Text as Data in Social Science: Discovery, Measurement and Causal Inference

Brandon Stewart
Based on joint work with Molly Roberts, Justin Grimmer, Dustin Tingley, Rich Nielsen, Jacob Montgomery, Luwei Ying and others.

Princeton Sociology and Office of Population Research

December 6, 2019

Source Material

- *Text as Data: How to Make Large Scale Inferences from Language* — book manuscript in preparation
  (with Grimmer and Roberts)
- "stm: R package for Structural Topic Models" *Journal of Statistical Software*
  (with Roberts and Tingley)
- "Adjusting for Confounding with Text Matching" *American Journal of Political Science*
  (with Roberts and Nielsen)
- "Inferring Concepts from Topics: Towards Procedures for Validating Topics as Measures"
  (with Ying and Montgomery)
- and others...

Copies of papers at BrandonStewart.org

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- This talk $\rightsquigarrow$ designing models for social science applications.

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   - text as treatment, outcome and confounder

Roadmap

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1) Trends in the literature
2) STM and Designing Methods of the Social Sciences
   - theory of use
   - customization
   - workflow
   - validation
3) Applications in Three Tasks
   - discovery
   - measurement
   - causal inference
4) Conclusions

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- Both strategies amplify human effort, each in different ways.

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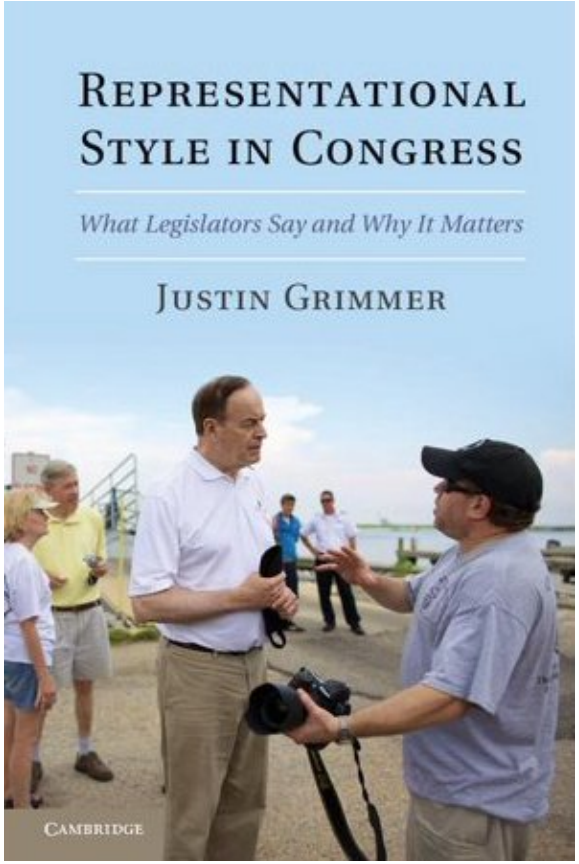

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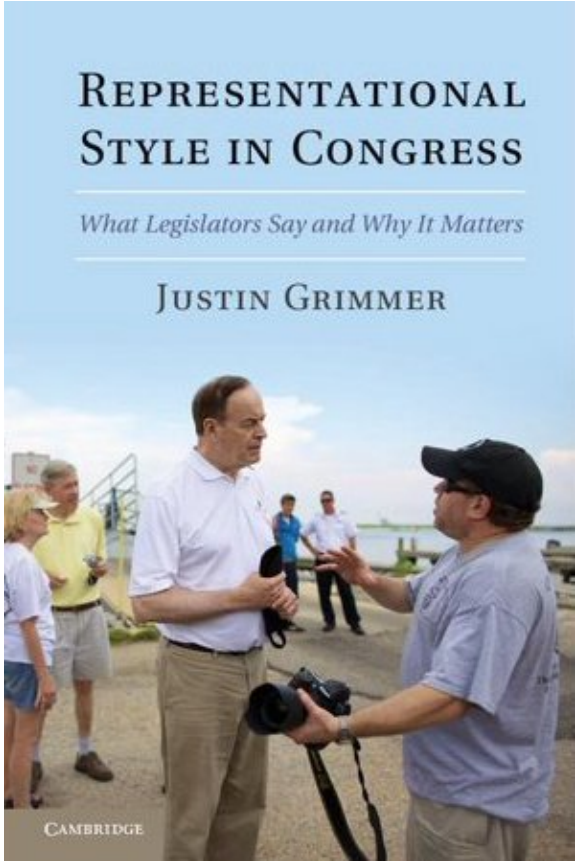

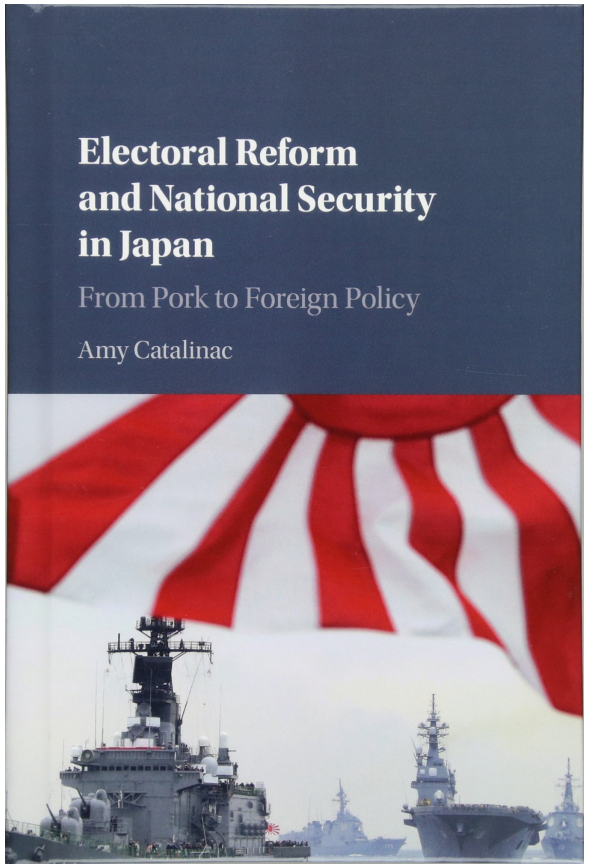

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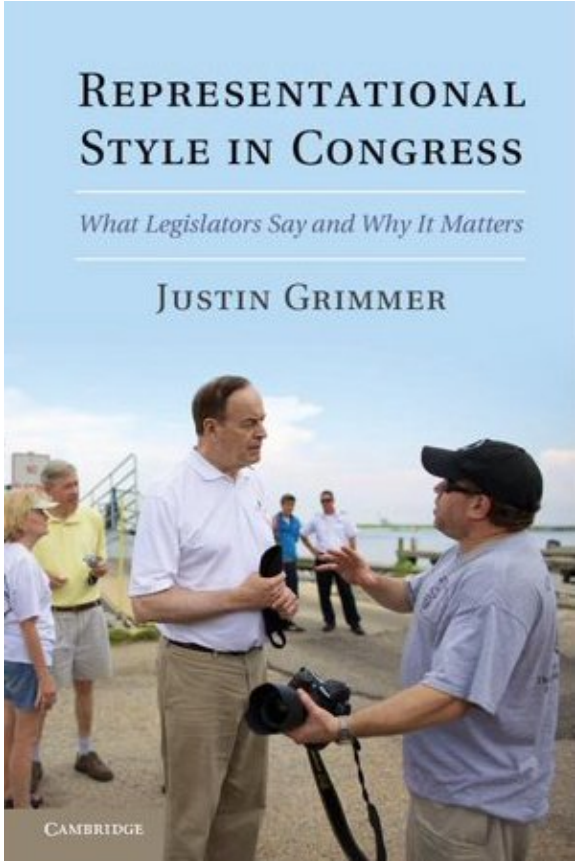

Making Austerity Popular: The Media and Mass Attitudes toward Fiscal Policy

Lucy Barnes University College London
Timothy Hicks University College London

Is the Left-Right Scale a Valid Measure of Ideology?

Individual-Level Variation in Associations with "Left" and "Right" and Left-Right Self-Placement

Paul C. Bauer[1] · Pablo Barberá[2] · Kathrin Ackermann[3] · Aaron Venetz[4]

From Pork to Policy: The Rise of Programmatic Campaigning in Japanese Elections

Amy Catalinac, New York University

Islamophobia and Media Portrayals of Muslim Women: A Computational Text Analysis of US News Coverage

Rochelle Terman

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- We can learn the topics because:
  - the model rewards a topic which contains as few words as possible
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- This tension is what encourages the model to develop semantically cohesive sets of topics.

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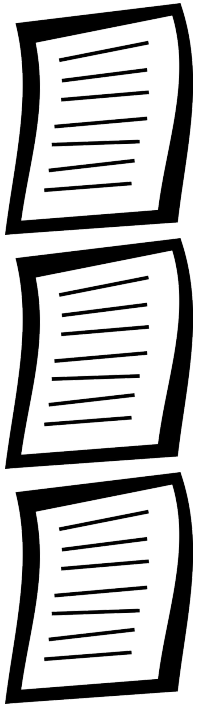

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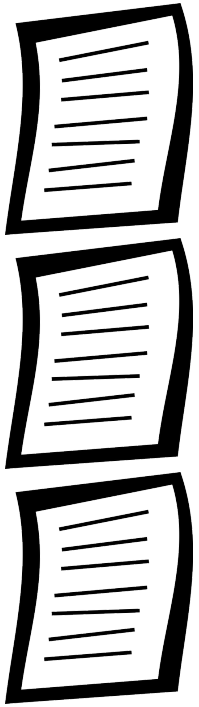

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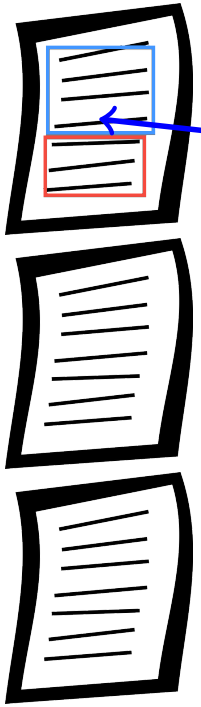

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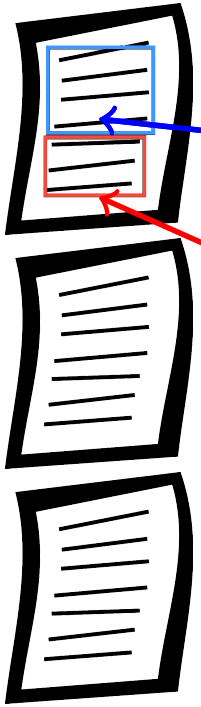

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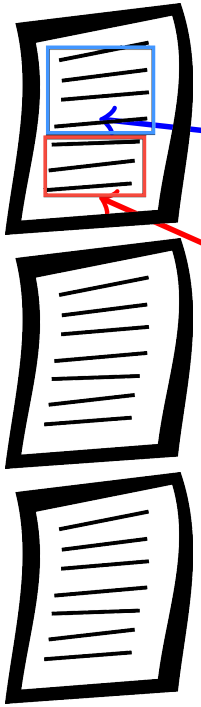

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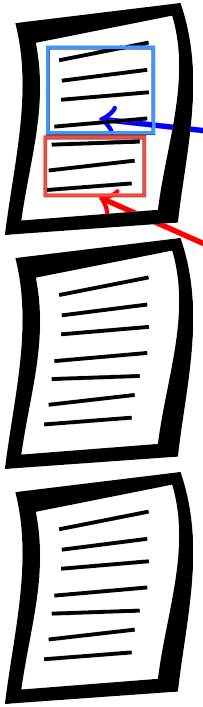

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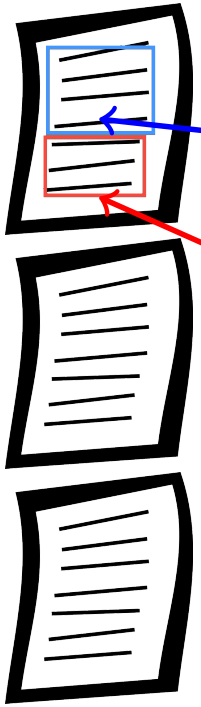

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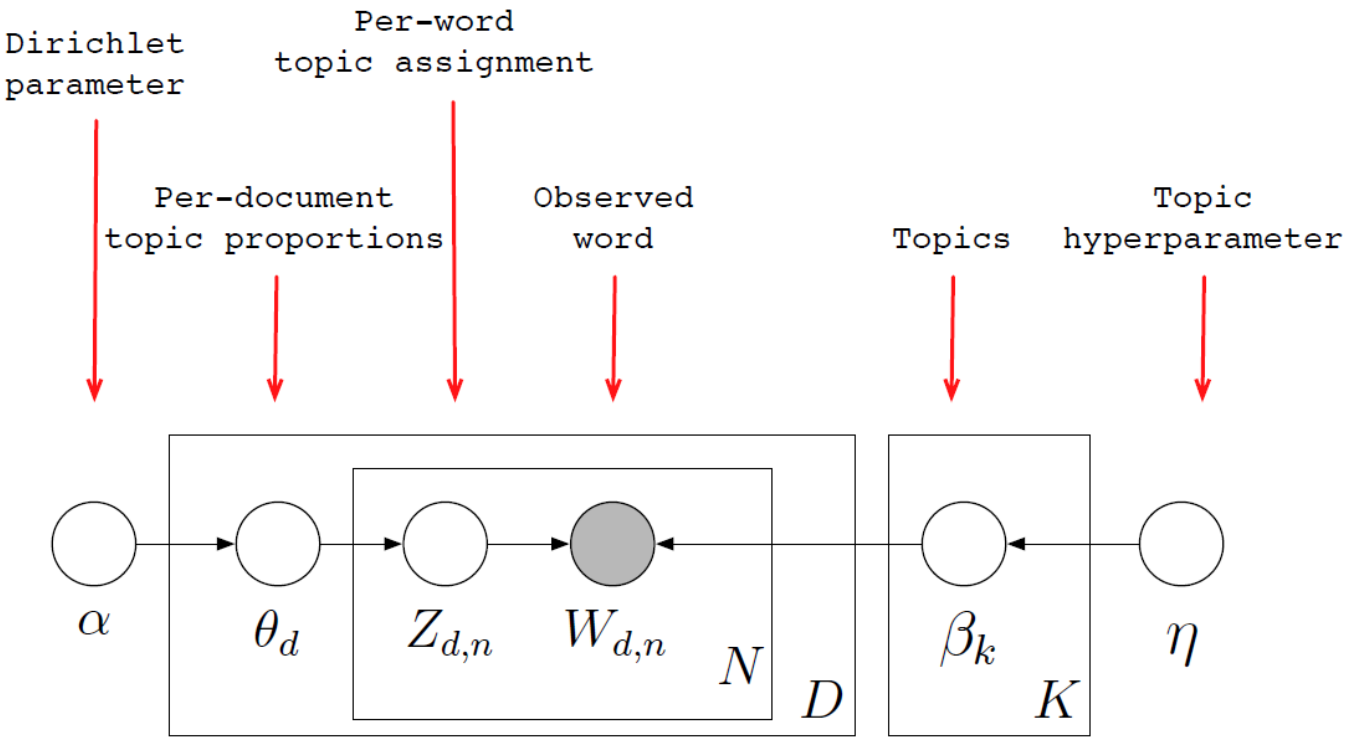
2. The proportion of each document in each topic

This is a Bayesian Model

Figure: Plate Notation of Latent Dirichlet Allocation



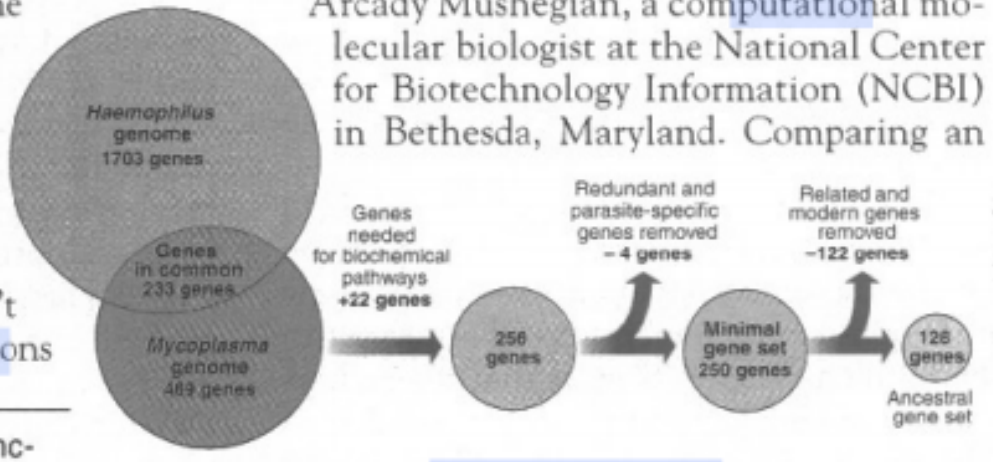
Graphic from Dave Blei

A Statistical Highlighter (With Many Colors)

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

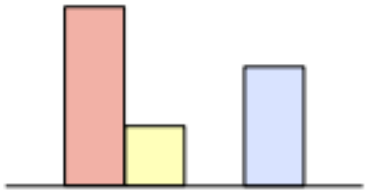


Image from Hanna Wallach

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  - we want to tell a story not just about what, but how and why

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- Illustration through the Structural Topic Model

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- Our understanding: social scientists using document-level latent variables to tell stories about how and why topics allocated attention over time.

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- Topic content can vary by metadata
  - e.g. Democrats are less likely to use the word "life" when talking about abortion than Republicans

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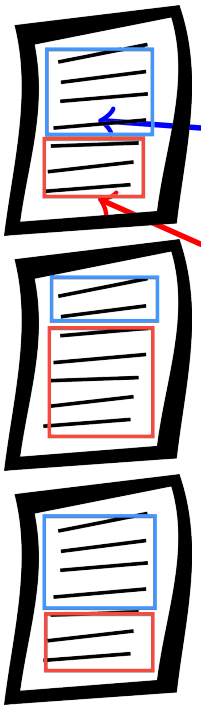

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- User specifies the number of topics: K
- Observed data for standard topic models
  - Each document ($d \in 1 \ldots D$) is a collection of N_d tokens
  - Each token is a particular word from a dictionary of V entries
  - Data summarized in a single matrix $D \times V$ matrix $\mathbf{W}$
- Additional data for STM
  - Topic prevalence covariates: $D \times P$ matrix $\mathbf{X}$
  - Topical content groups: D length vector $\mathbf{Y}$
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The Structural Topic Model

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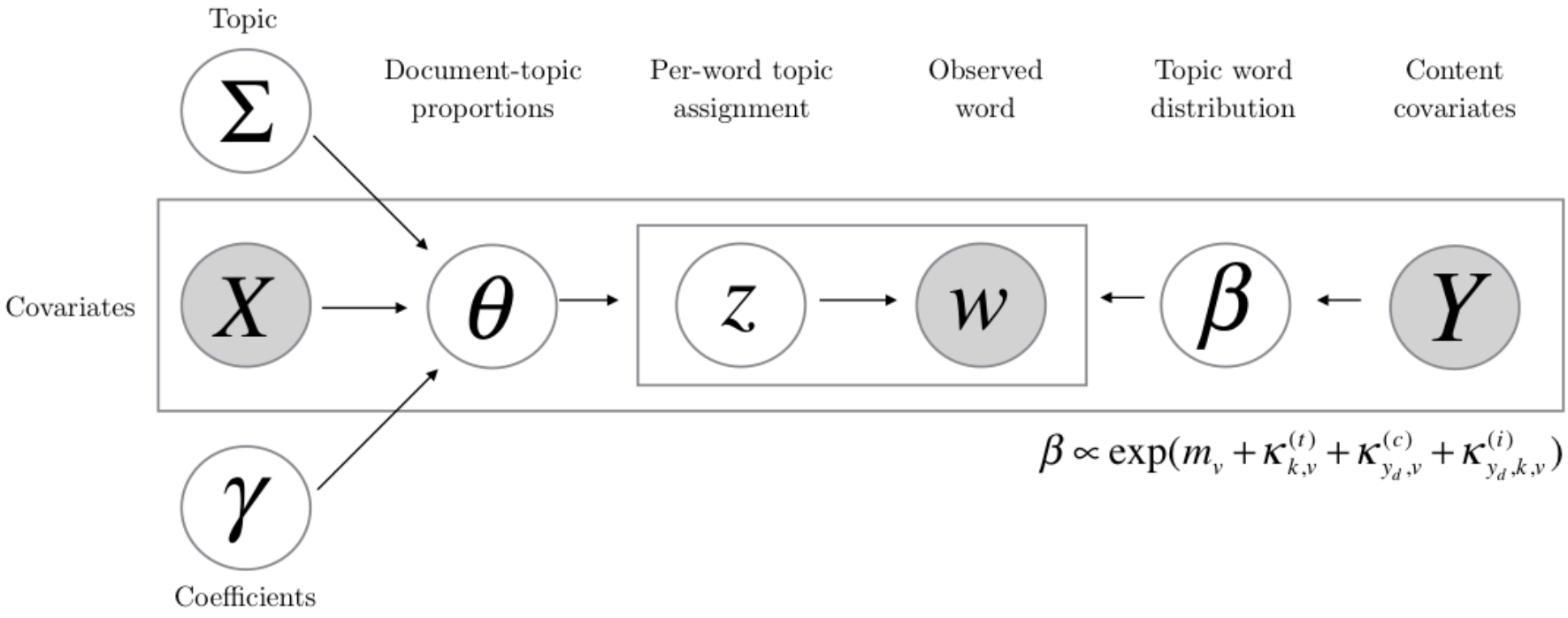
Structural Topic Model



$$\beta \propto \exp(m_v + \kappa^{(t)}_{k,v} + \kappa^{(c)}_{y_d,v} + \kappa^{(i)}_{y_d,k,v})$$

Problem Solving for Practical Use

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- Multilingual Text (Lucas et al 2015)
  modeling of a translated term-document matrix with modeled language difference

3) Designing the Workflow

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- `stm` Package in `R`
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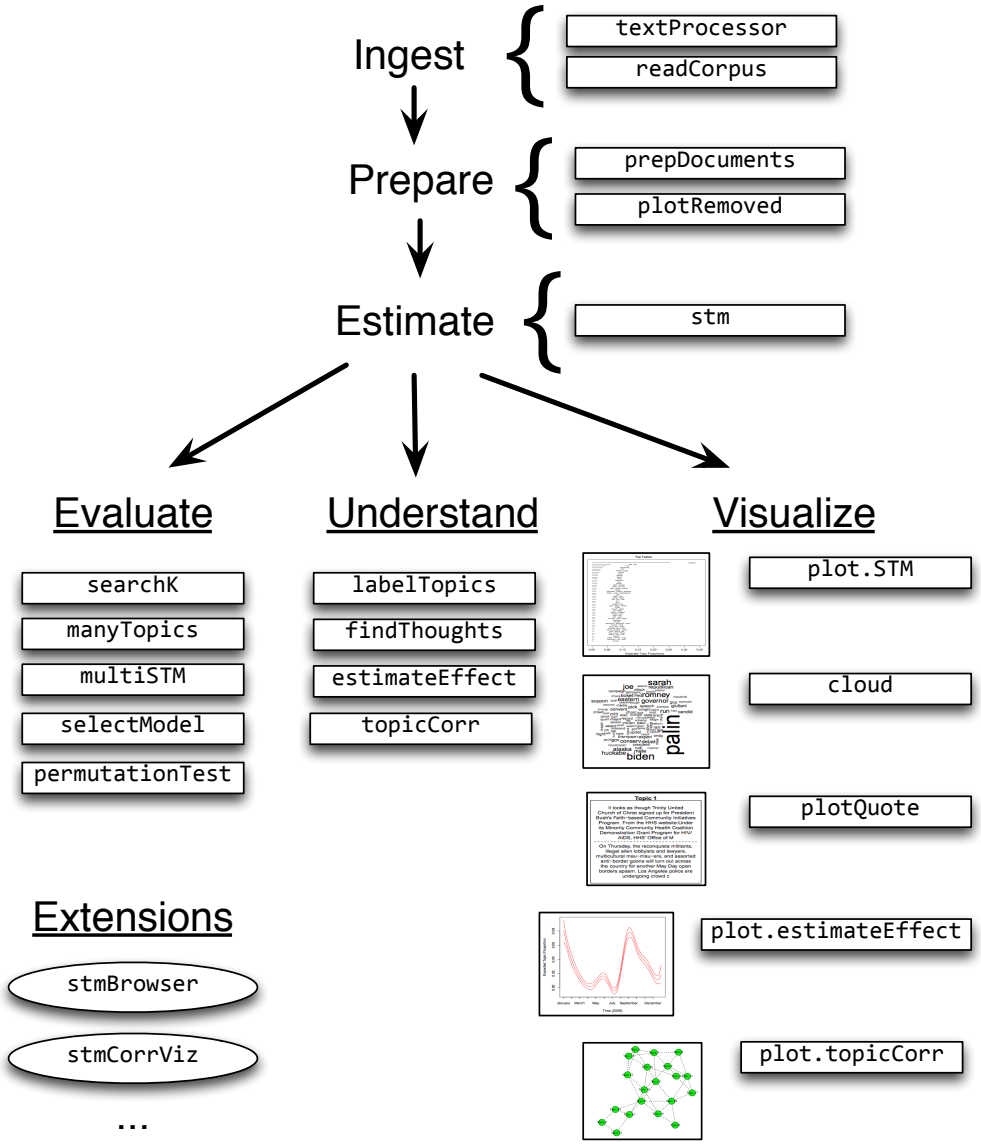
- Complete vignette online with examples

Workflow


Ingest
textProcessor
readCorpus
Prepare
prepDocuments
plotRemoved
Estimate
stm
Evaluate
searchK
manyTopics
multiSTM
selectModel
permutationTest
Understand
labelTopics
findThoughts
estimateEffect
topicCorr
Visualize
plot.STM
cloud
plotQuote
plot.estimateEffect
plot.topicCorr
Extensions
stmBrowser
stmCorrViz
...

Auxiliary Visualization Packages

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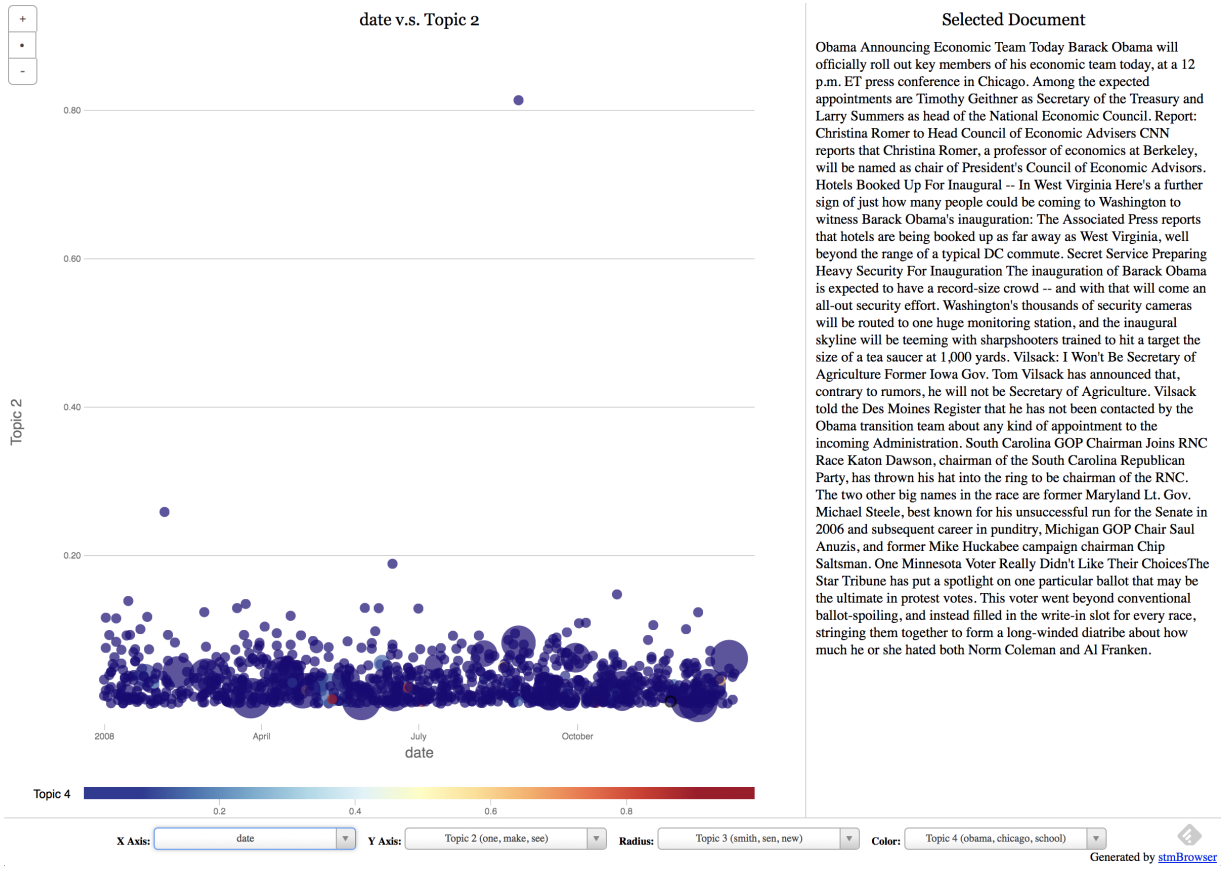
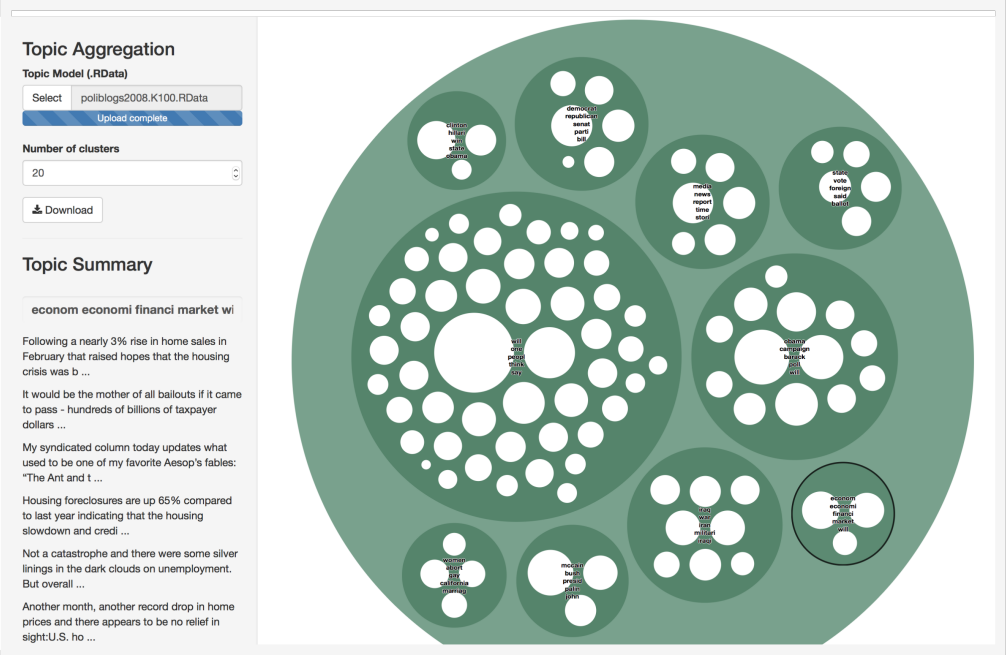
`stmBrowser`

(with Freeman, Chuang, Roberts and Tingley)



Auxiliary Visualization Packages

Trellis
(with Chaney and Schaffner)



Creating Validations

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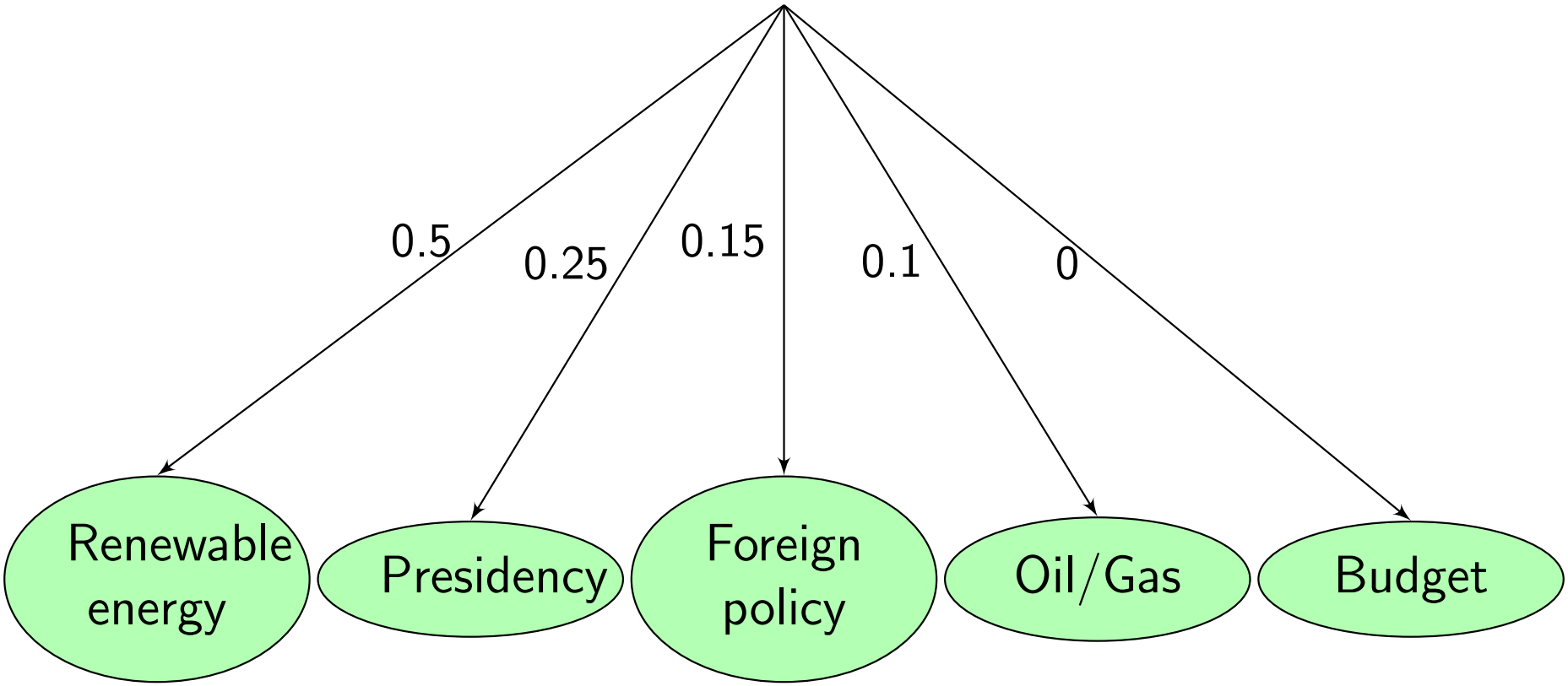
- CS has advanced through clear, shared benchmarks
  shared task framework, leaderboards, and 'state-of-the-art' performance
- Difficult in social science — evaluation depends on the goal
  do custom measurements imply custom validations?

Topic Models as Presented (Ying et al 2019)

Why is Obama tapping oil reserves without adopting a national energy policy that will lessen America's dependence on foreign oil?



Topic Models Under the Hood

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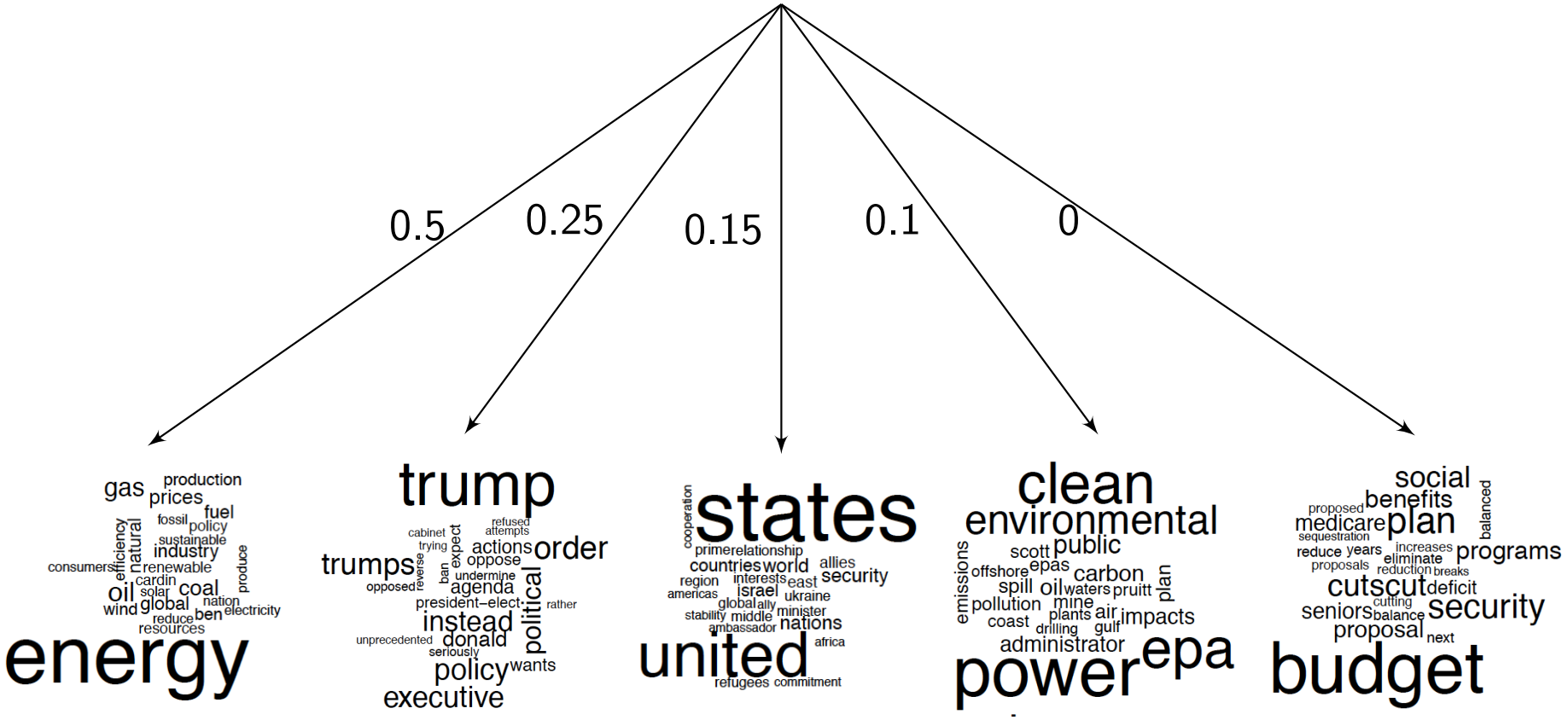
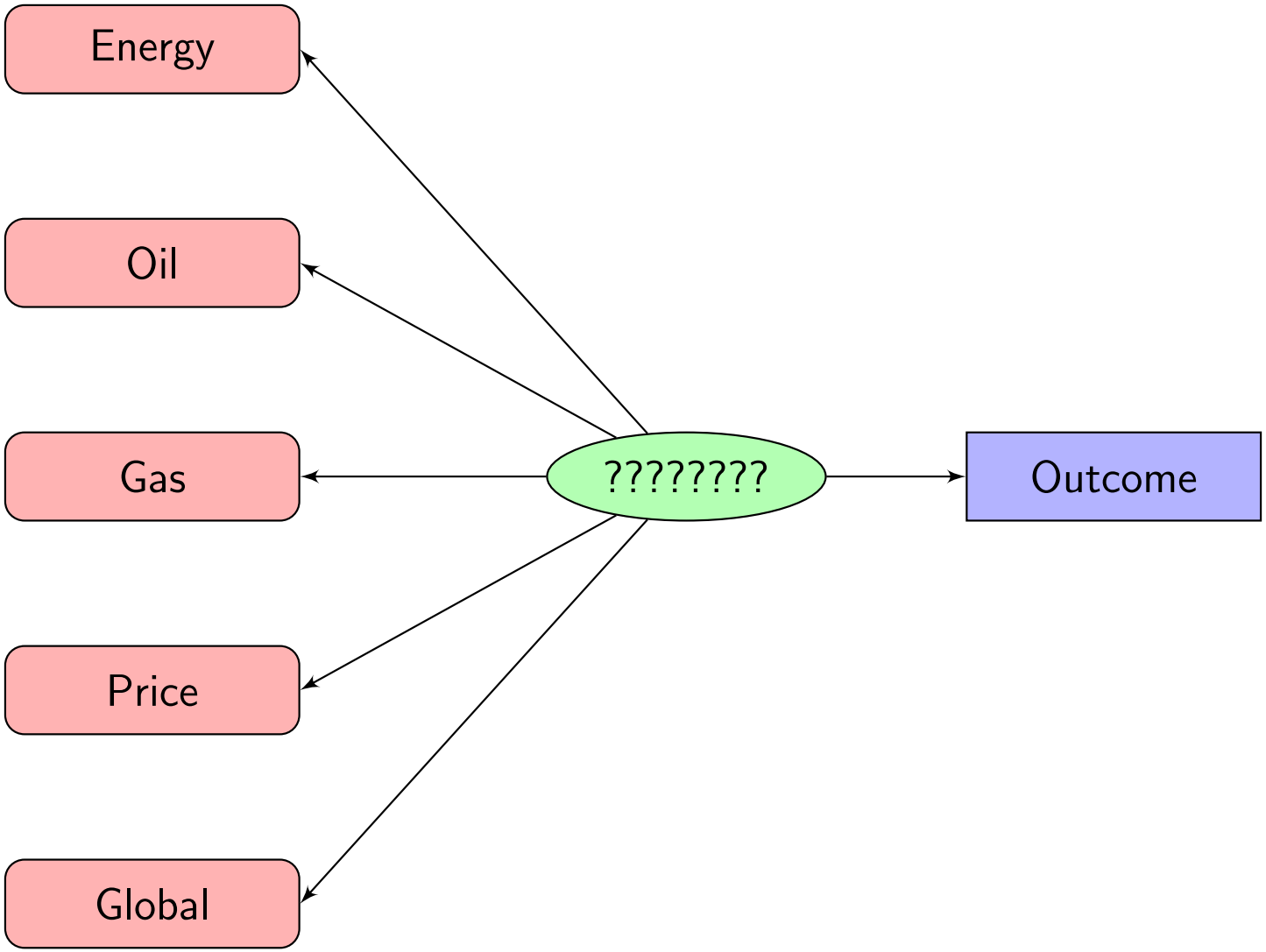
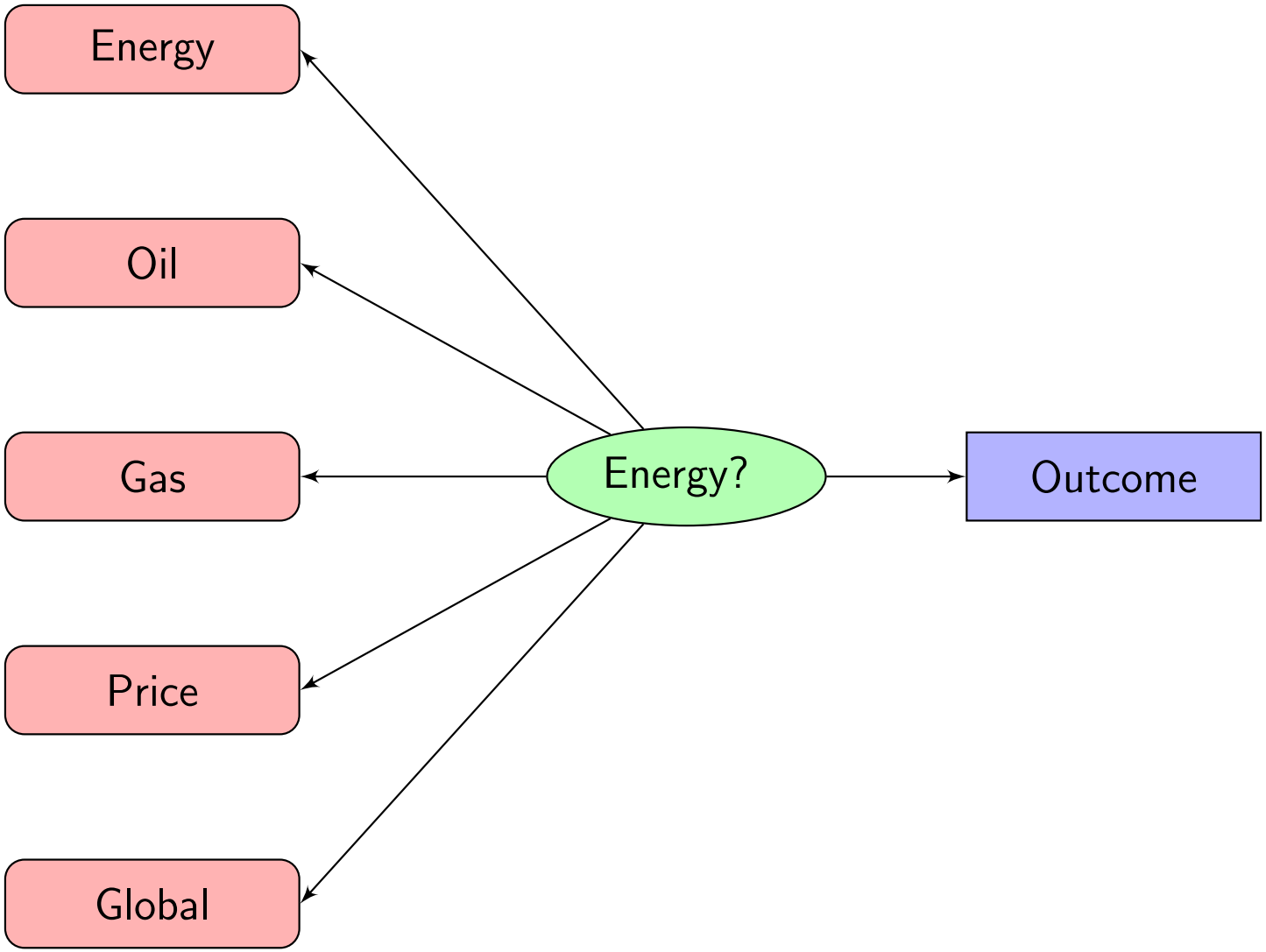


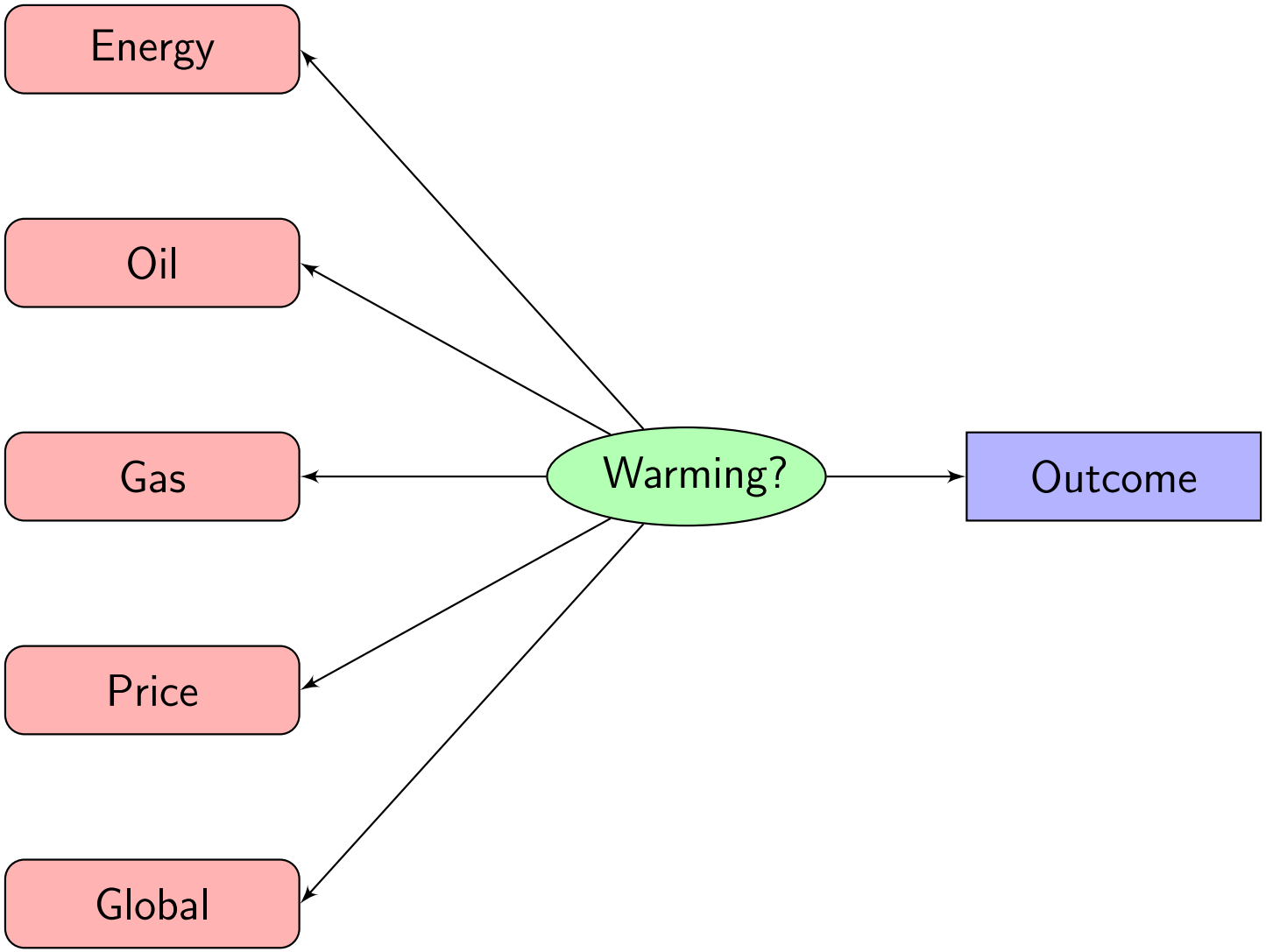
What's the concept in this cloud?: It matters



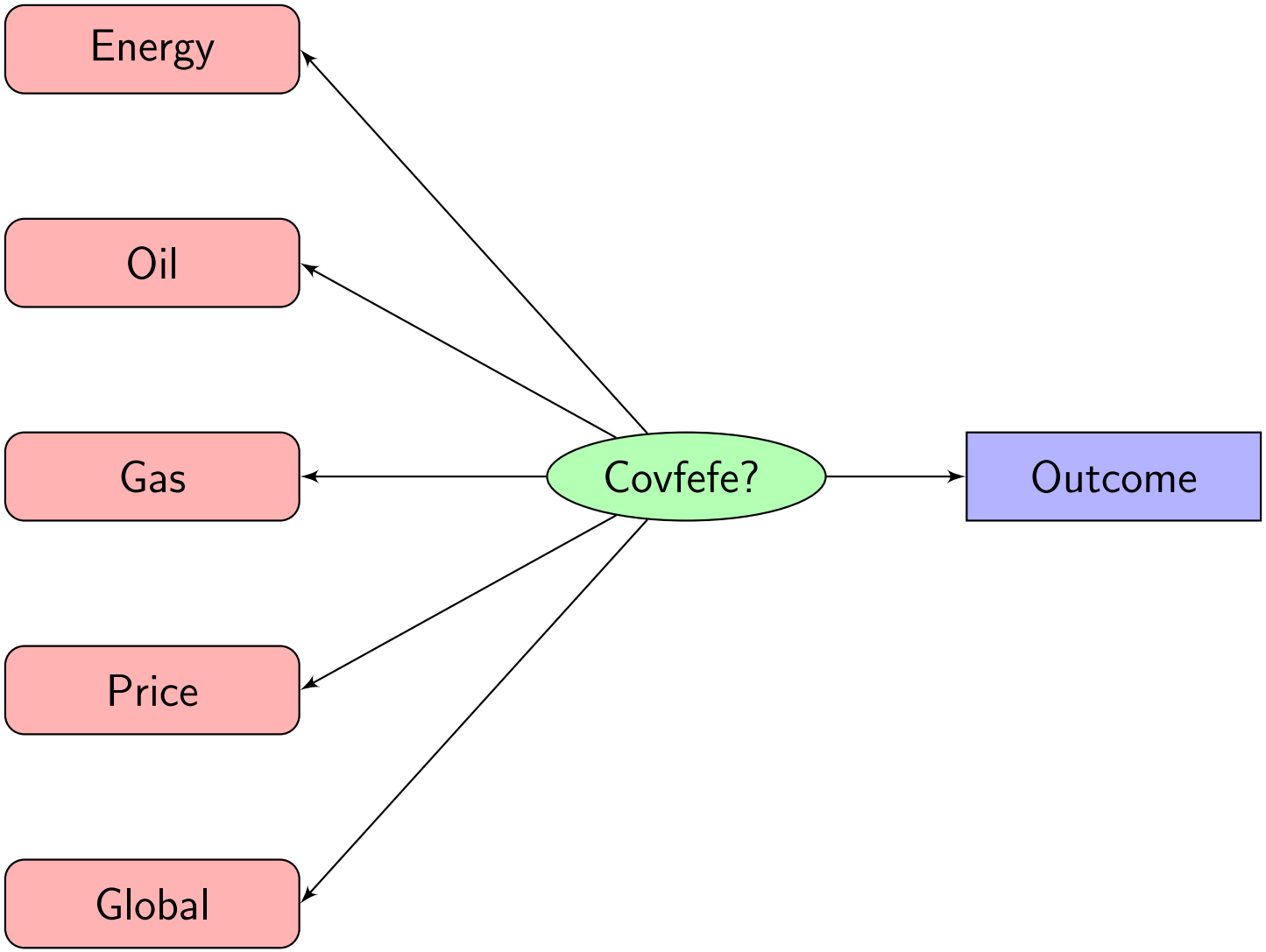
Energy?



Global Warming?



Are we just modeling a mashup?



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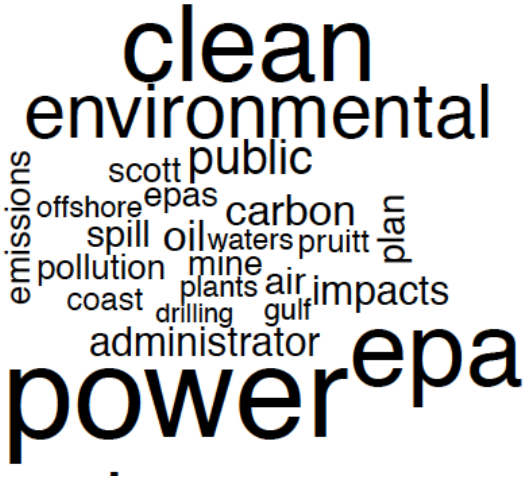
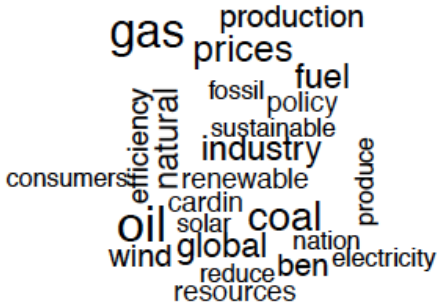
4) Bespoke Evaluation
   alternate measures, external events, supervised checks
   public-ish, application-specific, maybe scalable?

Validations as a Reader: Wordclouds





When you explain qualitative validation

Wisdom of crowds (Ying et al 2019)

- Topics validation as a set of little games

[PDF] **Reading tea leaves**: How humans interpret topic models

J Chang, S Gerrish, C Wang… - Advances in neural …, 2009 - papers.nips.cc

Probabilistic topic models are a popular tool for the unsupervised analysis of text, providing both a predictive model of future text and a latent topic representation of the corpus. Practitioners typically assume that the latent space is semantically meaningful. It is used to …

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Example: Random 4 Word Set Intrusion

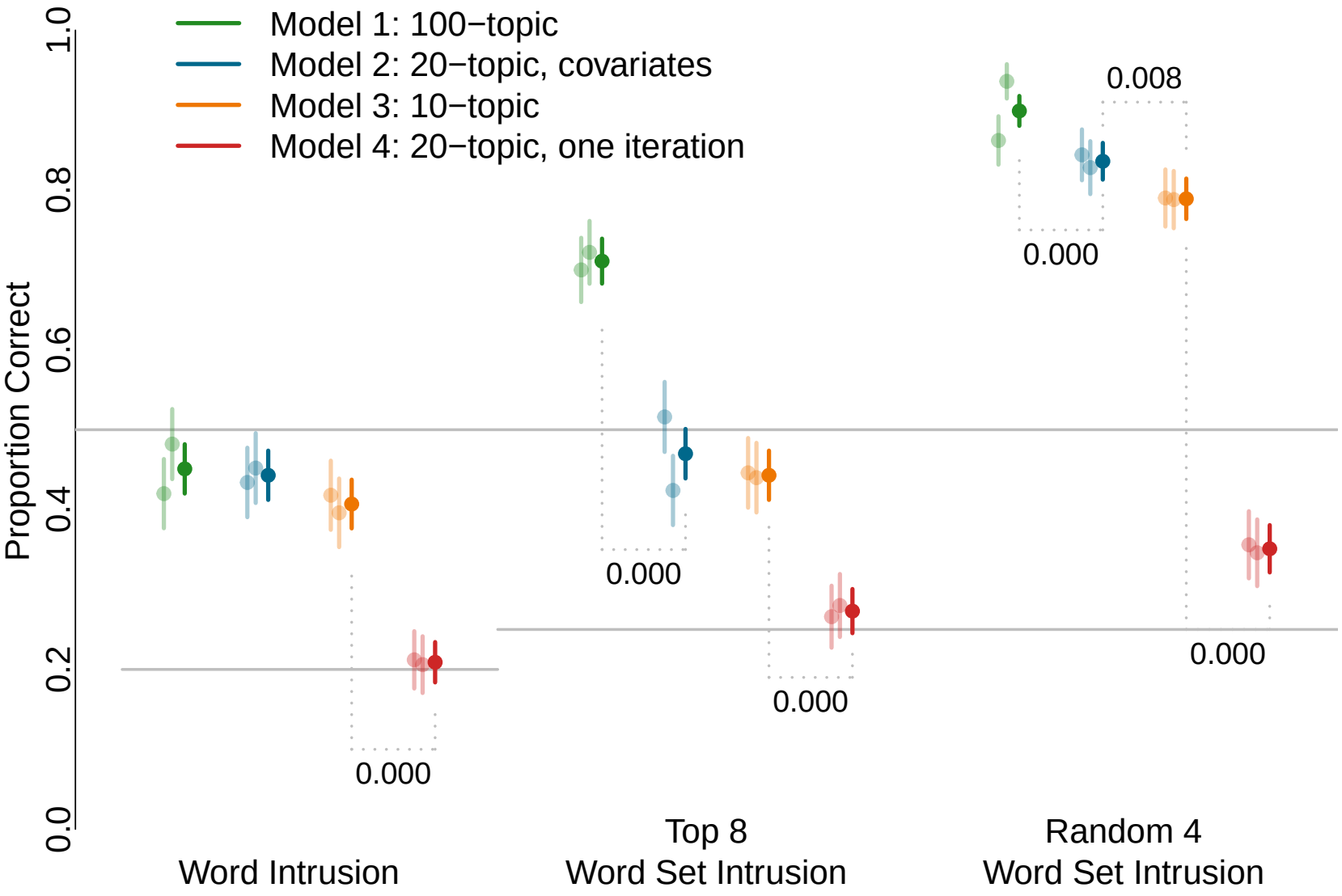
When it comes to medical treatment, children are not small adults, and the EMSC program recognizes the special care and attention they deserve. This low-cost program has saved the lives of countless children and adolescents in the past 30 years, and I urge my colleagues to support this critically important program.

After reading the above passage, please click on the set of words below that is MOST UNRELATED to the passage.

- health, human, hospital, planned
- visiting, pictured, tour, visit
- care, access, serves, women
- human, centers, medical, improve

Submit

New Games Discriminate Better



Example: Label Intrusion (LI)

Great to visit a Kansas energy producer today. They are creating jobs and energy for Kansas and the nation. Keep up the good work!

After reading the above passage, please click on the label below that is MOST UNRELATED to the passage.

- Renewable Energy
- Jobs & Keystone Pipeline
- Raising the Debt Ceiling
- Economic & Job Growth

Submit

Adoption

stm: An R Package for the Structural Topic Model

Website: www.structuraltopicmodel.com

Vignette: Here

Authors: Molly Roberts, Brandon Stewart and Dustin Tingley

Please email all comments/questions to bms4 [AT] princeton.edu

CRAN 1.3.4 | build passing | downloads 5682/month | downloads 113K

Adoption

View on GitHub

stm

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tar.gz .zip

Download the Vignette

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News

July 31, 2018

1. We were honored to win the Political Methodology Society's Statistical Software Award for 2018.
2. Added Mikael Johannesson's stmprinter package to Supporting Packages.

Adoption

Published Applications

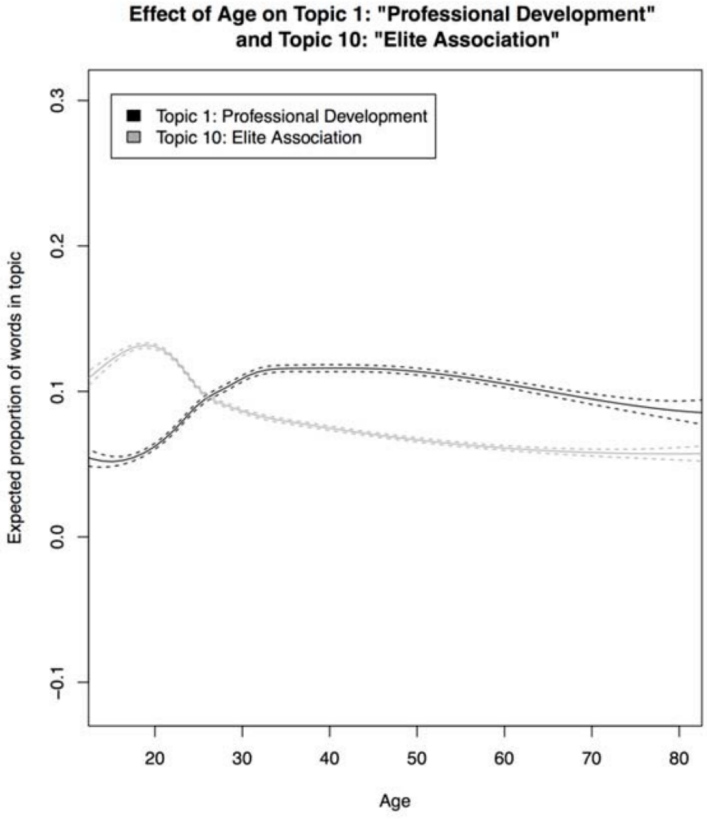
If you have published a paper using stm that you would like to see included here please email us.

1. Schwemmer and Ziewiecki. "Social media Sellout: The Increasing Role of Product Promotion on YouTube." *Social Media + Society.* 2018.
2. Dybowski and Adämmer. "The economic effects of U.S. presidential tax communication: Evidence from a correlated topic model" *European Journal of Political Economy* 2018.
3. Rothschild, Howat, Shafranek, Busby. "Pigeonholing Partisans: Stereotypes of Party Supporters and Partisan Polarization." *Political Behavior* 2018.
4. Chandelier, Steuckardt, Mathevet, Diwersy, Gimenez. "Content analysis of newspaper coverage of wolf recolonization in France using structural topic modeling." *Biological Conservation* 2018.
5. Cerchiello and Nicola. "Assessing News Contagion in Finance" *Econometrics* 2018.
6. Nelson, Laura K. "Computational Grounded Theory: A Methodological Framework" *Sociological methods & Research* 2018.
7. Bohr and Dunlap. "Key Topics in environmental sociology, 1990–2014: results from a computational text analysis"*Environmental Sociology* 2018.
8. Banks, Woznyj, Wesslen and Ross. "A Review of Best Practice Recommendations for Text Analysis in R (and a User-Friendly App)"*Journal of Business and Psychology* 2018.
9. Hagen, Harrison and Dumas. "Data Analytics for Policy Informatics: The Case of E-Petitioning" *Policy Analytics, Modelling, and Informatics* 2018.
10. Kuhn, Kenneth D. "Using structural topic modeling to identify latent topics and trends in aviation incident reports" *Transportation Research Part C: Emerging Technologies* 2018.
11. Tvinnereim, Flottum, Gjerstad, Johannesson and Nordo. "Citizens' preferences for tackling climate change. Quantitative and qualitative analyses of their freely formulated solutions "*Global Environmental Change* 2017.

Applications: Discovery

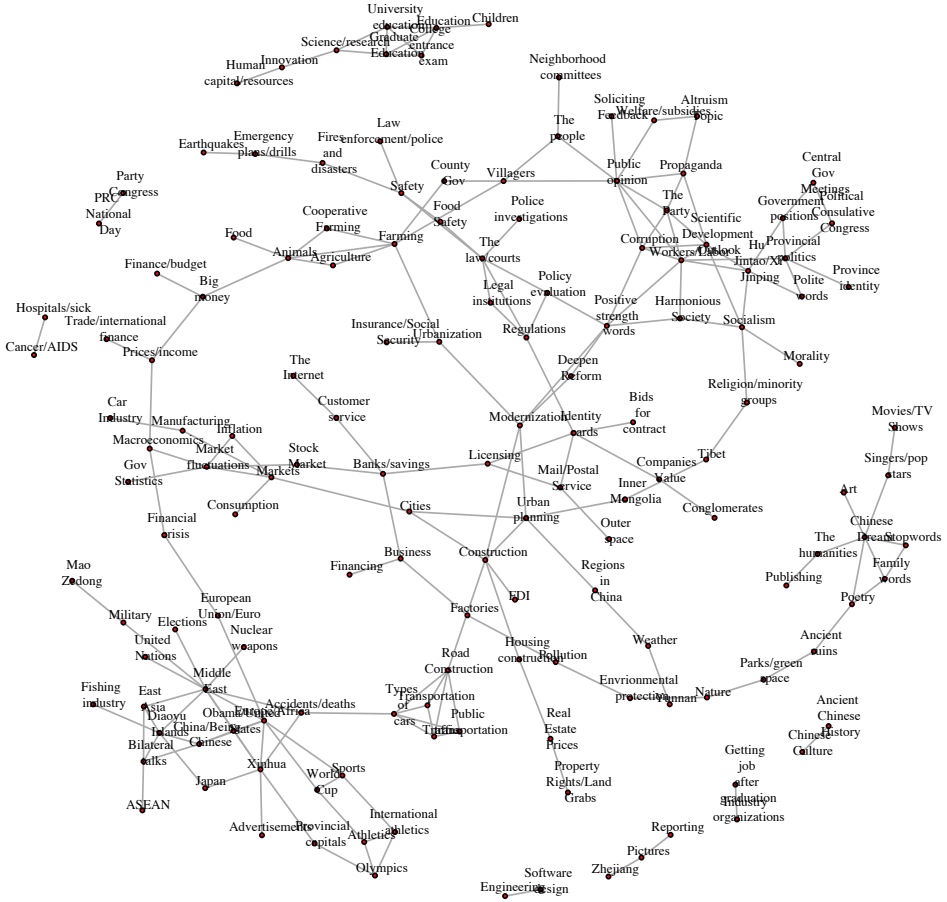
Applications: Discovery

Computer-Assisted Reading and Discovery for Student-Generated Text in Massive Open Online Courses
(with Reich et al in *Journal of Learning Analytics*)



Applications: Discovery

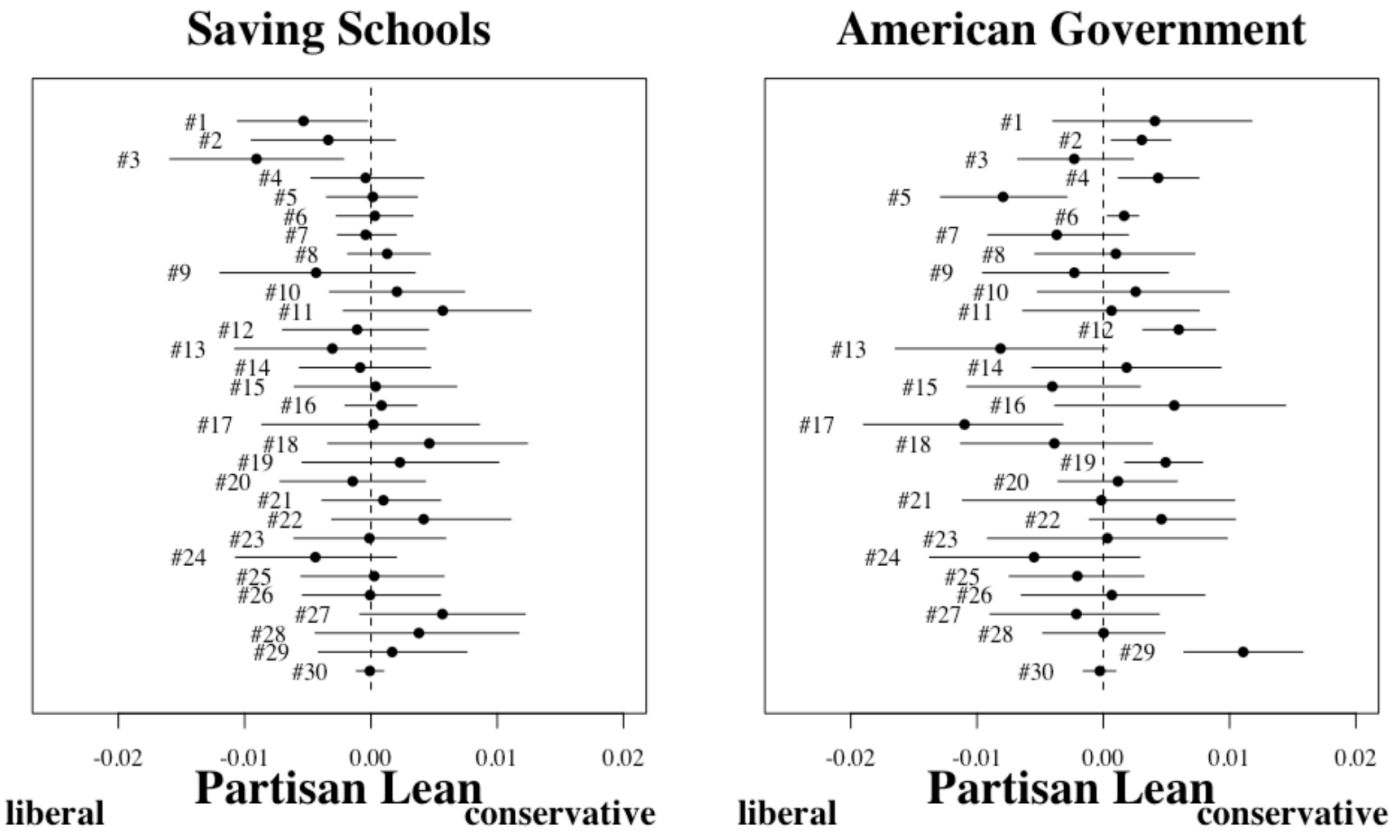
Propaganda in China
(with Roberts)



Applications: Measurement

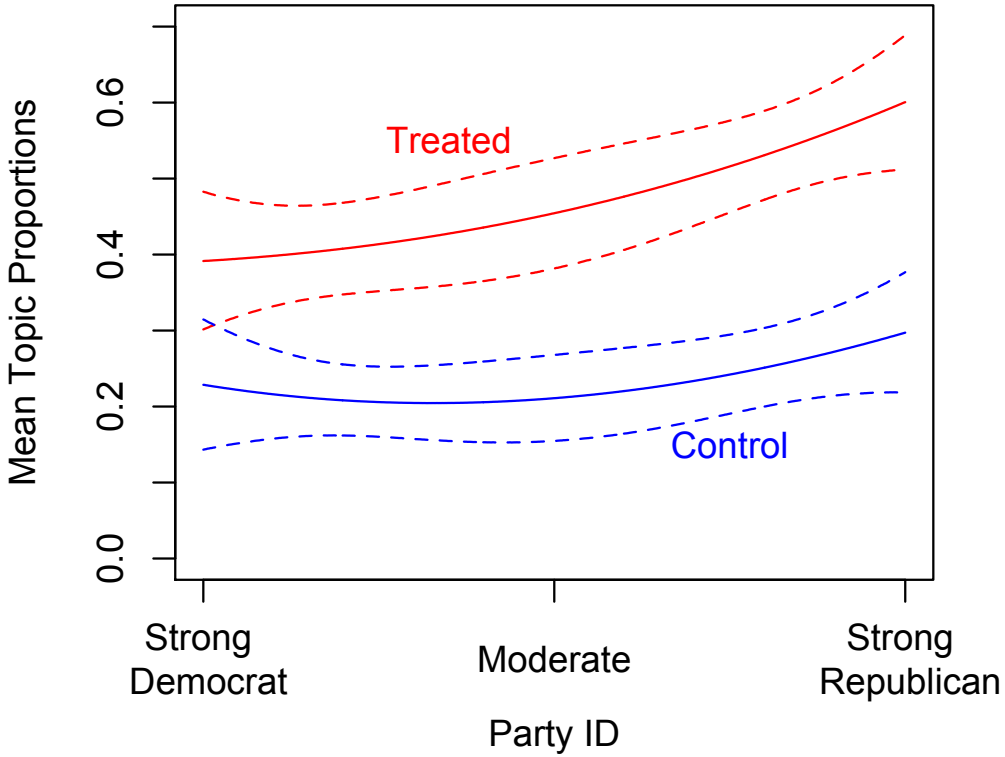
Applications: Measurement

The Civic Mission of MOOCs: Computational Measures of Engagement Across Differences in Online Courses.
(with Yeomans et al in *IJAED*)



Applications: Measurement

Structural topic models for open-ended survey responses
(with Roberts et al in *American Journal of Political Science*)



Applications: Causal Inference

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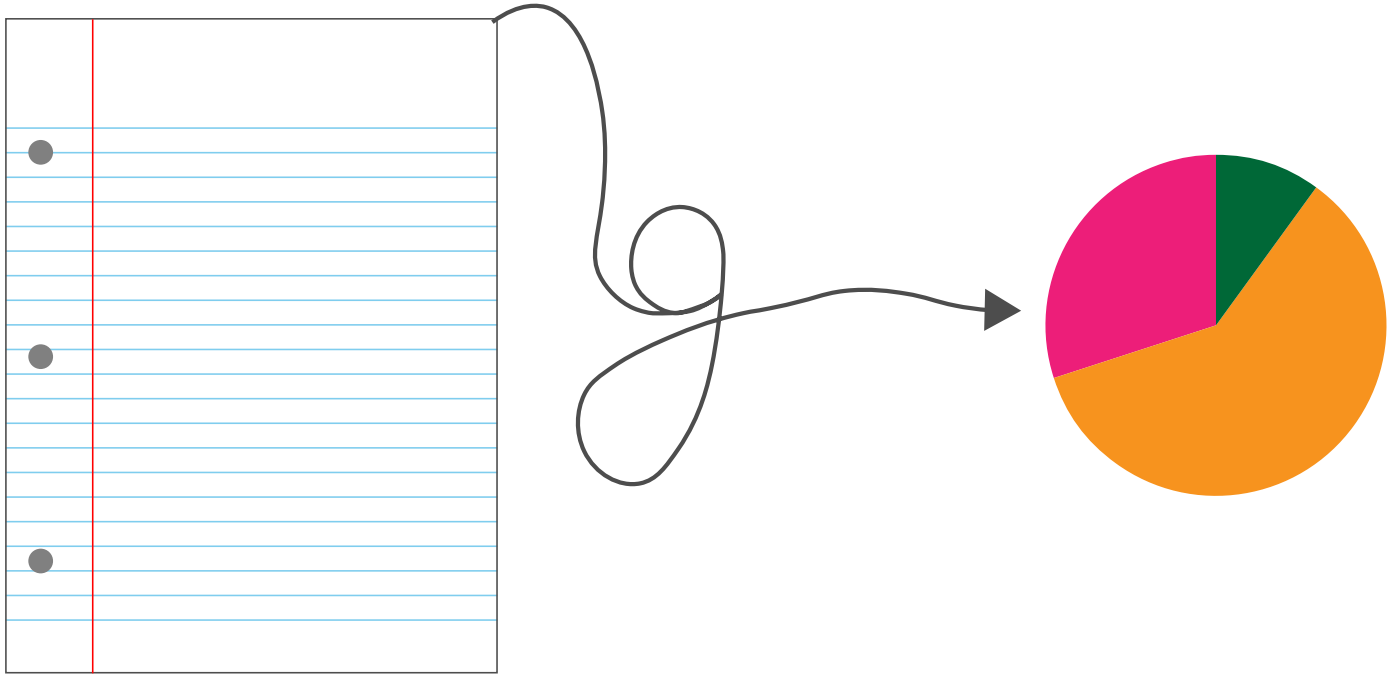
How to Make Causal Inferences Using Text
(with Egami, Fong, Grimmer and Roberts)



Application: "Adjusting for Confounding with Text Matching" (Roberts, Stewart and Nielsen)

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- Repression of speech in China $\rightsquigarrow$ internet censorship

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- Repression of speech in China $\rightsquigarrow$ internet censorship
- But, censoring the whole internet is hard
  (# of bloggers $\gg$ # of censors)
- Limited external enforcement $\rightsquigarrow$ self-policing & targeting

Application: "Adjusting for Confounding with Text Matching" (Roberts, Stewart and Nielsen)

- Repression of speech in China $\rightsquigarrow$ internet censorship
- But, censoring the whole internet is hard
  (# of bloggers $\gg$ # of censors)
- Limited external enforcement $\rightsquigarrow$ self-policing & targeting
- People aren't censored at random $\rightsquigarrow$ causality is tricky

The Perfect Experiment

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2. Randomly assign censorship

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3. See what bloggers write after censorship

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Problem 1: unethical
Problem 2: we aren't the Chinese government

Approximating the Perfect Experiment

An approximation:

Find two bloggers

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Find two bloggers

✓similar users,

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An approximation:

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✓similar users,
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An approximation:

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Approximating the Perfect Experiment

An approximation:

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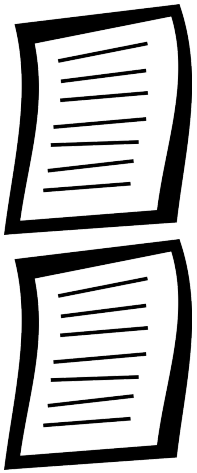

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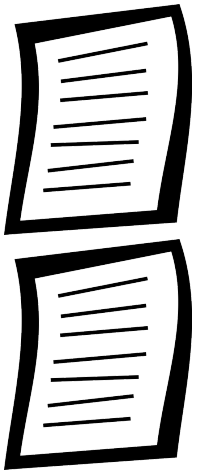

written on the same day

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Find two bloggers

Only one censored

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Censorship 'Mistake'

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Censorship 'Mistake'

Does the censored blogger's behavior change?

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- Retain interpretability of matches for human evaluation.

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Censored users have almost double the censorship rate but still post at the same rate.
Consistent with algorithmic targeting or increased posting of sensitive content.

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  - create validations
- Future directions in new kinds of data and new forms of supervision

For more information

brandonstewart.org

structuraltopicmodel.com