The Grammar of Conflict

Discovering Universal Patterns in Armed Violence

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We all like stories

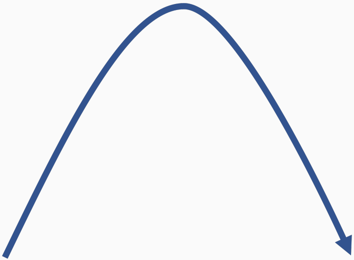


Figure 1: Tragedy

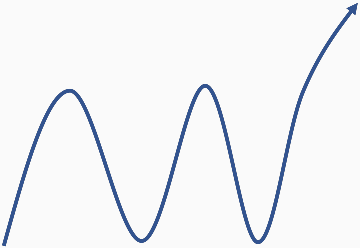
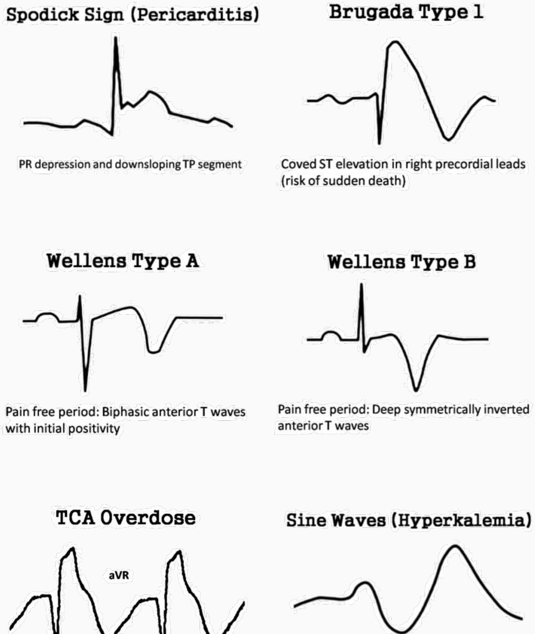


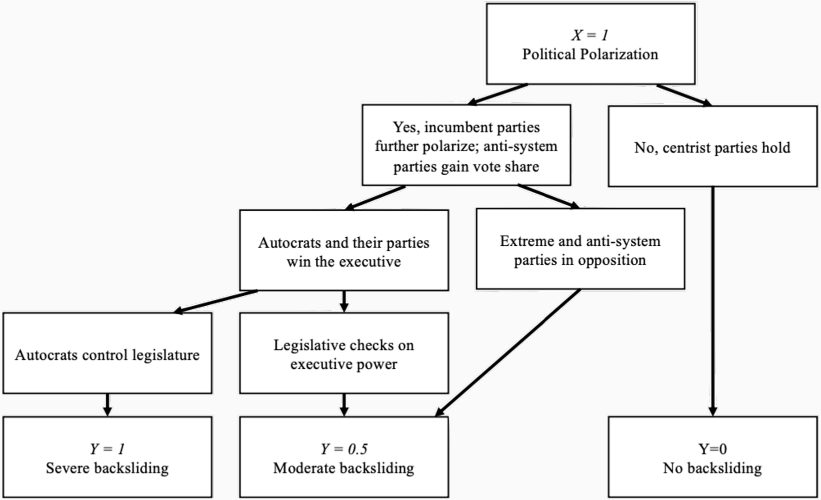
Figure 2: Seven Point Story

Financial analysts like stories

Doctors like stories



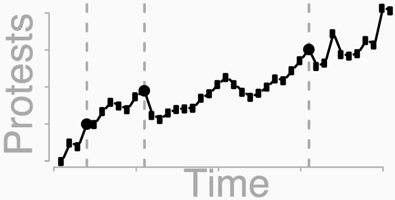
Qualitative social scientists like stories



Based on Haggard and Kaufman (2021).

Theorists likes stories

Conflict researchers DO NOT like stories



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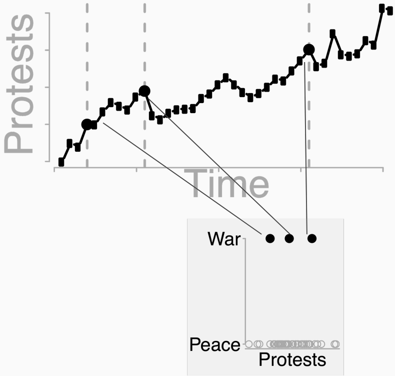

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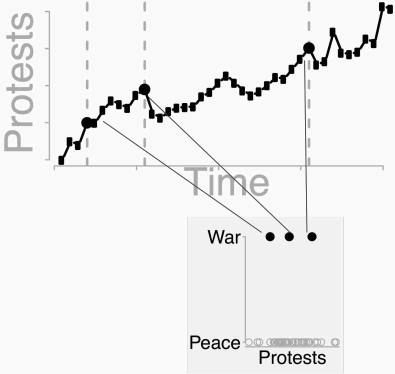

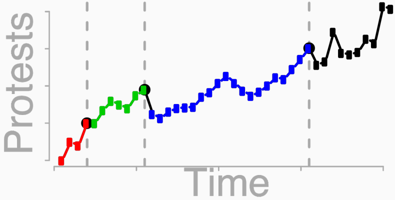

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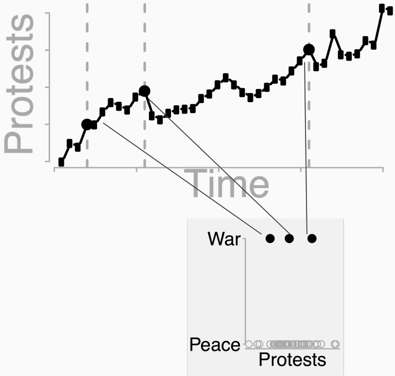
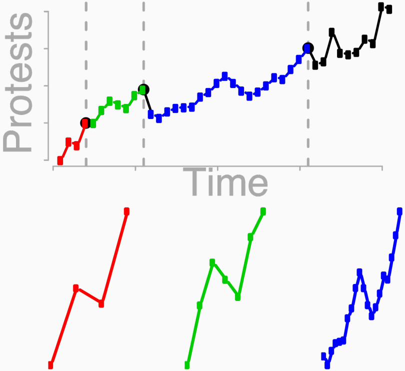




Why patterns (might) emerge

Hypothesis: Armed conflicts follow systematic temporal patterns

Language Grammar

- Universal rules constrain word order
- Limited set of sentence structures
- Surface variation, deep structure
- Predictable patterns

Conflict Grammar

- Universal rules constrain event sequences
- Limited set of trajectory types
- Surface variation, deep structure
- Predictable patterns

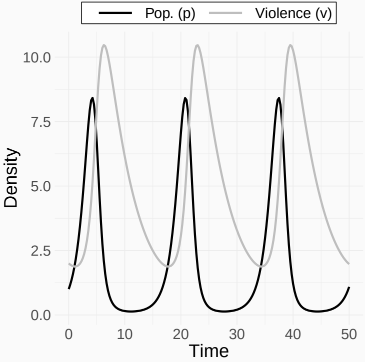
Mechanism 1: Patterns from Simple Rules

Complex dynamics can emerge from simple differential equations

Toy Model

$$\frac{dp}{dt} = \alpha p - \beta pv$$
$$\frac{dv}{dt} = \delta pv - \gamma v$$

- p: Civilian population
- v: Violence intensity
- Violence ↑ when population ↑
- Population ↓ when violence ↑ (displacement)



Predator-prey dynamics generate cycles

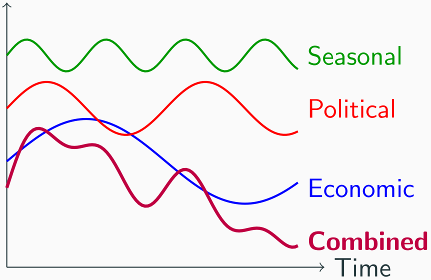
Mechanism 2: Patterns in Driving Variables

If causal variables follow patterns, so will outcomes

Structured Drivers

- **Economic cycles**: Harvest seasons, commodity prices
- **Political cycles**: Elections, budget cycles
- **Climate cycles**: Rainy/dry seasons
- **Resource cycles**: Mobilization/exhaustion

These combine to create **complex temporal structures** in conflict

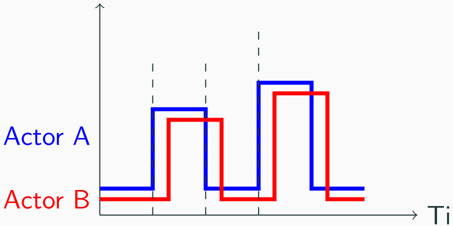


Mechanism 3: Strategic Adaptation

Actors detect patterns and respond to them

- Humans excel at pattern recognition
- Build mental models of sequences
- Make decisions based on perceived trends
- Anticipate opponent behavior

Example: Tit-for-Tat



Action-reaction cycles create patterns

Evidence: How People Process Conflict Sequences

Experimental findings (Han & Chadefaux 2026): People evaluate diplomatic sequences

Three Temporal Dimensions

1. **Direction**: Cooperation increasing or decreasing?
2. **Consistency**: Regular or erratic progression?
3. **Acceleration**: Speeding up or slowing down?

People construct **narratives** from event sequences

Positive Signal

Inconsistent Signal

Consistent increasing cooperation → trust

Inconsistent → skepticism

Conflict Data

What Are We Measuring?

Armed Conflict Events

- Organized violence between actors
- *Predict: Battle-related deaths*
- Georeferenced incidents
- Daily/monthly aggregation

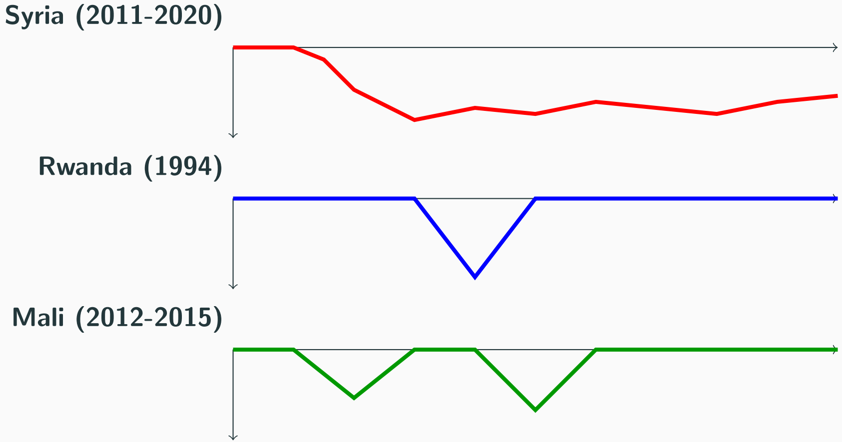
Data Sources

- Uppsala Conflict Data Program (UCDP)
- 1989–2025 (36 years)
- Global coverage
- Updated monthly

Example: Event Record

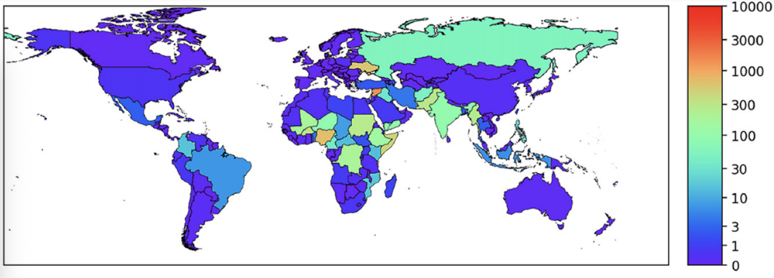
Field	**Value**
Date	2015-03-12
Country	Syria
Location	Aleppo (36.2$\circ$N, 37.1$\circ$E)
Fatalities	47
Actor 1	Government
Actor 2	Rebel group

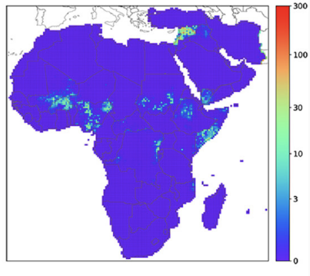
Sample Trajectories: Three Countries



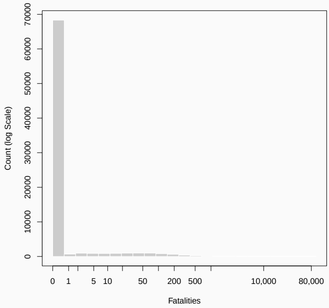
Different conflict profiles: Sustained, spike, episodic

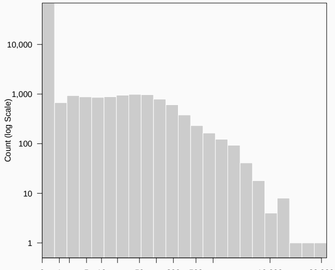
Aggregation: Country- vs Grid-level





Zero Inflation





The Problem

- Most country-months: **zero fatalities**
- Distribution extremely skewed

Heterogeneity

- Small civil wars: 10s of deaths/year
- Major conflicts: 10,000s of deaths/month
- **Orders of magnitude difference**
- Heavy-tailed distribution

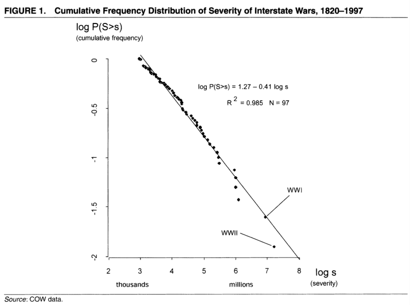


Figure 3: Source: Cederman 2003

Power law: $P(X > x) \sim x^{-\alpha}$

Our solution: **Min-max normalization** within subsequences

Measurement Issues

Reporting Bias

- Remote areas: under-reported
- Media attention varies
- Government censorship

Temporal Variation

- Data quality improves over time
- Cell phones, social media increase reporting
- 1990s data sparser than 2010s

Spatial Variation

- Syria: heavily documented
- Central African Republic: less coverage
- Urban vs rural differences

The Forecasting Problem

Traditional Approach: Structural Covariates

The Standard Model

- Economic: GDP, inequality, resources
- Political: Regime type, institutions
- Demographic: Population, youth bulge
- Social: Ethnic fractionalization
- Historical: Past conflict

Examples

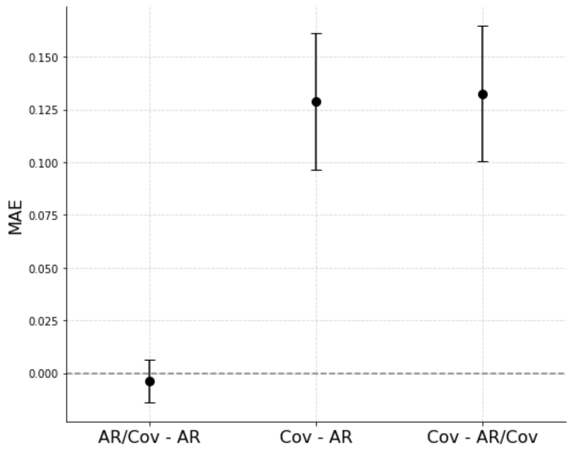
- Goldstone et al. (2010)
- Hegre et al. (2013)
- ViEWS System

Regression Framework

$$\Pr(\text{Conflict}_{i,t}) = f(\text{GDP}_{i,t}, \text{Democracy}_{i,t}, \text{Population}_{i,t}, \text{Neighbors}_{i,t}, \text{History}_{i,t-1}, \ldots)$$

Often 20-50+ covariates

Yet, adding covariates does not really improve forecasts



AR $\approx$ AR+Cov $>>$ Cov

$\rightarrow$Temporal information is more predictive than structural covariates

(source: Schincariol & Chadefaux 2026)

Methods

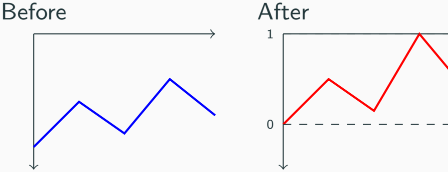
Preprocessing: Windows and Normalization

Windowing

- Divide each time series into subsequences
- Length $w = 12, 24, \text{or } 36$ months
- Overlapping: Slide by 1 month
- Each window is a potential pattern

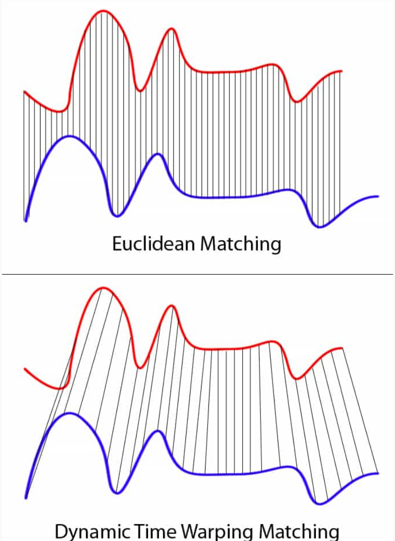
Normalization

- Within each window: Min-max scale
- $x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}$
- Maps to [0, 1]
- Preserves shape, removes scale



Comparing Sequences: Dynamic Time Warping (DTW)

Problem: Standard distance metrics (Euclidean, correlation) assume alignment



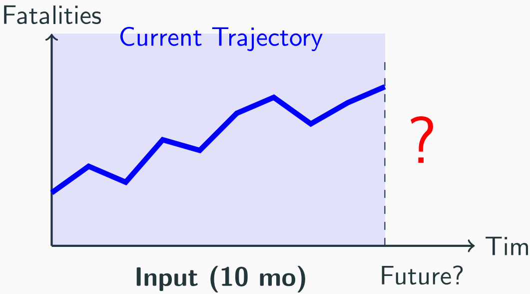
Shape Finder: The Input Sequence

What we're trying to forecast
Input = Recent Trajectory

- Last 10 months of fatalities
- Example: Afghanistan Mar–Dec 2021
- This is the *shape* we'll match

Goal

- Predict next 12 months (2022)
- Find: What happened after similar patterns historically?



Shape Finder: Building the Historical Repository

Creating a library of all possible patterns

Key features:

- **Rolling windows**: Overlapping 10-month subsequences
- **Flexibility**: Windows 8–12 months (captures different speeds)
- **Comprehensive**: Every country, every month, 1989–2020

Shape Finder: Finding Similar Patterns (DTW)

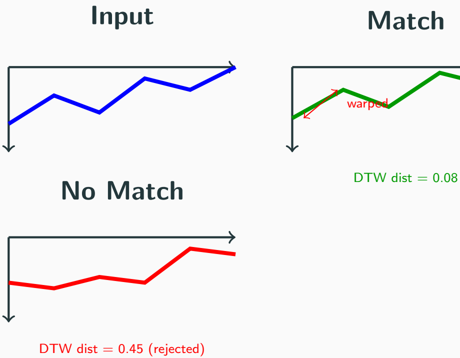
Which historical cases look like the current situation?

Comparison Method: DTW

- Compare input to all N subsequences
- DTW distance measures similarity
- Accounts for speed differences
- Focuses on *shape*, not scale

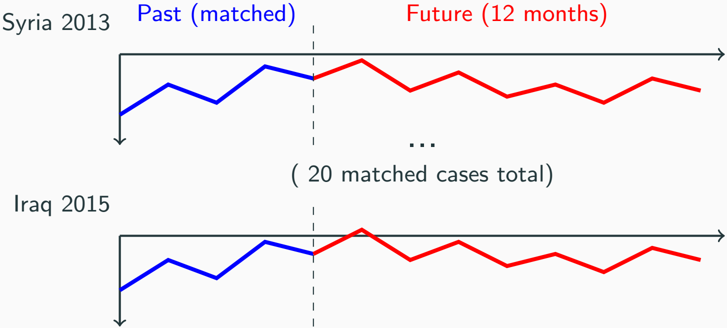
Adaptive Filtering

- Keep only similar matches
- Threshold: Start at 0.1, increase until ≥ 5 matches
- Typically find 15–30 analogues
- Result: p_{filtered}



Shape Finder: What Happened Next? (Extracting Futures)

Look at outcomes following similar patterns



For each of the ∼20 matches, extract the 12 months that followed

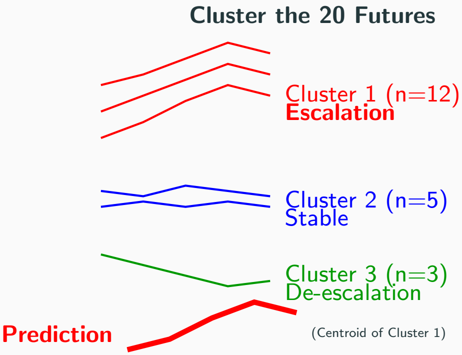
Shape Finder: Clustering Futures & Making Prediction

Find the most common outcome
Clustering Step

1. Take all 20 futures
2. Apply hierarchical clustering
3. Cut tree at optimized height
4. Result: 2–4 clusters (scenarios)

Prediction = Majority Cluster

- Select largest cluster
- Compute centroid (average)
- This is the forecast



Shape Finder: Key Advantages

Methodological

- **Purely autoregressive**: Uses only past fatalities
- **No covariates**: No need for GDP, regime type, etc.
- **Flexible**: Handles varying speeds via DTW
- **Robust**: Clustering filters outliers

Practical

- **Fast**: Minutes, not hours
- **Always available**: No lag for covariate updates

Performance

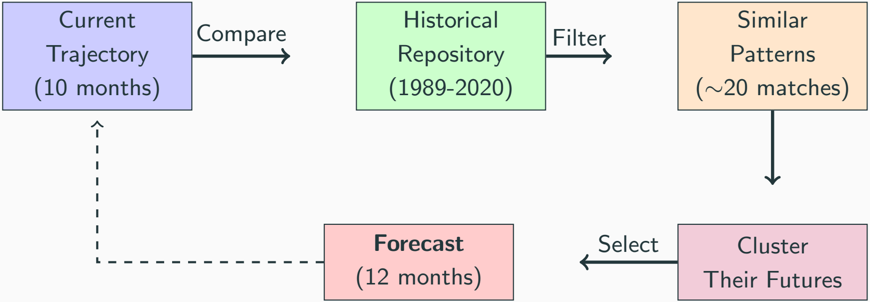
- **Captures variability**: Predicts surges/declines
- **Risk-taking**: Not just flat mean predictions
- **Excels in high-complexity cases**

Interpretability

- Can cite specific historical analogues: "Trajectory similar to Syria 2012, Iraq 2015"
- Policymakers understand the reasoning

Shape Finder: Overview

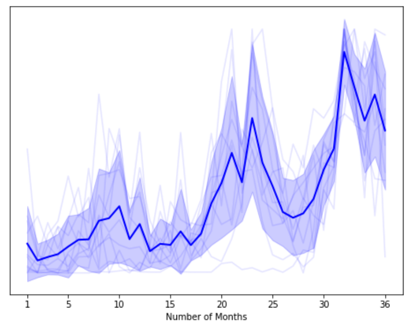
Goal: Forecast fatalities by finding similar historical trajectories



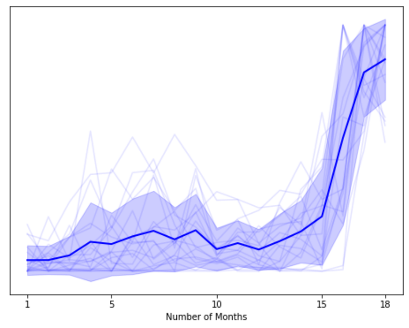
Results: Four Questions

Four Research Questions

1. Do conflict sequences repeat?
2. Do conflict sequences repeat across space and time?
3. Do similar patterns predict similar futures?
4. Can we model richer shapes?



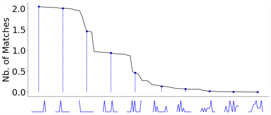
Motif 1: M-shaped



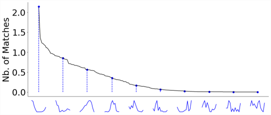
Motif 2: Delayed Escalation

Q1: Do Conflict Sequences Repeat?

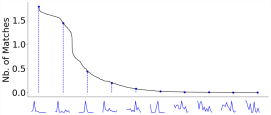
Groups similar sequences together (combine if $d_{dtw}(s_1, s_2) < threshold$) and plot distribution.



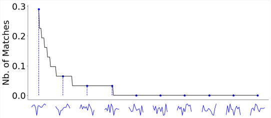
Earthquakes



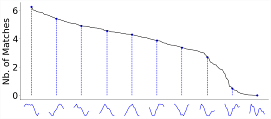
Rainfall



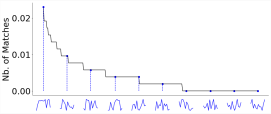
Conflict



Stock Market

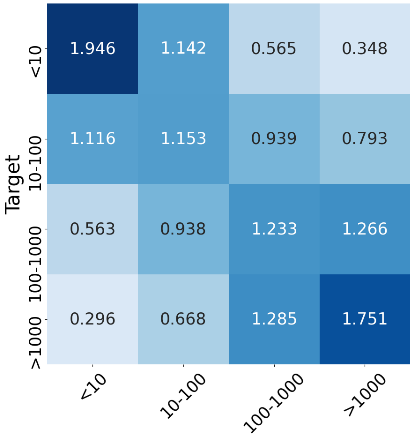


Temperature

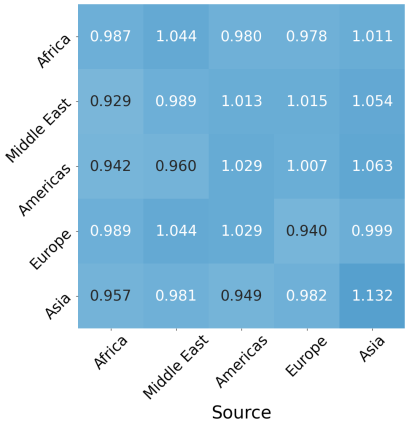


White Noise

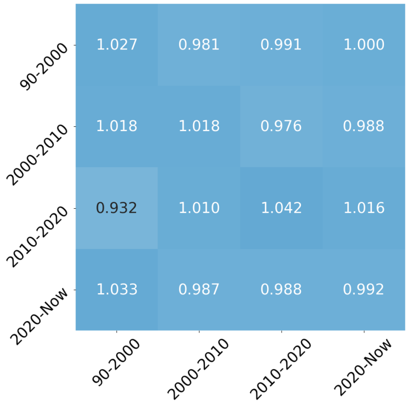
Q2: Do Motifs Generalize Across Space and Time?



Q2: Do They Travel Across Space and Time?



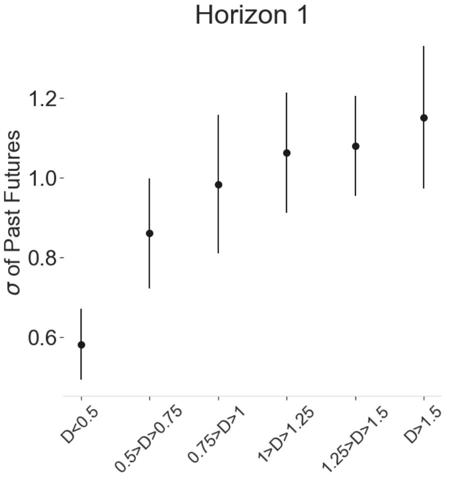
Across Regions



Across Decades

Q3: Do Patterns Predict The Future?

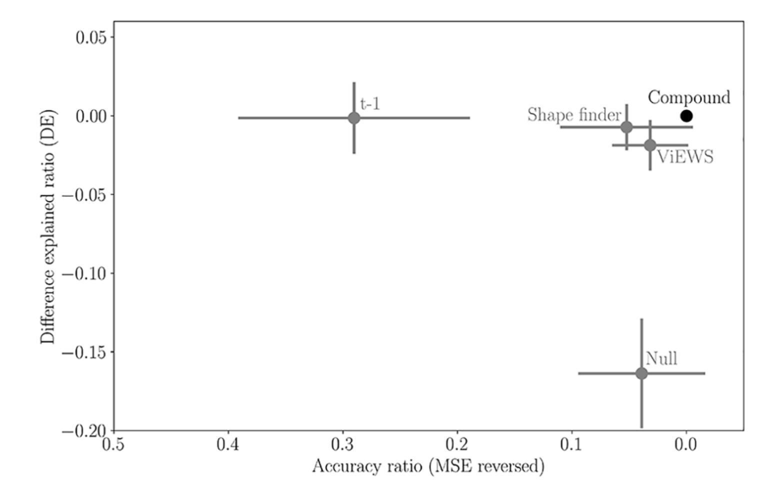
Do Similar Patterns Predict Similar Futures?



Q3: Do Patterns Predict The Future?

Test set: fatalities 2022–2023

Learning set: Fatalities 1989–2020



Q3: Do Patterns Predict The Future?

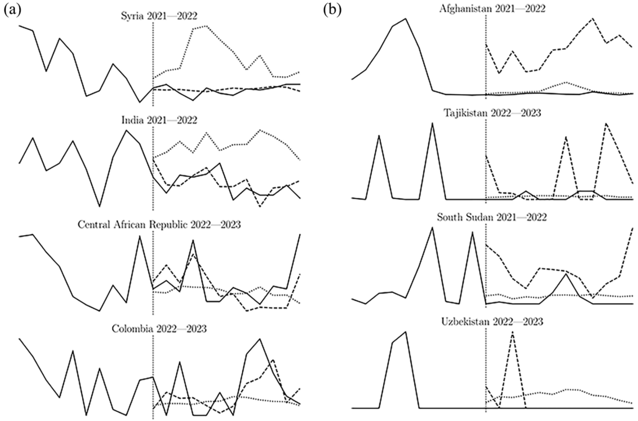
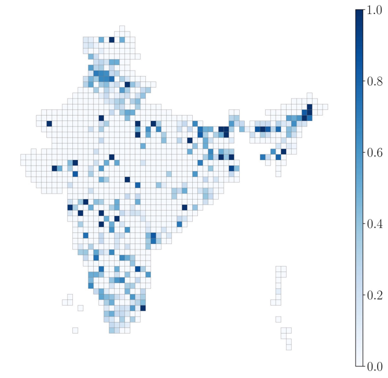
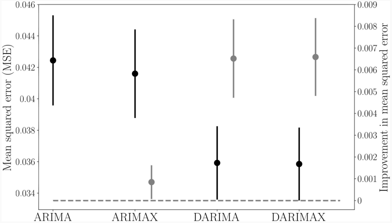


Figure 5. Comparison of input series and predictions for best (a) and worst (b) cases. Input series are to the left of the vertical line. The solid line represents actuals, the dotted line represents VIEWS predictions, and the dashed line represents Shape finder predictions. For high complexity input series with substantial variability (a), Shape finder provides more accurate predictions and captures variability, while VIEWS either over- or underpredicts. For low complexity (b), Shape finder produces overpredictions, while VIEWS offers more accurate forecasts.

Q3: Do Patterns Predict The Future?

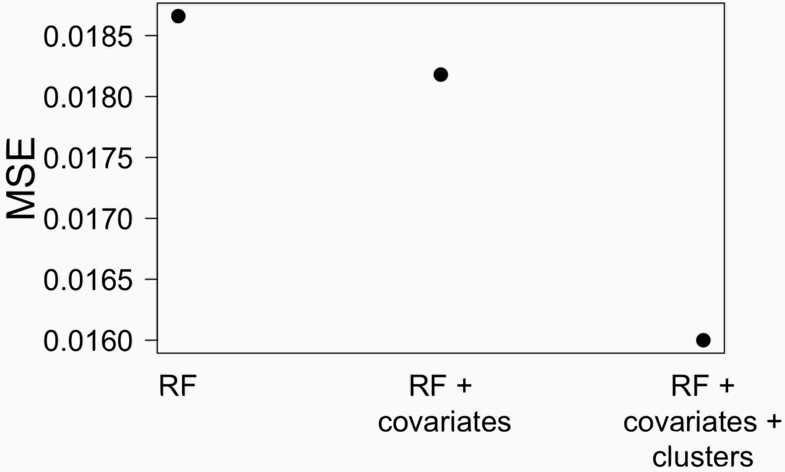
Protest patterns → Future protests





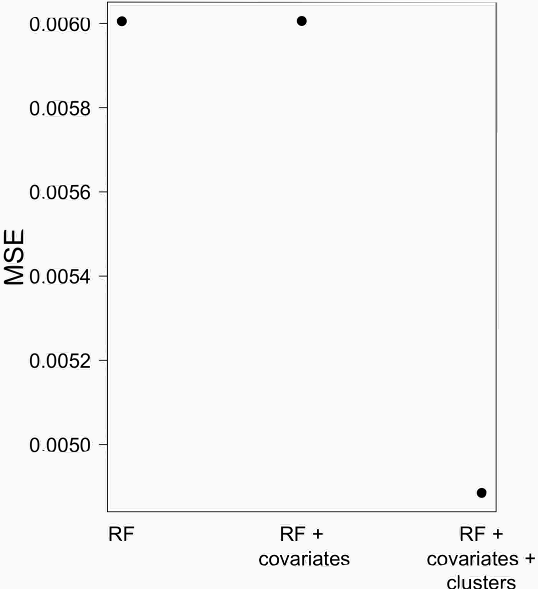
Q3: Do Patterns Predict The Future?

Protest patterns $\rightarrow$ future conflict

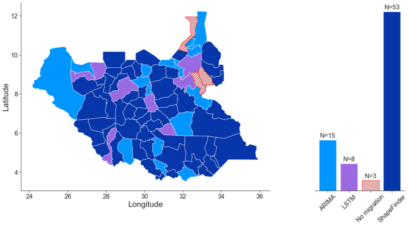


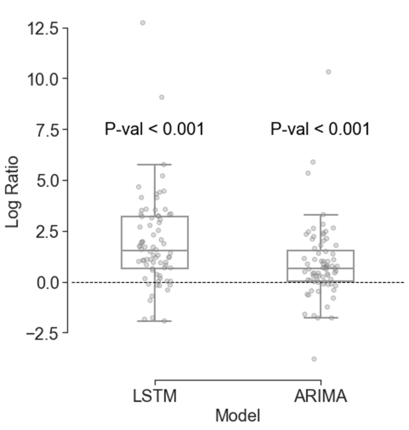
Q3: Do Patterns Predict The Future?

Protest patterns → future one-sided violence



Migration patterns $\rightarrow$ future migration



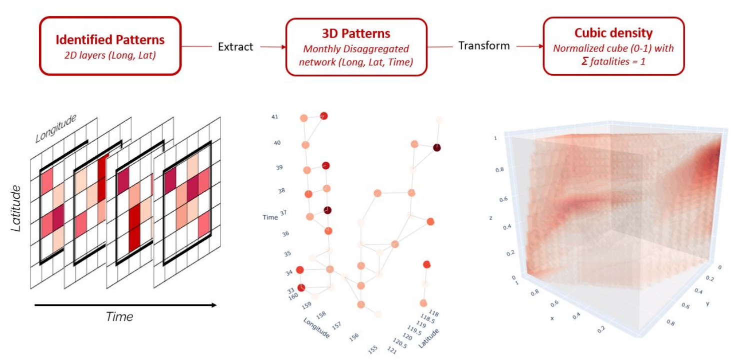


Q3: Do Patterns Predict The Future?

Stock market $\rightarrow$ Rockets

Q5: Can We Model Richer 3D Shapes?

Extension: Incorporate spatial dimension alongside temporal



source: Schincariol 2026

Applications & Future Directions

Live Operational Forecasting

Operational system: Monthly forecasts 6 months ahead, all countries

Performance (2024)

- Forecasts for Feb-July 2024
- Validated against observed fatalities
- Compared to ViEWS and ConflictForecast

Results

- Outperformed ViEWS in 75% of cases
- Outperformed ConflictForecast in 70-74%
- Best performance in high-intensity conflicts

Advantages

- Timing specificity
- Interpretable (shows historical analogs)
- Minimal data requirements
- Fast computation

Use Cases

- Humanitarian early warning
- Diplomatic planning
- Resource allocation
- Risk assessment

Limitations

Important caveats

Data Limitations

- UCDP coverage varies
- Remote conflicts under-reported
- Measurement error in fatalities

Methodological Challenges

- Window length choice
- Normalization decisions
- Number of clusters (k)
- Distance metric choice

External Validity

- Low-visibility conflicts
- Novel conflict types
- Unprecedented escalations
- Structural breaks

Forecast Limitations

- Accuracy degrades with horizon
- Uncertainty quantification challenging
- Rare events hard to predict
- No causal identification

Irreducible Sources of Error

Why we can't achieve perfect forecasts (Schrodt 2018)

Model & Data Issues

1. **Specification error**
2. **Measurement error**

Fundamental Limits

3. **Quasi-random structural error**
    - Complex systems
    - Chaotic systems
4. **Rational randomness**
    - Mixed strategies in zero-sum games
    - Strategic unpredictability

Irreducible Sources of Error (cont.)

Human and policy factors

5. **Arational randomness**
   - Free will and individual agency
   - Unpredictable decisions by leaders
   - Idiosyncratic factors

6. **Effective policy response**
   - Successful prevention = wrong forecast
   - Model predicts escalation
   - Policy intervenes, prevents it
   - Model appears to have "failed"

7. **Natural phenomena**
   - Exogenous shocks
   - Example: 2004 tsunami → reduced Aceh conflict
   - Unpredictable events with large effects

The Forecasting "Speed Limit"

~80-85% accuracy ceiling

Convergent finding across projects and methodologies

Future Directions

Next steps for the research program

- Deep learning
- Onset prediction
- Theory Development

Broader Implications

- Forecasting is underused in the social sciences
- Pattern recognition is almost never used in social science
- Interpretability matters: patterns are more intuitive than black boxes
- Temporal structure can substitute for expensive covariate collection

- Conflicts are somewhat predictable
- Focus on dynamics, not just drivers

PaCE

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