Forecasting Rebellion

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January 16, 2014

Introduction

Foreign policy is ultimately based on prediction. Policymakers base their decisions on how they think another state is going to react or respond. They are essentially making educated guesses based on the knowledge they have and the opinions of so-called area experts. In recent years, there has been a push to be more scientific in our predictions. The US government funds multiple projects, such as the Integrated Conflict Early Warning System (ICEWS) and the Political Instability Task Force (PITF), in an effort to develop statistical models capable of predicting events of interest.

Unfortunately, the field of political science, particularly conflict studies, has lagged behind in this effort. Research pays more attention to finding statistically significant coefficient estimates using marginally different model specifications, rather than how well these models predict what they claim to explain. Our approach differs by focusing exclusively on developing models that are able to forecast. For the purposes of this study, we attempt to forecast the occurrence of rebellions in Southeast Asian countries using publicly available event data from the Global Database of Events, Language, and Tone (GDELT). We use several statistical methods from the field of data mining that we believe may be more useful than the linear regression methods commonly used in political science.

Our paper proceeds as follows. First, we provide a brief overview of previous conflict-related forecasting research. A description of the data used follows and then a summary of the methods applied. Next, we discuss the results of our models. Finally, we conclude by providing an overview of our findings, as well as possible avenues for future research.

Review of Literature

Conflict literature primarily tests hypotheses by looking for statistically significant coefficient estimates for key variables. The predictive ability of these models is rarely tested. Studies that have focused on testing the predictive ability of these models have proven that they are practically useless for forecasting their events of interest (King, Beck, Zeng 2000; Ward, Greenhill, Bakke 2010). As a result, there has being a growing call for the development of models with better forecasting ability (Schrodt 2013). Schrodt (2000) demonstrates that pattern recognition techniques used in conjunction with event data can be useful tools for predicting levels of conflict. The US government-backed ICEWS has had some success in predicting events of interest such as rebellions and domestic political crises in Southeast Asian countries using logistic regression in combination with event data and structural variables (O'Brien 2010). We previously expanded on the ICEWS approach by incorporating GDELT as a new source for the event data and models from data mining (Arva et al. 2013). This paper builds on the work in Arva et al. by narrowing the focus on optimizing our predictive accuracy using event data from GDELT.

Data

Our data is derived from the GDELT dataset (http://gdelt.utdallas.edu), which is comprised of event data. At its core, event data records human interactions in a who-did-what-to-whom format using news stories as source material. For example, a news story that begins "Syrian rebels attacked the town of Aleppo earlier Friday" would be recorded as: source actor - SYRREB, target - SYR, event - 19. Using this underlying data, we construct a dataset that records counts of interactions between various groupings of actors. As an example, one such category records the number of violent events between government actors, such as a violent interaction between the governments of the United States and Russia. All told, our dataset has 70 columns recording these types of interactions for a group of countries involved in political events within Southeast Asia. For each country, time series of monthly data is constructed recording each of these counts. This data is fairly sparse, with a number of the 70 categories containing most, if not all, zeroes. The dependent variable in our analysis is whether a rebellion occurs within a given country within the next six months. This variable is dichotomous, and is coded a 1 if a rebellion occurred and 0 otherwise. This dependent variable is also rather sparse, with only 19% of the data being coded as a positive observations. As an illustration of the data, for a country such as Cambodia, data on the interactions of Cambodian actors with other actors in January is recorded and used to predict whether a rebellion will happen within Cambodia in July. The total number of observations within the dataset is 4,350.

Method

We perform tests using 4 different models: logistic regression, random forest, support vector machine, and adaptive boosting. We split the data into a 75-25% train-test split before performing any analysis. Each start out with a 75-25% split. All hyper-parameters are then tuned using 5-fold grid-search cross validation. Where appropriate (SVM) multiple rounds of k-fold CV are used to ensure unbiased estimates. The data is pre-divided in order to ensure that all the models are working with the same data so that estimates are consistent across models. The data is also scaled to have mean 0 and standard deviation of 1 for all models. This is especially important since our data is both sparse and has a wide range of values.

Experiments

Following rounds of 5-fold cross validation, the following hyper-parameter settings are found to be optimal. For random forest, we use 250 trees, with trees grown to their maximum depth, the minimum number of samples for each split set to 1, and the Gini criterion used to determine splits. Adaptive boosting determines that the number of base estimators is 100, and we use the SAMME.R algorithm for the boosting portion. Logistic regression settles on a `C` parameter of 1, with class weightings inversely proportional to the class frequencies[1], and L1 normalization. Finally, SVM settles on hyper-parameters of 2 for `C`, auto class weightings, an RBF kernel, and a gamma value of 0. The below table shows the results of various metrics for these given models.

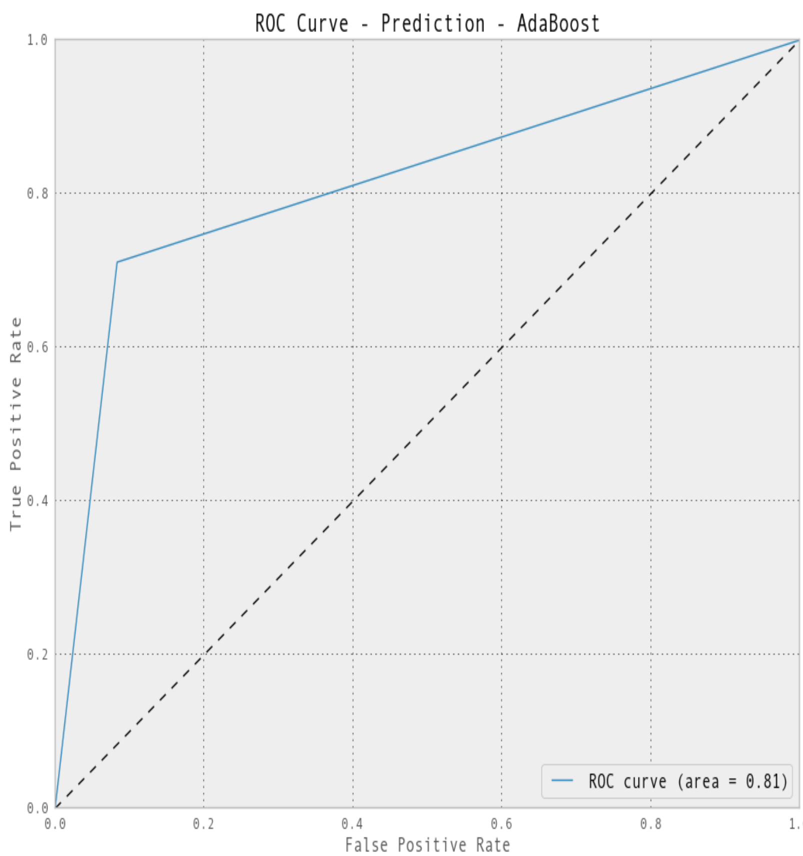
Table 1: Model Scores

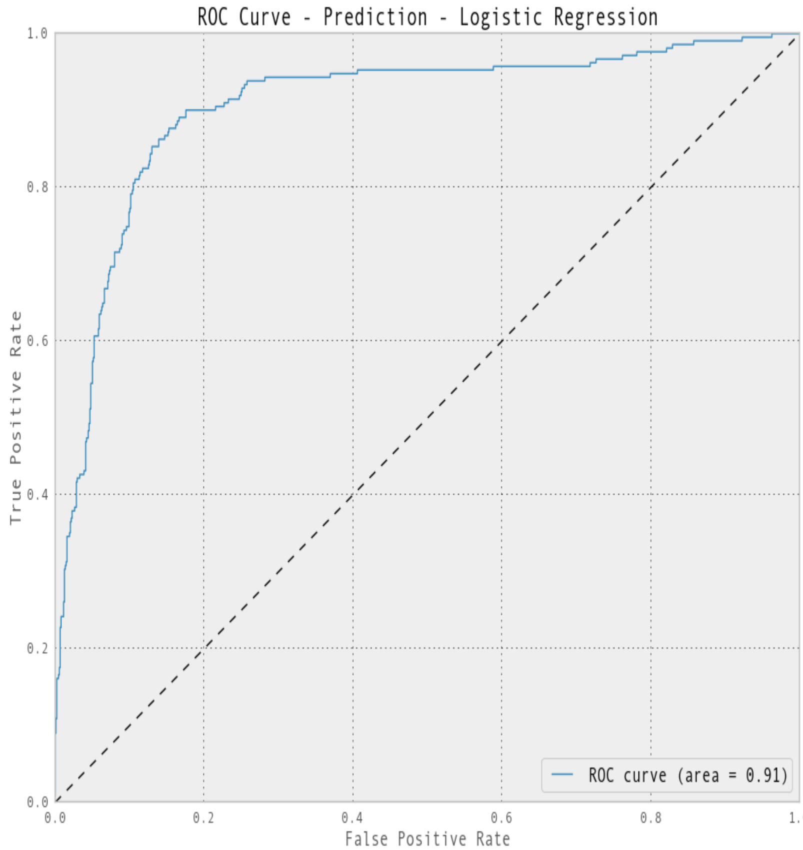
Model	Precision	Recall	F1
AdaBoost	67%	71%	69%
Logistic Regression	63%	**81%**	71%
Random Forest	**81%**	74%	**77%**
SVM	66%	74%	70%
Scores are from out-of-sample test set.			

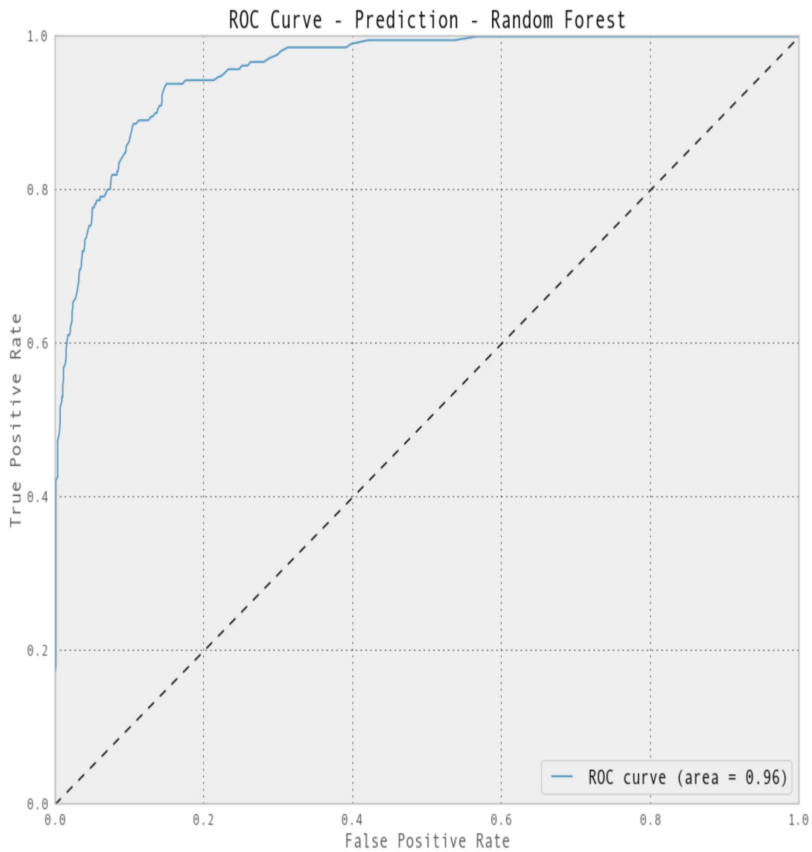
We choose to present these scores rather than base accuracy scores due to the nature of our data: the data is unbalanced and we are attempting to predict political behavior. This means that a raw accuracy score is not the best descriptor of model performance for our situation. Given this, we use the precision, recall, and F1 scores, with the precision score

[1]This is the "auto" weighting in the scikit-learn Python library

representing how well a classifier can avoid labeling a negative sample as positive, recall representing how well all the positive observations can be found, and the F1 score the weighted combination of the two. The above table shows that the random forest performs best on both precision and F1 scores, while the logistic regression is best at picking out the positive observations. In addition, we present ROC curves and classification tables in order to better understand our results.




ROC Curve - Prediction - Logistic Regression
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.91)


ROC Curve - Prediction - Random Forest
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC curve (area = 0.96)

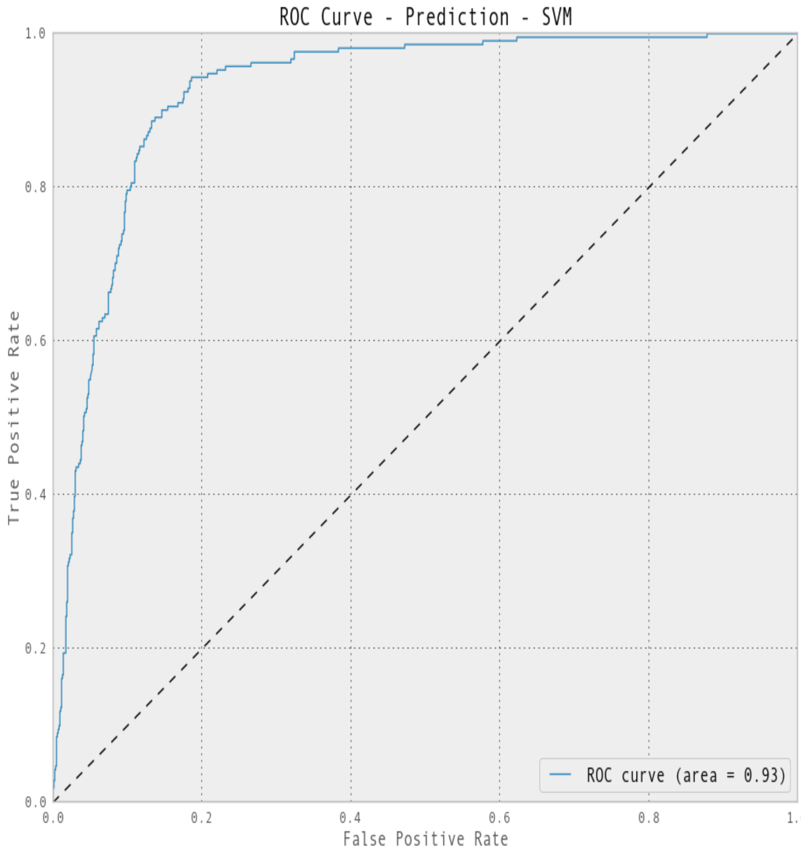


Table 2: Classification Table - AdaBoost

	Predicted	
Actual	0	1
0	804	73
1	61	150

Table 3: Classification Table - Logistic Regression

	Predicted	
Actual	0	1
0	778	99
1	40	171

Table 4: Classification Table - Random Forest

	Predicted	
Actual	0	1
0	840	37
1	55	156

Table 5: Classification Table - SVM

	Predicted	
Actual	0	1
0	796	81
1	55	156

In general, it appears that the random forest performs the best. This is to be expected for a few reasons. First, the fact that random forest is nonparametric and ignores the functional form of the data should make it better suited to our analysis than parametric models. This is important since our data is highly complicated, even post scaling. Additionally, the random forest is able to construct complex decision rules that fully capture the nature of the underlying processes that lead our outcome of interest, rebellions.

All of the models seem to achieve good accuracy. SVM performs the best with a mean accuracy of about 93%. However, the other models are not far behind. Random forest has an accuracy of just over 91%, while logistic regression and adaptive boosting each achieve approximately 89% accuracy. Random forest has the best precision, F1 score, and the most area under the curve (AUC), while logistic regression has the best recall. Adaptive boosting is clearly at the bottom in terms of performance.

Highest accuracy is not necessarily an indicator of the best model in our case. Because our dependent variable is relatively sparse, one could achieve 81% accuracy by simply predicting that there will never be any rebellions. This does us no good. We are ultimately concerned with identifying when a rebellion will occur so that policymakers can react accordingly. Because one of the aims of our research is to be policy relevant, we are more interested in minimizing false negatives, rather than false positives. It is a "better safe than sorry" approach. We would prefer that policymakers prepare for a rebellion that does not occur instead of predicting no rebellion and being caught by surprise.

With this in mind, it becomes a decision between between logistic regression and random forest. While random forest has a better overall accuracy, it has more false negatives and fewer true positives than logistic regression. Logistic regression does a superior job of minimizing the false negatives. However, it generates many more false positives than random forest. In this case, logistic regression is probably better suited to our analysis due to our goal of minimizing false negatives.

In terms of features, the one that consistently appears most often as an "important" feature is `gov_opp_matcf`. This represents the number of physically conflictual, e.g., an attack, events between government actors and opposition actors. For example, if the Syrian government attacks a Syrian opposition group, this would count as a `gov_opp_matcf` event. Intuitively, it makes sense why this variable will be important for predicting whether a rebellion will occur; the more violent the government is towards the groups that oppose it, the more likely there is to be a rebellion by those opposition groups. Other important variables capture the interactions between government actors, e.g., actions between the Syrian government and the U.S. government. This finding is also unsurprising, since the actions of one government may serve to temper or exacerbate the actions of another.

There are a few ways we could potentially improve our accuracy. The main issue we have is that our data is unbalanced, with many more 0s than 1s. We could correct for this by reweighing the observations and doubling the number of positive observations. This could help achieve our goal of reducing false negatives. We could also transform our features using multiplicative or polynomial terms. Finally, we might see improvement if we also included non-event variables, such as GDP, ethnic fractionaliztion, etc., into our models. This would likely give a better idea of which states are more susceptible to rebellion generally than others. Of course, all this is not to say we are unhappy with our results. Our mean accuracy is very high, as well as the scores for the other metrics. The fact that we are achieving these kind of results in our first attempt is very promising.

Future Work

There is still much work to be done. Right now, we do not use all the data we probably should. We are currently making predictions using data six months prior to our month of interest and ignoring all months before that. Future work should find a way to incorporate and weight data from the months leading up to the six month cutoff.

In addition, we may not be predicting our real event of interest in our data's current form. Our primary goal is really to predict the onset of rebellion, and we do not know for sure if the analysis in this paper actually does that. The dependent variable is coded as 1 for all months when a rebellion is active. A better approach would be to code only the month when a rebellion begins and when a rebellion ends. We could then alter the independent variables from counts to the change in the number of events from the previous month to better capture the change from peace to conflict and conflict to peace.

As previously discussed, future research should also include non-event variables. While this covers commonly used structural variables, we are most interested in making better use of the GDELT data. We are particularly interested in incorporating its geolocation data into future models. This should allow us to better pinpoint where we expect conflict to occur within a country and allow us to understand how it spreads.

Conflict forecasting research faces several challenges. First of all, data availability limits us. While the GDELT data are updated on a daily basis, we have to either rely on human-coded data for our dependent variable or code it ourselves. This also means that our event of interest is sensitive to how the coders define it. Determining when exactly a rebellion began may be a matter of opinion, and whether the occurrence of internal conflict even constitutes a rebellion is another issue. The GDELT data presents other sorts of problems. The data is very noisy and unbalanced. As a result, we have to develop methods of correcting for this in our analyses.

This paper contributes to the field of conflict forecasting by testing the utility of several models from data mining using event data from the recently released GDELT dataset. Overall, we achieve very good results, with logistic regression performing the best for our purposes. Future research should focus on predicting rebellion onset specifically and include structural and geographical data. While it is unlikely that there will ever be a philosopher's stone of conflict forecasting, a model that turns common events into perfect predictions, the field is making great strides in terms of predictive ability and policy relevance.

References

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