LDA and Beyond: Topic Models in the Social Sciences

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[1]My sincere thanks to my many collaborators and particularly Justin Grimmer, Molly Roberts and Dustin Tingley from whom many of these slides are derived. Many of the framing insights here are due to an in-progress book with Justin and Molly.

Papers

- Overview of Text Analysis:
  - "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts" (*Political Analysis*, 2013) with Grimmer
- Structural Topic Model:
  - Structural Topic Models for Open-Ended Survey Responses (*American Journal of Political Science, 2014*) with Roberts, Tingley et al.
  - Computer Assisted Text Analysis for Comparative Politics (*Political Analysis 2015*), with Lucas et al.
  - A Model of Text for Experimentation in the Social Sciences (*2016*) with Roberts and Airoldi

Copies at BrandonStewart.org

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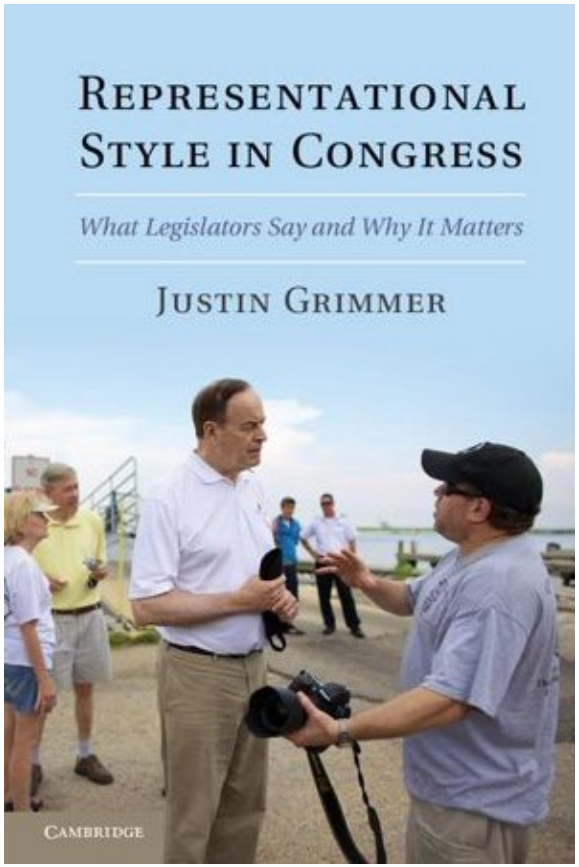

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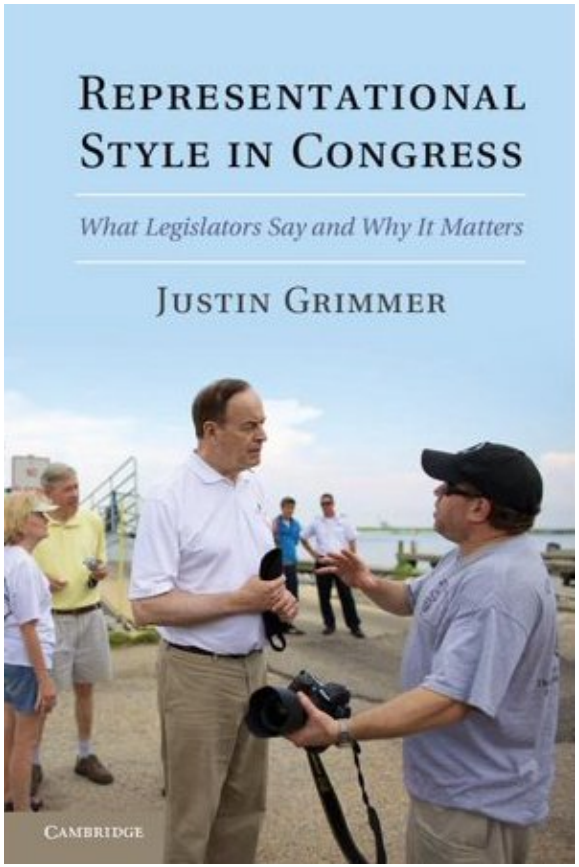

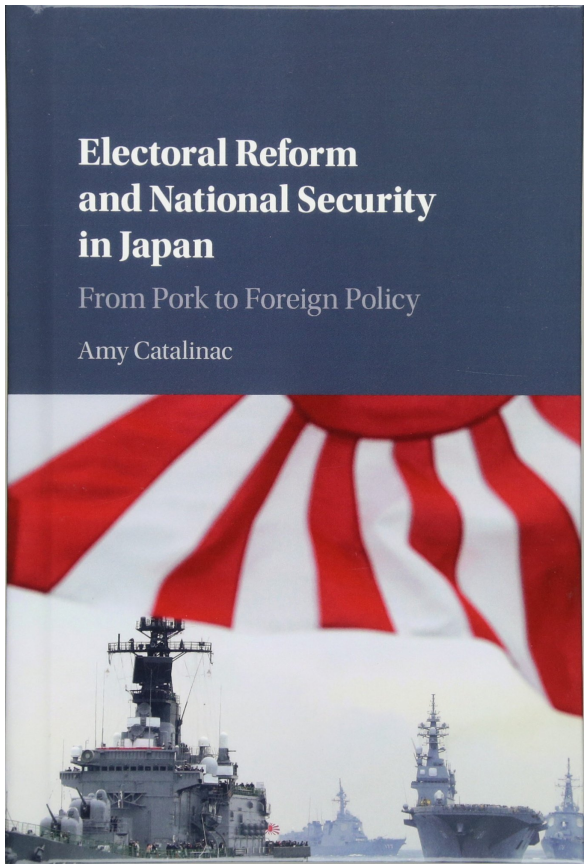

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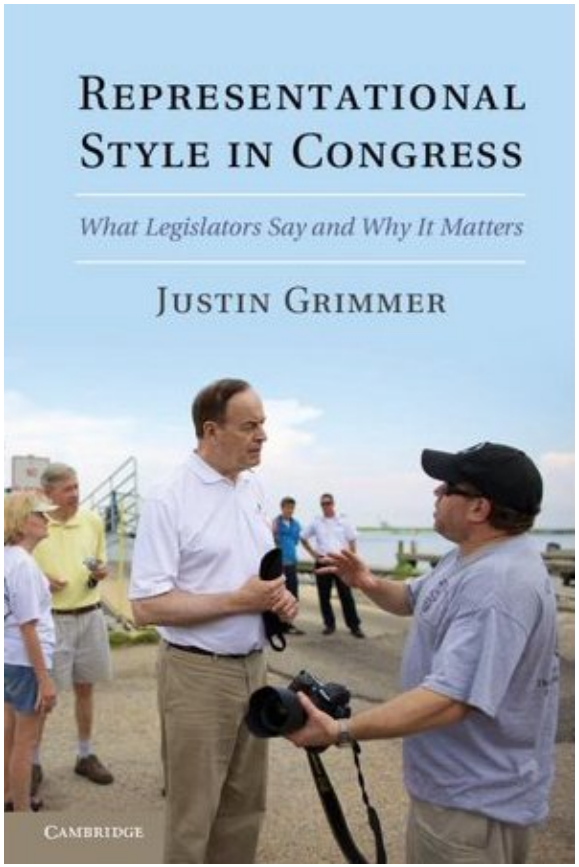

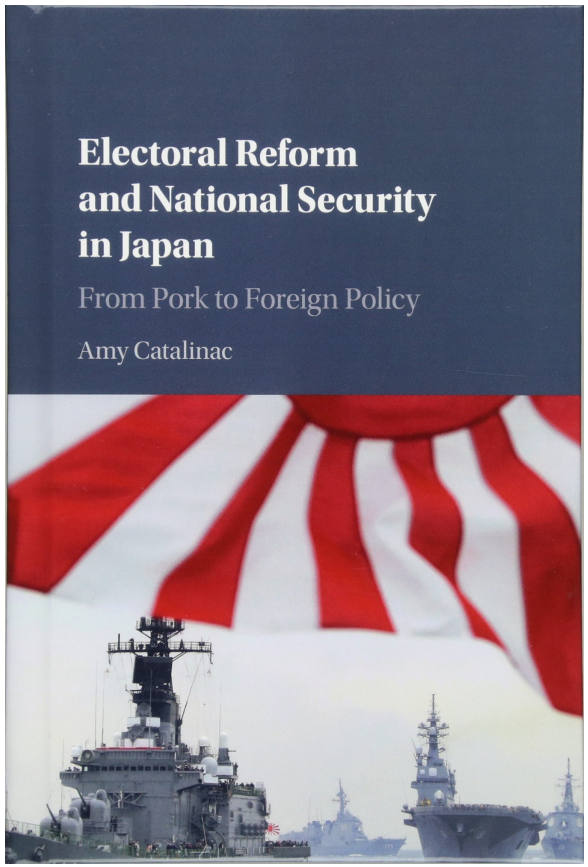

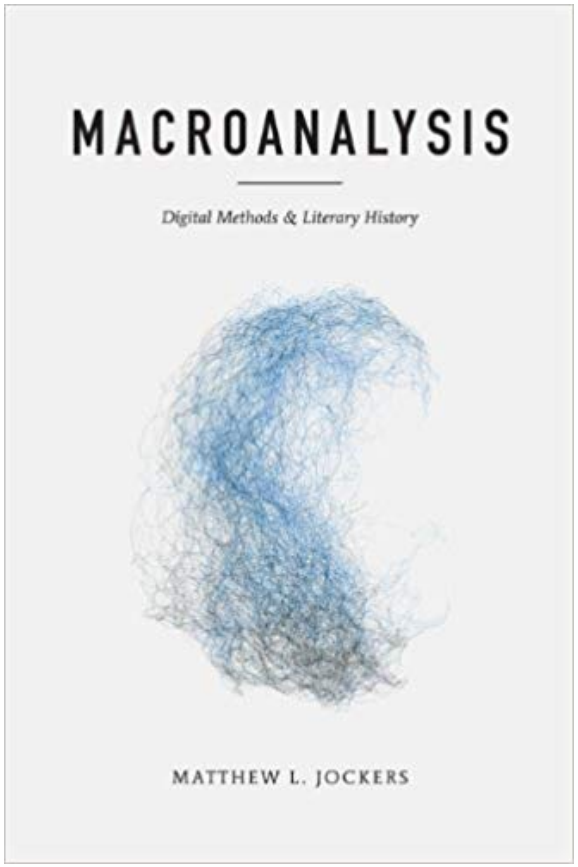

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- This representation is good at capturing subject matter of documents but not nuance.

Preprocessing (A Quick Review)

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Compound Words: With substantive justification, words can be combined or split to improve inference.

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Preprocessing

Finally, we can turn tokens and documents into a "document-term matrix."

Imagine we have a second document in addition to the Mao quote, which tokenizes as follows.

Document #1: [polit], [power], [grow], [out], [barrel of a gun]
Document #2: [wessi], [compar], [polit], [wessi]

Output: Term-Document Matrix

$$\begin{pmatrix} & Doc1 & Doc2 \\ polit & 1 & 1 \\ power & 1 & 0 \\ grow & 1 & 0 \\ out & 1 & 0 \\ barrel\ of\ a\ gun & 1 & 0 \\ wessi & 0 & 2 \\ compar & 0 & 1 \end{pmatrix}$$

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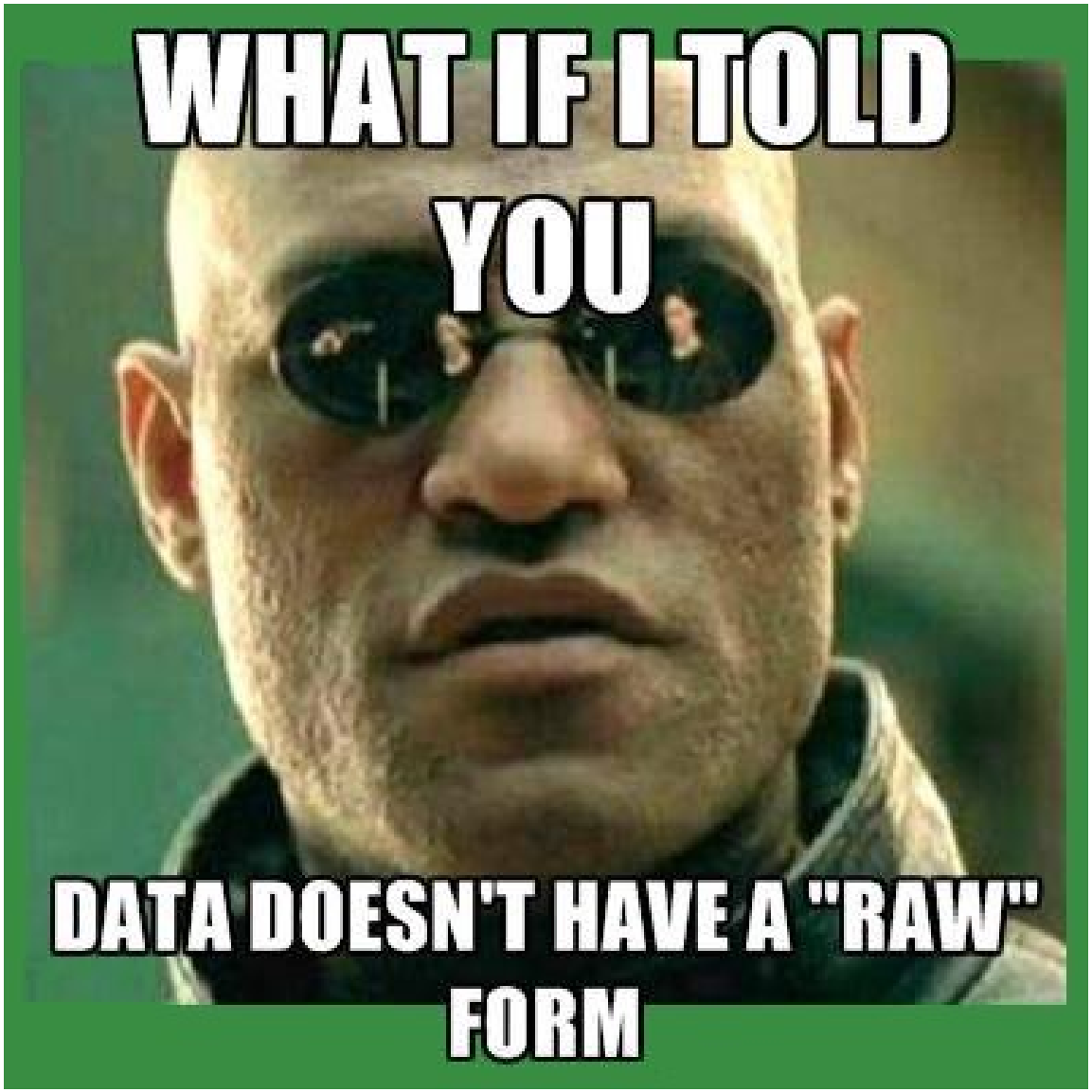

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Remember: folk wisdom is always a product of its time.

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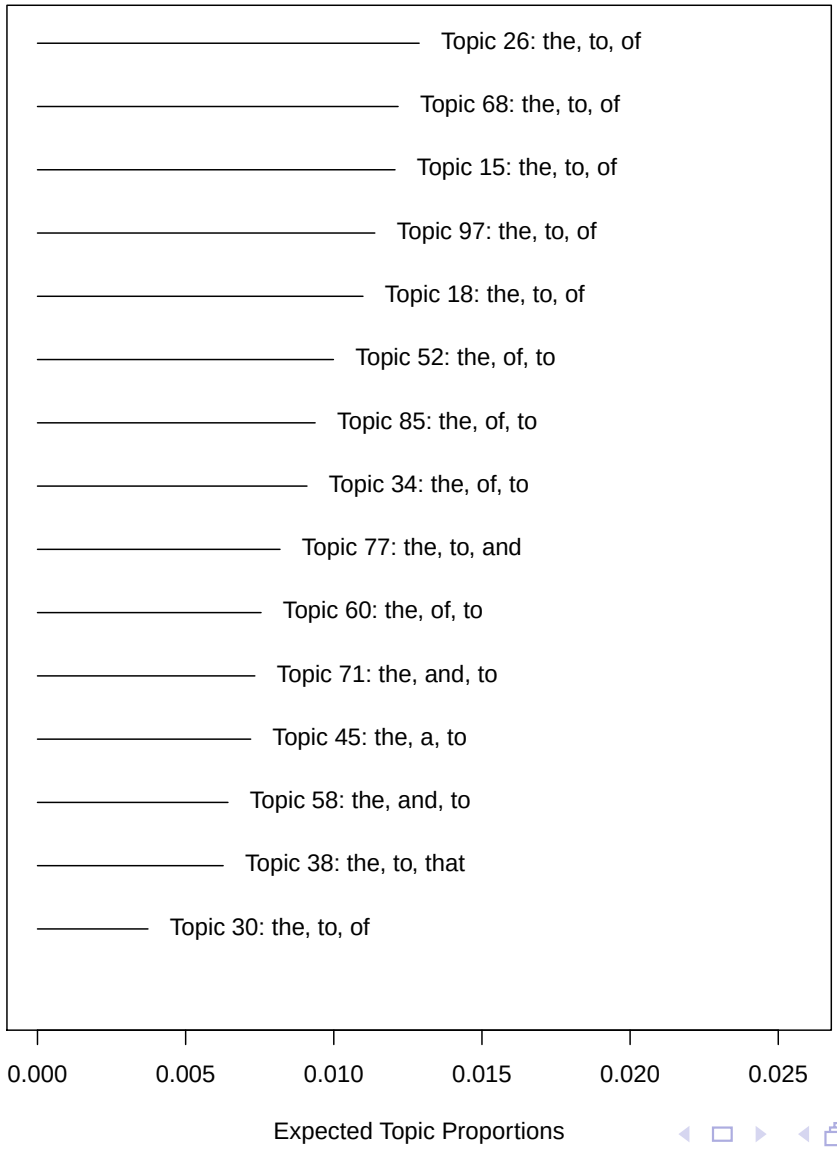

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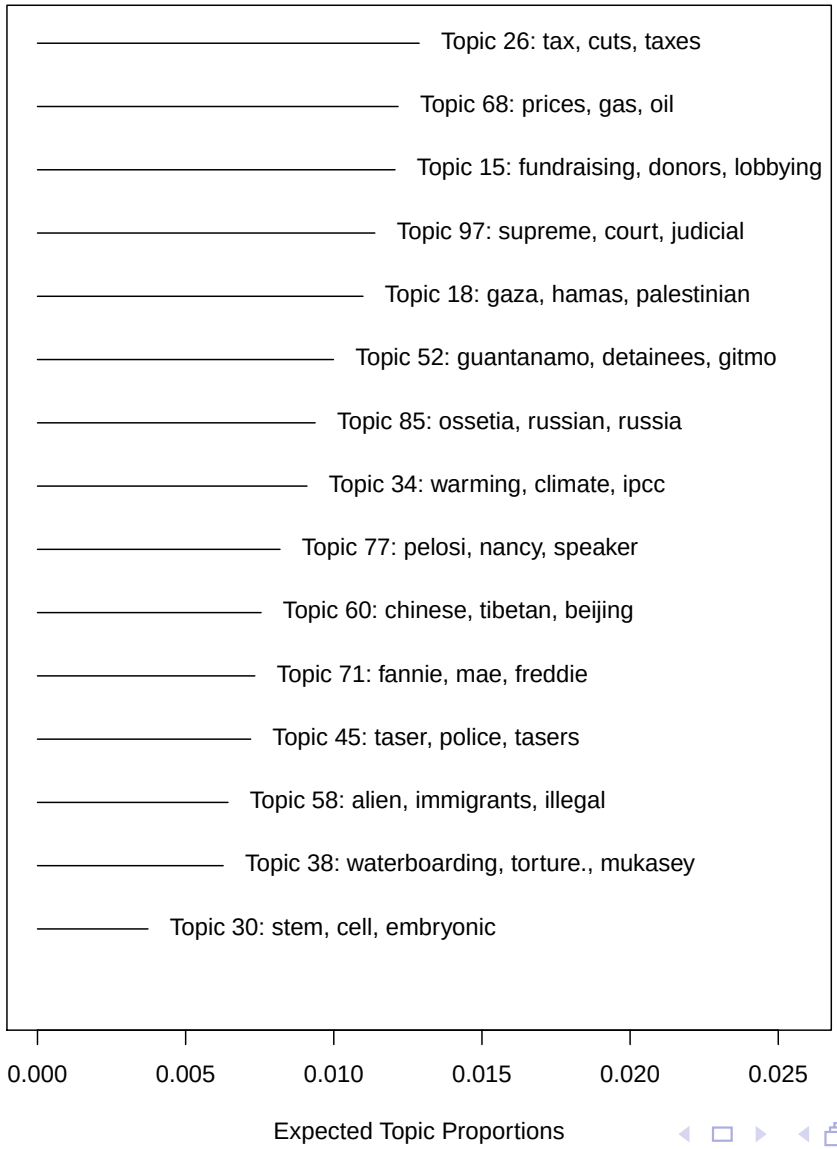

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Practical Issue: We have a lot of moving pieces in text analysis and we want people to be able to get their work done.

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Maintained assumptions: Bag of words/fix number of topics ex ante.

What this means in pictures

Say you have
a lot of people.

What this means in pictures

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Each writes
some texts

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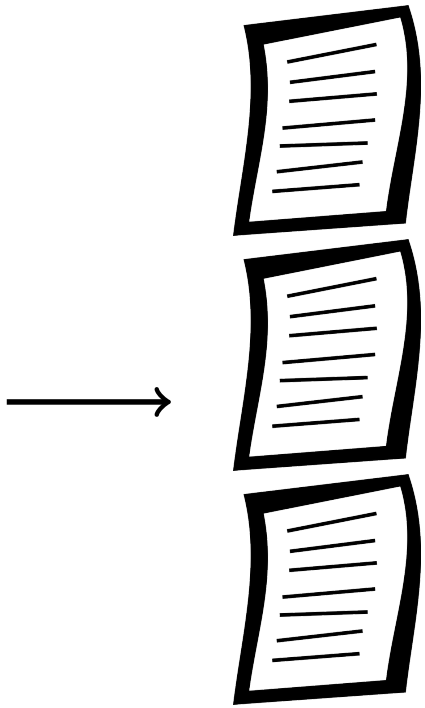

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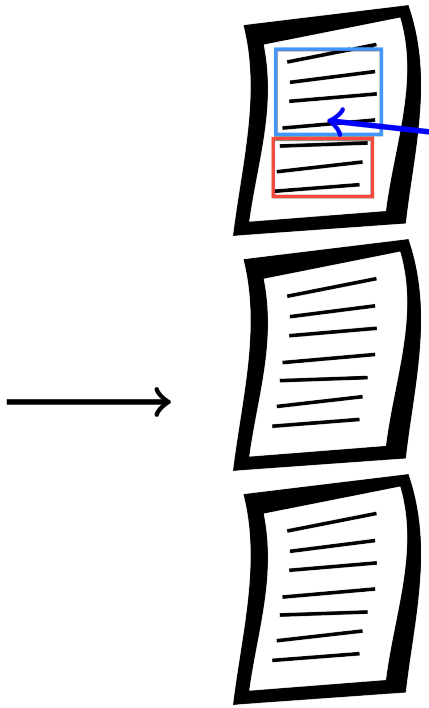

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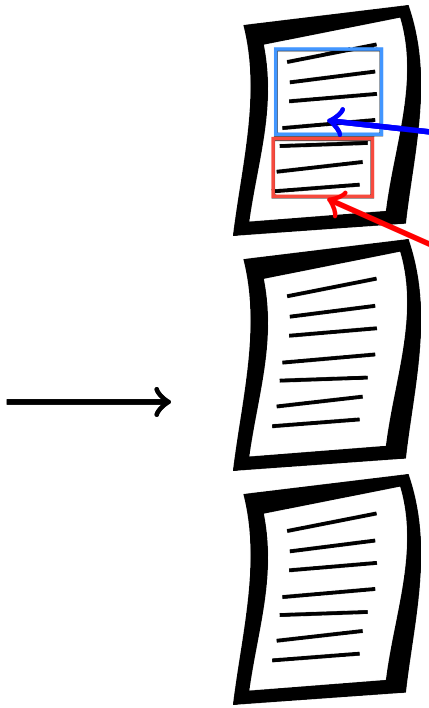

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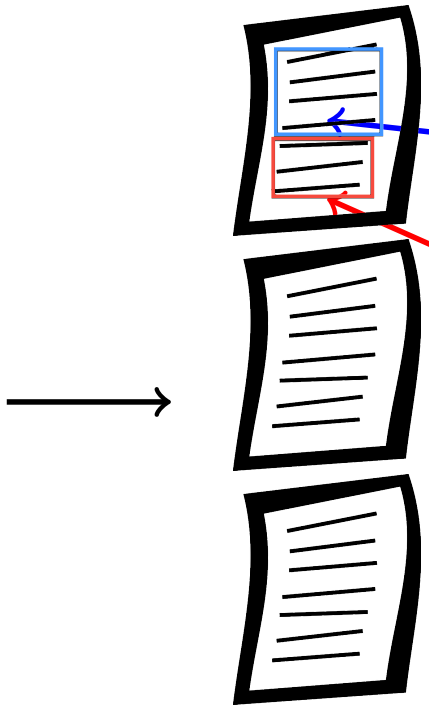

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Topic 1

Topic 2

The Latent Dirichlet Allocation estimates:

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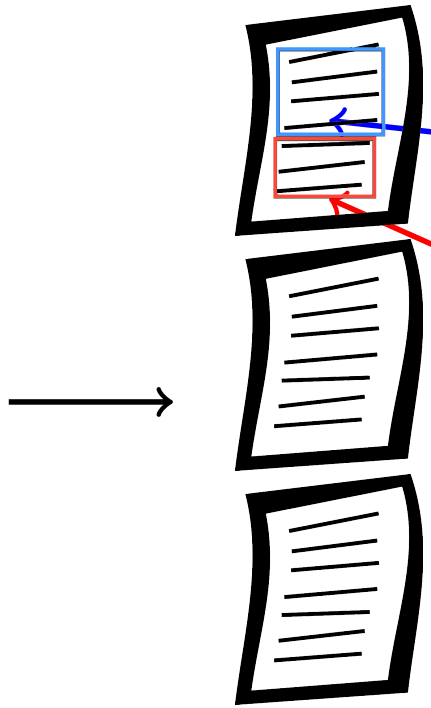

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congress, nations, power, votes, agreement, bargaining

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estimator, data, analysis, variance, model, inference

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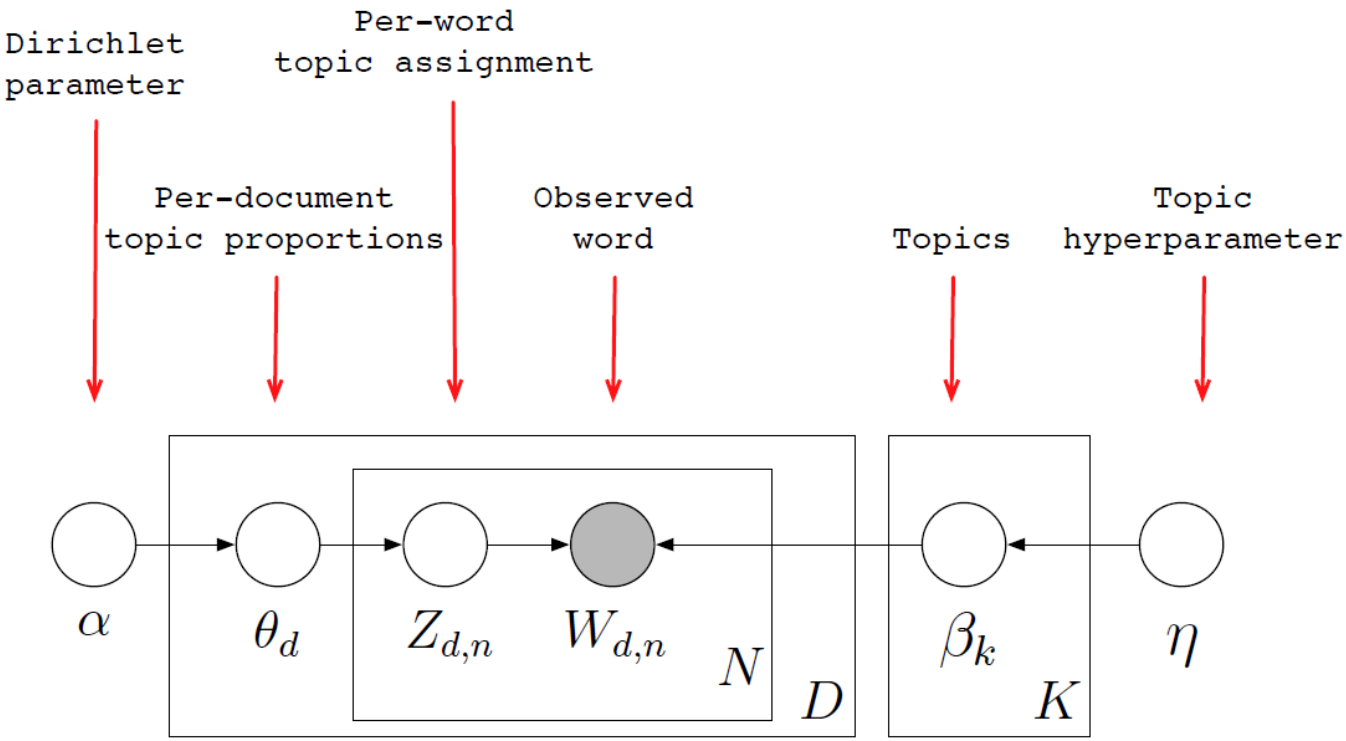
The Latent Dirichlet Allocation estimates:

1. The topics- each is a distribution over words
2. The proportion of each document in each topic

This is a Bayesian Model

Figure: Plate Notation of Latent Dirichlet Allocation



Graphic from David Blei's Website

LDA as a Bayesian Model

$$
\begin{aligned}
\boldsymbol{\beta}_k|\boldsymbol{\eta} &\sim \text{Dirichlet}(\boldsymbol{\eta}) \\
\boldsymbol{\theta}_i|\boldsymbol{\alpha} &\sim \text{Dirichlet}(\boldsymbol{\alpha}) \\
z_{im}|\boldsymbol{\theta}_i &\sim \text{Multinomial}(1, \boldsymbol{\theta}_i) \\
w_{im}|\boldsymbol{\beta}_k, z_{imk} = 1 &\sim \text{Multinomial}(1, \boldsymbol{\beta}_k)
\end{aligned}
$$

LDA as a Bayesian Model

$$
\begin{aligned}
\textbf{Unigram Model}_k &\sim \text{Dirichlet}(\eta) \\
\textbf{Doc. Prop}_i &\sim \text{Dirichlet}(\textbf{Pop. Proportion}) \\
\textbf{Word Topic}_{im} &\sim \text{Multinomial}(1, \textbf{Doc. Prop}_i) \\
\text{Word}_{im} &\sim \text{Multinomial}(1, \textbf{Unigram Model}_k)
\end{aligned}
$$

"Vanilla" Latent Dirichlet Allocation

1) Task:

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    - Discover thematic content of documents

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   - Collapsed Gibbs Sampling$\rightsquigarrow$ MCMC algorithm

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   - Spectral/Factorization Methods

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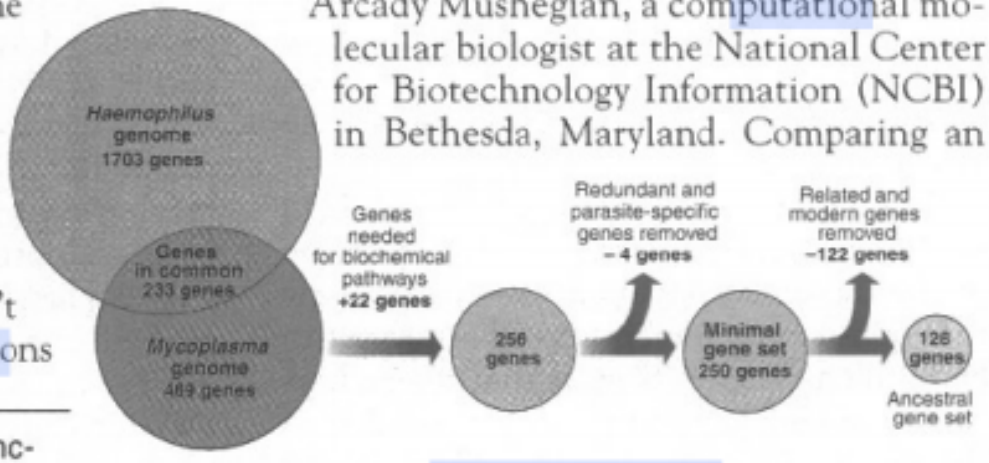
   - Spectral/Factorization Methods
4) Validation$\rightsquigarrow$ application-specific

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.

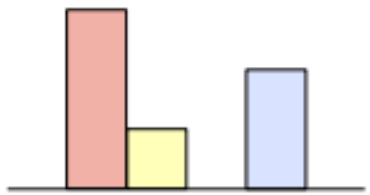


Image from Hanna Wallach

Why does this work$\rightsquigarrow$ Co-occurrence

Where's the information for each word's topic?

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Reconsider document-term matrix

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	Word_1	Word_2	$\ldots$	Word_J
Doc_1	0	1	$\ldots$	0
Doc_2	2	0	$\ldots$	3
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
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We are learning the pattern of what words occur together.

The model wants a topic to contain as few words as possible, but a document to contain as few topics as possible. This tension is what makes the model work.

Extensions to LDA

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Have there been extensions to LDA proposed?

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correlated topic models,

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different methods for every problem

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different methods for every problem
What is going on with all of these extensions?

1. Introduction
2. Preprocessing
3. Latent Dirichlet Allocation
4. Structured Topic Models
5. Structural Topic Models
6. Sample Applications
7. Applications
8. Conclusion

1 Introduction

2 Preprocessing

3 Latent Dirichlet Allocation

4 Structured Topic Models

5 Structural Topic Models

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7 Applications

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Correlated Topic Models (Blei and Lafferty 2007)

Dirichlet distribution$\rightsquigarrow$ Assumes negative covariance between topics

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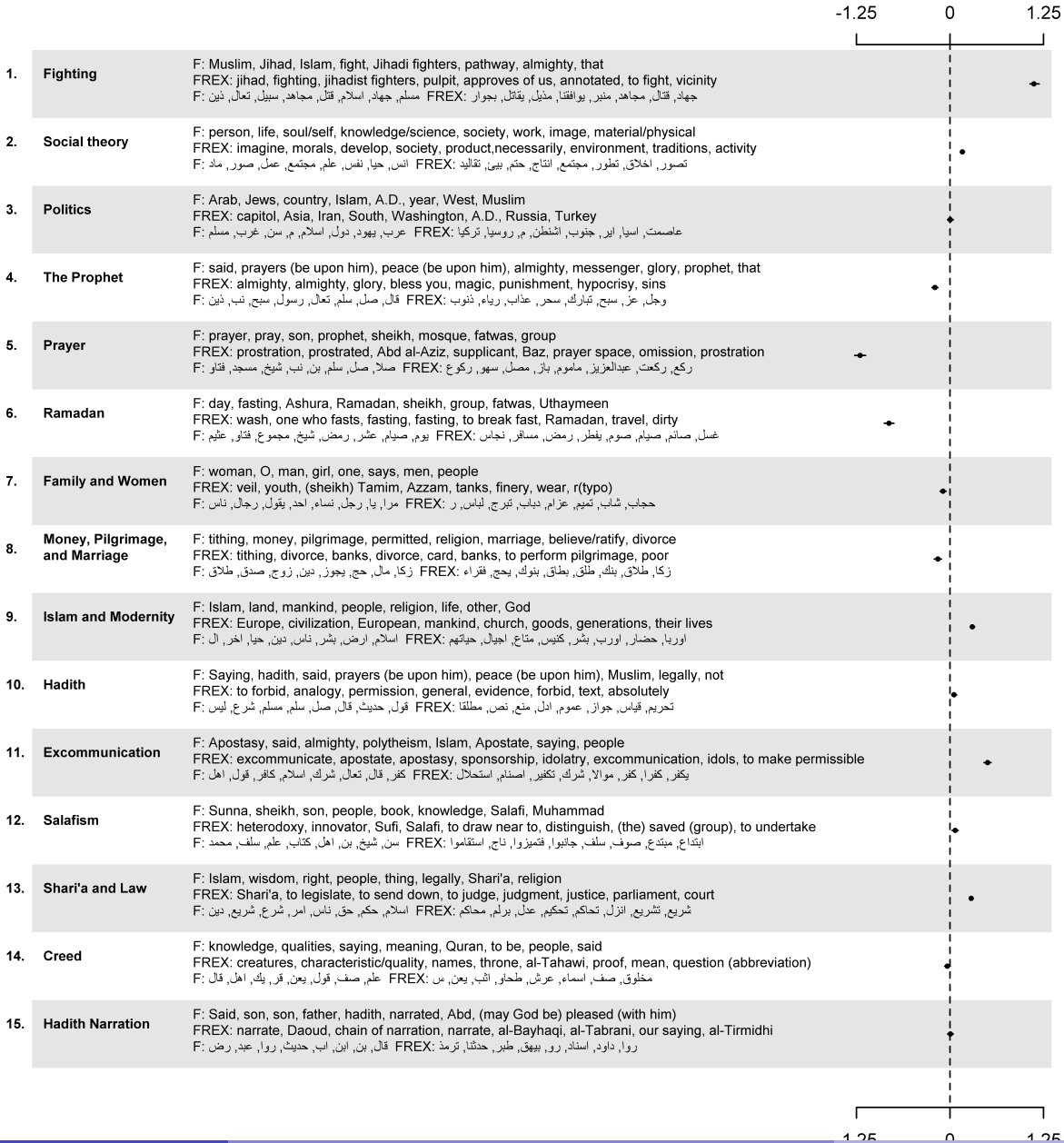
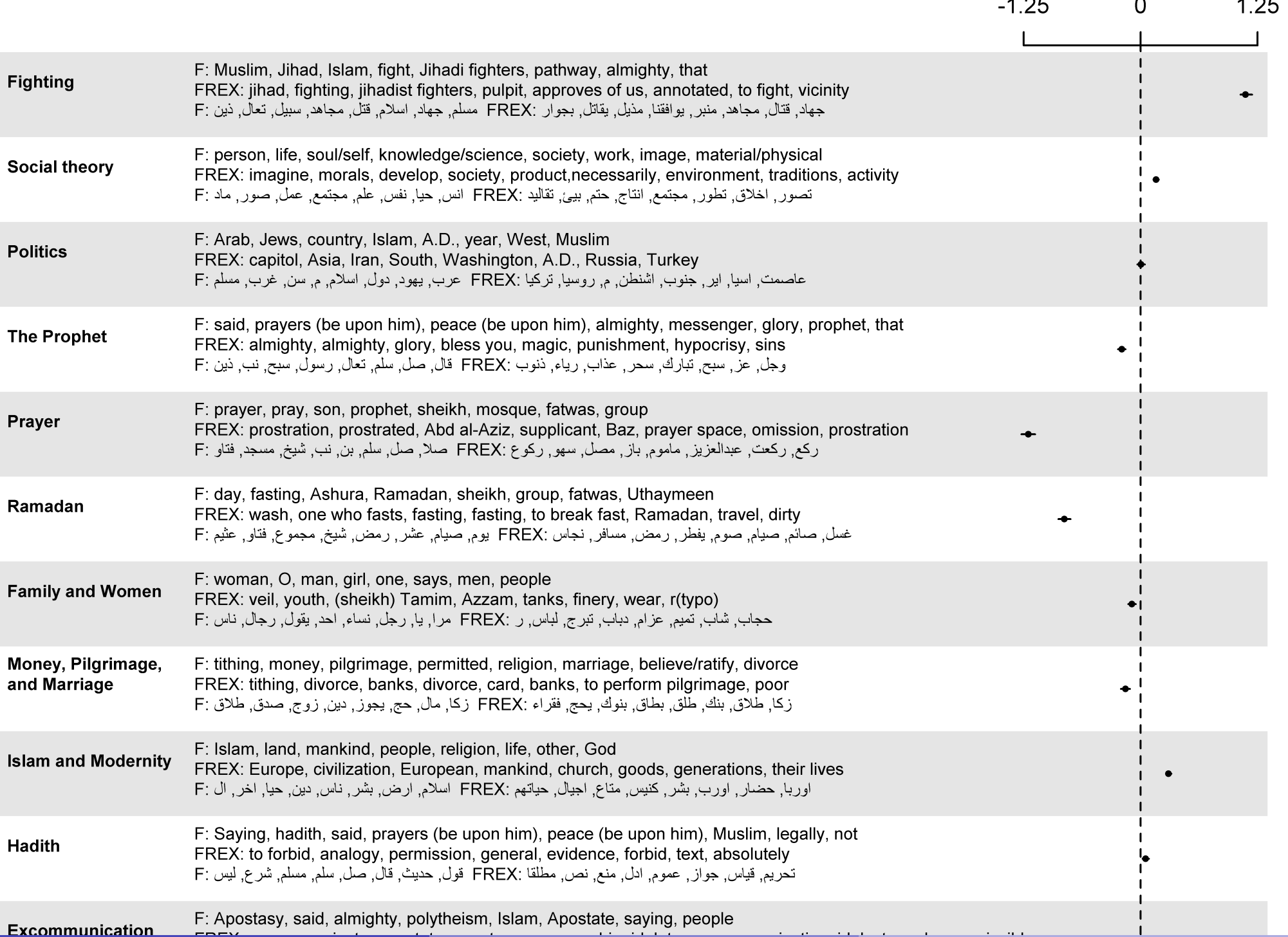
$$
\begin{aligned}
\boldsymbol{\beta}_k &\sim \text{Dirichlet}(\mathbf{1}) \\
\boldsymbol{\eta}_i | \boldsymbol{\mu}, \boldsymbol{\Sigma} &\sim \text{Multivariate Normal}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \\
\boldsymbol{\theta}_i &= \frac{\exp(\boldsymbol{\eta}_i)}{\sum_{k=1}^{K} \exp(\eta_{ik})} \\
\boldsymbol{z}_{im} | \boldsymbol{\theta}_i &\sim \text{Multinomial}(1, \boldsymbol{\eta}_i) \\
w_{im} | \boldsymbol{\beta}_k, z_{imk} = 1 &\sim \text{Multinomial}(1, \boldsymbol{\beta}_k)
\end{aligned}
$$

Jihad Example



1.	**Fighting**	F: Muslim, Jihad, Islam, fight, Jihadi fighters, pathway, almighty, that FREX: jihad, fighting, jihadist fighters, pulpit, approves of us, annotated, to fight, vicinity F: جهاد, قتال, مجاهد, منبر, يوافقنا, مذيل, يقاتل, بجوار FREX: مسلم, جهاد, اسلام, قتل, مجاهد, سبيل, تعال, ذين
2.	**Social theory**	F: person, life, soul/self, knowledge/science, society, work, image, material/physical FREX: imagine, morals, develop, society, product,necessarily, environment, traditions, activity F: تصور, اخلاق, تطور, مجتمع, انتاج, حتم, بيى, تقاليد FREX: انس, حيا, نفس, علم, مجتمع, عمل, صور, ماد
3.	**Politics**	F: Arab, Jews, country, Islam, A.D., year, West, Muslim FREX: capitol, Asia, Iran, South, Washington, A.D., Russia, Turkey F: عاصمت, اسيا, اير, جنوب, اشنطن, م, روسيا, تركيا FREX: عرب, يهود, دول, اسلام, م, سن, غرب, مسلم
4.	**The Prophet**	F: said, prayers (be upon him), peace (be upon him), almighty, messenger, glory, prophet, that FREX: almighty, almighty, glory, bless you, magic, punishment, hypocrisy, sins F: وجل, عز, سبح, تبارك, سحر, عذاب, رياء, ذنوب FREX: قال, صل, سلم, تعال, رسول, سبح, نب, ذين
5.	**Prayer**	F: prayer, pray, son, prophet, sheikh, mosque, fatwas, group FREX: prostration, prostrated, Abd al-Aziz, supplicant, Baz, prayer space, omission, prostration F: ركع, ركعت, عبدالعزيز, ماموم, باز, مصل, سهو, ركوع FREX: صلا, صل, سلم, بن, نب, شيخ, مسجد, فتاو
6.	**Ramadan**	F: day, fasting, Ashura, Ramadan, sheikh, group, fatwas, Uthaymeen FREX: wash, one who fasts, fasting, fasting, to break fast, Ramadan, travel, dirty F: غسل, صائم, صيام, صوم, يفطر, رمض, مسافر, نجاس FREX: يوم, صيام, عشر, رمض, شيخ, مجموع, فتاو, عثيم
7.	**Family and Women**	F: woman, O, man, girl, one, says, men, people FREX: veil, youth, (sheikh) Tamim, Azzam, tanks, finery, wear, r(typo) F: حجاب, شاب, تميم, عزام, دباب, تبرج, لباس, ر FREX: مرا, يا, رجل, نساء, احد, يقول, رجال, ناس
8.	**Money, Pilgrimage, and Marriage**	F: tithing, money, pilgrimage, permitted, religion, marriage, believe/ratify, divorce FREX: tithing, divorce, banks, divorce, card, banks, to perform pilgrimage, poor F: زكا, طلاق, بنك, طلق, بطاق, بنوك, يحج, فقراء FREX: زكا, مال, حج, يجوز, دين, زوج, صدق, طلاق
9.	**Islam and Modernity**	F: Islam, land, mankind, people, religion, life, other, God FREX: Europe, civilization, European, mankind, church, goods, generations, their lives F: اوربا, حضار, اورب, بشر, كنيس, متاع, اجيال, حياتهم FREX: اسلام, ارض, بشر, ناس, دين, حيا, اخر, ال
10.	**Hadith**	F: Saying, hadith, said, prayers (be upon him), peace (be upon him), Muslim, legally, not FREX: to forbid, analogy, permission, general, evidence, forbid, text, absolutely F: تحريم, قياس, جواز, عموم, ادل, منع, نص, مطلقا FREX: قول, حديث, قال, صل, سلم, مسلم, شرع, ليس
11.	**Excommunication**	F: Apostasy, said, almighty, polytheism, Islam, Apostate, saying, people FREX: excommunicate, apostate, apostasy, sponsorship, idolatry, excommunication, idols, to make permissible F: يكفر, كفرا, كفر, موالا, شرك, تكفير, اصنام, استحلال FREX: كفر, قال, تعال, شرك, اسلام, كافر, قول, اهل
12.	**Salafism**	F: Sunna, sheikh, son, people, book, knowledge, Salafi, Muhammad FREX: heterodoxy, innovator, Sufi, Salafi, to draw near to, distinguish, (the) saved (group), to undertake F: ابتداع, مبتدع, صوف, سلف, جانبوا, فتميزوا, ناج, استقاموا FREX: سن, شيخ, بن, اهل, كتاب, علم, سلف, محمد
13.	**Shari'a and Law**	F: Islam, wisdom, right, people, thing, legally, Shari'a, religion FREX: Shari'a, to legislate, to send down, to judge, judgment, justice, parliament, court F: شريع, تشريع, انزل, تحاكم, تحكيم, عدل, برلم, محاكم FREX: اسلام, حكم, حق, ناس, امر, شرع, شريع, دين
14.	**Creed**	F: knowledge, qualities, saying, meaning, Quran, to be, people, said FREX: creatures, characteristic/quality, names, throne, al-Tahawi, proof, mean, question (abbreviation) F: مخلوق, صف, اسماء, عرش, طحاو, اثب, يعن, من FREX: علم, صف, قول, يعن, قر, يك, اهل, قال
15.	**Hadith Narration**	F: Said, son, son, father, hadith, narrated, Abd, (may God be) pleased (with him) FREX: narrate, Daoud, chain of narration, narrate, al-Bayhaqi, al-Tabrani, our saying, al-Tirmidhi F: روا, داود, اسناد, رو, بيهق, طبر, حدثنا, ترمذ FREX: قال, بن, ابن, اب, حديث, روا, عبد, رض


-1.25
0
1.25
Fighting
F: Muslim, Jihad, Islam, fight, Jihadi fighters, pathway, almighty, that
FREX: jihad, fighting, jihadist fighters, pulpit, approves of us, annotated, to fight, vicinity
F: مسلم, جهاد, اسلام, قتل, مجاهد, سبيل, تعال, ذين FREX: جهاد, قتال, مجاهد, منبر, يوافقنا, مذيل, يقاتل, بجوار
Social theory
F: person, life, soul/self, knowledge/science, society, work, image, material/physical
FREX: imagine, morals, develop, society, product,necessarily, environment, traditions, activity
F: انس, حيا, نفس, علم, مجتمع, عمل, صور, ماد FREX: تصور, اخلاق, تطور, مجتمع, انتاج, حتم, بيئ, تقاليد
Politics
F: Arab, Jews, country, Islam, A.D., year, West, Muslim
FREX: capitol, Asia, Iran, South, Washington, A.D., Russia, Turkey
F: عرب, يهود, دول, اسلام, م, سن, غرب, مسلم FREX: عاصمت, اسيا, ايرا, جنوب, اشنطن, م, روسيا, تركيا
The Prophet
F: said, prayers (be upon him), peace (be upon him), almighty, messenger, glory, prophet, that
FREX: almighty, almighty, glory, bless you, magic, punishment, hypocrisy, sins
F: قال, صل, سلم, تعال, رسول, سبح, نب, ذين FREX: وجل, عز, سبح, تبارك, سحر, عذاب, رياء, ذنوب
Prayer
F: prayer, pray, son, prophet, sheikh, mosque, fatwas, group
FREX: prostration, prostrated, Abd al-Aziz, supplicant, Baz, prayer space, omission, prostration
F: صلا, صل, سلم, بن, نب, شيخ, مسجد, فتاو FREX: ركع, ركعت, عبدالعزيز, ماموم, باز, مصل, سهو, ركوع
Ramadan
F: day, fasting, Ashura, Ramadan, sheikh, group, fatwas, Uthaymeen
FREX: wash, one who fasts, fasting, fasting, to break fast, Ramadan, travel, dirty
F: يوم, صيام, عشر, رمض, شيخ, مجموع, فتاو, عثيم FREX: غسل, صائم, صيام, صوم, يفطر, رمض, مسافر, نجاس
Family and Women
F: woman, O, man, girl, one, says, men, people
FREX: veil, youth, (sheikh) Tamim, Azzam, tanks, finery, wear, r(typo)
F: مرا, يا, رجل, نساء, احد, يقول, رجال, ناس FREX: حجاب, شاب, تميم, عزام, دباب, تبرج, لباس, ر
Money, Pilgrimage, and Marriage
F: tithing, money, pilgrimage, permitted, religion, marriage, believe/ratify, divorce
FREX: tithing, divorce, banks, divorce, card, banks, to perform pilgrimage, poor
F: زكا, مال, حج, يجوز, دين, زوج, صدق, طلاق FREX: زكا, طلاق, بنك, طلق, بطاق, بنوك, يحج, فقراء
Islam and Modernity
F: Islam, land, mankind, people, religion, life, other, God
FREX: Europe, civilization, European, mankind, church, goods, generations, their lives
F: اسلام, ارض, بشر, ناس, دين, حيا, اخر, ال FREX: اوربا, حضار, اورب, بشر, كنيس, متاع, اجيال, حياتهم
Hadith
F: Saying, hadith, said, prayers (be upon him), peace (be upon him), Muslim, legally, not
FREX: to forbid, analogy, permission, general, evidence, forbid, text, absolutely
F: قول, حديث, قال, صل, سلم, مسلم, شرع, ليس FREX: تحريم, قياس, جواز, عموم, ادل, منع, نص, مطلقا
Excommunication
F: Apostasy, said, almighty, polytheism, Islam, Apostate, saying, people

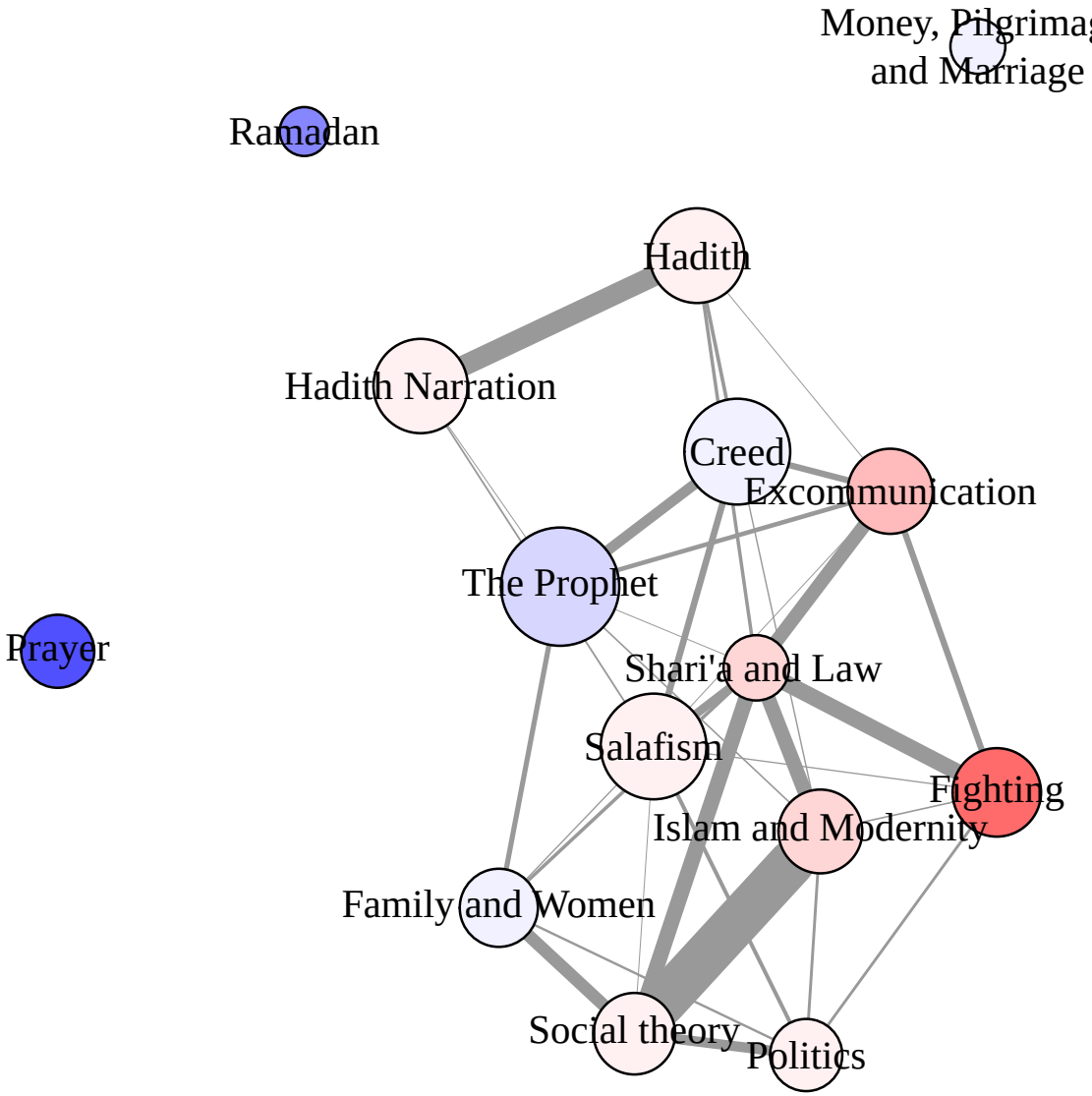
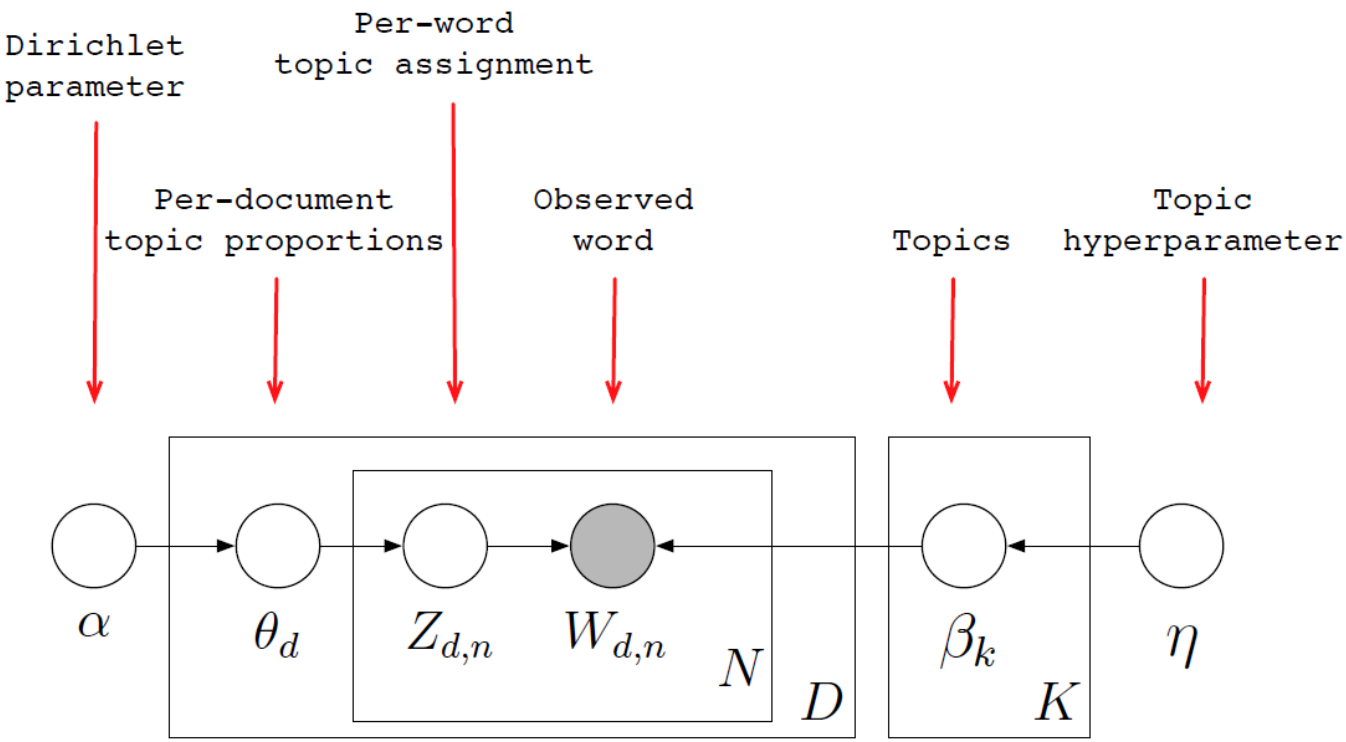


Figure: The network of correlated topics for a 15-topic Structural Topic Model with Jihadi/not-Jihadi as the predictor of topics in Arab Muslim cleric writings.

LDA $\rightsquigarrow$ Dynamic Topic Model (Blei and Lafferty 2007)

Figure: Plate Notation of Latent Dirichlet Allocation



Graphic from David Blei

LDA $\rightsquigarrow$ Dynamic Topic Model

Figure: Dynamic Topic Model

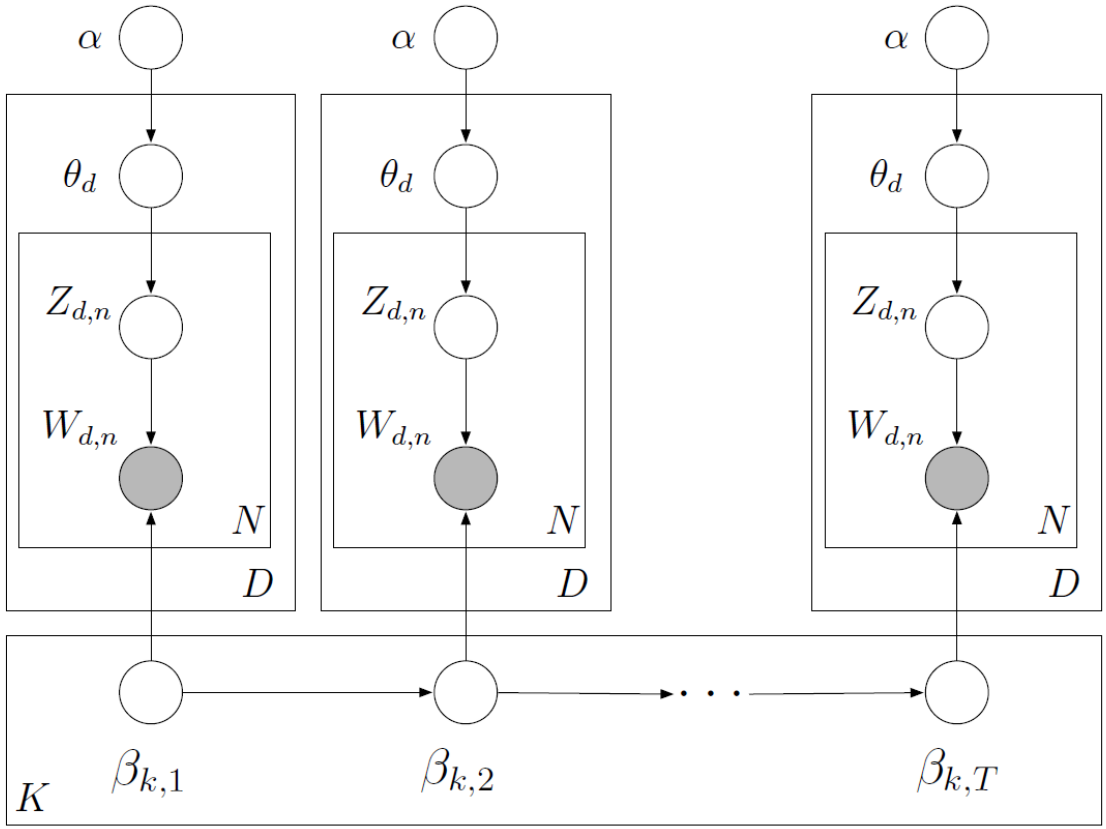


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Figure: Topic Evolution over Time

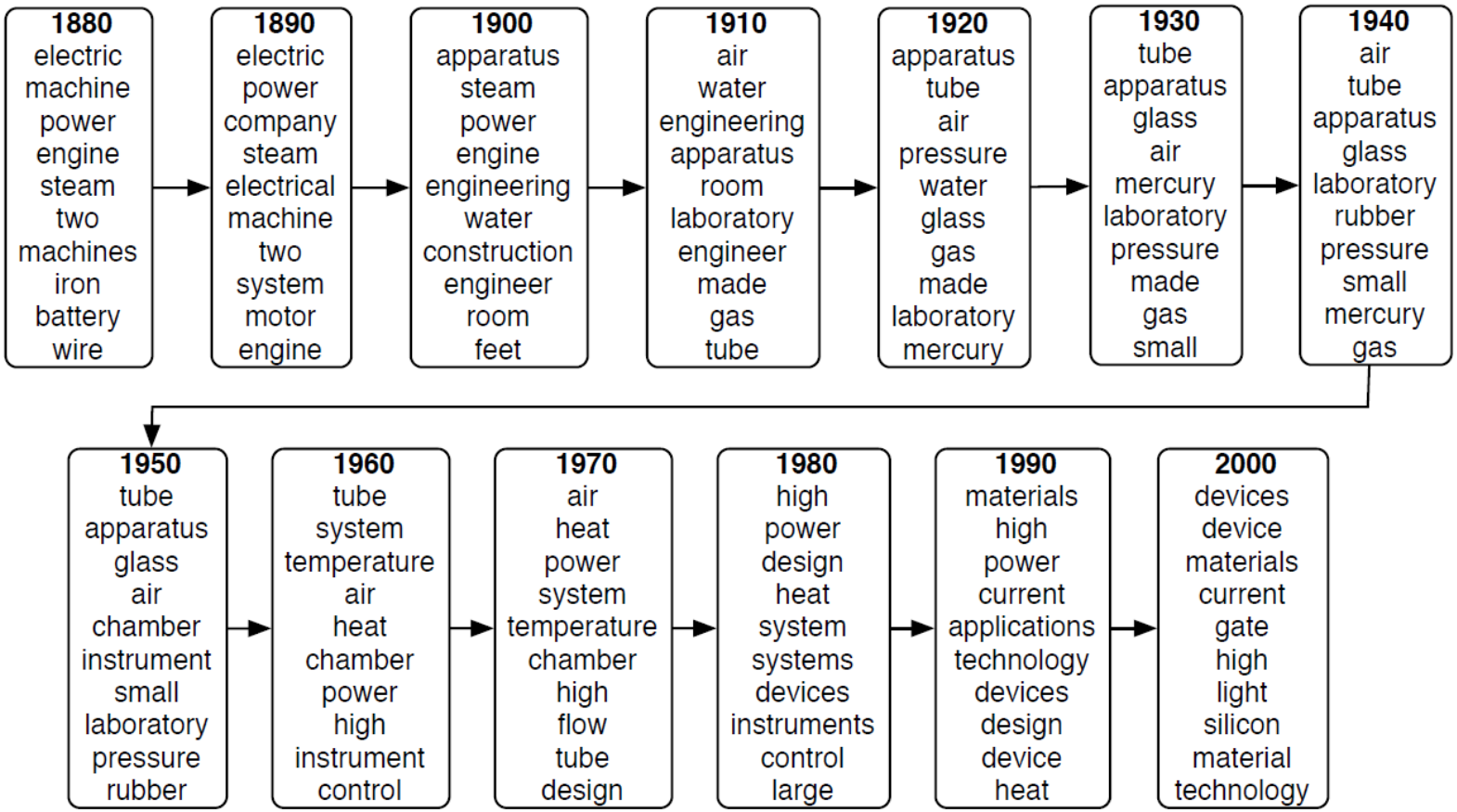

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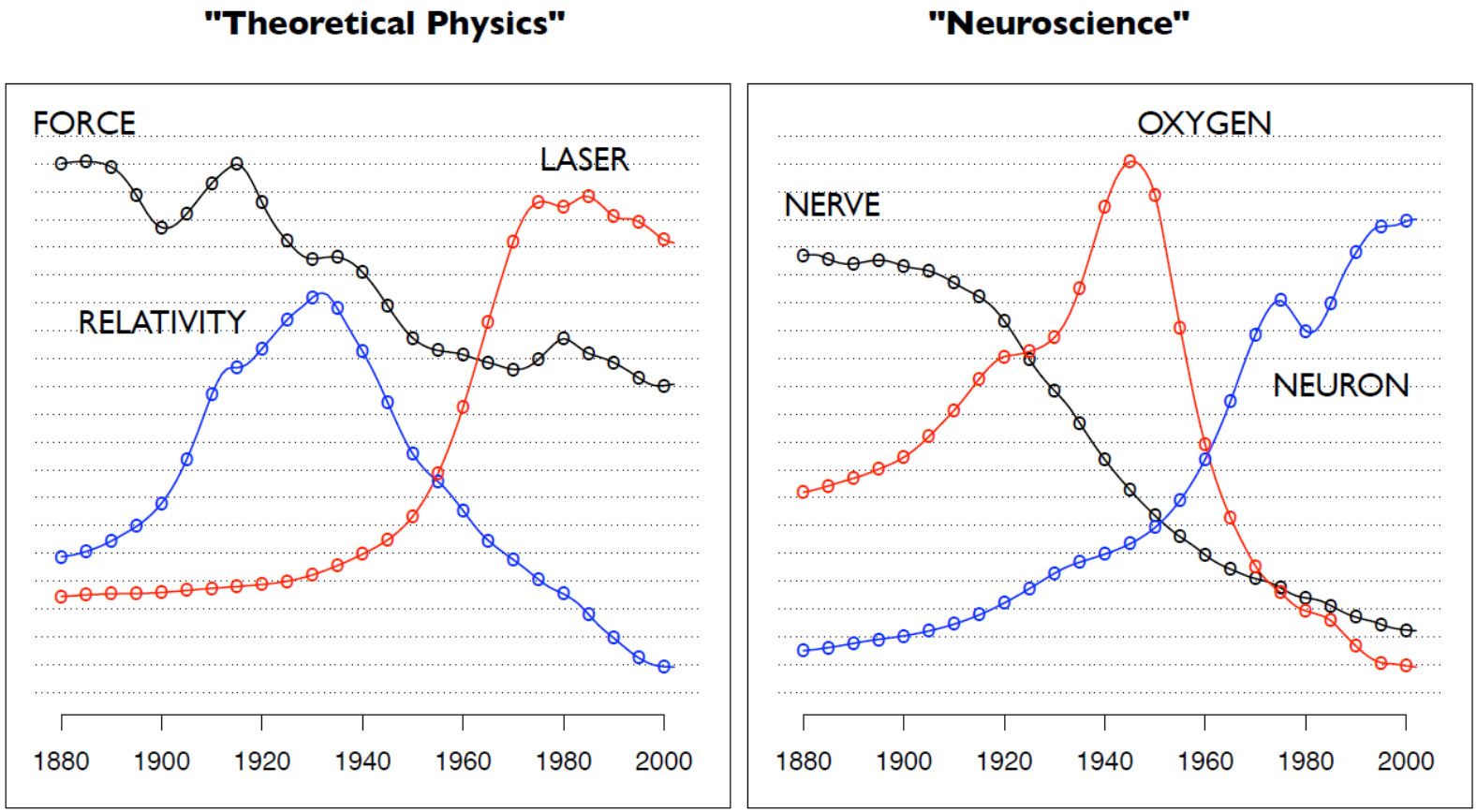
Figure: Word Use in Topics Over Time



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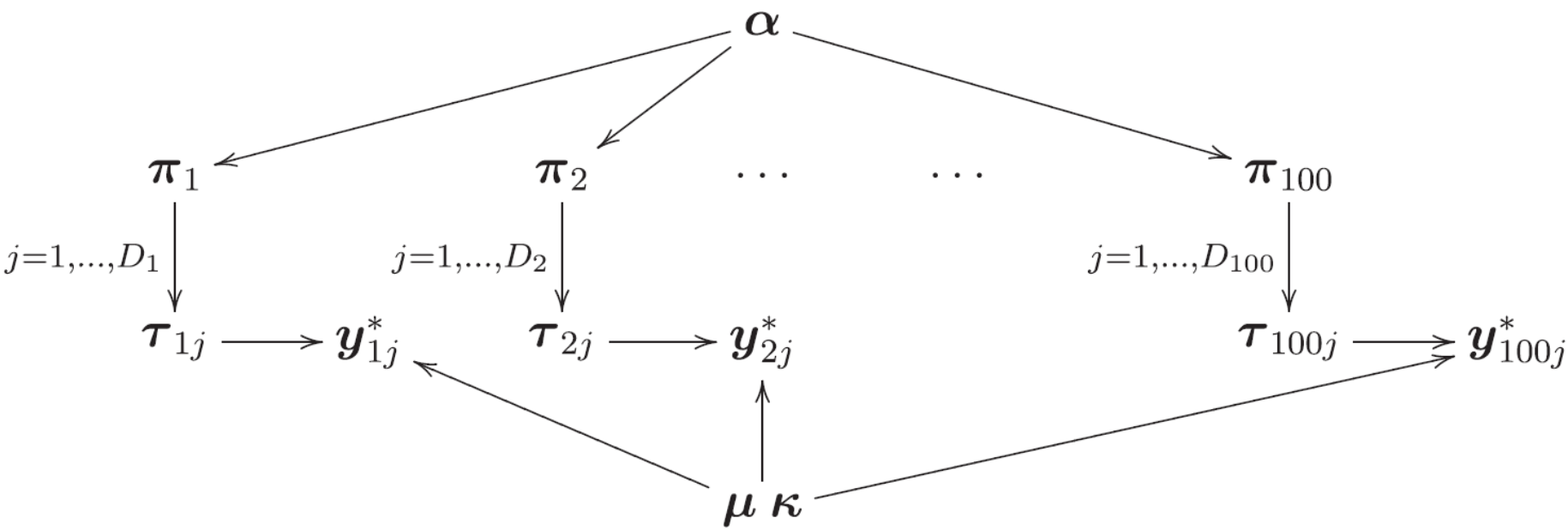
Expressed Agenda Model

Figure: Expressed Agenda Model



Graphic from Grimmer 2010

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2. Preprocessing
3. Latent Dirichlet Allocation
4. Structured Topic Models
5. Structural Topic Models
6. Sample Applications
7. Applications
8. Conclusion

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  - better qualitative interpretability

STM: What this means in pictures

Say you have a lot of people.

Each writes some text

that discuss a few different topics

Politics

congress, nations, power, votes, agreement, bargaining

Statistics

estimator, data, analysis, variance, model, inference

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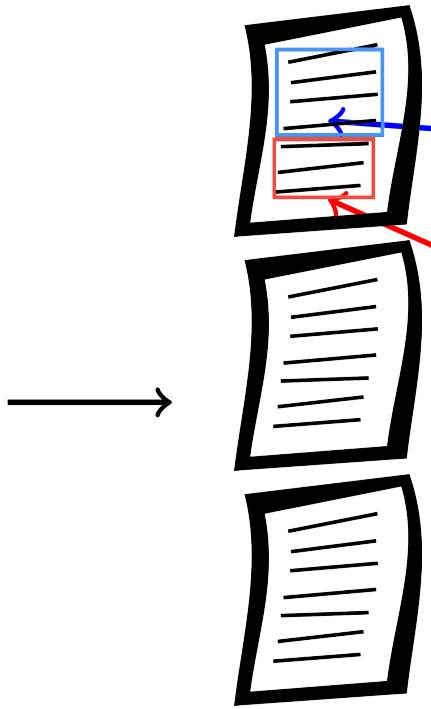

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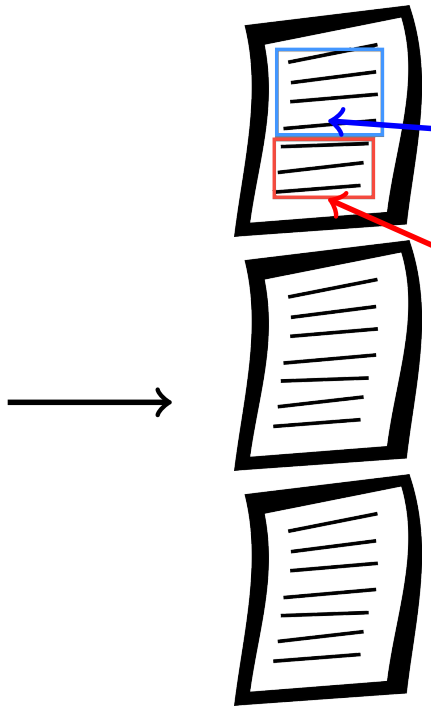

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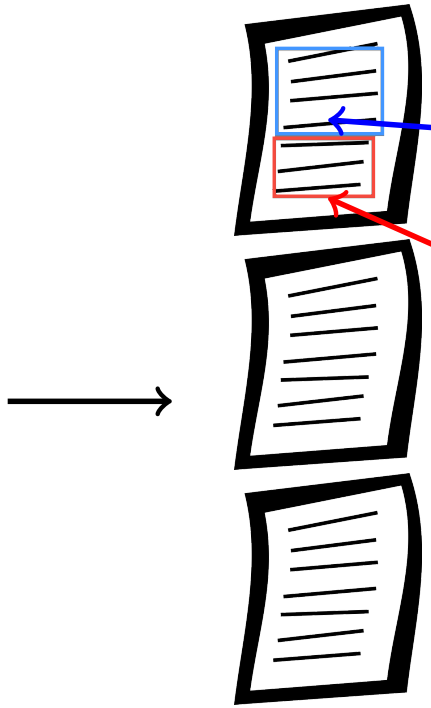

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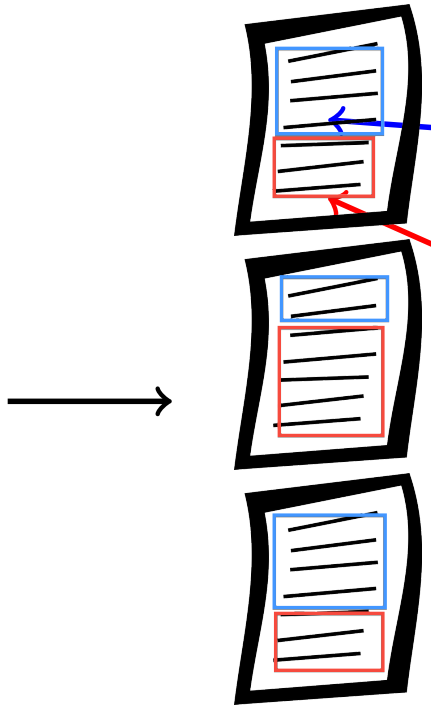

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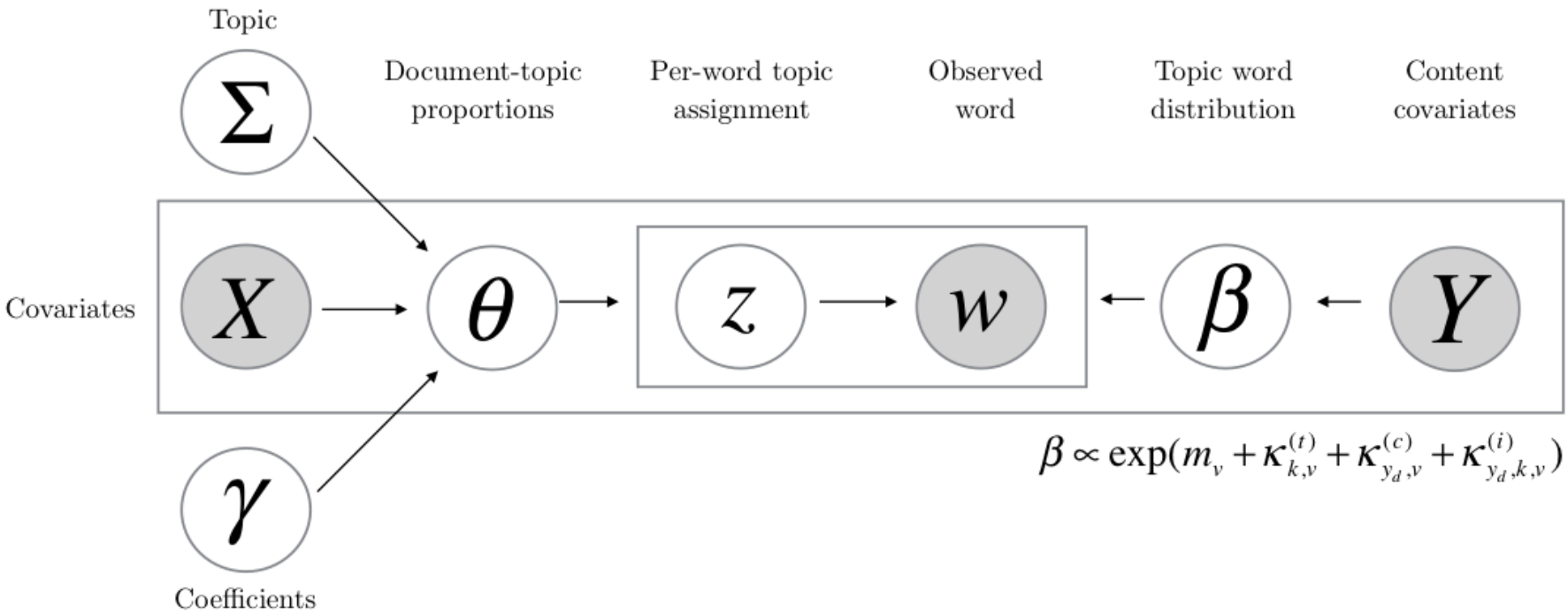
Structural Topic Model



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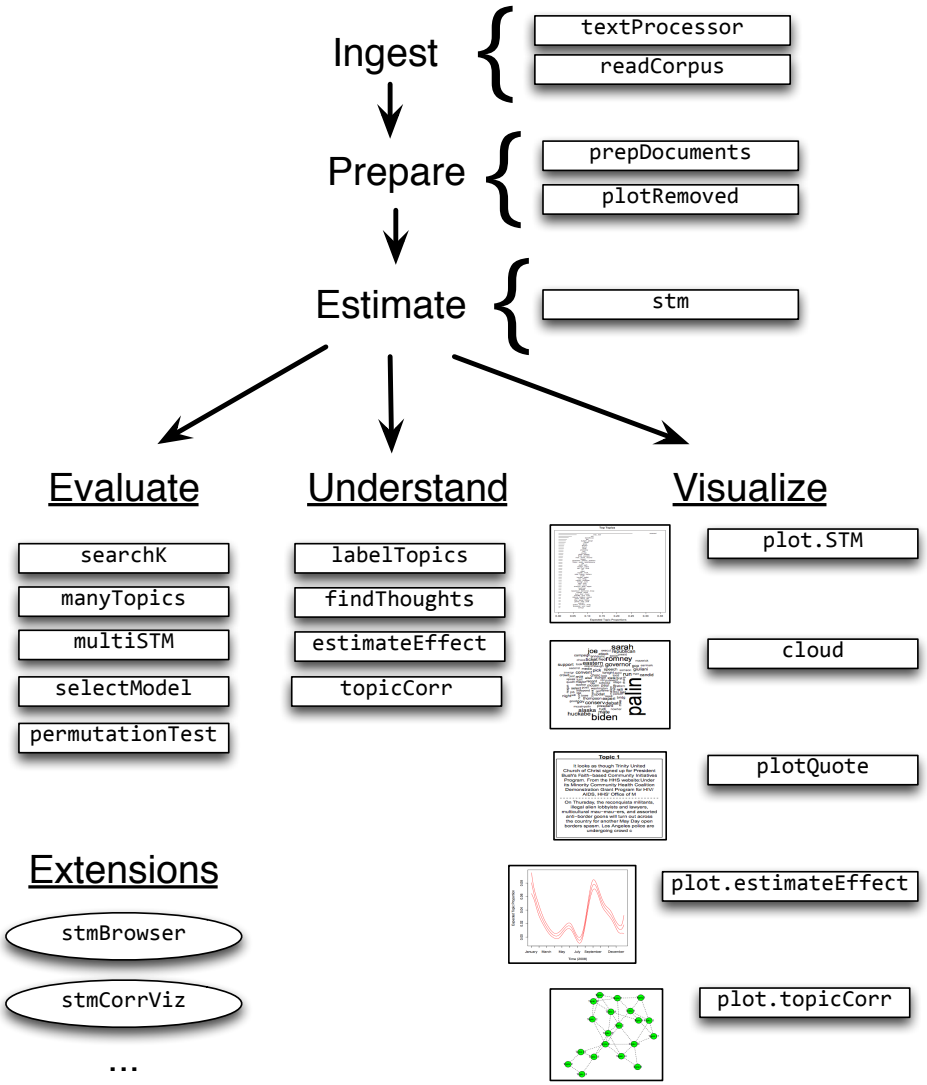
You can do this with your data!

stm is Full of Functions to Help You!



1. Introduction
2. Preprocessing
3. Latent Dirichlet Allocation
4. Structured Topic Models
5. Structural Topic Models
6. Sample Applications
7. Applications
8. Conclusion

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Auxiliary Visualization Packages

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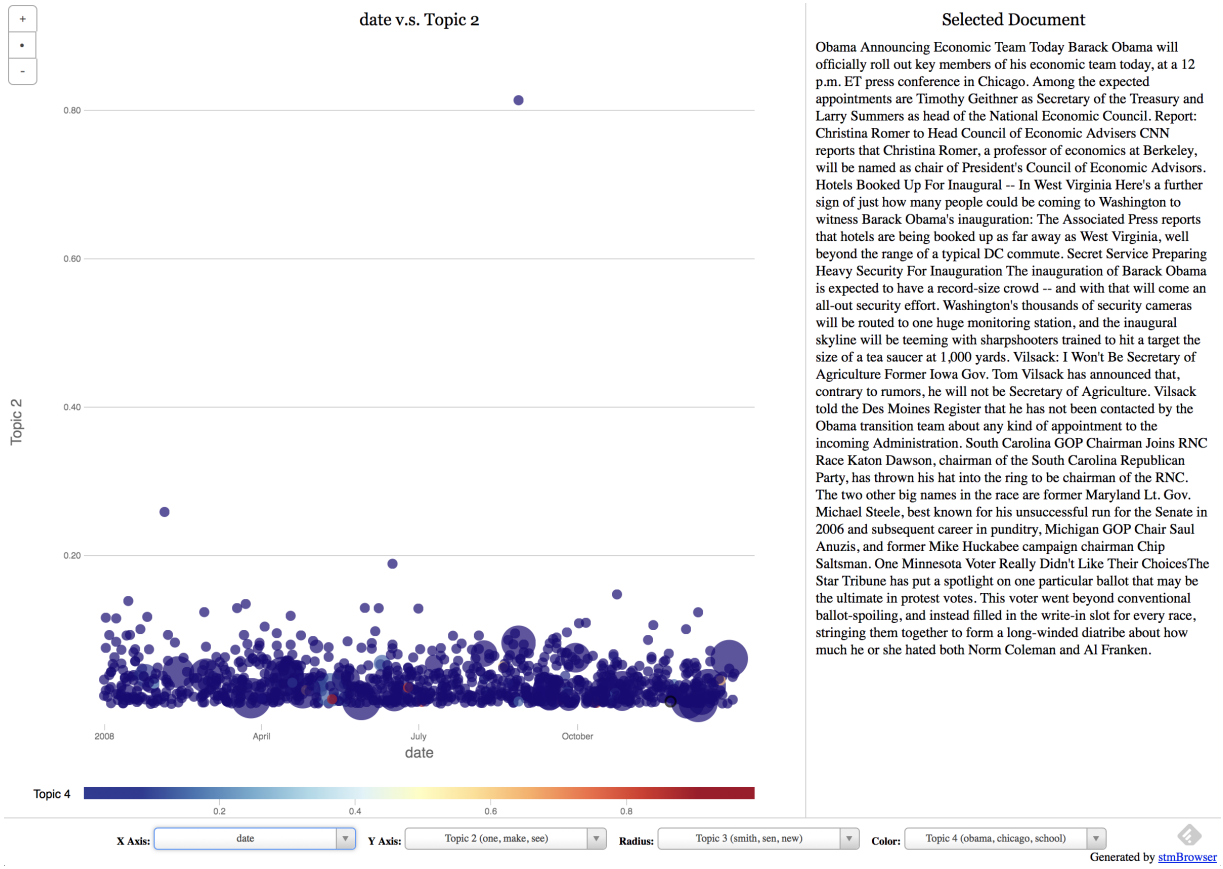
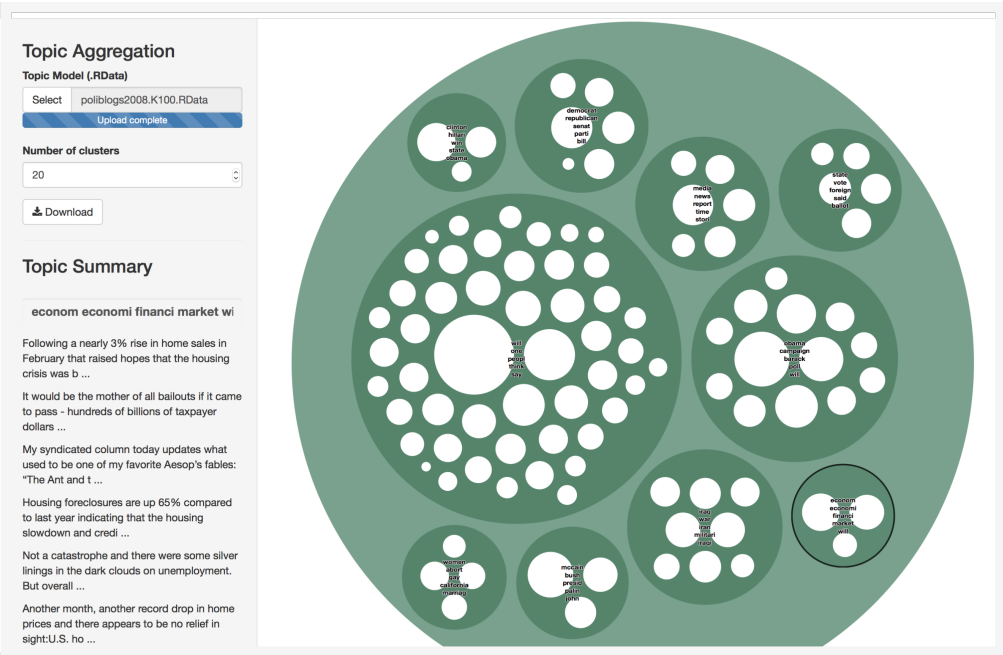
`stmBrowser`
(with Freeman, Chuang, Roberts and Tingley)



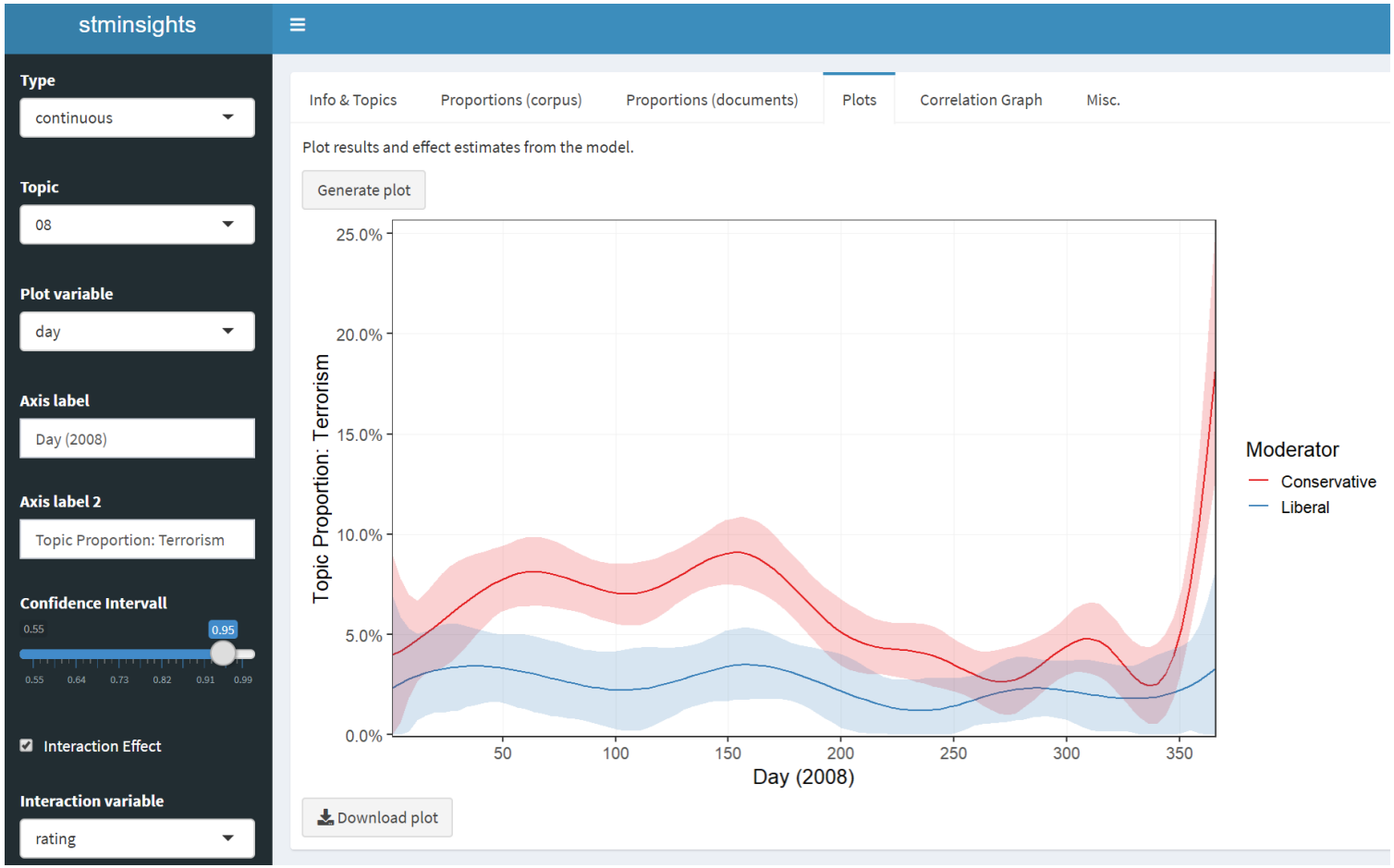
Auxiliary Visualization Packages

Trellis
(with Chaney and Schaffner)



Auxiliary Visualization Packages

`stminsights`
(Carsten Schwemmer - a SICSS alum!)



Adoption

README.md

stm: An R Package for the Structural Topic Model

Website: www.structuraltopicmodel.com

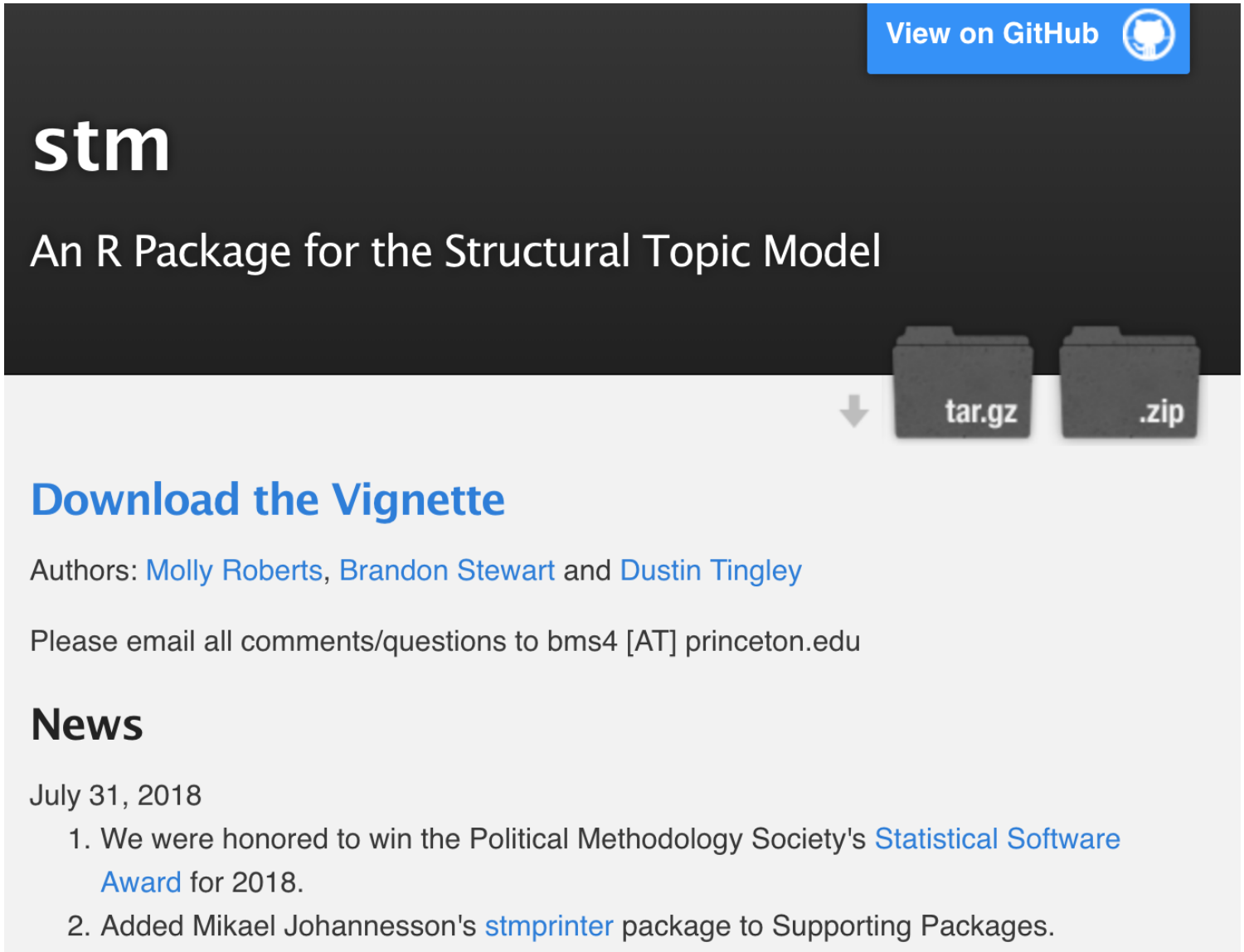
Vignette: Here

Authors: Molly Roberts, Brandon Stewart and Dustin Tingley

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

Summary

Adoption


View on GitHub
stm
An R Package for the Structural Topic Model
tar.gz
.zip
Download the Vignette
Authors: Molly Roberts, Brandon Stewart and Dustin Tingley
Please email all comments/questions to bms4 [AT] princeton.edu
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.

Adoption

JULIA SILGE

BLOG ABOUT RESUME

THE GAME IS AFOOT! TOPIC MODELING OF SHERLOCK HOLMES STORIES

Jan 25, 2018 · 7 minute read · rstats

In a recent release of tidytext, we added tidiers and support for building Structural Topic Models from the stm package. This is my current favorite implementation of topic modeling in R, so let's walk through an example of how to get started with this kind of modeling, using *The Adventures of Sherlock Holmes*.

Adoption

TRAINING, EVALUATING, AND INTERPRETING TOPIC MODELS

Sep 8, 2018 · 12 minute read · rstats

At the beginning of this year, I wrote a blog post about how to get started with the stm and tidytext packages for topic modeling. I have been doing more topic modeling in various projects, so I wanted to share some workflows I have found useful for

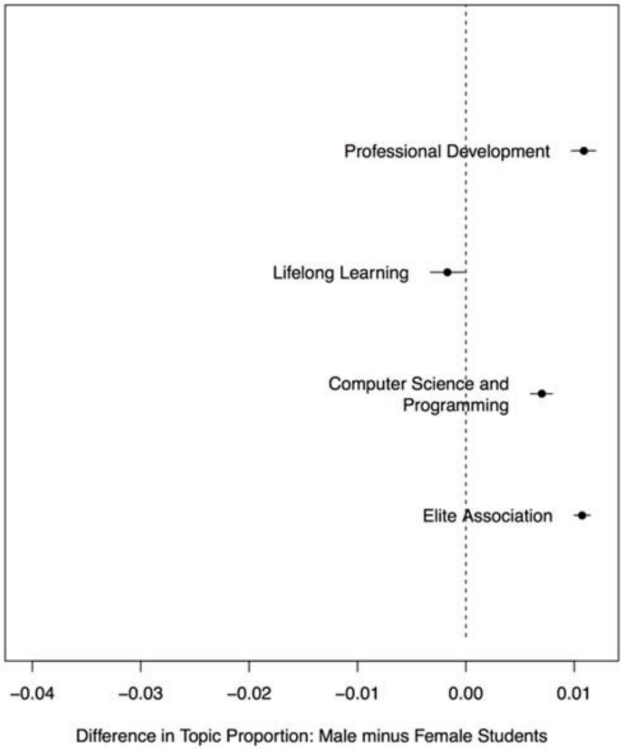
- training many topic models at one time,
- evaluating topic models and understanding model diagnostics, and
- exploring and interpreting the content of topic models.

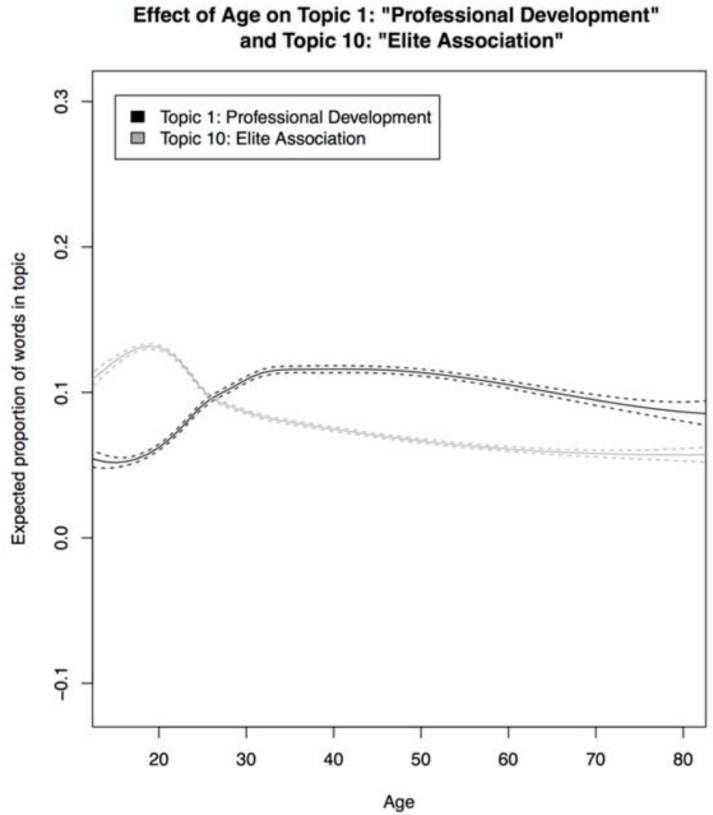
I've been doing all my topic modeling with Structural Topic Models and the stm package lately, and it has been ✨GREAT✨. One thing I am not going to cover in this blog post is how to use document-level covariates in topic modeling, i.e., how to train a model with topics that can vary with some continuous or categorical characteristic of your documents. I hope to build up some posts about that, but in the meantime, you can check out the stm vignette and perhaps Carsten Schwemmer's Shiny app for more details on this.

Applications: Discovery

Applications: Discovery

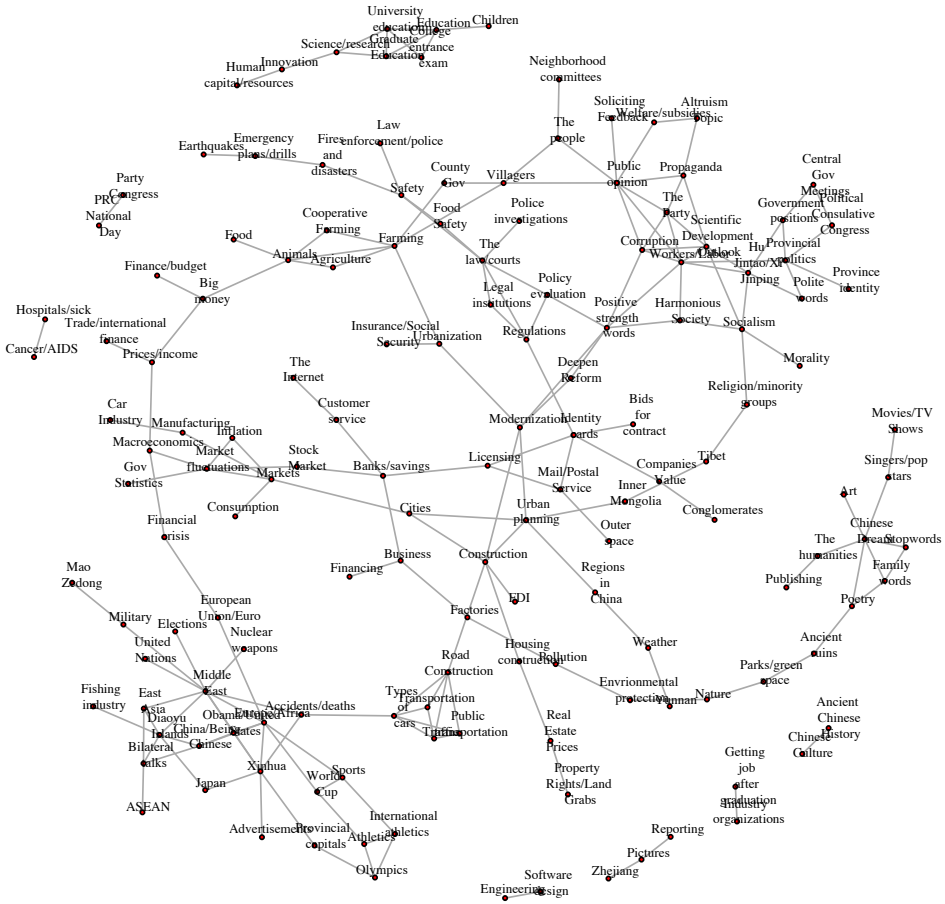
Computer-Assisted Reading and Discovery for Student-Generated Text in Massive Open Online Courses
(with Reich et al in *Journal of Learning Analytics*)





Applications: Discovery

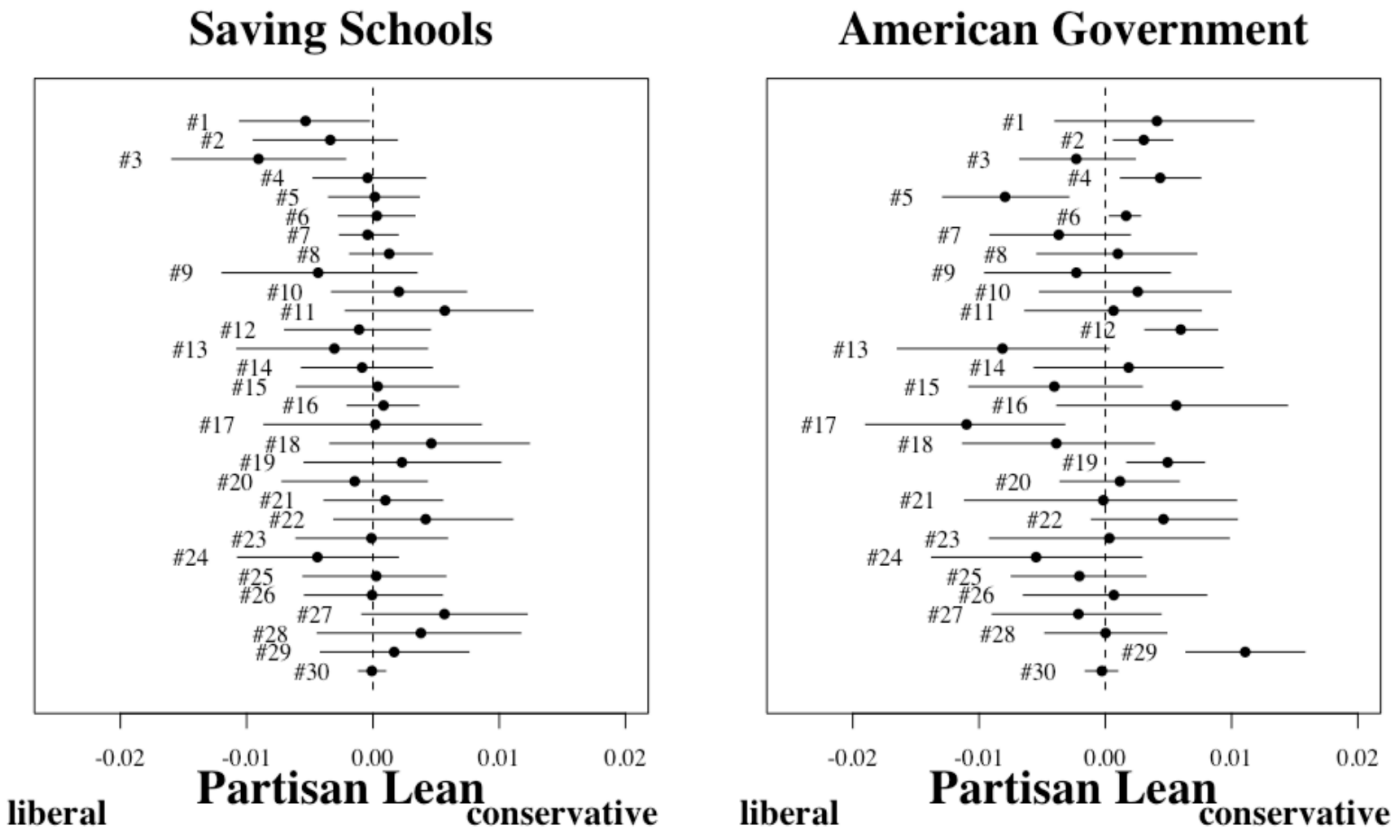
Propaganda in China (with Roberts)



Applications: Measurement

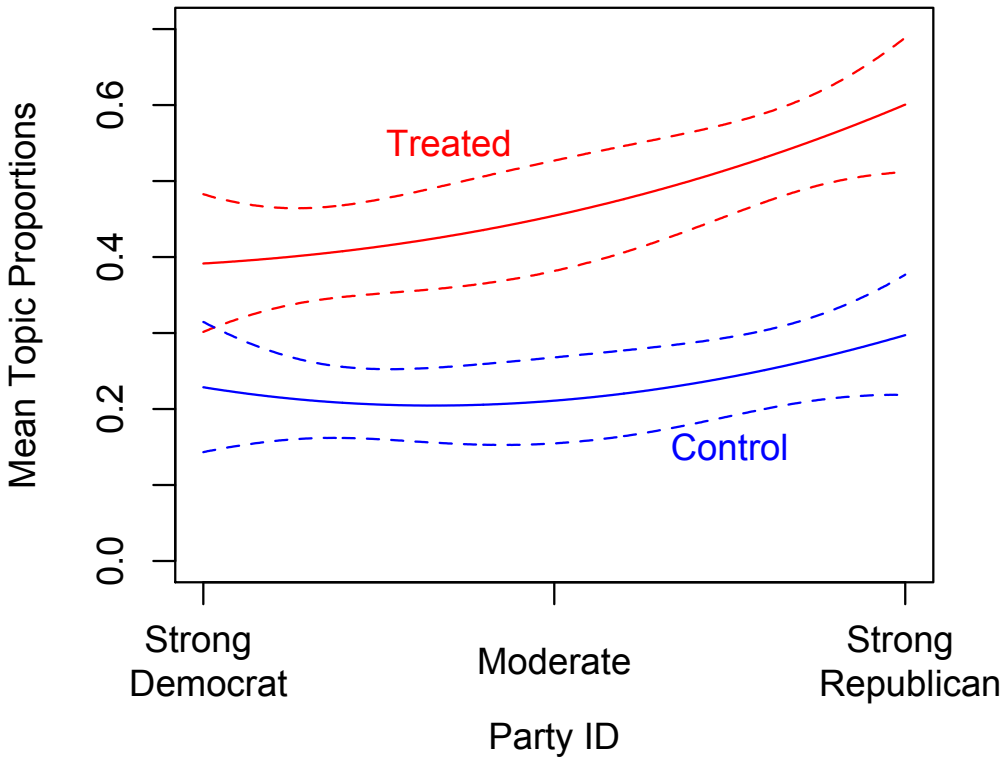
Applications: Measurement

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



Applications: Measurement

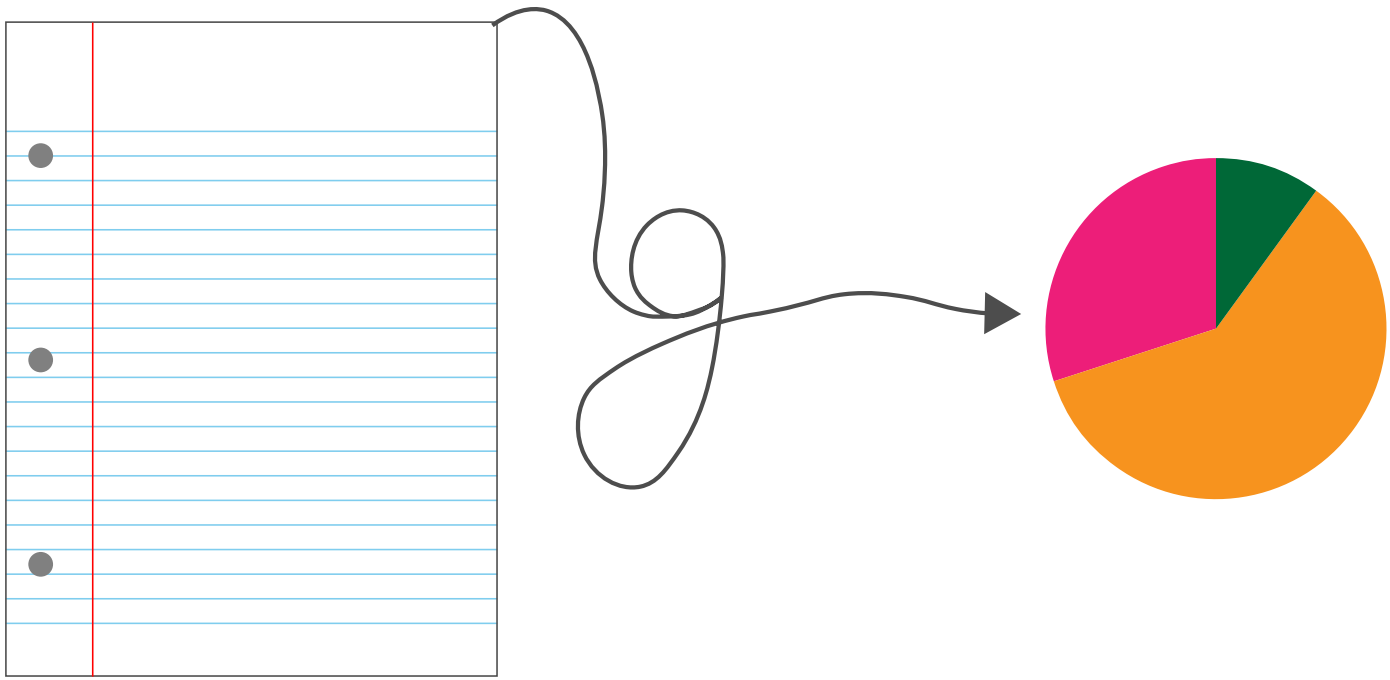
Structural topic models for open-ended survey responses
(with Roberts in *American Journal of Political Science*)



Applications: Causal Inference

Applications: Causal Inference

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



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- Talk has necessarily skipped over many, many important details-be sure to read more!

Go try out the software today!

Suggested Reading

- Blei (2012) "Probabilistic Topic Models" *Transactions of the ACM*.
- Wallach, Mimno and McCallum (2009) "Rethinking LDA: Why Priors Matter" *NeurIPS*
- Grimmer and Stewart (2013) "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts" *Political Analysis*
- Roberts et al. (2014) "Structural topic models for open-ended survey responses" *American Journal of Political Science*
- Boyd-Graber, Mimno and Newman (2016) "Care and Feeding of Topic Models: Problems, Diagnostics and Improvements" in *Handbook of Mixed Membership Models*

For more information

BrandonStewart.org

structuraltopicmodel.com