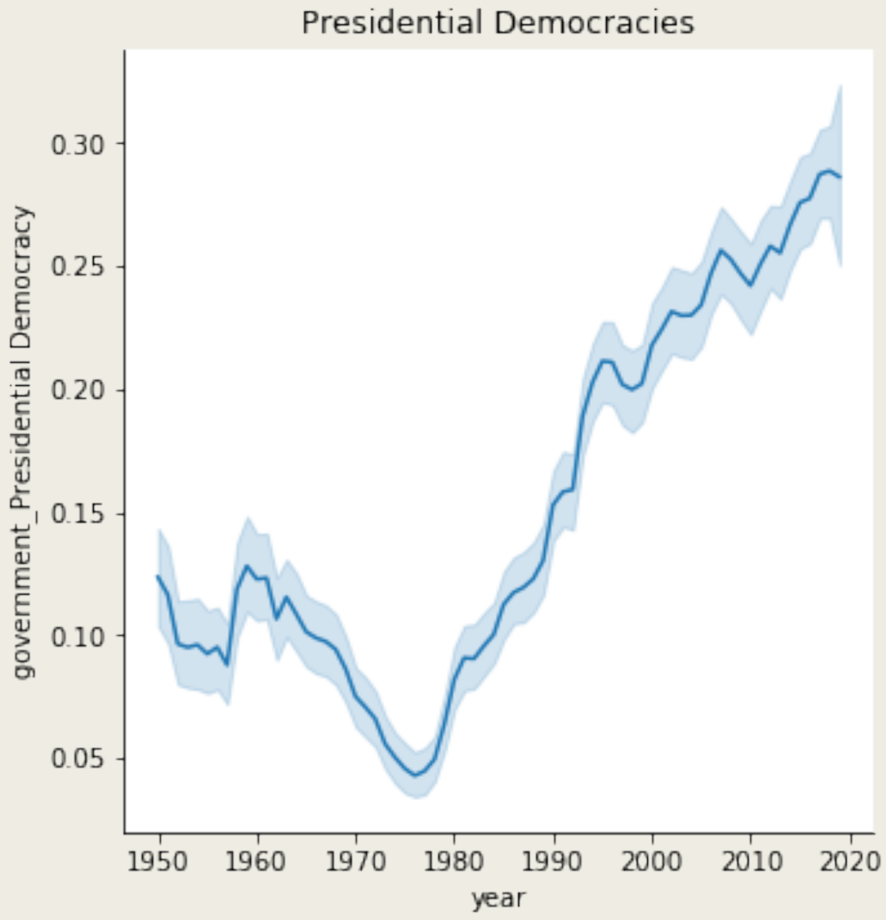


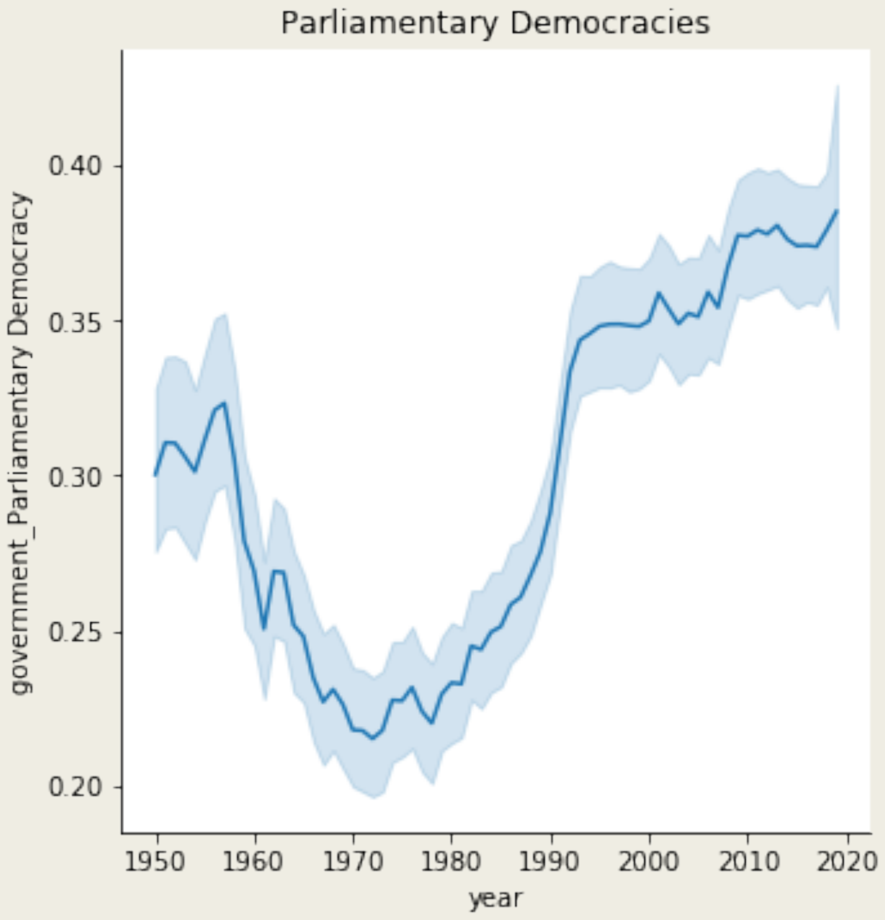




Democratic Government Trends

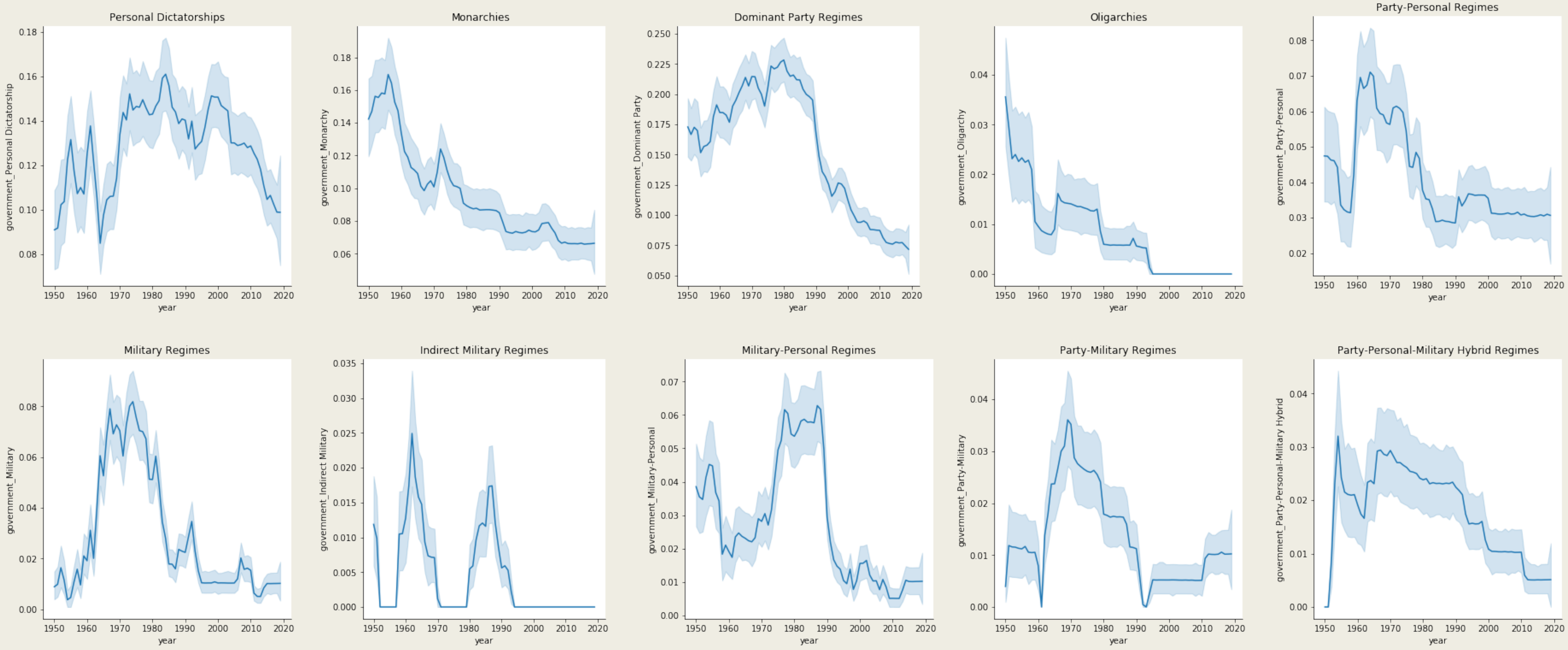
- There is a clear trend towards greater democratization after a steep decline from the 1960s until the 1980s.





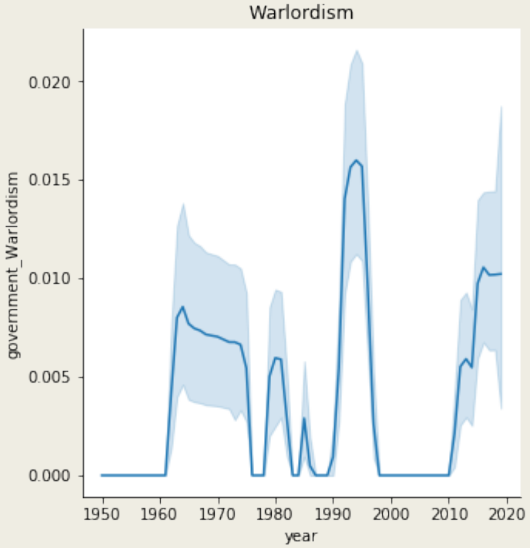
Non-Democratic Government Trends

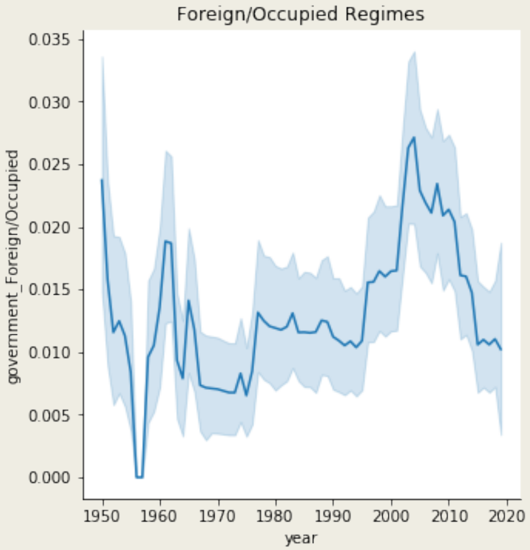
- There has been a distinct decline in all forms of non-Democratic government, particularly after 1980.

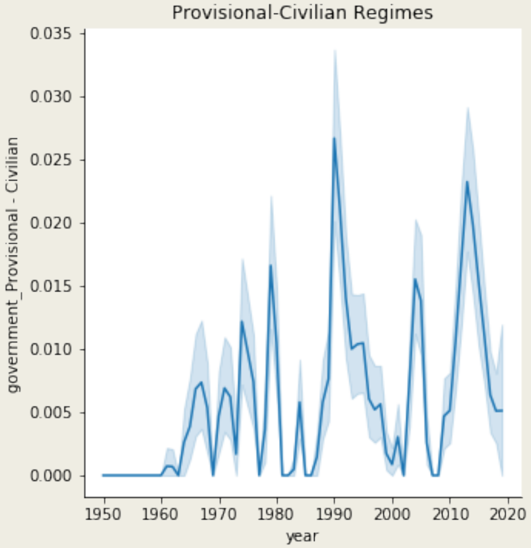


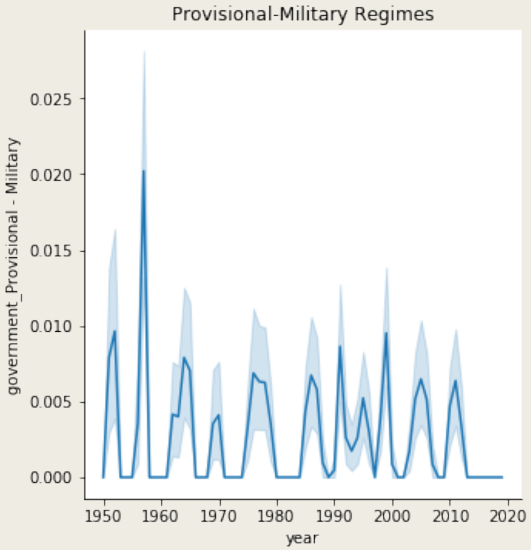
Temporary Government Types

- There is no clear trend in the other, temporary forms of government. One commonality is that they are all exceedingly rare.



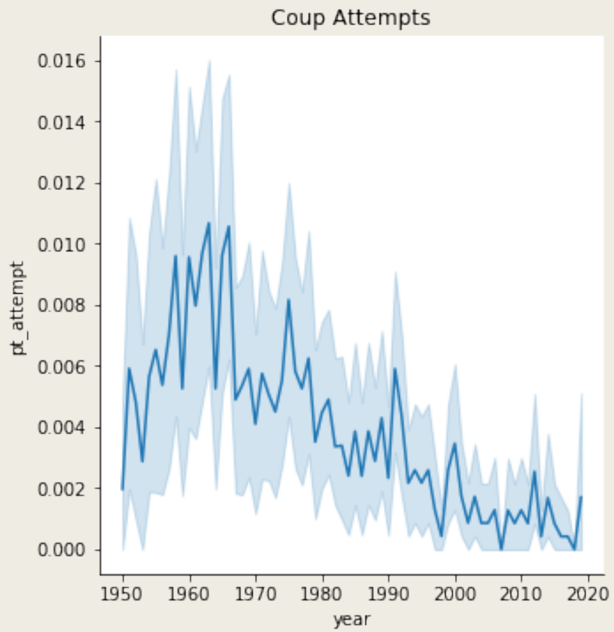


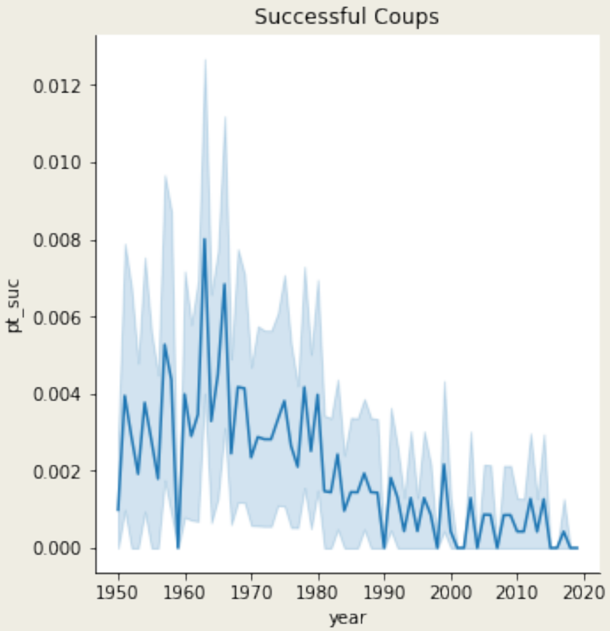


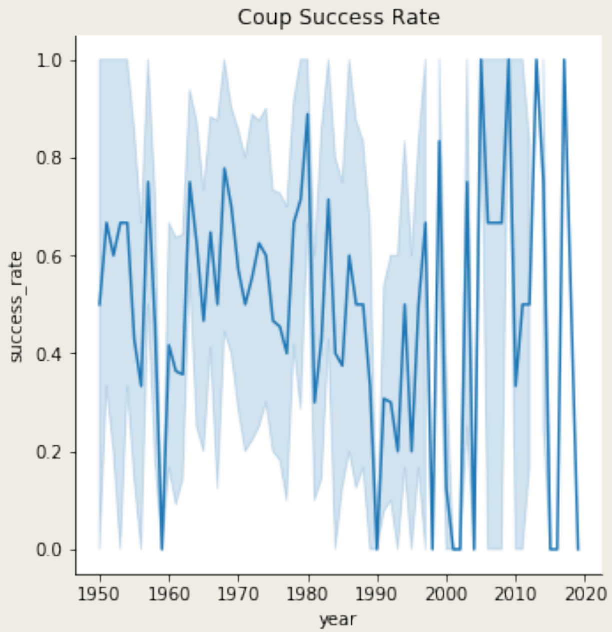


Coup Trends

- We see, clearly, the relative infrequence and variability of coup attempts.
- It appears that coups initially rose in frequency during the 1950s and 1960s, but have since declined asymptotically towards 0.
- When we look at coup success rates over time we see that they were consistently more successful during the 1960-1990 but have since become more inconsistent.







BUILDING THE MODEL

Picking the Right Model

- We will be using a Random Forest model.
- However, we will not be using a Random Forest *Classifier* model.
- This is due to extremely unbalanced data – a classifier will result in classifying all observations as *not* being a coup attempt.
- Therefore, the better choice is a Random Forest Regressor model, which allows us to select our own threshold.
- We chose 3 optimal thresholds, and 1 reference threshold:
  - *Precision: the fraction of relevant instances among the retrieved instances*
  - *Recall: the fraction of relevant instances that have been retrieved over the total amount of relevant instances*
  - *F1 Score: the harmonic average of the precision and recall*
  - *Reference: 0.5, the default threshold used in Random Forest Classifier*

The Model

- The model first establishes an instance of the Random Forest Regressor model using 10,000 estimators (i.e. 10,000 decision trees). This significantly increases the run-time of the model, but what we lose in speed we gain in model sensitivity.
- We then fit the model to the training data, established the model's predictions on the test set, and created a new Data Frame to analyze the results.
- In order determine the optimal thresholds for precision, recall, and the F1 score, we ran a for-loop that iterated over 1,000 possible thresholds from 0.0 to 1.0.
- We then separated out the false negatives, true positives, true negatives, and false positives. We then calculated the model's precision, recall, and F1 score.
- Finally, we determined the optimal thresholds to maximize the model's precision, recall, and F1 score (as well as including a default threshold of 0.5 as reference threshold).

The Results

- After running the model we arrived the following optimized thresholds:

```
### Optimal Precision Threshold ###
threshold    0.222222
precision    0.054054
recall       0.026490
f1_score     0.035556
```

```
### Optimal Recall Threshold ###
threshold    0.000000
precision    0.005366
recall       0.814570
f1_score     0.010662
```

```
### Optimal F1 Threshold ###
threshold    0.127127
precision    0.040000
recall       0.046358
f1_score     0.042945
```

```
### Default Threshold ###
threshold    0.500501
precision    0.000000
recall       0.000000
f1_score     0.010101
```

The Results (cont.)

- After running the model we arrived the following confusion matrices:

```
### Optimal Precision Confusion Matrix ###
False Negatives:  147
True Positives:  4
True Negatives:  39,637
False Positives:   70
```

```
### Optimal F1 Confusion Matrix ###
False Negatives:  144
True Positives:  7
True Negatives:  39,539
False Positives:   168
```

```
### Optimal Recall Confusion Matrix ###
False Negatives:  28
True Positives:  123
True Negatives:  16,909
False Positives:   22,798
```

```
### Default Confusion Matrix ###
False Negatives:  151
True Positives:  0
True Negatives:  39,699
False Positives:   8
```

ANALYZING THE RESULTS

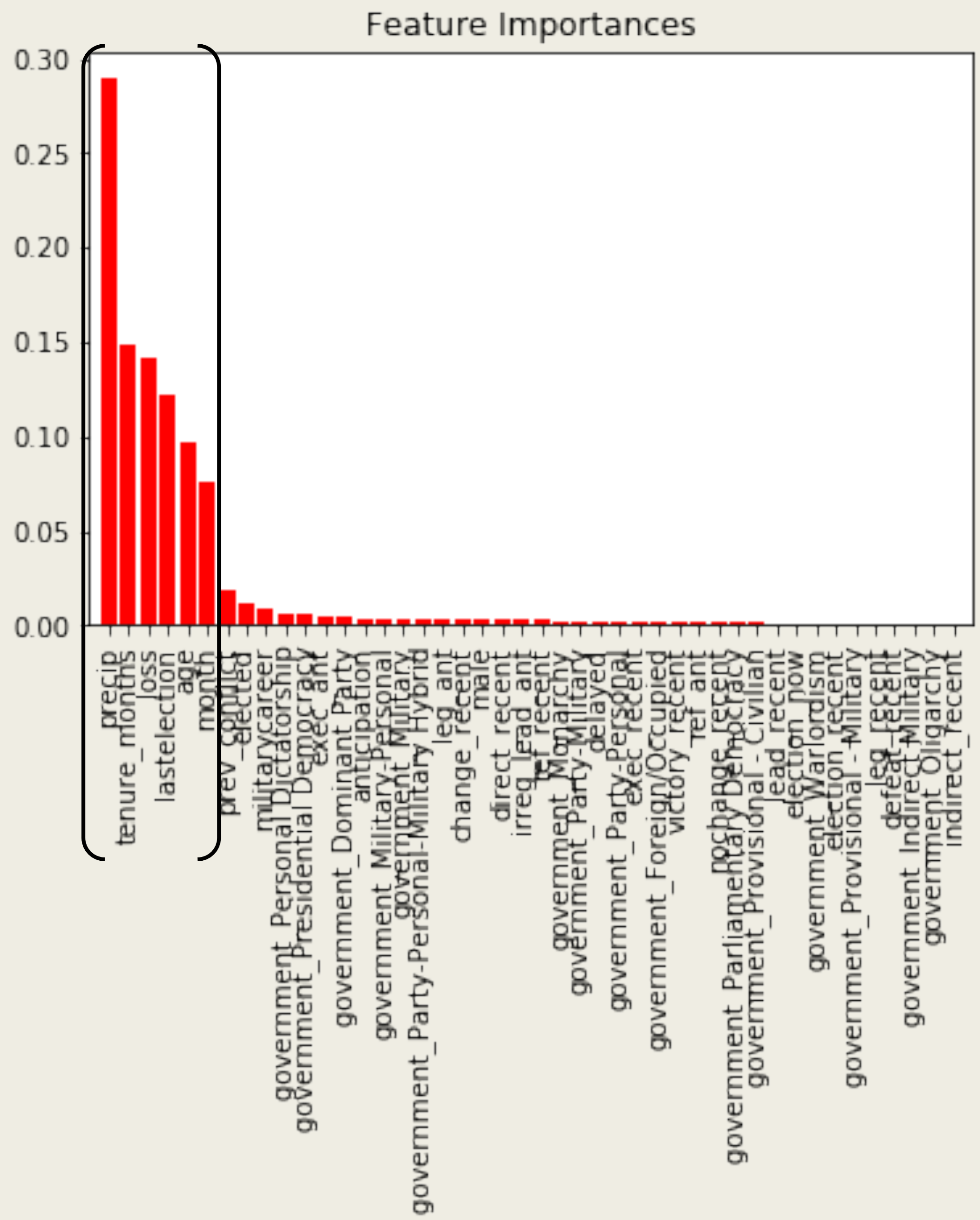
Optimal Thresholds

- When we analyze the results of our model, we see three different, optimal thresholds:
  - *Precision: 0.222222*
  - *Recall: 0.0*
  - *F1: 0.127127*
- The optimal precision recall threshold of 0.222222, as expected, results in the largest precision value, resulting in 4 out of 151 (~3%) actual positives and 39,637 out of 39,707 (~99.8%) actual negatives.
- An optimal recall threshold of 0 make sense given the severe imbalances in the underlying data; the model must be extremely sensitive in order to capture the true positives. As a result, the optimal recall threshold results in the largest recall value, resulting in 123 out of 151 (~81%) actual positives, but at the expense of only correctly identifying 16,909 out of the 39,707 (~42%) actual negatives.
- The optimal tradeoff between precision and recall – the F1 score – results in our model being able to correctly call 7 out of 151 (~5%) actual positives and 39,539 out of 39,707 (~99.6%) actual negatives.

Feature Importance

When we analyze which features are the most important in explaining the variation in our dependent variable (coup attempts) six features stand out from the rest:

1. **precip** – 0.289332
2. **tenure_months** – 0.149101
3. **loss** – 0.142232
4. **lastelection** – 0.122175
5. **age** – 0.097177
6. **month** – 0.076125



At Risk Countries

- If we subset the data to examine only the most recent year and month (March 2019) and look at the model's predicted probability of a coup attempt by country, we can create a league table of countries ordered by likelihood of coup attempt.
- For March 2019, the 5 countries with the highest likelihood of coup attempt are:
  1. *Gabon – 0.0427*
  2. *Turkey – 0.0318*
  3. *Belgium – 0.0251*
  4. *Congo/Zaire – 0.0228*
  5. *Yemen – 0.0192*
- If we refer back to our thresholds, we see that none of these top five countries meet our F1 score threshold of 0.127127, and so we would not predict a coup attempt in the current period.

CONCLUSIONS

The Importance of Water Infrastructure

- The results seem to indicate that greater democratization of the globe over the past half century appears to, at least in part, drive the secular decline in coup attempts.
- How?
- Mesquita and Smith note in their paper that leaders who face challengers maintain their coalition of supporters by taxing and spending in ways that allocate mixes of public and private resources. The nature of the mix depends on the size of the winning coalition.
- Democracies are characterized by large coalitions. As such, Democracies spend a greater percentage of their tax revenues on public goods like dykes, dams, levees, aqueducts, and other forms of infrastructure that smooth out extreme precipitation events.
- Thus, increased democratization leads to greater infrastructure spending, which in turn results in less detrimental effects of extreme precipitation events, which results in fewer coup attempts.

Advice

- All regimes, whether democratic or authoritarian, must invest in water infrastructure if the regimes wish to remain in power.
- By investing in water infrastructure, the regime lessens the blow of extreme precipitation events and thus removes the largest threat to their continuation in power.
- Therefore, autocratic regimes must allocate some resources away from paying off their winning coalition and into water infrastructure as a way to minimize the outside chance of a coup.
- This may anger some members of the winning coalition as their near-term profits may be reduced; however, the net present value of continued payments far into the future as a result of these investments in water infrastructure may outweigh these near-term reductions.
- Firms that operate in politically unstable countries can lower their risk of politically driven asset forfeiture if they, as part of their negotiations with host countries, promise to dedicate a portion of their proceeds toward water infrastructure investment.