Predicting War with AI: Forecasting battle-related fatalities and conflict onsets

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Motivating Problem

How can the accuracy of the current early conflict warning models be improved for better decision-making and prevention?

Proactive investments in conflict prevention yield exceptionally high economic returns. Prevention policies in countries with no recent violence generate returns ranging from $26 to $75 per $1 invested, while in post-conflict high-risk settings, returns can rise to $103 per $1 spent.

Main Contributions

- Open-source framework for conflict forecasting.
- Data post-processing technique for more accurate forecasting
- Systematic comparison between state-of-the-art classifiers applied to conflict forecasting.
- Probabilistic regression model to predict number of battle-related fatalities in 14 months.
- Classification models to forecast probability of conflict outbreak in next 12 months.

Available Data

- Dependent variable is imbalanced and highly skewed to the right.
- Dataset consists of 190 features on a monthly level for 175 countries since 1990.
- Available features are number of fatalities via UCDP and ACLED, World Development Indices, Varieties of Democracy, water accessibility via AQUASTAT, region data and news background derived via news topic modeling.

Data Preparation

- Countries with poor data coverage are removed from the dataset
- Only median point for zero clusters is kept
- Only max number of fatalities from non-zero clusters in kept

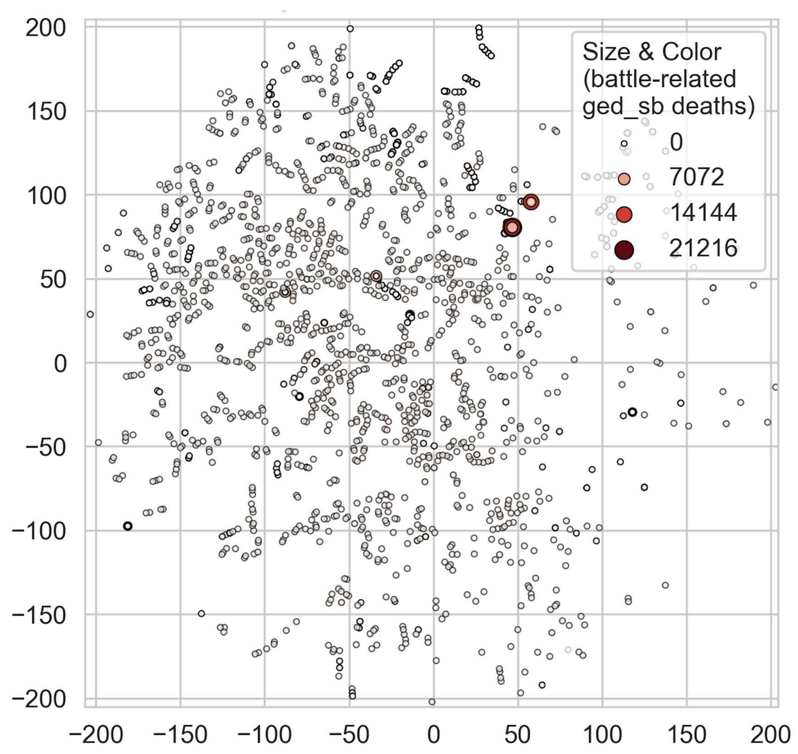

Figure 1. Clusters of similar points are visible when T-SNE is applied

Probabilistic regression models

We use Natural Gradient Boosting for probabilistic forecasting, but it tends to underestimate fatalities.

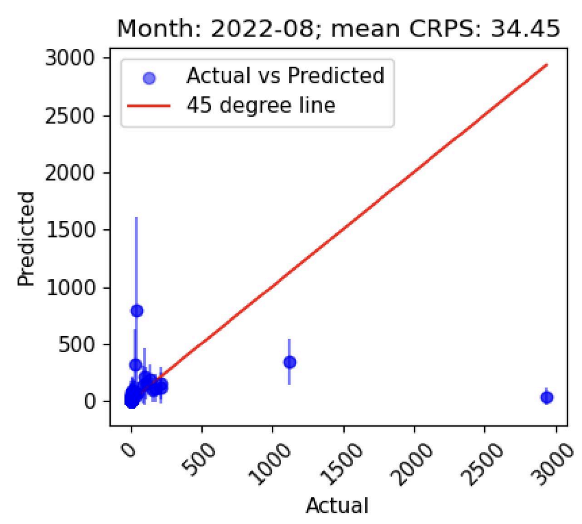

Figure 2. Example of predictions

To mitigate this issue we use softly gated mixture of experts approach. We train two regression models, one trained on conflict samples and the other one on peaceful samples. We use forecasts of classification models as a soft gate.

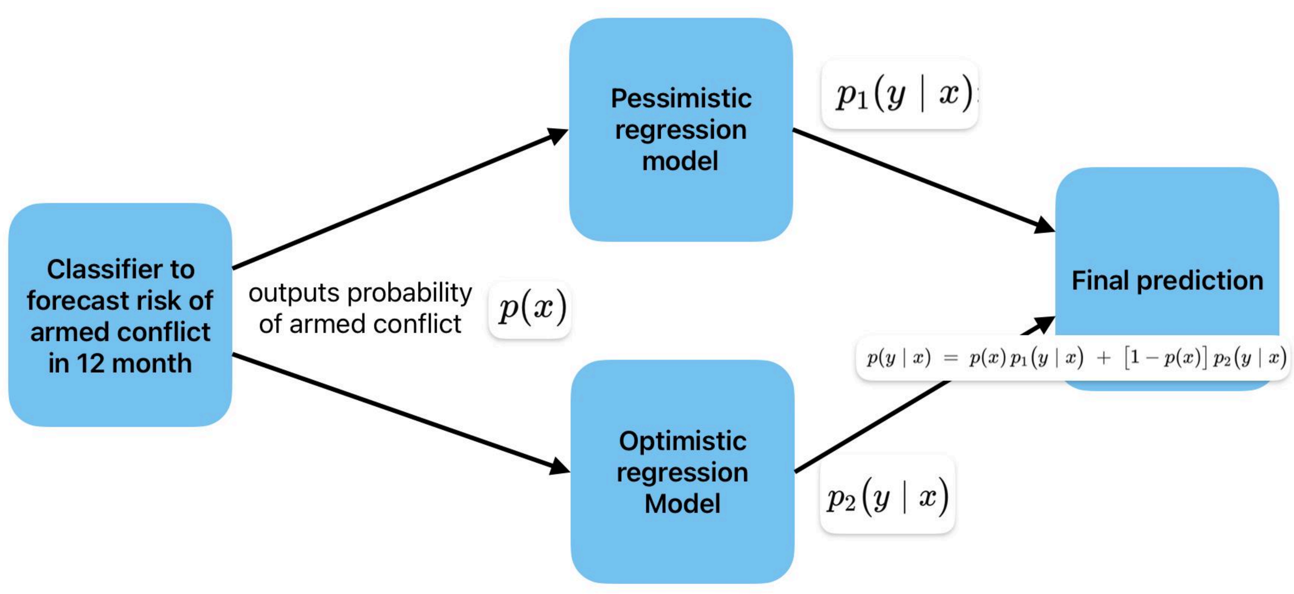

Figure 3. Softly Gated Mixture of Experts

Classification models

We employ three frameworks to build classifiers: XGBoost, Autogluon and TabPNF.

We train our models of 1990-2018 years, validate on 2019-2022 and test on 2023.

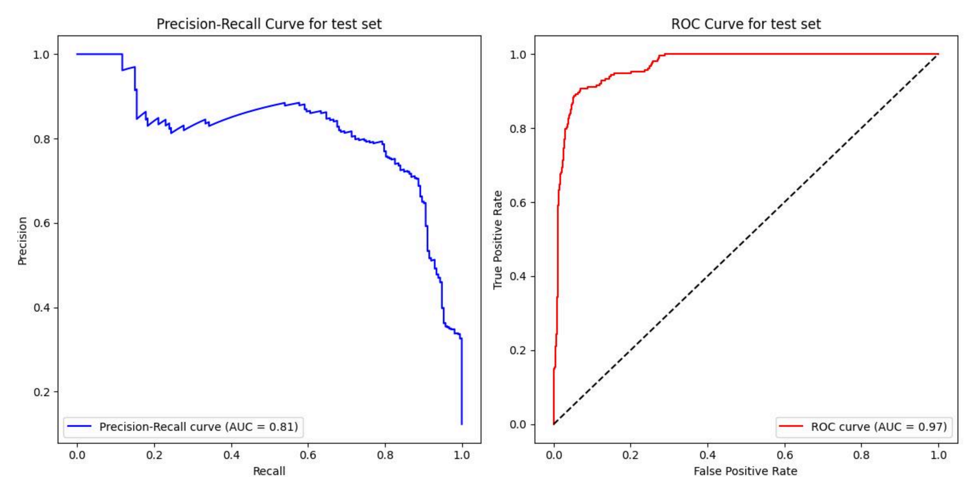

Figure 4. AutoGluon model performance for 2023 test set

Evaluation results

- Regression models are compared to heuristic competition benchmarks
- Classification models are compared to Conflict Forecast models

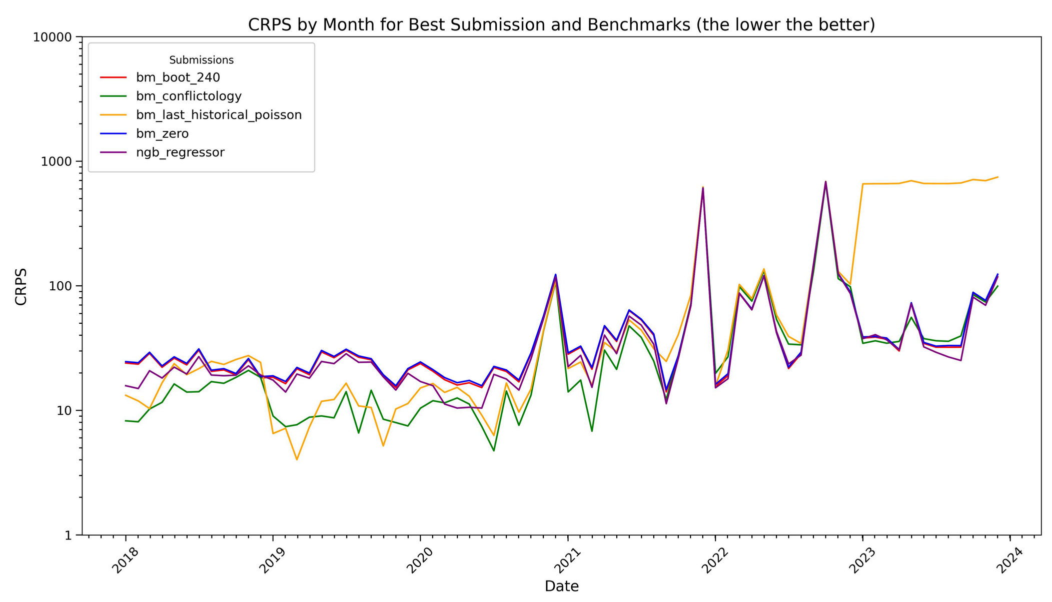

Figure 5. Comparison of best regression model submission to competition benchmarks

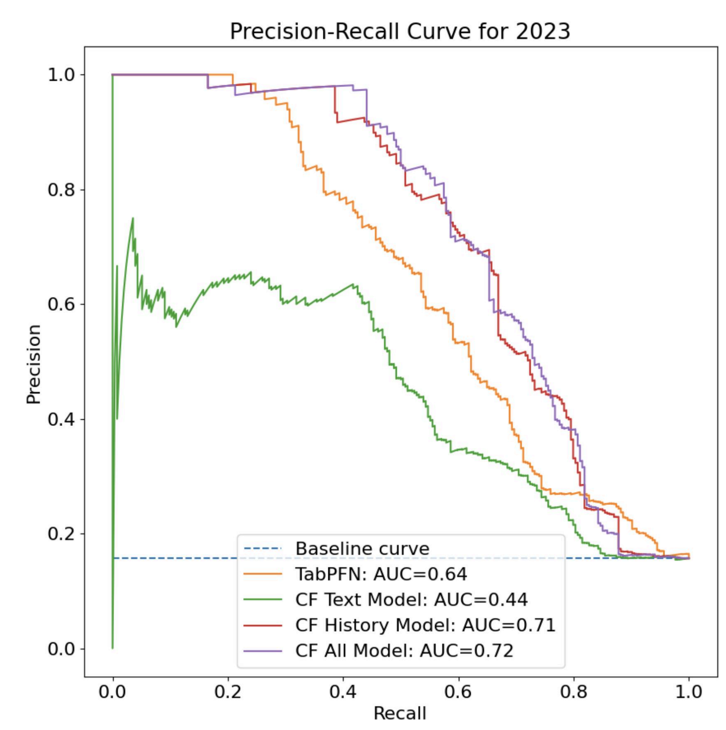

Figure 6. Comparison of TabPNF model with Conflict Forecast models trained on Conflict Forecast data

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