Diversifying Media Sources For The Forecasting Of Armed Conflict:

Avoiding Biases In Violence Prediction Algorithms

Capstone Research Proposal[1]

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[1] *Note:* small sections of the research proposal have been paraphrased and/or copied from my ARW literature review

List of Abbreviations

Abbreviation	Definition
GDELT	Global Database of Events, Language, and Tone
EWS	Early Warning System
KEDS	Kansas Event Data System
ViEWS	Violence & Impacts Early-Warning System
CAMEO	Conflict and Mediation Event Observations
ICEWS	Integrated Crisis Early Warning System
ACLED	Armed Conflict Location & Event Data Project
API	Application Programming Interface

Summary

The conflict-predicting field has advanced substantially in recent years, and state-of-the-art methods using machine learning are showing promising results. Yet, the field is still limited in its applicability for peacebuilding, due to low interpretability and low accuracy in tricky cases. Some have posed the incorporation of features from the media as a possible solution, due to its ability to provide more complete data and capture early signs of tensions. This has redirected attention in the field to big-data solutions, such as the event and sentiment data provided by the GDELT project. However, the blind application of media-based big data exposes prediction algorithms to biases and misinformation, which could produce dangerously misleading forecasts. Therefore, this paper argues that more attention must be paid to the careful selection of sources, and, to substantiate the importance of this, proposes to investigate the relative predictive power of local and global news.

Keywords: armed conflict, prediction, machine learning, bias, media

Introduction

Being able to forecast the outbreak of violent conflict is one of the most crucial and fundamental tasks within peace research. The potential of reliable forecasts and early warning systems to enable timely interventions, compare policy responses and evaluate existing theories, has motivated an ambitious field of peace research that aims to find reliable forecasting methods (Bressan et al., 2019).

In recent years, the advance of machine learning methods in the field has yielded promising results, but one of the most prominent limitations remains the prediction of conflict in otherwise peaceful countries (Hegre et al., 2017), referred to in the field as the “hard problem” (Mueller & Rauh, 2022a). Along with interpretability problems of complex models, this significantly limits the applicability of conflict prediction for peacebuilding on the ground. Several authors have tried to address this problem with creative methodological innovations, and one of the most promising avenues is the incorporation of features from the media, which has resulted in the use of large media-based event and sentiment databases, like the GDELT project.

However, others argue that the use of mass-scraped media sources is accompanied by a significant risk of bias and misrepresentative data, which is a potentially dangerous endeavour. Therefore, this paper argues that more attention should be paid to diversifying and selecting sources for conflict prediction. To aid this mission, it is proposed to investigate the differences in the predictive power of local and global news for forecasting armed conflict. This could furthermore underline the importance of a diverse forecasting framework, uncover biases in global conflict coverage, and highlight the value of local sources for conflict prediction.

Research Context

Although the use of big-data methods for peace and conflict studies has increased in the last decade, it is far from a new development. Since the early 1960s peace researchers have set out to systematically collect data on conflict, to enable the quantitative validation and development of theory, and be able to predict conflict ahead of time (Small et al., 1997; Suzuki et al., 2002). It has long been argued that ultimately the ability to forecast peace and conflict is fundamental to the field (Hegre, Metternich, et al., 2017) and the ambitious mission was even dubbed by some as “the number one task of peace research” (J. David Singer et al., 1973).

Significant progress has been made since. Data on conflict has become increasingly more granular, due to important early contributions to systemic data collection (i.e. Azar, 1980), but most prominently the KEDS project of Schrodt et al. (1994) and the CAMEO framework by Gerner et al. (2002). Fine-grained event data enabled the use of more advanced computational methods and led to increasingly promising results (Schrodt, 1991, 2006; Schrodt et al., 2001; Subramanian & Stoll, 2006). These codifying methods have since been developed further and resulted in large-scale event databases such as the ICEWS program (O’Brien, 2010) and the GDELT project (Leetaru & Schrodt, 2013).

Still, the real boost for the conflict forecasting field came after the realisation that prediction methods play a crucial role in theory development. Conventional p-value-based quantitative studies have been argued to be highly misleading (Ward et al., 2010), and usually focus on explaining historical events at the cost of a tendency to overfit theoretical models to past events (Chadefaux, 2017). Through the lens of theories with little predictive relevance, "the future tends to surprise us" (Bressan et al., 2019, p. 6), and therefore many argue that to evaluate theories, explanatory and predictive power are both a must (Gleditsch & Ward, 2013; Hegre, Metternich, et al., 2017; Schrodt, 2013; Ward et al., 2010). Schrodt (2013) even lists the development of theory in the absence of prediction as one of the “Deadly Sins” of quantitative political analysis. This marked a major turn in the field, and researchers started increasingly focusing on the use of out-of-sample methods. With this increased attention came many methodological innovations, as researchers started drawing methods and practices from the machine learning field (Colaresi & Mahmood, 2017). This resulted in a significant improvement in accuracy and has pushed the field into the mainstream of conflict research (Bressan et al., 2019).

However, despite the recent successes and steady improvements in accuracy, the applicability of conflict prediction for early warning systems (EWS), interventions and humanitarian response is still significantly limited. Although it is well-established that early peacebuilding interventions can have a significant conflict-reducing effect (Hegre et al., 2019), there is a lack of a clear link between forecasted violence and potential interventions on the ground (Caldwell, 2022). Research into EWS in Africa has shown that the data-driven EWS is often too detached from local reality to inform meaningful early action responses (Eze & Osei Baffour Frimpong, 2020). This gap between research and practice significantly limits the practical usefulness of violence forecasting for EWS or policy advice (Hegre, Metternich, et al., 2017) and a report on behalf of OCHA[2] concluded that the “currents state of the art is not sufficient for application in humanitarian response” (Caldwell, 2022, p. 11).

This applicability gap has two main causes. Firstly, the introduction of complex machine learning methods into the field was accompanied by a trade-off between explanation and prediction accuracy (Hegre, Metternich, et al., 2017). More complicated models are more accurate, but often impossible to interpret (Hegre et al., 2022), leading to what Ettensperger

[2] *United Nations Office for the Coordination of Humanitarian Affairs*

(2019) labels as the “black box problem”. This is furthermore complicated by the fact that the best-performing models are often a combination of different methods, making them even harder to disentangle (Vesco et al., 2022). However, understanding the rationale behind a prediction is of pivotal importance for applicable results, and therefore the increase in accuracy achieved by complex but ambiguous methods might not be worth the loss of interpretability (Ettensperger, 2019; Hegre, Metternich, et al., 2017).

Secondly, predicting sudden changes in conflict, especially its onset after a period of no violence, remains difficult. Predicting the escalation of conflict after a long period of peace or the de-escalation after a long period of violence is something even the best-performing models struggle with (Bazzi et al., 2021; Hegre et al., 2022; Vestby et al., 2022) and has been labelled in the field as the “hard problem of conflict prediction” (Mueller & Rauh, 2022a). This is due to the dominance of past conflict as a predictor for future conflict (Caldwell, 2022), making it significantly easier to predict conflict in a country that is already experiencing conflict (Hegre, Nygård, et al., 2017). In response, some authors have considered the possibility there might be theoretical limitations to predicting new conflict (Malone, 2022) or even that the presence of uncertainty is itself a requirement for war (Chadefaux, 2017), as has been posed before by political scientists (Gartzke, 1999).

Either way, these limitations have raised questions about the ethical implications of implementing forecasting methods that are hard to understand and have significant inaccuracies. Due to the predictive dominance of conflict history, models are often biased towards forecasting more conflict, which could perpetuate existing cycles of conflict (Hegre et al., 2022). In any case, it is widely agreed upon that quantitative forecasting methods should always be incorporated into a larger framework with theory, qualitative methods and human input, to avoid the overlooking of local circumstances or the creation of self-fulfilling prophecies (Chadefaux, 2017; Eze & Osei Baffour Frimpong, 2020; Hegre et al., 2022; Sweijs et al., 2022)

Nevertheless, in attempts to address the hard problem of prediction, researchers have looked for data that could contain more information on early warning signs for conflict, such as remotely sensed data (Levin et al., 2018; Racek et al., 2023) or Twitter (Dowd et al., 2020). Of particular interest has been the systemic extraction of information from the news, as it could function as a mirror of society (Cook, 2000), and thus provide nuanced indicators of looming conflict even before actual conflict has occurred. Research has shown that the news indeed shows early warning signs of conflict Chadefaux (2014), signals of early tensions (Hegre et al., 2022), and enables the successful classification of countries into peace and conflict (Liebovitch et al., 2023). Of particular importance is the work of Mueller & Rauh (2017, 2022a, 2022b), who showed that the incorporation of newspaper articles achieves a modest increase in prediction accuracy on hard cases. Additionally, many pose that indicators derived from new media could become more important in the future, coinciding with a general shift of public discourse to the virtual realm. (Bazzi et al., 2021; Dowd et al., 2020; Sweijs et al., 2022).

A database of particular significance for this purpose is the aforementioned GDELT project (Leetaru & Schrodt, 2013) which systemically archives worldwide online news in over 60 languages, and codifies themes, sentiments, tone, locations, events and networks of actors (Saz-Carranza et al., 2020). It is recognized as the most comprehensive event and sentiment database that exists (Raleigh et al., 2023), and since its launch in 2011, the big data of GDELT has been applied to many areas in the social sciences. In the context of conflict prediction, it has been used to forecast social upheaval (Galla & Burke, 2018; Halkia et al., 2020; Keertipati et al., 2014; Korkmaz et al., 2015; Qiao & Chen, 2016), political risk (Sun et al., 2021), conflict intensity (Levin et al., 2018), global peace index (Voukelatou et al., 2022) and even the future of international relations as a whole (Chen et al., 2020). The response to GDELT has been enthusiastic, and some even explicitly argue that forecasting methods using its data could be useful for early interventions by peacekeepers (Voukelatou et al., 2022), and humanitarian organisations like the UN or the Red Cross (Keertipati et al., 2014).

However, critics argue that peace researchers should be wary of the blind application of big-data methods without carefully considering their nature and limitations. Research into GDELT has uncovered many limitations of its data, such as noise (Halkia et al., 2020), fake news (Raleigh et al., 2023), missing or duplicate data (Saz-Carranza et al., 2020), and a bias for urban events (Weidmann, 2016). Furthermore, despite efforts to diversify the sourcing of GDELT, most data consists of English and Western-based media (Saz-Carranza et al., 2020). Finally, there is a lack of transparency behind important classifying decisions such as “What counts as conflict?” (Day et al., 2015). Due to these limitations, Raleigh et al. (2023) argue that the claims by Keertipati et al. (2014) that GDELT can be used for humanitarian organizations to “important decisions” are misinformed. Using the right data is important, especially in the field of conflict prediction, as wrong data can lead to wrong policy responses or lack of one (Raleigh et al., 2023), but the limitations of GDELT are often overlooked (Raleigh & Kishi, 2019).

The incorporation of the media into conflict prediction opens up many opportunities but also opens the door to biases and misrepresentation issues in the data. It is well established in the field of media studies that the media is subject to many biases, especially so in their coverage of conflicts (Weidmann, 2016; Wolfsfeld, 2011). Conflict coverage often contains a geographical bias (Barron & Sharpe, 2008) cultural bias (Barranco & Wisler, 1999), fake news (Day et al., 2015; Sweijs et al., 2022), censorship (Baum & Zhukov, 2015) and a bias towards violent events

(Day et al., 2015). During conflict in particular, the societal mirror of the media is heavily distorted (Cook, 2000), and selecting a representative collection of stories is hard, even manually (Davenport & Ball, 2002). When the bulk of news that is used comes from Western and mostly English sources, events might be covered with certain prejudices (Demarest & Langer, 2018), not covered correctly (Demarest & Langer, 2022), or be missed entirely (Raleigh et al., 2023).

Therefore, using mass-scraped media sources for conflict prediction is dangerous, and can result in warnings based on inaccurate information (Sweijs et al., 2022) or contain a bias towards violence. Using incompatible data results in misinforming policy decisions with an expectation of conflict and could thus result in a conflict-predicting trap (Raleigh et al., 2023). It is important that conflict prediction research carefully evaluates its sources, and prefers unbiased and explainable forecasts over dry predictive power. Hence, this present research will use GDELT to investigate the relative predictive power of global and local news, and the implicit bias present in the data. The hypothesis is two-fold: 1) global media coverage will have a significant bias towards coverage of violence, and 2) local media will provide more nuanced forecasting indicators as opposed to global media.

Methodology

To investigate the biases in the GDELT database and the relative predictive value of local and global news coverage, this study will use the themes that GDELT codifies in its GKG database, rather than the events in the event database. As (Raleigh et al., 2023) argue, the event data are not a reliable source of conflict data, due to the many missing values and duplicate entries, but the themes that GDELT identifies may still be relatively reliable sources for tone and media focus (Raleigh et al., 2023). The themes are extracted using Latent theme identification (LTI), and categorized into labels that are found in GDELT's labeling systems, or recognized taxonomies like CrisisLex or that of the World Bank Group (Saz-Carranza et al., 2020). GDELT contains news from sources from more than 200 countries and territories, but for this study, only a small subset of countries will be selected and treated as case studies. The selection criteria will be based on the cases of violence that a country has experienced in the period between 2017 and 2024, and in particular the amount of "hard cases" that have occurred.

First, the themes in the worldwide coverage of these countries will be scraped through the GDELT DOC API[3]. Following the article selection criteria of Mueller & Rauh (2022), an article will be considered to concern a country when it either mentions its name or the name of its capital. The data will then be preprocessed, and the intensity of the themes will be grouped and smoothed monthly for global, regional and local news coverage. Second, the study will apply different machine learning methods to the preprocessed theme data, in particular random forest models, as successfully applied by Mueller & Rauh (2022). It is expected that this will be the most successful method for prediction, but other machine-learning methods might be applied if deemed suitable. The study will aim to predict the countrywide change in conflict intensity on a monthly level, following the standard recommended by Hegre et al. (2022). For the reference of the intensity level this study will use data from the ACLED database, as it is widely recognized to be the most reliable and complete source of conflict statistics and has a high validity (Raleigh et al., 2010; Raleigh & Kishi, 2019). Finally, the study will evaluate the performance of different combinations of theme information, and evaluate our hypotheses.

[3] See https://blog.gdeltproject.org/gdelt-doc-2-0-api-debuts/

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