Learning to Extract International Relations from Political Context

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Reference:

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Automated Text Analysis

- Automated content analysis tools for *discovery and measurement of concepts, attitudes, events*
- Natural language processing, information retrieval, data mining, and machine learning as quantitative social science methodology.

Problem Statement

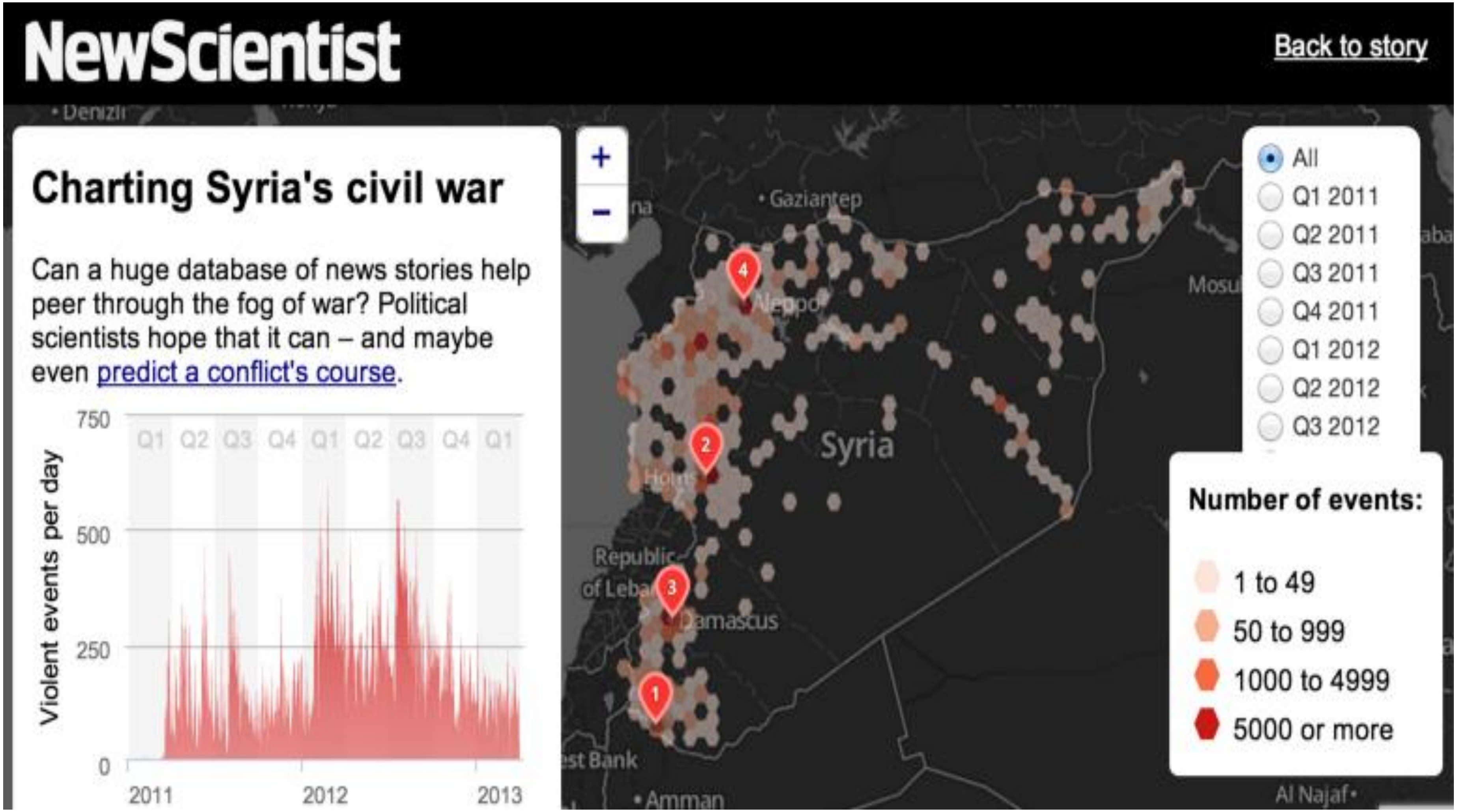


Image Courtesy: **http://gdelt.utdallas.edu**

Datasources

- 6.5 million newswire articles from English Gigaword 4th edition
- Verb patterns from OpenSource TABARI Software
- New York Times AnnotatedCorpus (1987–2007)

Working

- Event types
- Verb patterns per event type
- Extract events from news text

Issues

- Low precision.
- Hard to maintain and adapt to newer domains.

Working(contd.)

- Unsupervised learning to extract information to following tuple type:

  <Source Entity>,<Receiver Entity>,<Time>,<$W_{predpath}$>)

- “Pakistan promptly accused India” [1/1/2000]

$\Rightarrow$(PAK, IND, 268, SRC -nsubj> accuse <dobj- REC)

- “In another violence Thursday,Israeli **forces attacked** a rocket launching site in northern Gaza strip,**killing** one military,paramilitary medics said.”

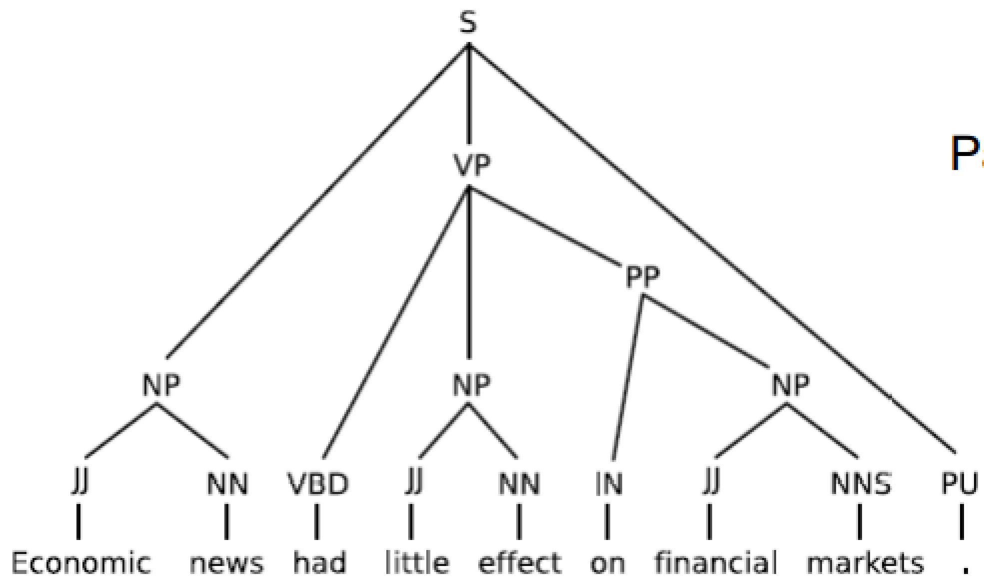
⇒SRC: ISR

⇒REC: PSE

⇒W:Attack(verb)

Methodology

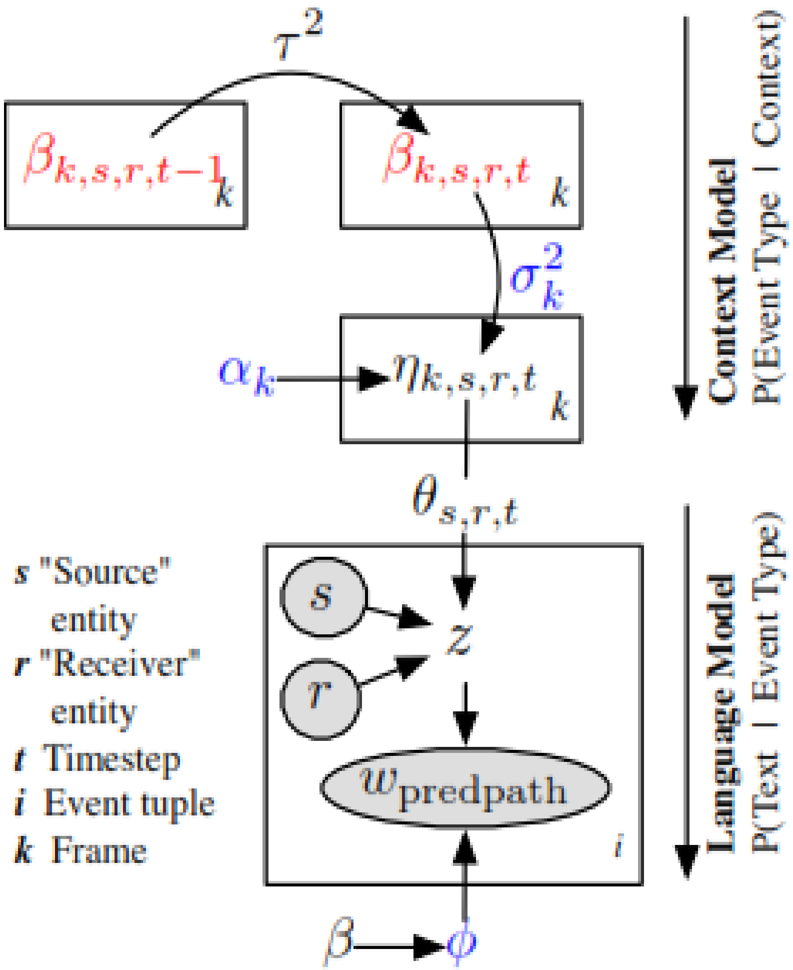
- Entities: As Noun Phrases
- Events: As verbs (and arguments)
- Preprocess with Stanford CoreNLP for part-of-speech tags and syntactic dependencies.



Parse tree

Model

One (s,r,t) slice of graphical model



Smoothed Model

Linear dynamical system (Random walk)

$$\beta_{k,s,r,1} \sim N(0, 100)$$
$$\beta_{k,s,r,t} \sim N(\beta_{k,s,r,t-1},\ \tau^2)$$
$$\eta_{k,s,r,t} \sim N(\alpha_k + \beta_{k,s,r,t},\ \sigma_k^2)$$

Vanilla Model

Independent contexts

Frame learning from verb co-occurrence within contexts

Frame prior log-odds in this context

Overall prevalence of frame (event class)

$$\eta_{k,s,r,t} \sim N(\alpha_k,\ \sigma_k^2)$$

Frame prior in this context

$$\theta_{k,s,r,t} = \frac{\exp \eta_{k,s,r,t}}{\sum_{k'=1}^{K} \exp \eta_{k',s,r,t}}$$

$$z \sim \theta_{s,r,t}$$

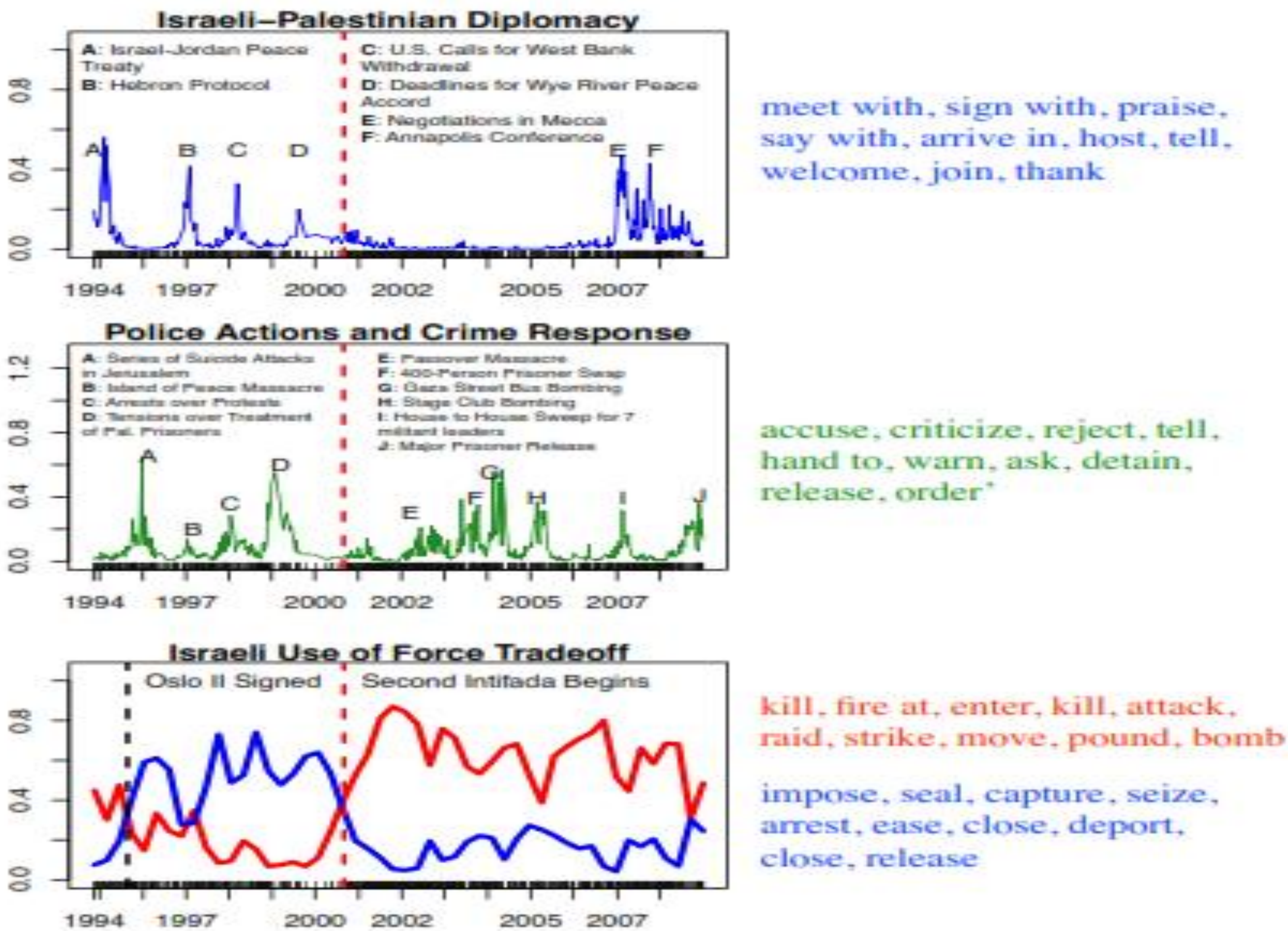
$$w \sim \phi_z$$

Training: blocked Gibbs sampling
(Markov Chain Monte Carlo)

Learned Event Types

- Diplomacy:
  - arrive in, visit, meet with, travel to, leave, hold with, meet, meet in, fly to, be in, arrive for talk with, say in, arrive with, head to, hold in, due in, leave for, make to, arrive to, praise
- Verbal Conflict:
  - accuse, blame, say, break with, sever with, blame on, warn, call, attack, rule with, charge, come from, suspect, slam, accuse government , accuse agency, criticize
- Material Conflict:
  - kill in, have troops in, die in, be in, wound in, have soldier in, hold in, kill in attack in, remain in, detain in, have in, capture in, stay in, kill, have troops,station in, station in, injure in, invade, shoot in

Case study


Israeli–Palestinian Diplomacy
A: Israel-Jordan Peace Treaty
B: Hebron Protocol
C: U.S. Calls for West Bank Withdrawal
D: Deadlines for Wye River Peace Accord
E: Negotiations in Mecca
F: Annapolis Conference
meet with, sign with, praise, say with, arrive in, host, tell, welcome, join, thank
Police Actions and Crime Response
A: Series of Suicide Attacks in Jerusalem
B: Island of Peace Massacre
C: Arrests over Protests
D: Tensions over Treatment of Pal. Prisoners
E: Passover Massacre
F: 400-Person Prisoner Swap
G: Gaza Street Bus Bombing
H: Stage Club Bombing
I: House to House Sweep for 7 militant leaders
J: Major Prisoner Release
accuse, criticize, reject, tell, hand to, warn, ask, detain, release, order'
Israeli Use of Force Tradeoff
Oslo II Signed
Second Intifada Begins
kill, fire at, enter, kill, attack, raid, strike, move, pound, bomb
impose, seal, capture, seize, arrest, ease, close, deport, close, release
1994
1997
2000
2002
2005
2007

Future work

- More data; deeper historical analysis
- Learning the entity database: domestic politics, other domains
- Hierarchy on the event types
- Location and temporal properties of events
- Network model
- Temporal dynamics

Goal: To use the model to learn new facts about international politics