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Early Warning System for Conflict Prediction

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Early Warning System for Conflict Prediction

Conflict Prevention

Why Conflict Prevention?

Conflict prevention holds utmost importance in the realm of international relations and diplomacy. Timely intervention can often lead to the resolution of conflicts before they escalate into more severe and devastating occurrences.

Example

- Hegre et al. (2012) simulated a scenario where the United Nations ceased its peacekeeping efforts after 2001 and found that, compared to the actual number of countries with ongoing peacekeeping efforts, three to four additional countries would have experienced major conflicts by 2013 in the absence of UN's efforts.

Conflict Prediction

Why Conflict Prediction?

In this context, conflict prediction and early warning systems play a crucial role by identifying potential risks and threats, offering decision-makers timely information to formulate policies for conflict mitigation and prevention.

The Aid of Data Science

the two possible ways of doing conflict prediction.

- Identification of potential conflicts relied heavily on individual diplomatic and political knowledge, intuition, and subjective judgment.
- Recognize the potential of current technology in the field of Data Science.

We chose Data Science!

Other works of conflict prediction

Logistic Regression (Halkia et al., 2020), Dynamic Multinomial Logit (Hegre et al., 2019), Random Forest (Muchlinski et al., 2016), naive Bayes classifiers (Perry, 2013), Neural Networks (Beck, King & Zeng, 2000) and many others.

Our Work

This article presents the development and outcomes of a new Early Warning System employing machine learning techniques, specifically leveraging **transformer** models.

Our Work

Aim: Our objective is to provide a probability, ranging from 0 to 1, that a given day is one of the 90 antecedent days preceding an unrest event. Thus, our Early Warning System aims to classify a day as either **"normal"** – significantly distant from any conflict – or **"pre-unrest"** – falling within the 90-day window prior to an unrest event.

Choosing the Datasets

The model is a heavily data-driven model

Social vs. Diplomatic Datasets

- **Social Datasets:** Twitter, Telegram, ecc...
- **Diplomatic Datasets:** ACLED, GDELT, ecc...

We need data that are stable, open source, updated on a daily/weekly basis → **Diplomatic Datasets**

Armed Conflict Location and Event Data Project (**ACLED**)

ACLED offers a comprehensive view of events such as conflicts, protests, and riots.

1. Human-coded
2. Disorder events recorded from news about social and political unrest (conflicts, protests, riots...)
3. Weekly update frequency

Armed Conflict Location and Event Data Project (**ACLED**)

Processing the dataset

To process the dataset effectively, data wrangling was necessary in order to obtain clear and functional variables.

- Filtered by date range and sub-event type
- Grouped by *ISO 3166-1 alpha-3 code* and date

This process resulted in a dataset where each row corresponded to a specific day in a country, including the number of events (and related fatalities) of a particular type that occurred on that day in that country.

Global Database of Events, Language and Tone (**GDELT**)

GDELT is the largest, most comprehensive, and highest resolution open database regarding diplomatic news.

1. Machine-coded
2. Focuses on NLP and sentiment analysis
3. Frequent updates – every 15 minutes -
4. News from various media sources in over 100 languages

Global Database of Events, Language and Tone (**GDELT**)

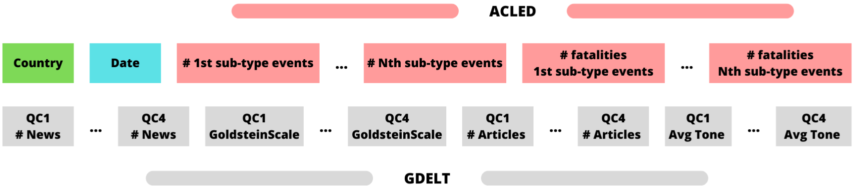
Processing the dataset

Again, to process the dataset effectively, data wrangling was necessary in order to obtain clear and functional variables.

- The dataset was reduced so that only the most significant items were retained (> 10 mentions)
- Grouped by *ISO 3166-1 alpha-3 code* and date, mirroring the approach taken with the ACLED dataset
- Working with 62 attributes wich are grouped in the following four macro-categories: **Verbal Cooperation**, **Material Cooperation**, **Verbal Conflict**, **Material Conflict**.

The Final dataset

The integration of these two processed datasets was accomplished by matching the *ISO 3166-1 alpha-3* code assigned to each country and the corresponding date. The final dataset incorporated additional attributes such as the number of news items, the *GoldsteinScale*, and the *Average Tone* associated with each news group falling under the same *QuadClass*, for every combination of country and date.



Weighted War

In addition to the daily variables extracted and grouped from the two databases, we introduced a new variable called **Weighted war**

Structure

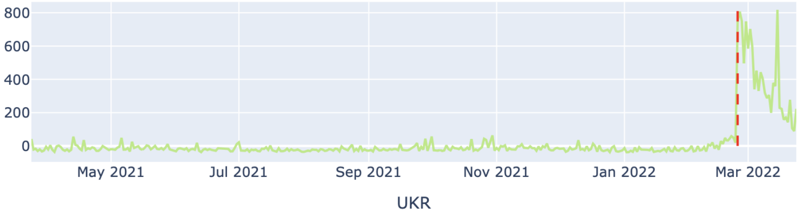
- Created through an examination of the temporal progression of ACLED variables across more than 50 wars and conflicts (2010-2022)
- The *Weighted war* index encompasses all ACLED variables, with their contributions weighted based on our examination.

Weighted War

What is an Unrest day?

We define a day as an unrest day when the Weighted war variable reach the top 0.5% value of its entire historical evolution.

- Country-specific definitions of an unrest event, as the 0.5% threshold in the Weighted war variable may vary across countries.



Transformer

Introduced in *"Attention is all you need"* by Vaswani et al. (2017)
Adapted to time-series by Zerveas et al. (2021).

How it works: Attention mechanism

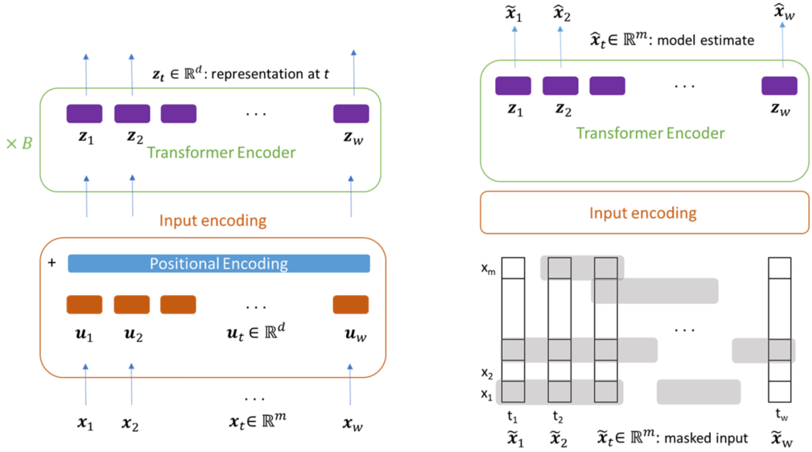
- Time-series data contains patterns and dependencies that change over time
- Capturing relevant temporal dependencies
  - It can dynamically assign different weights to different time steps, focusing more on the relevant information and less on irrelevant or noisy data

Advantages

- Ability to efficiently utilize GPU hardware
- It requires less long time-series

Trasformer

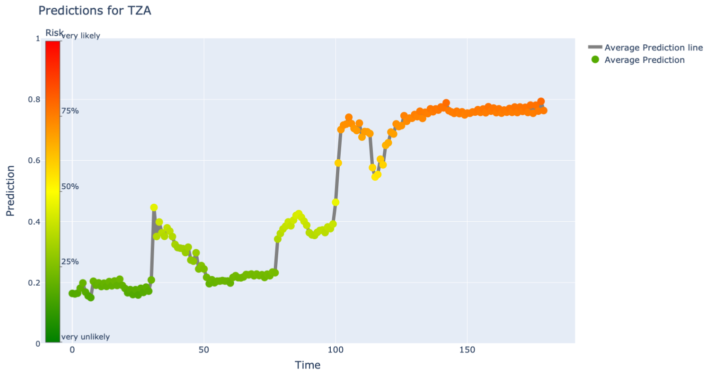
A Graphical Representation



Remember the aim

First of all, let us recall the goal of the project

For each country, the system was trained and tested to assess its ability to classify days as either “normal” or “pre-unrest” within the 90-day window preceding an unrest event.



Evaluation results

Performance Measure: the Area Under the Curve (AUC) and accuracy were used to evaluate the models' effectiveness

Table: Average Performance Measures Across 101 Countries

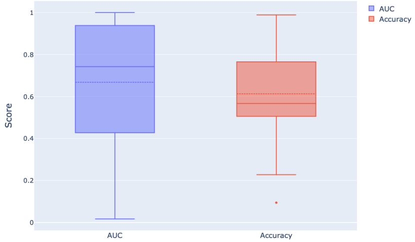
Performance Measure	Median	Mean	Standard Deviation
AUC	0.74	0.65	0.31
Accuracy	0.57	0.61	0.17

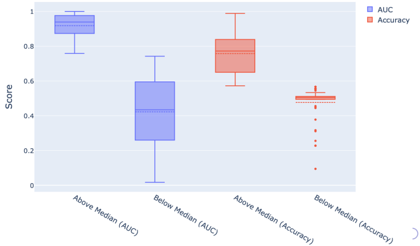
Analyze the results

Disparities of performances

Disparities between the underperforming and outperforming group:

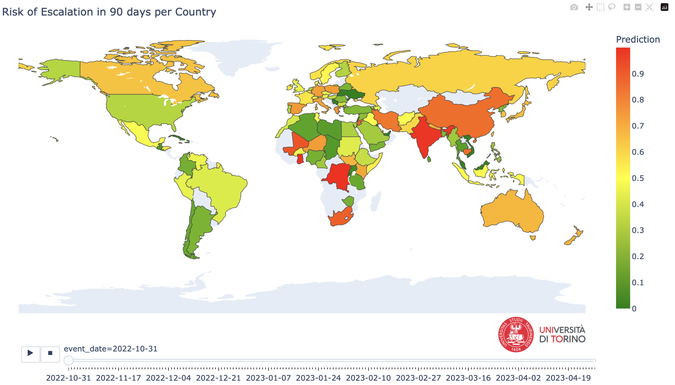
- **Countries above the median**: the mean and median of AUC above 0.9 and the mean and median of accuracy just below 0.8
- **Countries below the median**: results hovering around 0.5 for both AUC and accuracy





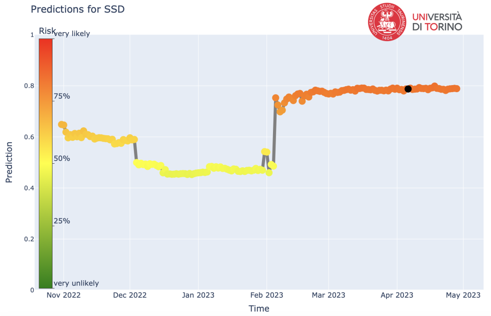
Operational system

Output 1:
Each country is associated with a color that indicates the probability that a day will be one of the 90 days prior to the onset of an escalation, i.e., of an Unrest day.



Operational system

Output 2: Probability, day by day, of being a Pre-unrest day.



April 6, 2023 (black point):

- Attack: 1
- Peaceful protest: 5
- Abduction/forced disappearance: 1

Conclusion

- New approach in conflict prediction
- Fully reproducible
- Excellent results already in its first version
- Excellent results with very modest computing power
- Future improvements (to assist utilization):
  - Explainability
  - Forecasting of disorder events
- Future imrovements (to increase performance):
  - including relational diplomatic data
  - including thematic dimensions beyond diplomacy (economical, social, environmental, ...)
  - sub-optimization for each country

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