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**Title:** Identifying Indicators of Sociopolitical Instability in Iran

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# Identifying Indicators of Sociopolitical Instability in Iran

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# Introduction: Socio Political Instability

Defined as “*the likelihood that a government will be overthrown by unconstitutional or violent means, including social unrest, violence, hostility, or terrorism.*”

- Global protests and demonstrations have increased **244%** in the last decade (Strohecker, K. 2021)
- Better understanding of the drivers and motivations behind this increasing instability may help inform preventative or de-escalation measures
  - Identifying measurable indicators and drivers of sociopolitical unrest is the first step in accomplishing this task and may aid with event forecasting through modeling

# Introduction: Socio Political Instability in Iran

Recent socio political unrest in **Iran** has potential implications within the Arab world including government, social and economic change

- The unrest initially erupted in response to the **death** of **Mahsa Amini** while in custody of Iran's morality police on September 16, 2022
- As a result of these protests, hundreds of protestors including children have died



# Approach



# Data Sources

## 1. ICEWS

The Integrated Crisis Early Warning System monitors national, sub-national, and internal crises via news and social media.

The "Global Event Data" project is a large-scale collection of global event data.

The Army and Air Force Research Laboratory (AARL) is a leading research organization in the field of political event data.

Basically, “**who**, did-**what**, to-**whom**, **when**, and **where**”

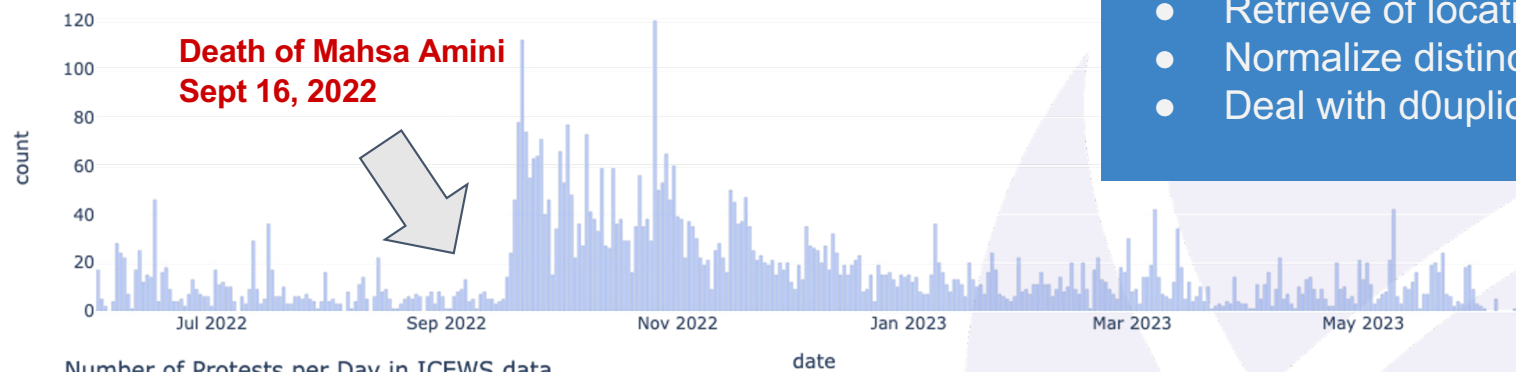
**source** | event type | **target** | temporal inf. | spatial inf.  
**intensity**

## 4. POLECAT

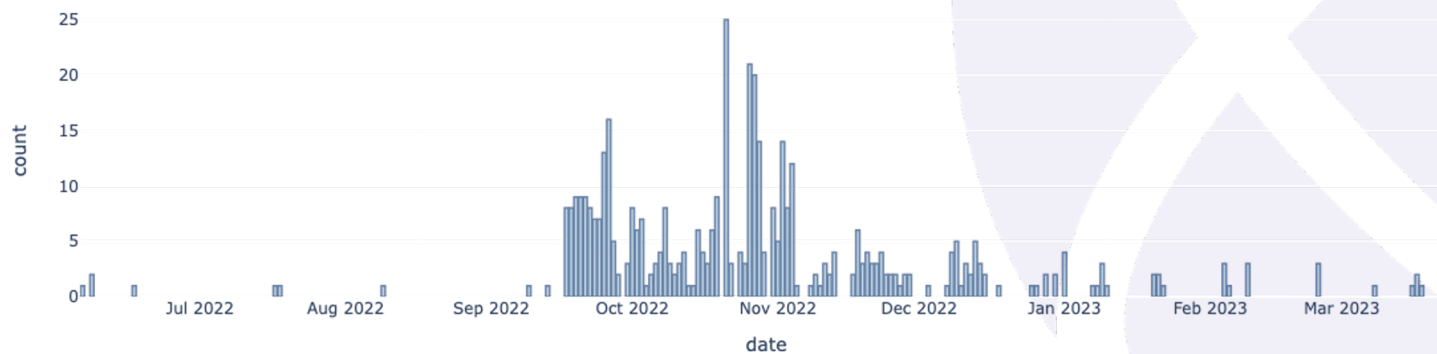
The POLitical Event Classification, Attributes, and Types project is a global political event dataset intended to succeed the ICEWS project.

# Aggregated Data Sources

Number of Protests per Day in Aggregated Data data



Number of Protests per Day in ICEWS data

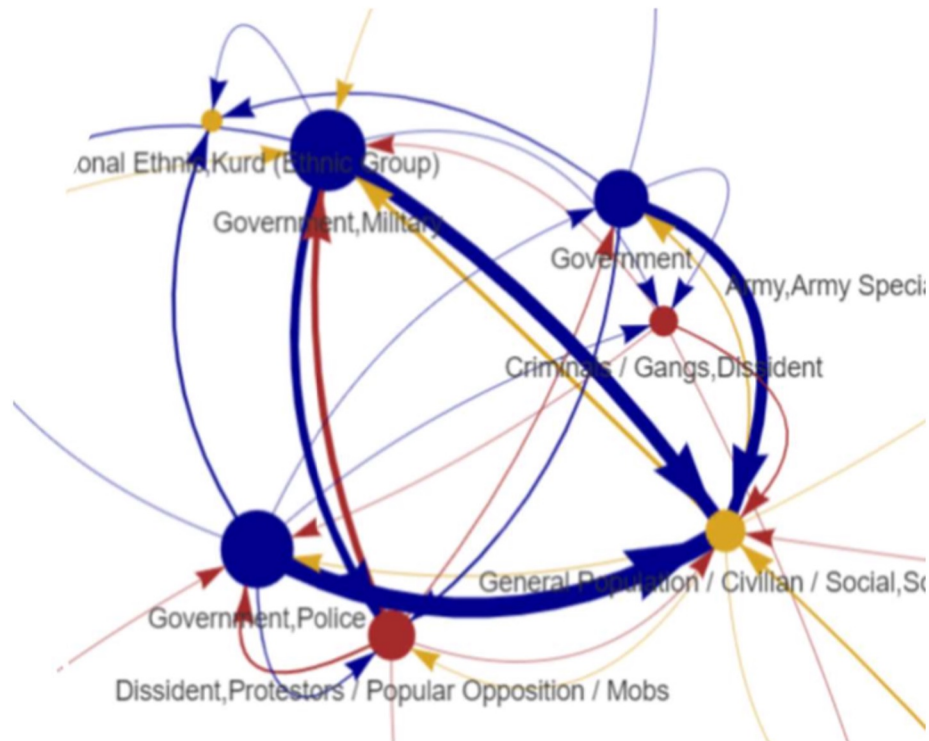


The data sources were harmonized

- Fill in missing values
- Retrieve of location information
- Normalize distinct event coding
- Deal with d0uplicates



# Bi-Directional Weighted Graph for Hostile Environments



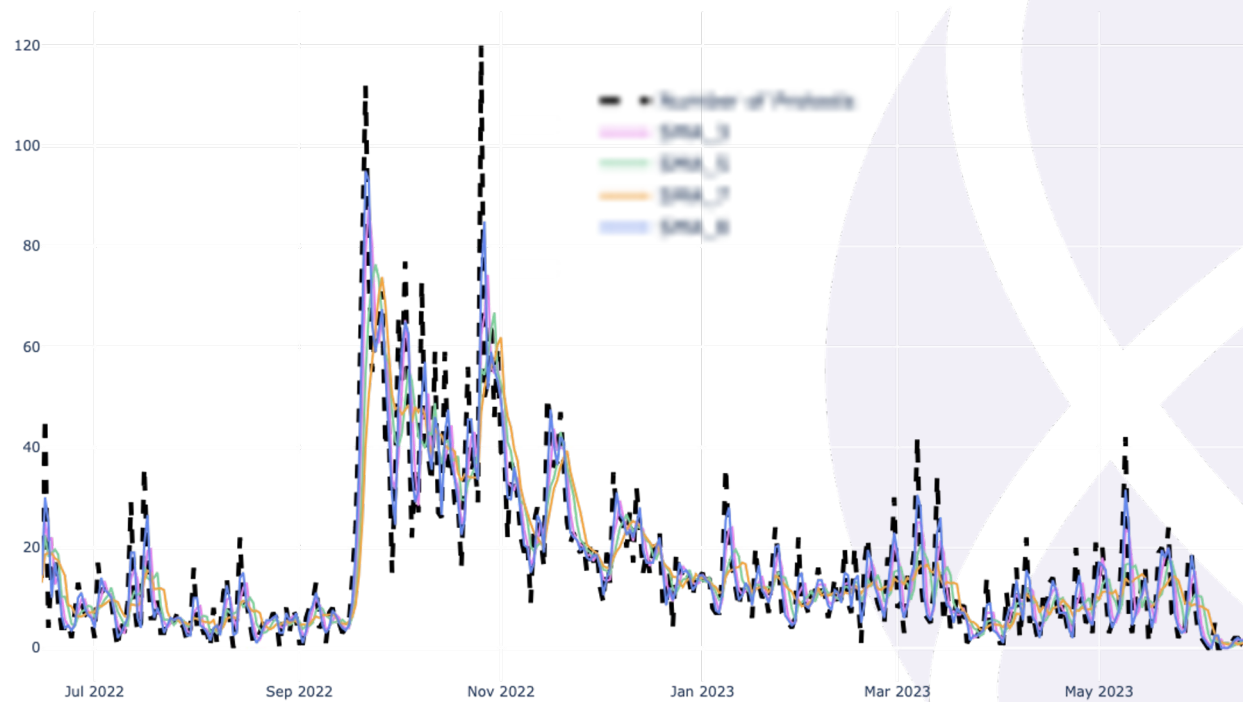
**Event Intensity:** ranges from **-10** to **10**

Hostile events (intensity between **-5** and **-10**)

- The most **hostile** actions were performed by **government** sectors upon **civilians**
- The second largest group of **hostile** actions were performed by **civilians** upon **government** sectors
- Hostile **government** aggressions occurred **3 times** more often than **civilian** protests

# Simple Moving Averages (SMA) to Predict Future Events

Simple Moving Average for Protests

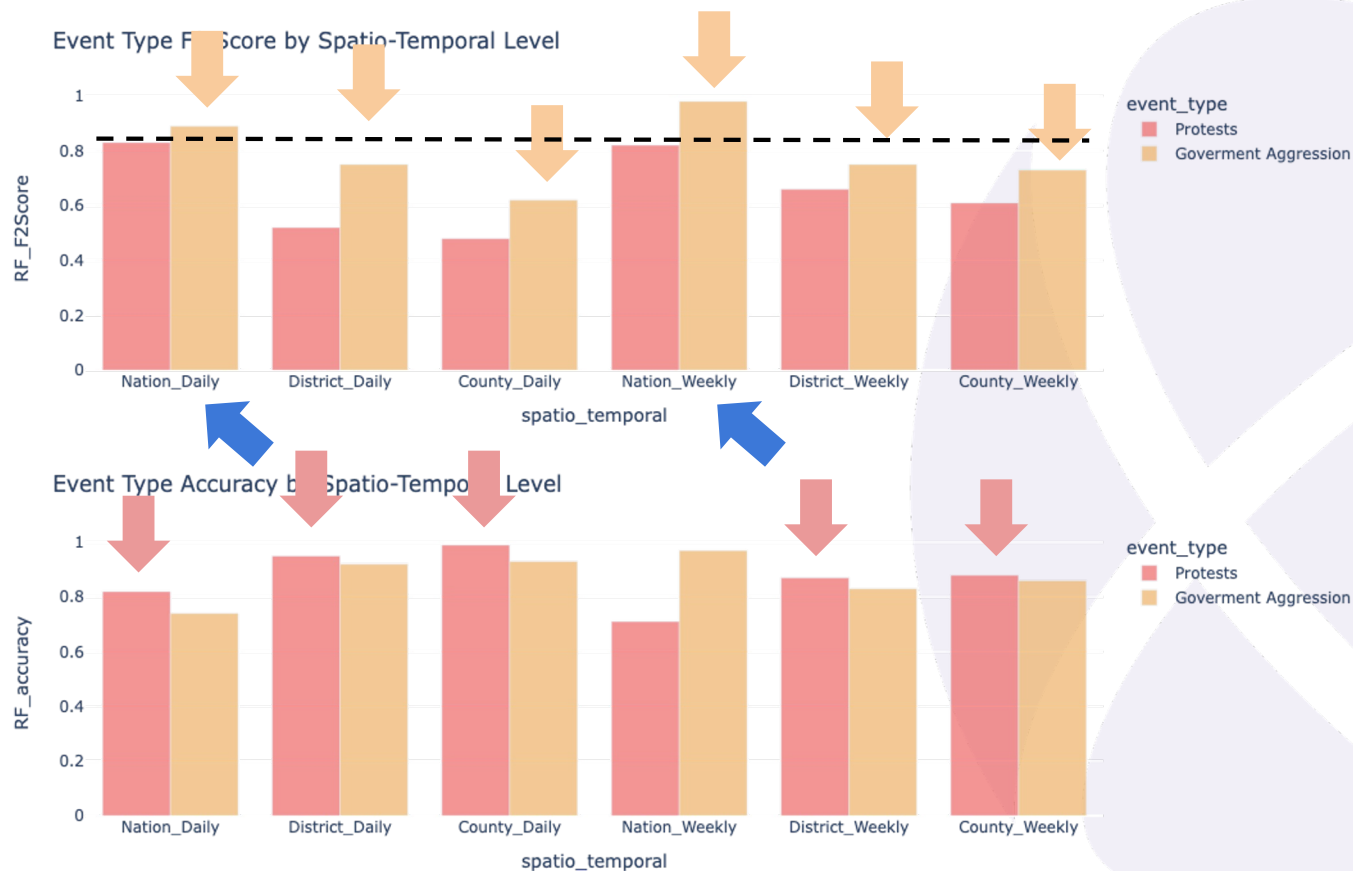


# Random Forest vs XGBoost to Forecast Events

Event Type	Time	Space	RF Accuracy	RF F2 Score	XGB Accuracy	XGB F2 Score
Protests	Daily	Nation	$0.82 \pm 0.1$	$0.83 \pm 0.10$	$0.82 \pm 0.05$	$0.53 \pm 0.05$
		District	$0.95 \pm 0.006$	$0.52 \pm 0.08$	$0.94 \pm 0.01$	$0.66 \pm 0.06$
		County	$0.99 \pm 0.1$	$0.48 \pm 0.07$	$0.98 \pm 0.003$	$0.28 \pm 0.0$
	Weekly	Nation	$0.71 \pm 0.15$	$0.82 \pm 0.13$	$0.88 \pm 0.16$	$0.88 \pm 0.14$
		District	$0.87 \pm 0.03$	$0.66 \pm 0.09$	$0.87 \pm 0.02$	$0.68 \pm 0.10$
		County	$0.88 \pm 0.001$	$0.61 \pm 0.06$	$0.95 \pm 0.006$	$0.72 \pm 0.20$
Government Aggression	Daily	Nation	$0.74 \pm 0.06$	$0.89 \pm 0.06$	$0.73 \pm 0.05$	$0.71 \pm 0.06$
		District	$0.92 \pm 0.01$	$0.75 \pm 0.05$	$0.92 \pm 0.01$	$0.58 \pm 0.05$
		Country	$0.93 \pm 0.005$	$0.62 \pm 0.03$	$0.95 \pm 0.004$	$0.57 \pm 0.04$
	Weekly	Nation	$0.97 \pm 0.02$	$0.98 \pm 0.11$	$0.99 \pm 0.05$	$0.98 \pm 0.05$
		District	$0.83 \pm 0.03$	$0.75 \pm 0.07$	$0.81 \pm 0.02$	$0.81 \pm 0.09$
		County	$0.86 \pm 0.02$	$0.73 \pm 0.05$	$0.88 \pm 0.01$	$0.77 \pm 0.0$

Accuracy and F2 score  
for the 2 event types  
at distinct  
spatio temporal levels

# Random Forest vs XGBoost to Forecast Events

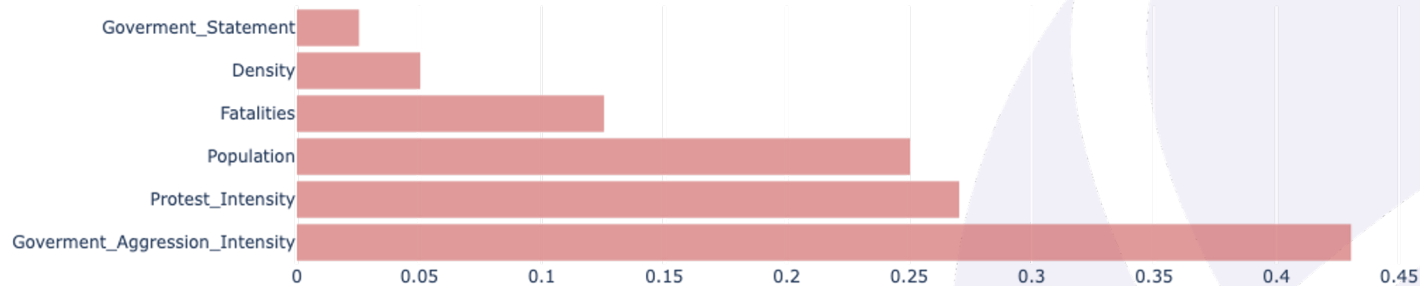


Both event types have higher F2 Scores at broader spatial levels (nation)

F2 Scores are higher for Government Aggression than for Protest at equal spatio-temporal levels

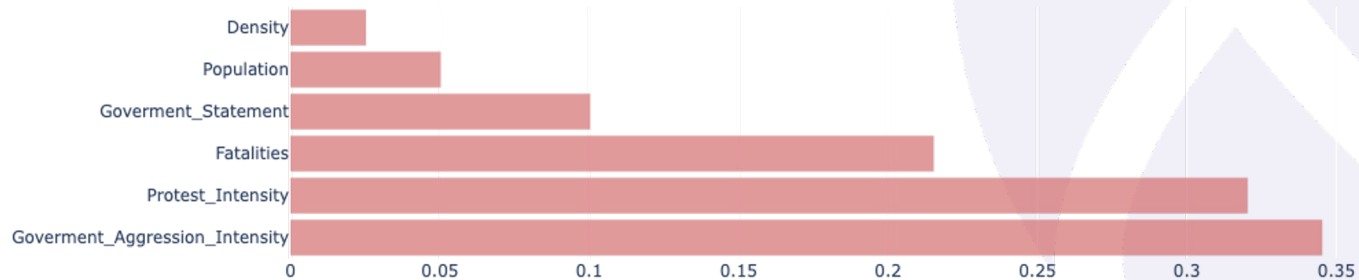
# Feature Importance

Feature Importance Random Forest: National Level Weekly Government Aggressions



Ranked features by relative importance at ***national*** level ***weekly*** events

Feature Importance Random Forest: National Level Weekly Protests



The **strongest feature** across all spatio-temporal levels and event type predictions was **government aggression intensity**

# Conclusions

## What worked

- More data helped cover gaps and missing events in the timeline
- **Government aggression** was established as the strongest predictor for both RF and XgBoost models

## What did not work

- Moving averages (SMA) to identify trends or patterns using **fatalities** counts
- Augmentation of the data did not produce as good results as expected for more granular spatial levels like county and district (the **nation** level models were the best when using one data source (ICEWS) and when using all data sources combined)

# Conclusions

## Next steps

- Exploring the data through **network analysis**
  - Model data as a network of source and target actors
  - Engineer features from network properties
- Test approach on other regions with socio political instability around the world

# Thank you





## Intensity scores (auxiliary slide)

