Text as Data

Brandon M. Stewart[1]

Department of Government, Harvard University

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[1] Thanks to Gary King, Justin Grimmer, Rich Nielsen and Molly Roberts for permission to include figures here.

Overview

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References

Grimmer Justin and Brandon M. Stewart. (2013) "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis*.

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3. New Quantities of Interest

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- Explosion in methods and programs to analyze texts

What Can Text Methods Do?

Haystack metaphor:

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What They Don't Do:

- Develop a comprehensive statistical model of language
- Replace the need to read
- Develop a single tool + evaluation for all tasks

How to Use Text as Data

A simple recipe for automated content analysis:

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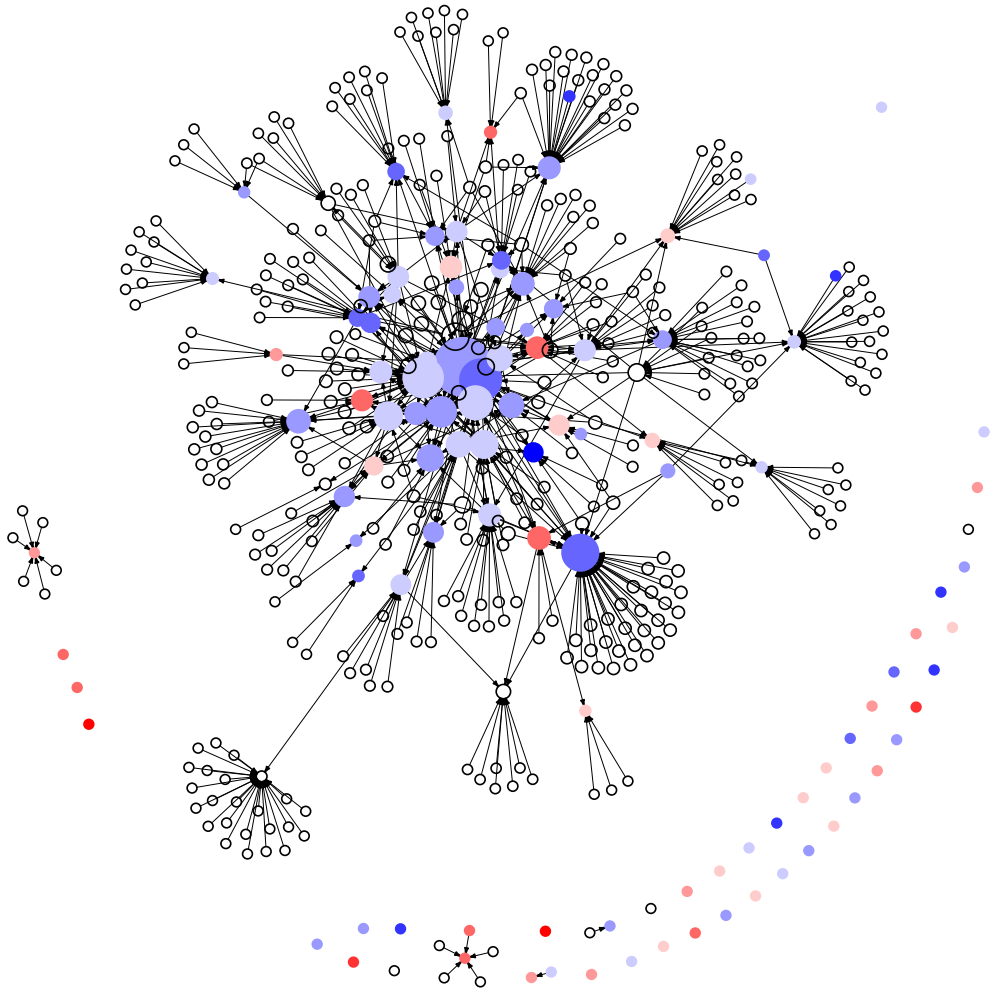
But seeing is believing...

Islamic Clerics and Jihad (Nielsen)

Why do some Islamic Clerics support militant Jihad?

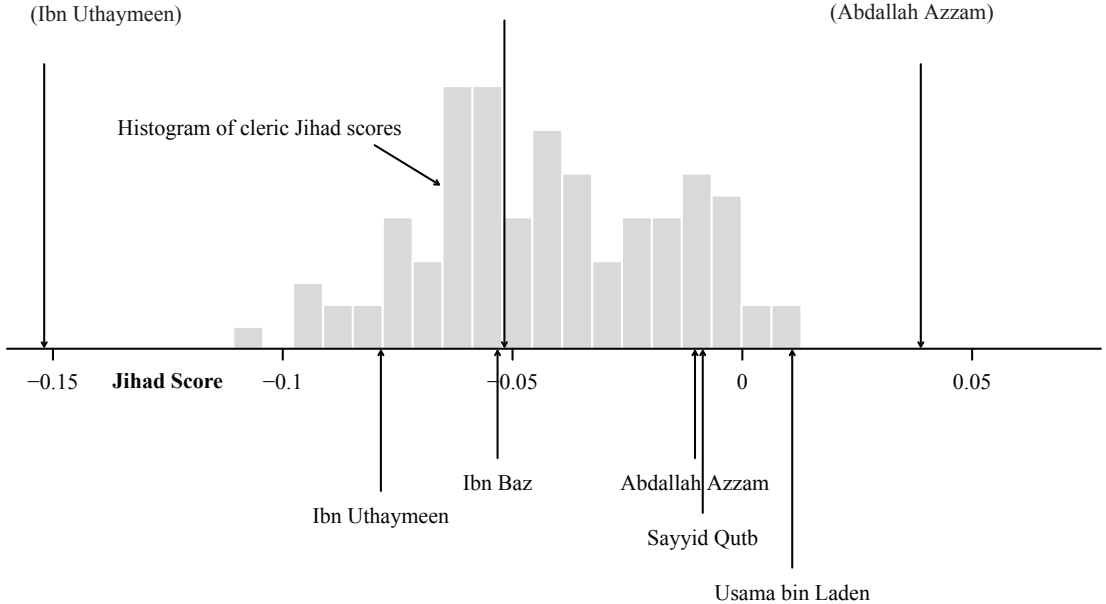


Islamic Clerics and Jihad (Nielsen)

If a person arrives while the Imam is preaching at Friday prayers, he should pray two brief prostrations and sit without greeting anyone as greeting people in this circumstance is forbidden because the Prophet, peace be upon him, says, "If your friend speaks to you during the Friday prayers, silence him while the Imam preaches because it is idle talk."
(Ibn Uthaymeen)

There is a fundamental fact about the nature of this religion and the way it works in people's lives. A fundamental, simple fact, but although it is simple, it is often forgotten or not realized at all. Forgetting this fact, or failing to recognize it arises from a serious omission from views of this religion: its truthfulness and historical, present, and future reality.
(Sayyid Qutb)

Ruling on Fighting Now in Palestine and Afghanistan. The foregoing has clarified that if an inch of Muslim lands are attacked, then Jihad is obligatory for the people of that area, and those near by. If they do not succeed or are incapable or lazy, the individual obligation widens to those behind them and then gradually the individual obligation expands until it is general for the whole land, from East to West.
(Abdallah Azzam)



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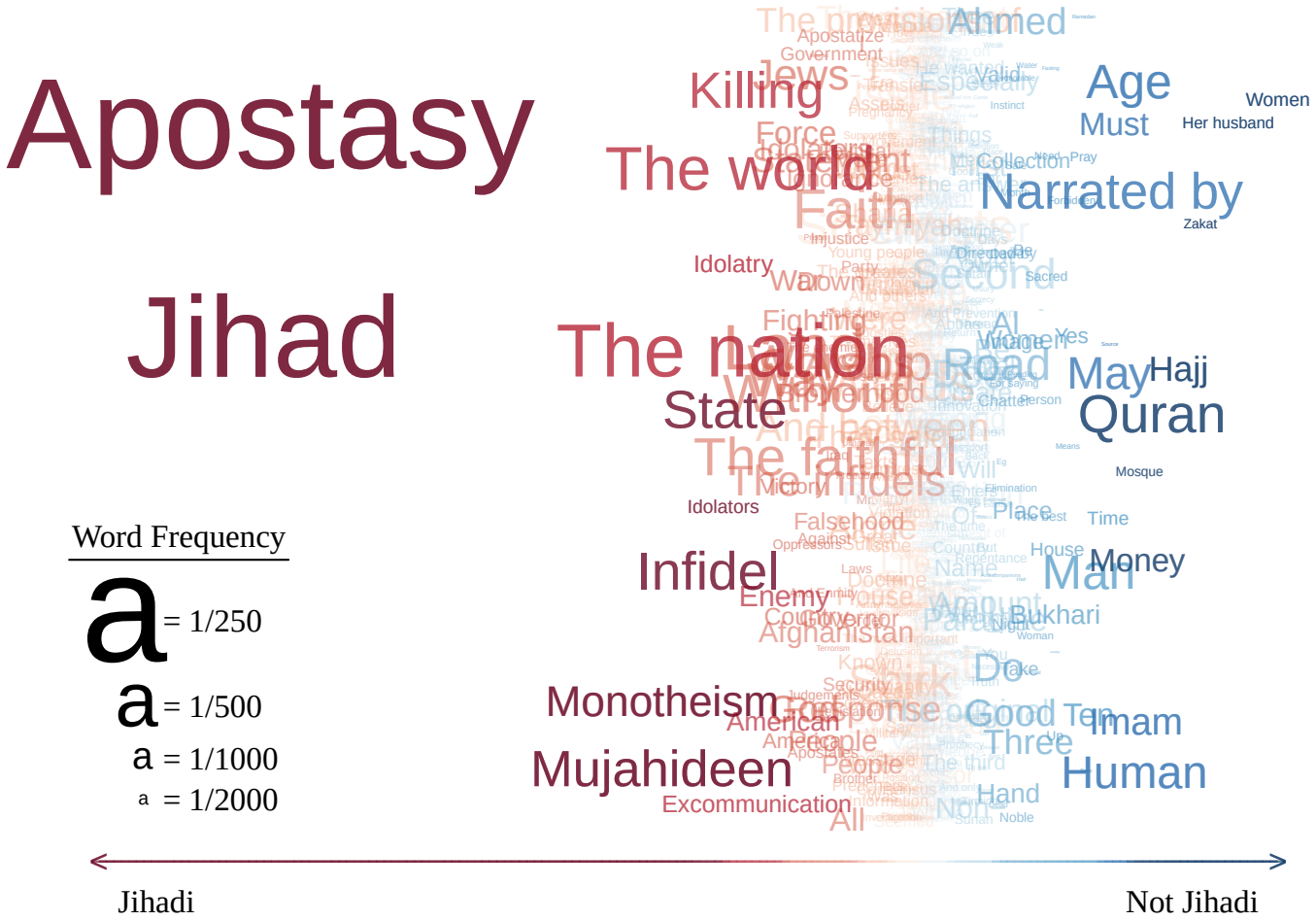
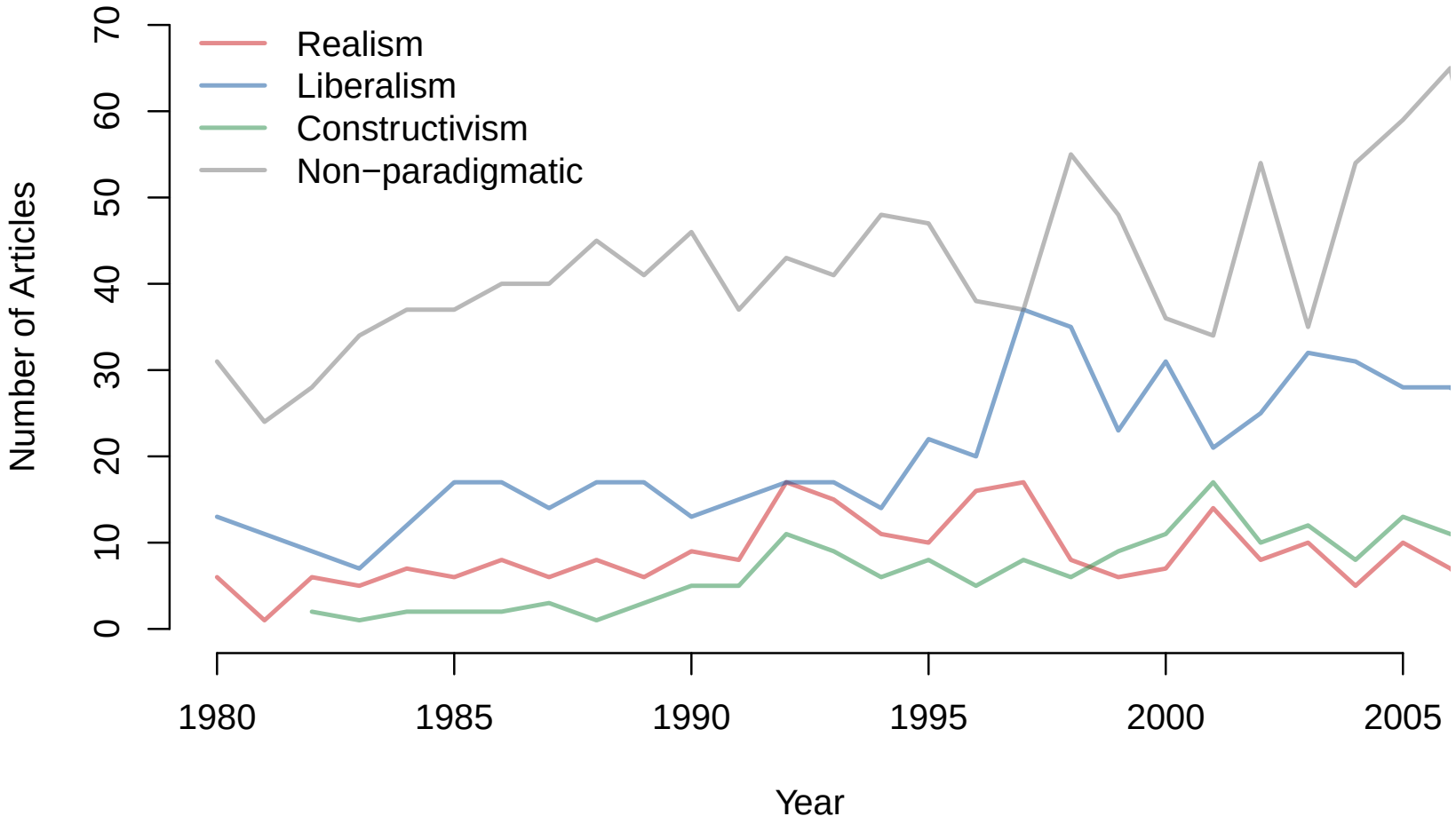


Digital Literature Reviews (Nielsen & Stewart)

The International Relations Literature



Digital Literature Reviews (Nielsen & Stewart)

Realism

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Liberalism

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Constructivism

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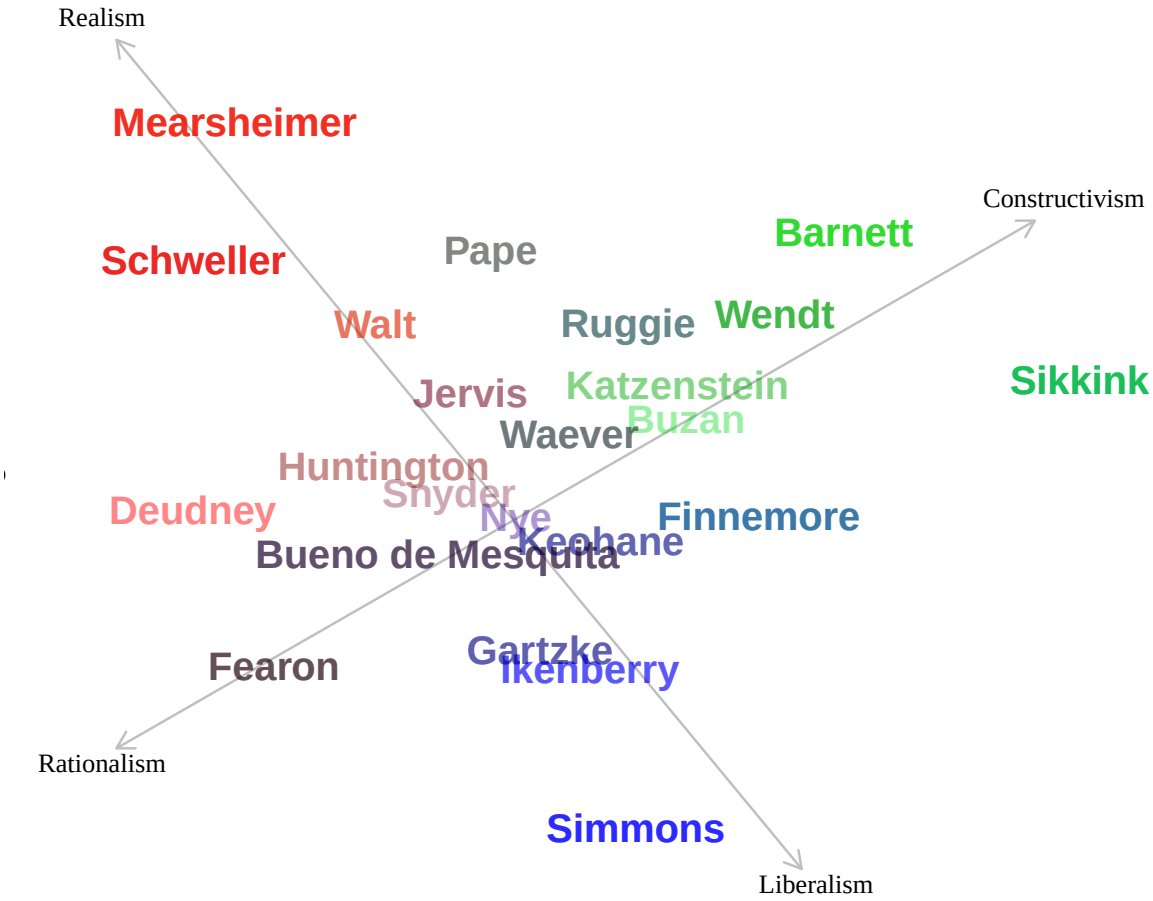
Who are the big names?



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- Original Approach: Manual Coding
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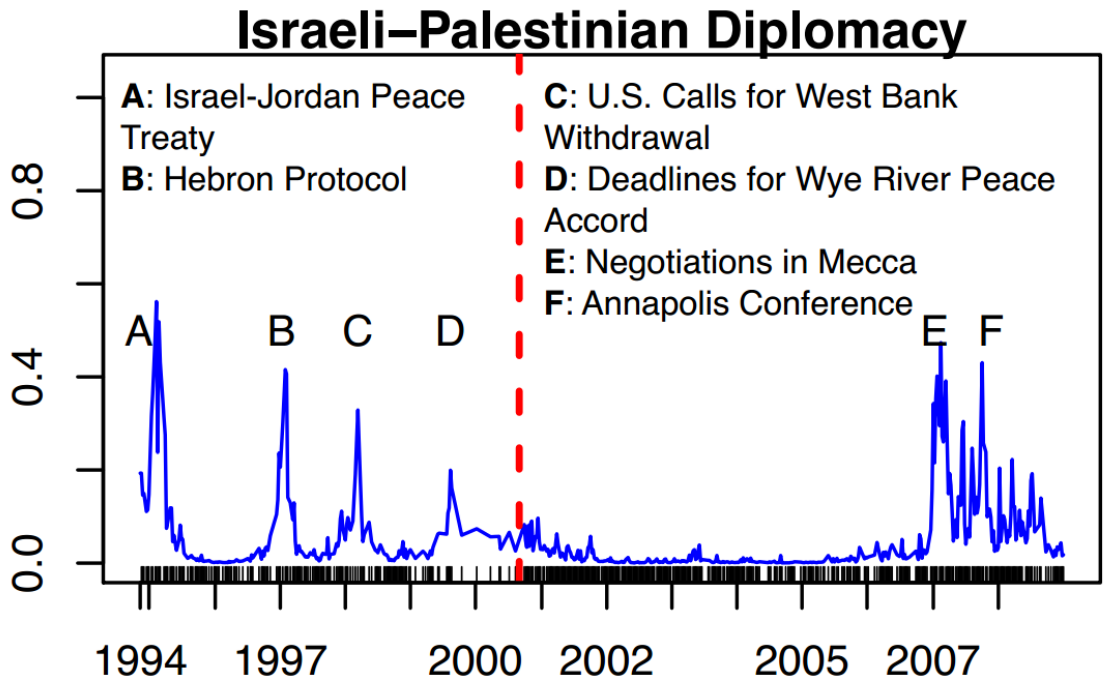
- Our Approach: Learn Event Types from the Text with a Probabilistic Model!

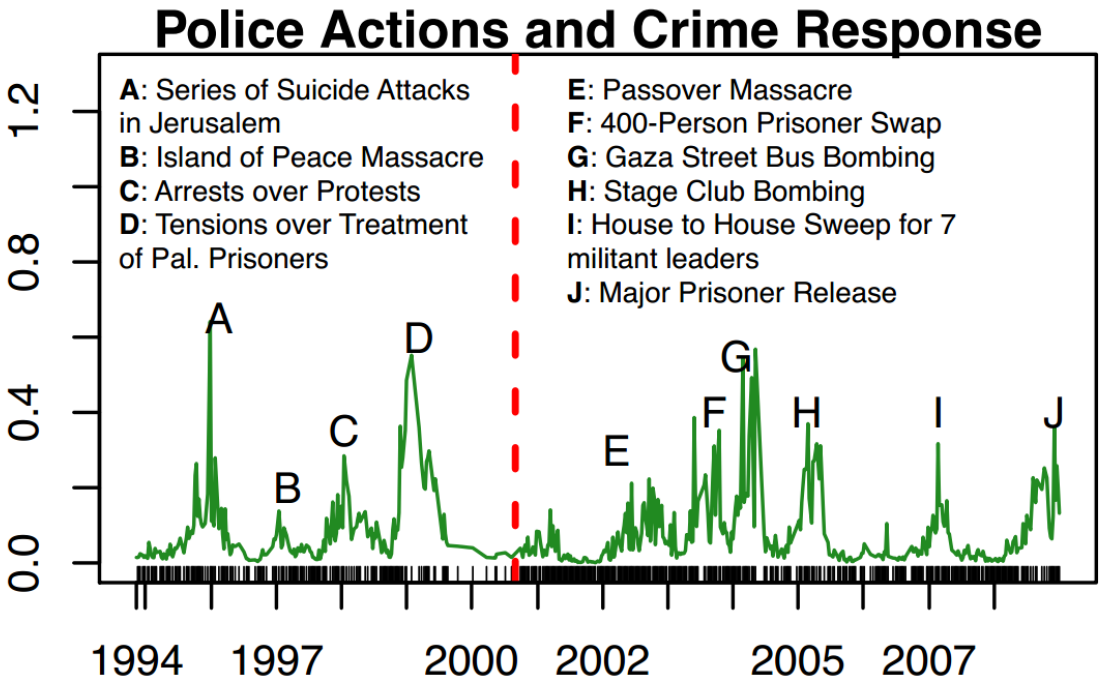
International Events (O'Connor, Stewart & Smith)

meet with, sign with, praise, say with, arrive in, host, tell, welcome, join, thank, meet, travel to, criticize, leave, take to, begin to, begin with, summon, reach with, hold with



International Events (O'Connor, Stewart & Smith)

accuse, criticize, reject, tell, hand to, warn, ask, detain, release, order, deny, arrest, expel, convict, free, extradite to, allow, sign with, charge, urge



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- Where does [insert party/legislator] fall on the ideological spectrum?
- Plus: Open-ended survey analysis (Roberts et. al 2013), Digital Humanities (Jockers 2012), Digital Historiography (Mimno 2012), Public Opinion (Hopkins and King 2010), Congressional Discourse (Quinn et al 2010), Legal Analysis (Gill and Hall 2013) etc.

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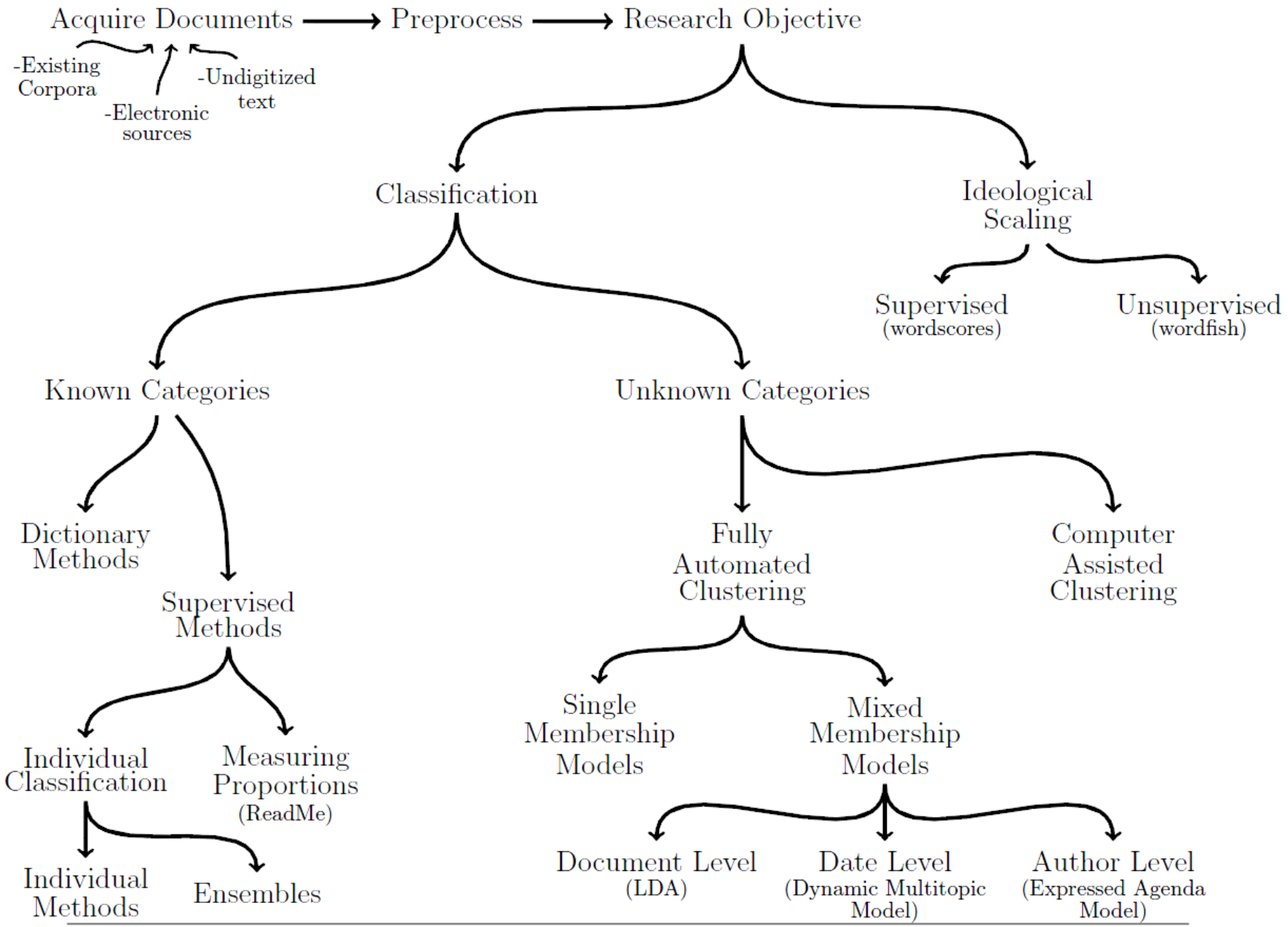
4. Validate, Validate, Validate.

A unifying view of text methods



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Examples of bad analytics (Jobs and Jordan).

Example: International Events

200 Million International Events

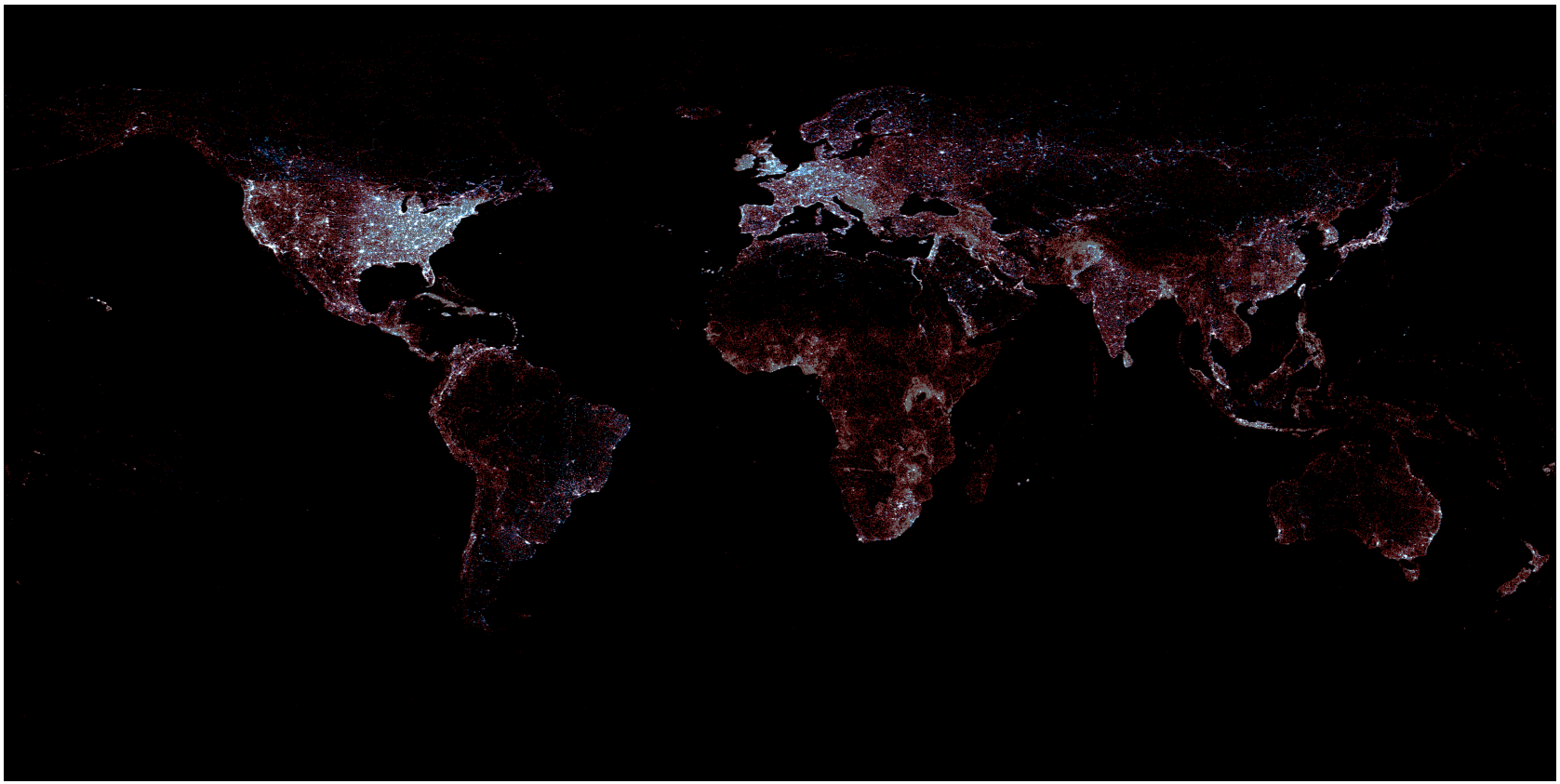
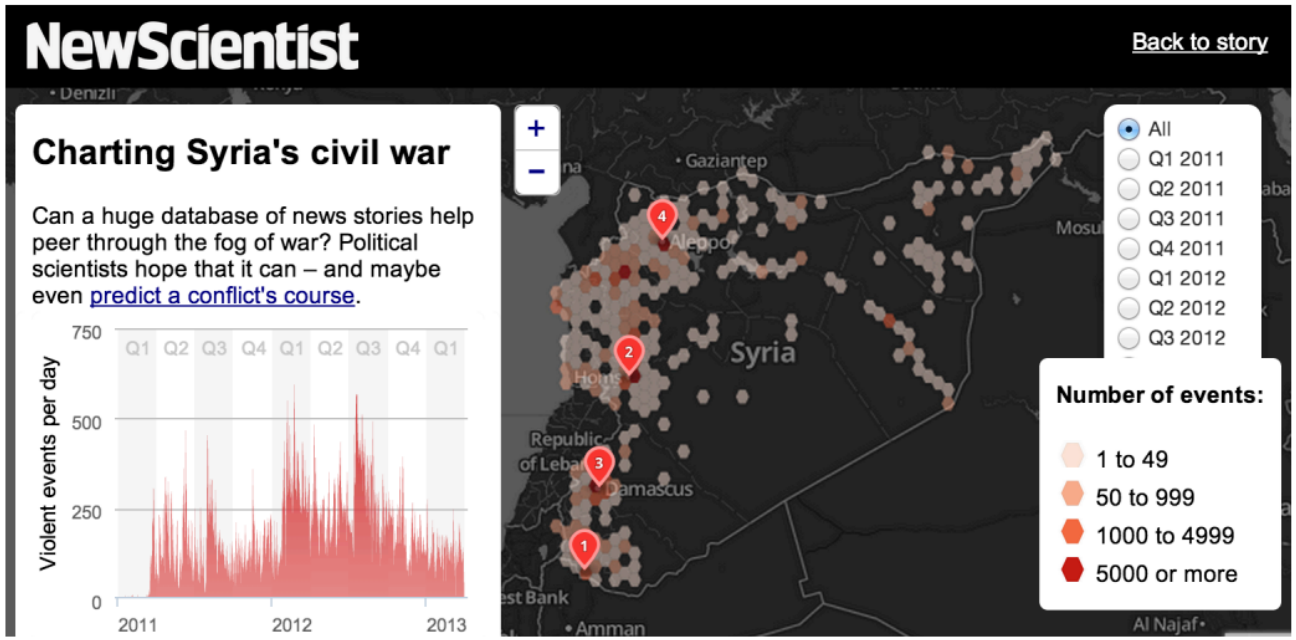


Image from GDELT data by Kalev Leetaru

Example: International Events

Able to track violence over time.



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Suddenly in the 1990's Jordan began attacking everyone.

Example: International Events

Because Michael Jordan was attacking the net.

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- 11 Million Posts analyzed, about 13% censored

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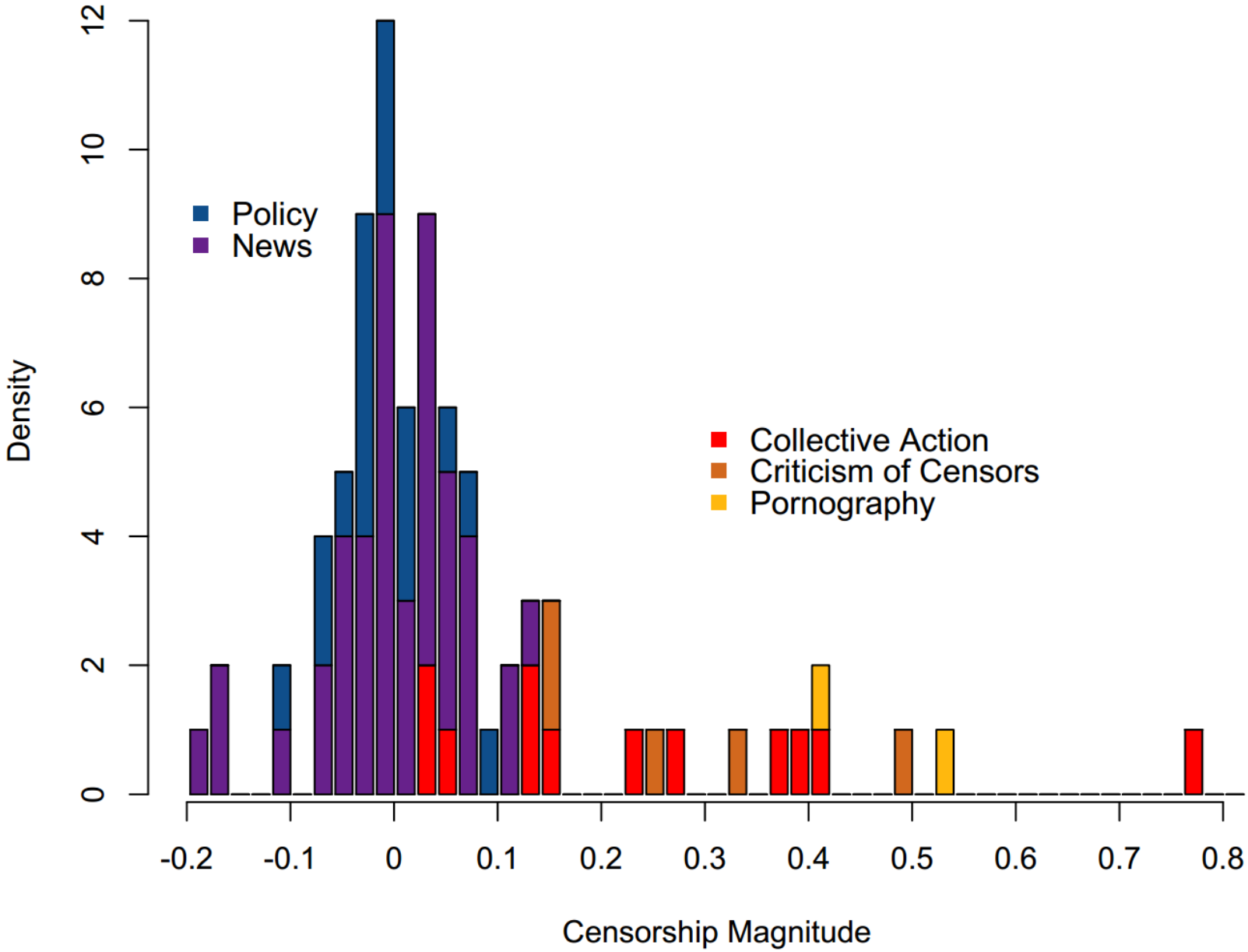

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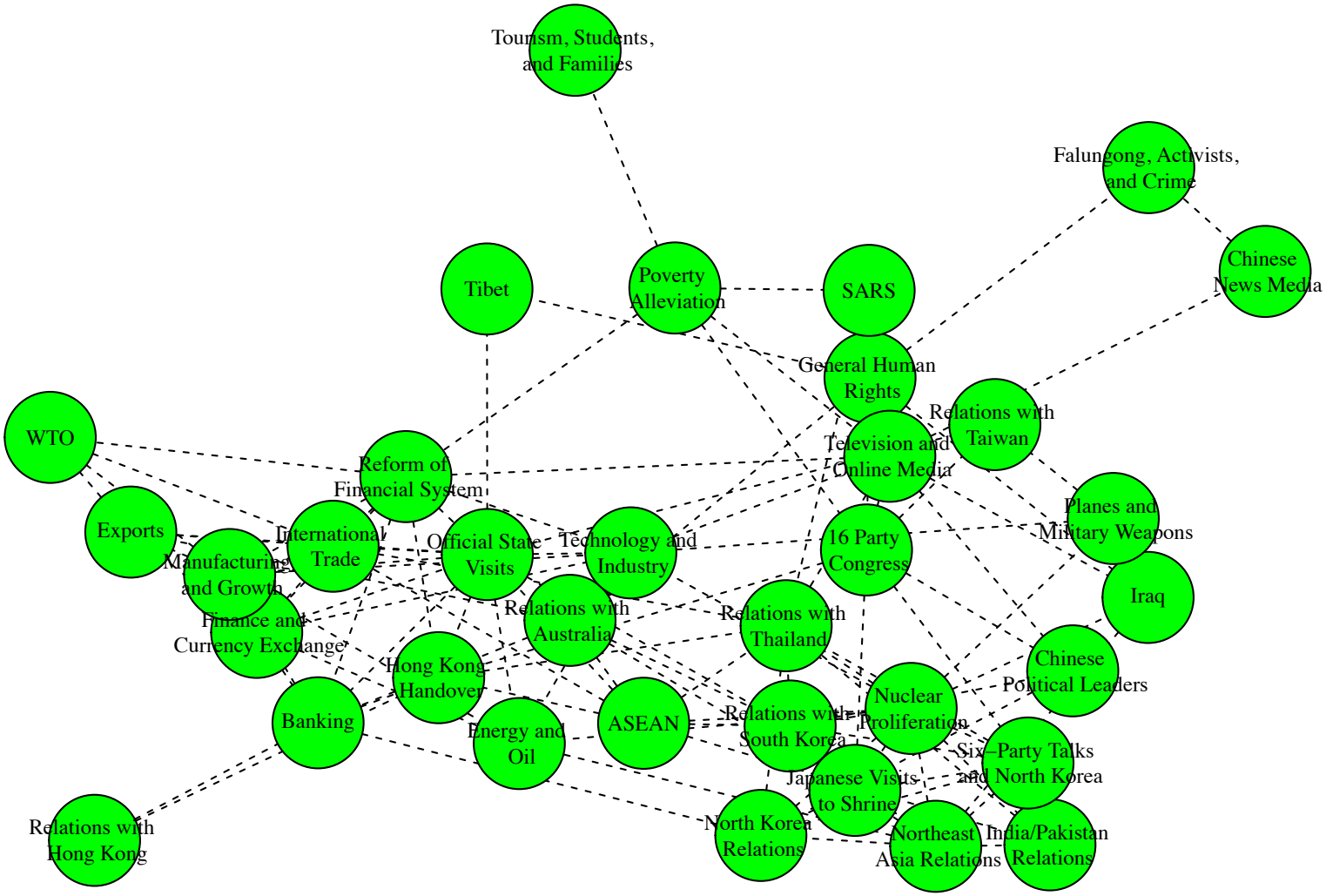
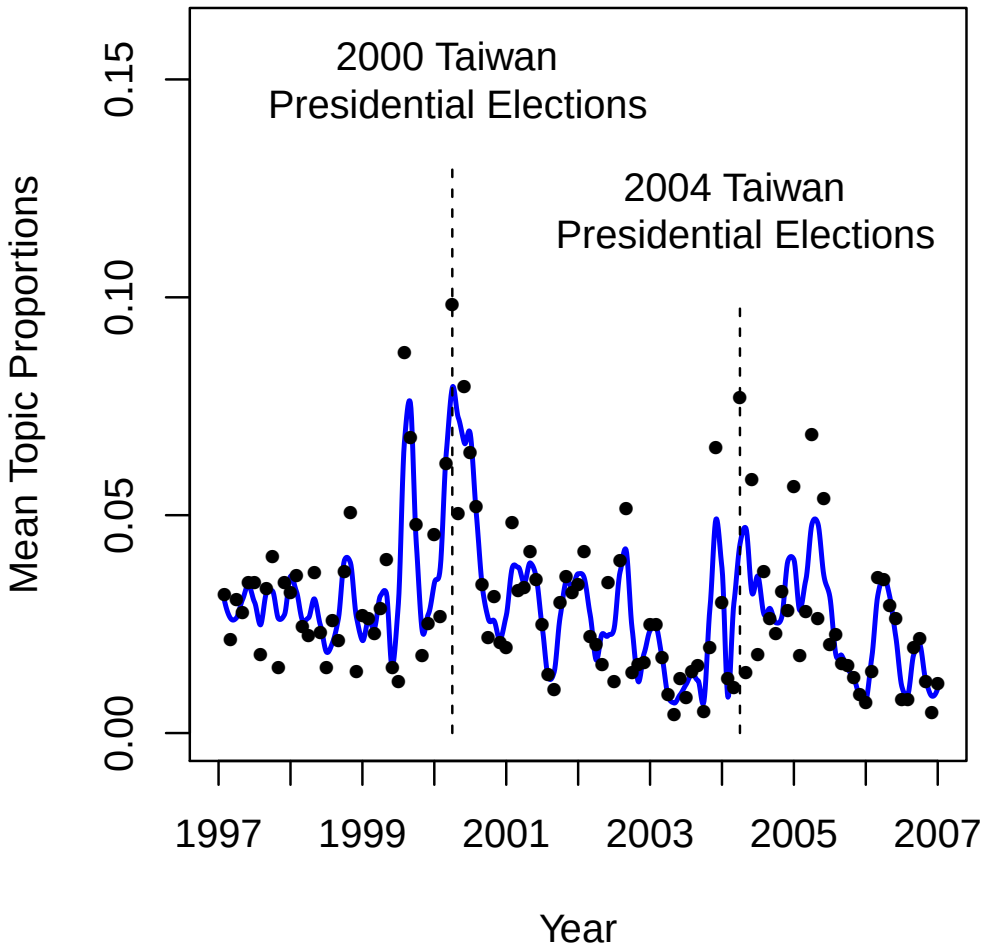


Topics by Time



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- Delayed coverage: SARS

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More Info: `scholar.harvard.edu/bstewart`

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Thank You!