Conflict Prediction

Qianyi Li, John T. H. Wong, James Pye, Haoning Ling

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Introduction

We will try to predict the occurrence of conflict by geographical grid. We will report the results from estimating a random effects model and from using two machine learning methods, RE-EM tree and an artificial neural network (ANN). We find that the RE-EM tree performs best in terms of accuracy, likely due to its ability to take advantage of panel data, its consideration of fixed effects in estimating the region means of each terminal node, and its consideration of autocorrelation.

Before we proceed, we should note the limitations of our research. First, we will see that the ANN has poor predictive performance. This is likely due to its inability to accommodate the panel structure of our data set. We are aware that some researchers, such as Yang et al., have developed neural network architectures which can allow panel data as an input. Due to our limited research capacity, we were unable to implement both a novel tree estimation method (RE-EM trees) and a novel neural network. For this reason, the prediction results by no means are an apples-to-apples comparison between trees and neural networks.

Second, since RE-EM trees can only generate regression trees, we opted not to attempt classification. This unfortunately makes our results less comparable to past work on the subject (which predominantly attempted to classify whether conflict occurs in a binary manner).

The report is structured as follows. In Section 1, we will discuss our motivation behind predicting conflict. Section 2 reviews past literature on conflict prediction. We will then discuss the data sets we use, our data cleaning process in brief, and how training and test sets are split in Section 3. Section 4 provides the descriptions of and justifications for the estimation methods we choose. We will also discuss and interpret the prediction accuracy of each method.

1. Motivation

Our motivation is simple: to build an early conflict warning system. Conflict prediction is one of the set goals of the United Nations. This goal dates back to Boutros-Ghali's *An Agenda for Peace* report to the United Nations Security Council, in which calls were made for 'preventative diplomacy' augmented by an early warning system equipped with information regarding material conditions such as the likelihood of social conflict. However, there are still exceedingly few explicit forecasting or early warning systems in existence, making the prediction and hence prevention of conflict a difficult task.

Indeed, conflict today, including government-sponsored violence against civilians, state- and non-state conflict as defined in the Uppsala Conflict Data Program (UCDP), is an indicator of political instability. Conflict not only ruins individual lives but also hinders the prospect of sustainable long-run economic development (Okafor; Barugahara). Hence, an early warning system able to predict the occurrence of conflict would enable international organizations to allocate scarce security and aid resources efficiently. This is particularly absent in Africa, in which conflict often does not respect porous national borders and economic prospects are severely limited by political instability and social conflict.

2. Literature review

Singer in 1973 made the earliest mention of prediction methods being proposed for ex ante forecasts of political events and conflict, in which prediction was declared to be 'fundamental' to peace research, building upon the wealth of knowledge which had been accumulated in the Correlates of War project which began in 1963 (Suzuki, Krause and Singer). This initial enthusiasm for prediction methods faded in the 1980s and explicit models predicting conflict of any sort were few in number, with only a few notable exceptions of researchers attempting to construct primitive models to predict war with 'hostile interactions' as the input (Ward; Zinnes and Muncaster). Schrodt in 1991 marked a turning point by introducing big data methods such as neural networks to predict conflict and saw 'significant' accuracy improvements upon earlier work, however no statistical model was able to predict conflict with over 50% accuracy.

Amidst this development in the field of predicting conflict, Boutros-Ghali presented his report to the UNSC in which great attention was brought to the potential use of predictive tools in preventing conflict. Since this report, there has been a renewed interest in creating predictive models to predict conflict, with the United States establishing the State Failure Task Force (SFTF) tasked in 1994 with developing an empirical approach to state failure using logistic regression, neural networks, and genetic algorithms to attempt to determine 'critical thresholds' which would herald state failure (Esty et al.). However, SFTF's methodology was criticized by King and Zeng, as with the addition of two variables and neural networks, the authors were able to significantly outperform the baseline SFTF model. Beck, King, and Zeng subsequently built upon earlier neural network prediction methods and improved accuracy with better quality data, while demonstrating the inadequacy of a logit-based approach. However, out-of-sample prediction accuracy remained a woeful 17%, indicating further progress required. O'Brien was later able to achieve prediction accuracy of up to 80% with pattern classification algorithms, namely fuzzy analysis of statistical evidence previously constructed by Chen and established that a country's macrostructural attributes (e.g. whether a country is a democracy, partial democracy, or autocracy) could be used to predict the intensity of instability five years hence.

Despite some advancements, Secretary-General Kofi Annan noted in 2006 that 'no significant progress' had been made in developing an early-warning system that could be effectively used to prevent conflict. Indeed, Zenko investigated the UN's existing early warning system and concluded that it was largely ineffective, with no coordinating mechanism resulting in different bodies performing the early warning system piecemeal. Alongside improvements in big data techniques, researchers such as Perry have applied the machine learning techniques random forests and naive Bayes algorithms to model state fragility and vulnerability to conflict and demonstrated its feasibility. Brandt concluded that no one tool is sufficient for assessing model performance, noting that since conflict processes are non-linear point metrics such as MSE are inadequate. Instead, Brandt suggests that a suite of tools such as verification rank histograms (VRH) and Continuous Rank Probability Score (CRPS) are required. Perhaps the most promising conflict early warning forecast system is ViEWS (Hegre et al.) based in Africa with over 90% accuracy utilizing methods such as dynamic simulation, notwithstanding its inability to forecast new unanticipated conflicts.

Since the end of WWII, most conflicts have not taken place between great powers but rather regions with less developed economies. This is especially true in Africa, where tribal and racial rivalries undermine state borders and regularly lead to inter- and intra-state conflict (Williams). Cillers outlines the African Union's fledgling Continental Early Warning System (CEWS) and details its many drawbacks, for instance its lack of openness and paucity of adequate expertise and funding. O'Loughlina et al. effectively utilised geographically disaggregated data to analyze the relationship between climate variability and conflict risk in Africa, noting that given porous borders, country-based predictions are unreliable and fail to take local factors into account.

Our model attempts to take into consideration local factors in two ways. First, we use grid-based data sets which tracks conflicts and conflict covariates by each geographical grid of a fixed size. Second, our use of RE-EM tree, an estimation method designed specifically for panel data, allows us to take 'local factors' into account by factoring in fixed object effects when estimating population effects, while not assuming that these object effects will hold for out-of-sample data (RE-EM tree will be crucial for this). We will compare the resulting RE-EM tree to a standard random (object) effects model estimated with OLS and an artificial neural network (ANN) which uses lagged cross-sectional data as the input. Our model deviates from the existing literature as we attempt to estimate the number of conflict occurrences in a given year (with regression) rather than whether conflict occurs (classification).

3. Data

Data Collection

Our data was collected from three sources. As mentioned above, we see the need for geographically disaggregated data to achieve a more sensible prediction of conflict. Therefore, we first start with the Prio-Grid dataset, which is a standardized spatial grid data structure at a 0.5x0.5 decimal degree cell resolution (Tollefsen, Forø, Bahgat, Nordkvelle and Buhaug). The Prio-Grid dataset tracks conflict-relevant variables such as the presence of oil and mineral deposits, rainfall, and land use. These predictions lay the foundation for our grid-based analysis. Our second dataset is the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED), which identifies conflicts at the grid level as well. Since each realization in both data sets are by grid and year, this makes merging the two data sets possible. Finally, we combine the two data sets with the Quality of Governance (GoQ) Basic Dataset, a compilation of key datasets on governance and conflict at the country-level, given that the key role politics and institutions play in causing or abating conflict. We limit our research to the conflicts that occur within grids on the African continent due to the vast amount of related literature and the unique nature of conflict in Africa (Porter).

Data Processing

Our variable of interest is the frequency of within-grid conflict events occurring in the same year. This provides us with a sparse vector of the outcome variable due to the fact that not all grids experienced conflicts across time, as well as a left skewed distribution reflecting that conflicts are frequent but small-scale. To address the uneven skew of the outcome variable, we employ a $ln(y + 1)$ transformation to the frequency of conflict to create a distribution which more closely approximates a normal distribution and reduce the effect of outliers on our estimation. By adding one to the total frequency, grids with no conflict retain a frequency of zero even after log-transformation.

To prevent realizations with missing values from being dropped, we linearly interpolate some missing covariates, reduce the years observed, and occasionally exclude predictors from our models (provided that they are not critical for conflict prediction). The data cleaning process eventually returns a panel with 45 predictors–including a lagged outcome variable with a lag of one period, a temporal coverage of 1994-2004, and a geographical coverage of 1857 grid cells.

Data Split

We choose not to conduct train-test split by time periods, contrary to the typical treatment for time-series data sets. This is to prevent the same grid cells appearing in both training and testing sets, which would cause the split data sets to become dependent, bias our test MAE/RMSE, and fail to address the overfitting problem. We therefore split the dataset by object, i.e. grids, which leaves 1486 unique grids in the training set, 371 in the test set. Since (i) the RE-EM tree conducts cross-validation for each iteration of its estimation process and (ii) neural networks do not require a separate validation set, we do not create one.

4. Estimation

Methodology

We estimate predictions in three ways. First, as a baseline, we estimate a mixed effects model, as in a linear model with fixed population-level effects for each predictor and random object effects. There are both practical and theoretical reasons for not estimating an object fixed effects model. First, we eschew a fixed effects model due to the structure of our train-test data splits. Since the split is by object (which is the geographical grid's id in our case), we cannot estimate object fixed effects for each grid, since no objects that will be present in the test set are present in the training set. As mentioned previously, we choose to split by object in order to ensure independence (to the extent we can) across sets. The second reason for not estimating object fixed effects is that there is no guarantee that the fixed effects we estimate will hold for objects which are out-of-sample. We do acknowledge that the assumption for a random effects model (for objects) is likely to fail given that some regions are likely more conflict-prone than others. This brings us to our following point about using RE-EM trees.

Our second method is to estimate a RE-EM tree. RE-EM tree is an estimation method developed by Rebecca Sela and Jefferey Simonoff which (i) is developed specifically for panel data and (ii) iteratively "enforces" the random effects assumption. The motivation for estimating RE-EM tree is that it accounts for object fixed effects from the past in its estimation of population effects, without requiring that they hold for the future.

To illustrate this feature, I will now describe the RE-EM Tree algorithm briefly. First, it estimates a typical initial tree (by minimizing mean-squared error), where each realization is treated as a separate observation. Second, the region means of each terminal node are each reconfigured into the coefficient of a step function, which then form a linear model of the outcome, from which we estimate object fixed effects. In other words, we estimate fixed object effects b_i from $y_{it} = Z_i b_i + \mathbf{I}(X_{it})\mathbf{u} + \epsilon_{it}$, where Z_i are a vector of object dummies and $\mathbf{I}(X_{it})$ a list of step functions. (Here, we also specify the error term as AR(1), i.e. $\epsilon_{it} = \rho\epsilon_{i,t-1} + \omega_t$). Third, the regression tree is re-estimated on the true outcome minus the respective object fixed effect for each realization (i.e. $y_{it} - Z_i b_i$). Then we reiterate between the second and third steps until the fixed effect model (from step two) no longer sufficiently increases the maximum likelihood of the model being true. At that point, the region means of each terminal node are used (estimated on the outcome minus the latest fixed effect) is used as the predicted response of each node. Essentially, fixed object effects are "partialled out" from predicted response; or in other words, we "enforce" our random object effects assumption by ensuring that the population effects are estimated without object fixed effects.

Finally, given the nonlinear nature of conflict, we found it appropriate to estimate a neural network. Although common neural network architectures are not suited for panel data, we settled on constructing an artificial neural network (ANN). For our data to fit into the network, we manipulate our data so that instead of predicting each realization (i.e. year) of conflict outcome for each object, we only estimate the most recent outcome. Time-variant predictor values from previous years are consolidated into the most recent realization of each object with 20 lags for each time-variant predictor. The resulting matrix is 1853 x 577 (n x p). We attempted several layer architectures: 16/1, 16/8/1, 5/3/1, 3/6/1, 16/8/4/1, and 16/8/4/2/1, with dropout rate set at 40 percent after each layer (except the output). Models are set to stop training if five consecutive epochs do not return at least a 0.01 reduction in test MSE. We ultimately settled on 5/3/1 as (i) it has one of the lowest test MAE and (ii) is relatively simple. Then, we compare this ANN to a RE-EM tree. Here, not only do we compare the two in terms of accuracy, but also in terms of whether it is more accurate to estimate the outcome of each realization, or only the outcome of the most recent realization with the predictors from past realizations.

Results and Interpretation

The results are as follows. We report both the MAE and RMSE of each methodology:

Table 1: Results

	Method	MAE	RMSE
1	Random Effects (OLS)	0.187	0.467
2	RE-EM Tree	0.164	0.344
3	ANN (last outcome only)	0.364	0.561

RE-EM tree has the best predictive performance among the three. ANN of the last outcome unfortunately performs worse than a random (object) effects model, despite that ANN takes into consideration lagged covariates from previous periods to predict the most recent outcome. To better understand the variables which are affecting conflict, we also include the regression table from the random effects model and the RE-EM tree structure (see Table 2 and Figure 1).

The superior performance of RE-EM tree is likely attributable to (i) its partialling out of fixed object effects in its estimation of population effects, (ii) its retaining the panel data's structure, and (iii) its ability to account for autocorrelation in errors, in contrast to a regular decision tree or our random effects model.

Table 2: Determinants of Conflict

Latitude	0.003*** (0.0004)
Longitude	0.0003 (0.0003)
Agricultural Land Barren Land Distance: centroid to border	0.000001 (0.00002)
Distance: centroid to capital	0.00001* (0.00001)
Drought Severity	−0.01*** (0.002)
Drought Length	−0.03 (0.04)
Drug Cultivation	−0.04*** (0.01)
Forest Land Gross Product, PPP	0.01*** (0.003)
Gem Deposits	−0.02 (0.03)
Grass Land Irrigation	0.000001 (0.000001)
Night Lights	0.22*** (0.07)
Pasture Land Petroleum Deposits	−0.03** (0.02)
Precipitation	0.00002*** (0.00001)
Savanna Land Shrub Land Temperature	−0.001 (0.001)
Urban Land Water Land Population Density	0.0001*** (0.00002)
Diamond Deposits	0.02 (0.02)
Gold Deposits	−0.06*** (0.02)
Corruption (higher, worse)	−0.16*** (0.03)
Dem Deliberativeness	0.23*** (0.07)
Egalitarianism	−0.28** (0.12)
Gender Equality	−0.16*** (0.03)
Media Corruption	0.06*** (0.01)
Dem Participation	0.04 (0.08)
Electoral Competitiveness	−0.19*** (0.07)
Age Dependency	0.004*** (0.001)
FDI	0.001** (0.0004)
Fertility	−0.05*** (0.01)
Life Expectancy	−0.004*** (0.001)
Unemployment	0.001 (0.001)
Length of Regime	0.002*** (0.0002)
Colonial Origin	0.02*** (0.002)
Lag 1, Log(1+Conflict Freq.)	0.51*** (0.005)
Constant	0.25*** (0.07)
Observations	31,206
R^2	0.33
Adjusted R^2	0.32
Residual Std. Error	0.39 (df = 31165)
F Statistic	376.47*** (df = 40; 31165)

*p<0.1; **p<0.05; ***p<0.01

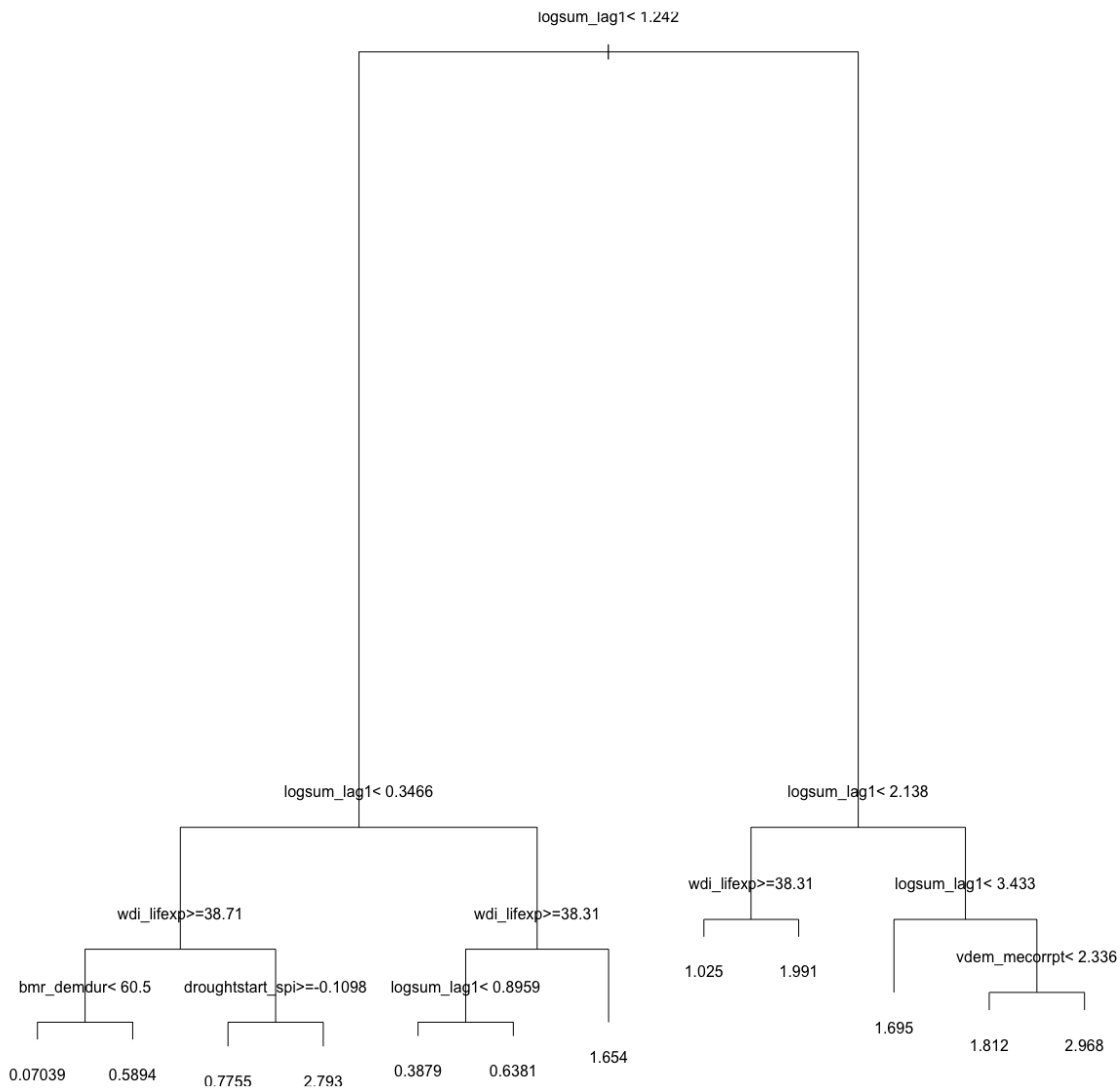

Figure 1: RE-EM Tree Plot

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