Mass Atrocity Forecasting

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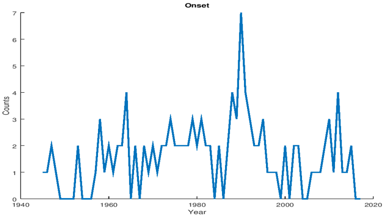
Overview

Final Project Topic

- We wish to forecast state-sponsored mass killing (SSMK) based on social, political, geographical, and economical predictors.
  - Specifically, we want to model the probability of a country either starting or maintaining a SSMK over the next year.
- Definition: A SSMK is any episode in which the actions of state agents result in the intentional death of at least 1,000 noncombatants from a discrete group in a period of sustained violence.

Challenges and Objectives

- Challenge: Low rate of occurrence under the working definition, and even lower rate of onset.
- Challenge: Fundamentally limited data, incomplete data.
  - Records begin in 1945, where data is partially available for 117/162 countries.
- Objective: Improve prediction rate, or more specifically reduce the "false negative" rate.
- Objective: Develop useful performance measures for comparing models.
- Objective: Provide a reasonable model interpretation.



The Data

- Found at `https://earlywarningproject.ushmm.org/` , the Early Warning Project
- Used a subset of 33 predictors which were reported on a yearly basis
  - "Any SSMK ever"
  - "Any ongoing SSMK"
  - Continent (Binary 1 iff the country is part of the continent)
  - Population size
  - Judicial Reform: Were the judiciary's powers reduced, increased, or held constant through institutional reform?
  - Religious freedom, civil rights...
- After omitting incomplete entries, there were 7020 samples ranging over 162 countries.

Previous Methodology

- J. Ulfelder used a unweighted ensemble averaging method where predictions from four different models for prediction
  - A multimodel ensemble for forecasting onsets of state-sponsored mass killing (2013)
- C. Hazlett most recently used Elastic Net for prediction
  - This reduced the relevant predictors down to 20
  - These results were used as a baseline for comparison
- In all previous attempts, it has been difficult determining the usefulness of the forecasts

New Methodology

- Idea: Use LASSO to select the most relevant data features from a "feature library", then fit common models to the selected features.
- Why is this different? Previous methods have not considered low-order interactions between predictors.
    - For example, it is possible that the combination of "being a part of South America" and "political killings occur" could be a stronger predictor than a linear combination of the two
- After features are selected, cross validation can be used to find the best fitting glms.

New Methodology - Feature Selection

- Create a "feature library". For example, include squared interactions:

$$\mathcal{X} = \left(\begin{array}{cccc|ccccc} \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots \\ \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots \\ X_1 & X_2 & \cdots & X_n & X_1^2 & X_1X_2 & \cdots & X_{n-1}X_n & X_n^2 \\ \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots \\ \vdots & \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots \end{array}\right)$$

- Apply LASSO to select most important features in feature library:

$$\beta^* = \min_{\beta} \frac{1}{N} ||Y - \mathcal{X}\beta||^2 + \lambda ||\beta||_1$$

- Fit various generalized linear models to the features selected in the previous step.

Results - Predictions and Performance

Our 2017 Risk Predictions			
Country	FS-Ridge	FS-Elastic-Net	KRLS
DRC	0.2724	0.3050	0.05905
South Sudan	0.1667	0.1562	0.05605
Afghanistan	0.142	0.1362	0.05590
Somalia	0.1134	0.1126	0.09162
Egypt	0.0804	0.1023	0.04824
Chad	0.0729	0.0520	0.05195
Pakistan	0.0709	0.0827	0.05235
Yemen	0.0659	0.0718	0.04855
Angola	0.0639	0.0744	0.07012
Sudan	0.0503	0.0687	0.07603

Previous EN 2017 Risk Predictions	
Country	Elastic Net
DRC	0.1377
Afghanistan	0.134
Egypt	0.08709
South Sudan	0.08947
Yemen	0.07602
Pakistan	0.07403
Somalia	0.0702
Turkey	0.0702
Angola	0.05646
Sudan	0.05609

- Notably higher predicted risk for top countries
- Alert countries with predicted risk $> 5\%$, and compare false alarms, false negatives, etc.
- Negative Performance Measure $NP(\hat{Y}, Y^{true}) = \frac{1}{N}\sum_{i=1}^{N} L(\hat{y}_i, y_i^{true}):$
  - KRLS: 3.160494
  - FS-Ridge: 0.987037
  - Elastic-Net: 0.9689459
  - FS-Elastic-Net: 0.9494302

Results - Model Interpretation

- The best performing model was most strongly influence by several interaction features, some shown below:

Fitted FS-Elastic-Net Coefficients (abbr.)	
Feature	Coefficient (10^{-2})
Political killings & ethnic fractionalization	0.95713
Political killings occur & non SSMK	0.86560
Ever SSMK & South Central Asia	0.70470
Judicial power was enhanced & ongoing MK	0.70048
Minority in control & successful coup	0.38293
In Africa & log battle related deaths	0.32372
SSMK ever & ethnic fractionalization	0.27303
Trade openness & South Central Asia	-0.2319
Freedom of men to move	-0.1824
Even civil rights	-0.0311