LDA and Beyond: Topic Models in the Social Sciences

Brandon Stewart[1]

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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.

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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- Validation $\rightsquigarrow$ demonstrate methods perform task

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- Few theorems to guarantee performance
- Apply methods $\rightsquigarrow$ validate
- Avoid: blind application of methods

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- We will breeze through this but these choices are consequential (see for example Denny and Spirling 2017, Schofield and Mimno 2016)

Preprocessing

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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{array}{c|cc}
 & Doc1 & Doc2 \\
\hline
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{array}
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Maintained assumptions: Bag of words/fix number of topics ex ante.

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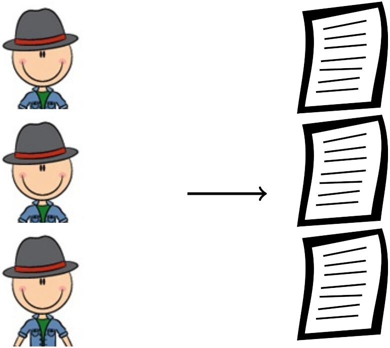

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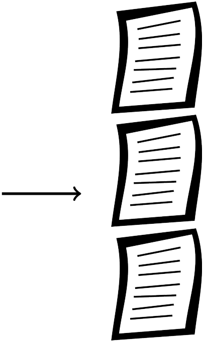

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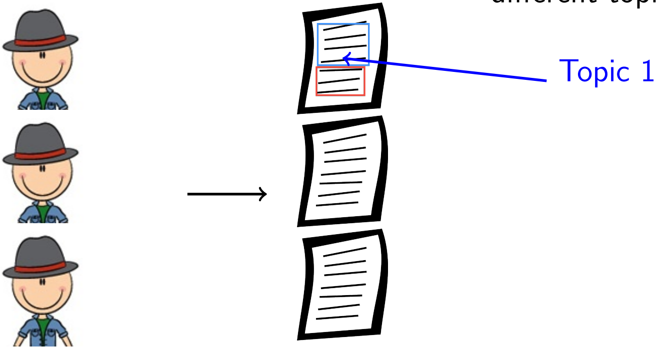

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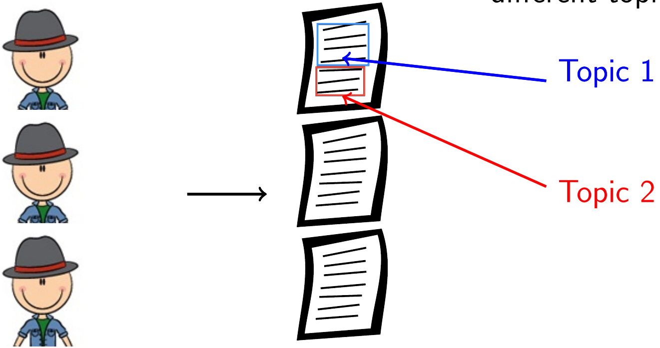

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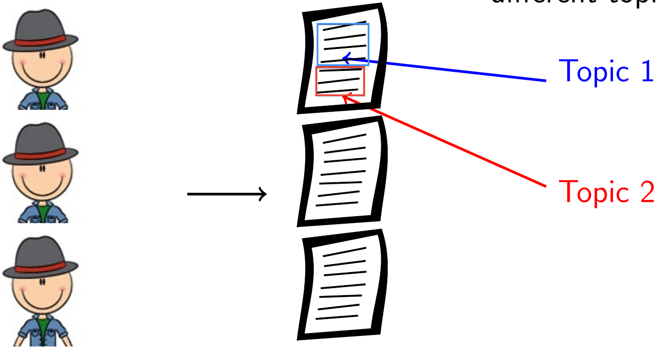

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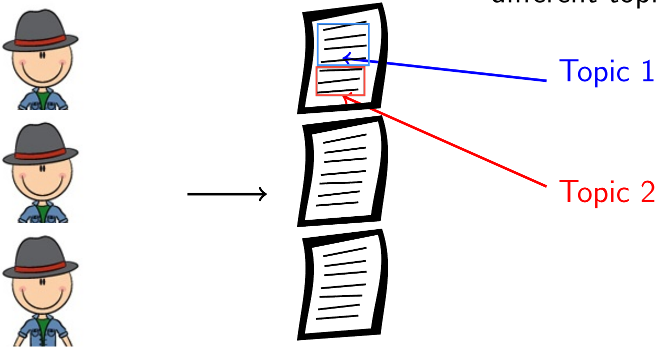

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congress, nations, power, votes, agreement, bargaining

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estimator, data, analysis, variance, model, inference

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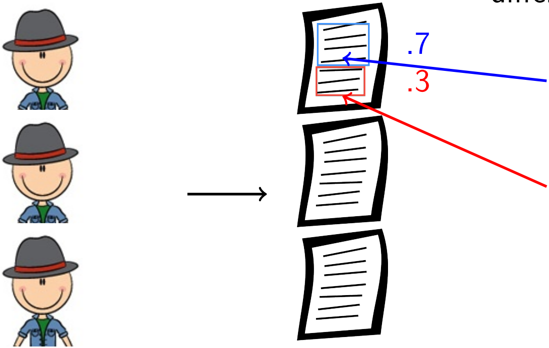

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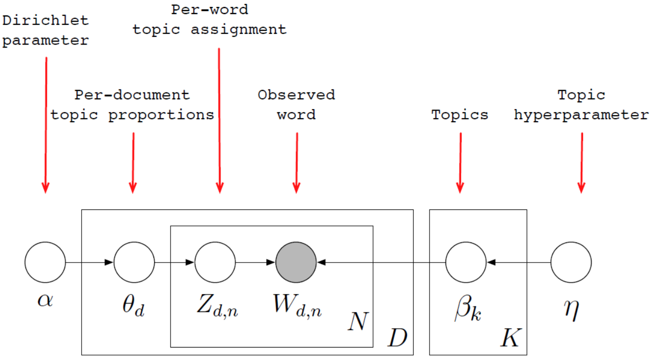
This is a Bayesian Model

Figure: Plate Notation of Latent Dirichlet Allocation



Graphic from David Blei's Website

LDA as a Bayesian Model

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

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)
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- $\boldsymbol{\beta} = K \times J$ matrix, with row $\boldsymbol{\beta}_k = (\beta_{1k}, \beta_{2k}, \ldots, \beta_{kJ}) \rightsquigarrow$topics

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   - $\boldsymbol{\beta} = K \times J$ matrix, with row $\boldsymbol{\beta}_k = (\beta_{1k}, \beta_{2k}, \ldots, \beta_{kJ}) \rightsquigarrow$topics
   - $\boldsymbol{\alpha} = K$ element long vector, population prior for $\boldsymbol{\Theta}$.

"Vanilla" Latent Dirichlet Allocation

1) Task:
   - Discover thematic content of documents
   - Quickly explore documents
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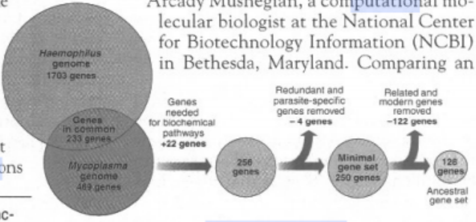
4) Validation$\rightsquigarrow$ application-specific

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.

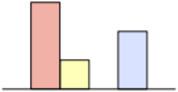


Image from Hanna Wallach

Why does this work $\rightsquigarrow$ Co-occurrence

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

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	Word_1	Word_2	$\ldots$	Word_J
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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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different methods for every problem
What is going on with all of these extensions?

Correlated Topic Models (Blei and Lafferty 2007)

Dirichlet distribution$\rightsquigarrow$ Assumes negative covariance between topics

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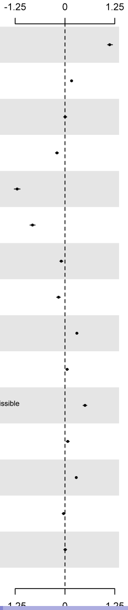
$$
\begin{aligned}
\boldsymbol{\beta}_k &\sim \text{Dirichlet}(\mathbf{1}) \\
\boldsymbol{\eta}_i | \boldsymbol{\mu}, \boldsymbol{\Sigma} &\sim \text{Multivariate Normal}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \\
\boldsymbol{\theta}_i &= \frac{\exp\left(\boldsymbol{\eta}_i\right)}{\sum_{k=1}^{K} \exp\left(\eta_{ik}\right)}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

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: مسلم, جهاد, اسلام, قتل, مجاهد, سبيل, تعال, ذين FREX: جهاد, قتال, مجاهد, منبر, يوافقنا, مذيل, يقاتل, بجوار
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: انس, حيا, نفس, علم, مجتمع, عمل, صور, ماد FREX: تصور, اخلاق, تطور, مجتمع, انتاج, حتم, بيئ, تقاليد
3.	**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, اير, جنوب, اشنطن, م, روسيا, تركيا
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: قال, صل, سلم, تعال, رسول, سبح, نب, ذين FREX: وجل, عز, سبح, تبارك, سحر, عذاب, رياء, ذنوب
5.	**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
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: يوم, صيام, عشر, رمض, شيخ, مجموع, فتاو, عثيم FREX: غسل, صائم, صيام, صوم, يفطر, رمض, مسافر, نجاس
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: مرا, يا, رجل, نساء, احد, يقول, رجال, ناس FREX: حجاب, شاب, تميم, عزام, دباب, تبرج, لباس, ر
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, مال, حج, يجوز, دين, زوج, صدق, طلاق FREX: زكا, طلاق, بنك, طلق, بطاق, بنوك, يحج, فقراء
9.	**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
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: قول, حديث, قال, صل, سلم, مسلم, شرع, ليس FREX: تحريم, قياس, جواز, عموم, ادل, منع, نص, مطلقا
11.	**Excommunication**	F: Apostasy, said, almighty, polytheism, Islam, Apostate, saying, people FREX: excommunicate, apostate, apostasy, sponsorship, idolatry, excommunication, idols, to make permissible F: كفر, قال, تعال, شرك, اسلام, كافر, قول, اهل FREX: يكفر, كفرا, كفر, موالا, شرك, تكفير, اصنام, استحلال
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: سن, شيخ, بن, اهل, كتاب, علم, سلف, محمد FREX: ابتداع, مبتدع, صوف, سلف, جانبوا, فتميزوا, ناج, استقاموا
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: اسلام, حكم, حق, ناس, امر, شرع, شريع, دين FREX: شريع, تشريع, انزل, تحاكم, تحكيم, عدل, برلم, محاكم
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: علم, صف, قول, يعن, قر, يك, اهل, قال FREX: مخلوق, صف, اسماء, عرش, طحاو, اثب, يعن, س
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: قال, بن, ابن, اب, حديث, روا, عبد, رض FREX: روا, داود, اسناد, رو, بيهق, طبر, حدثنا, ترمذ



Fighting

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F: person, life, soul/self, knowledge/science, society, work, image, material/physical
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F: woman, O, man, girl, one, says, men, people
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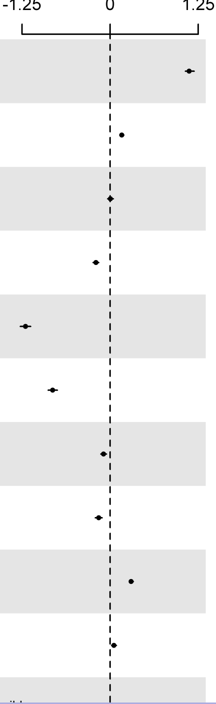


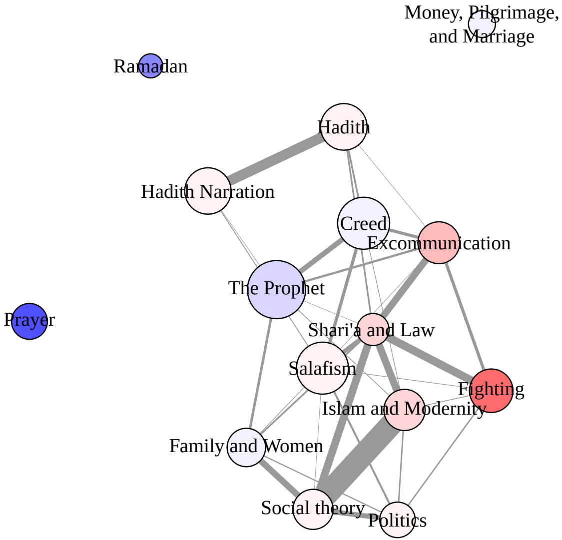
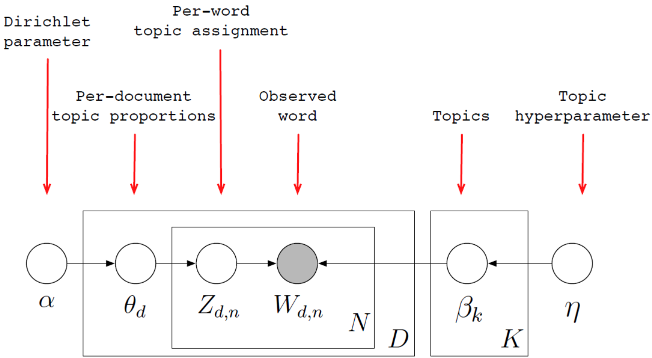


Figure: The network of correlated topics for a 15-topic Structural Topic Model with Jihadi/not-Jihadi as the predictor of topics in Arab Muslim cleric writings.

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

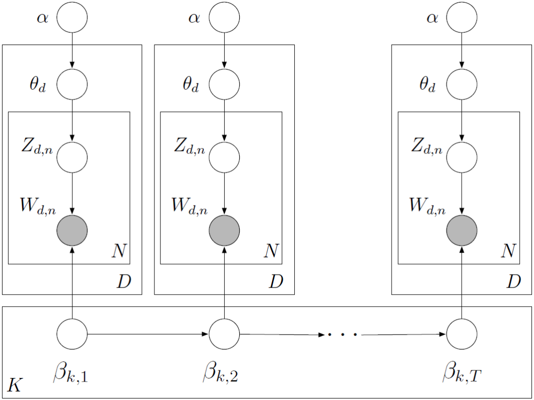
Figure: Plate Notation of Latent Dirichlet Allocation



Graphic from David Blei

LDA $\rightsquigarrow$ Dynamic Topic Model

Figure: Dynamic Topic Model



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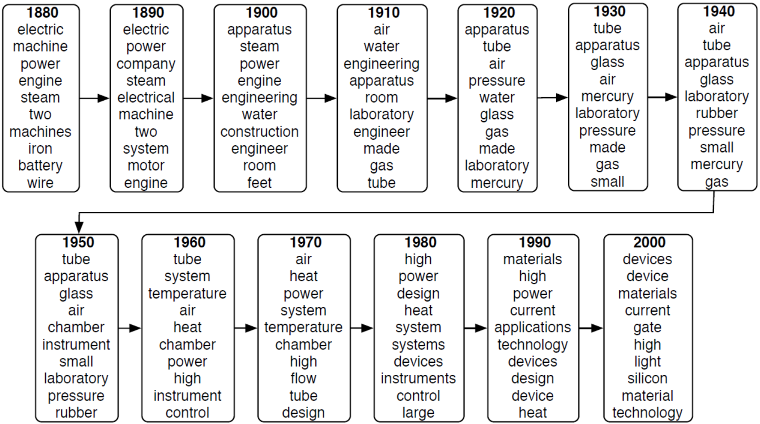
LDA $\rightsquigarrow$ Dynamic Topic Model

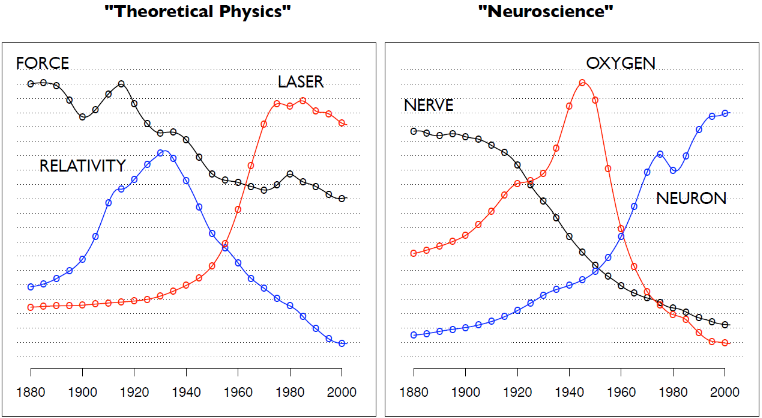
Figure: Topic Evolution over Time



Graphic from David Blei

LDA ⇝ Dynamic Topic Model

Figure: Word Use in Topics Over Time



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Expressed Agenda Model (Grimmer 2010)

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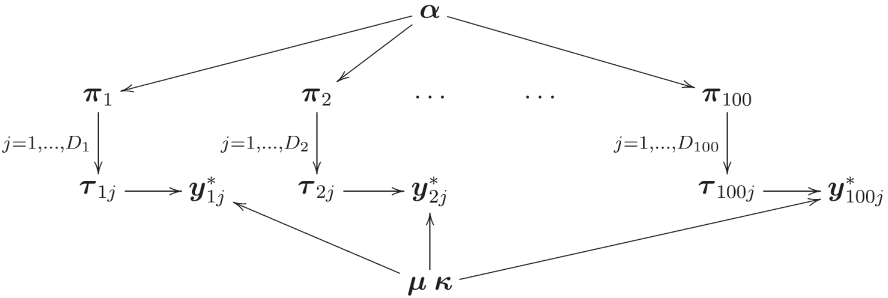
1. Assumes:
   1. Each document is assigned to one topic
   2. Each author allocates some hidden proportion of time to each topic
2. Grimmer's project seeks to quantitatively represent the content of senators' press releases.
3. It is called the Expressed Agenda Model because it captures the way they communicate that agenda to constituents.

Expressed Agenda Model

Figure: Expressed Agenda Model



Graphic from Grimmer 2010

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STM: What this means in pictures

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Each writes
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Politics

congress, nations, power, votes, agreement, bargaining

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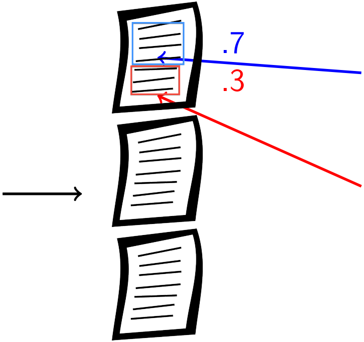

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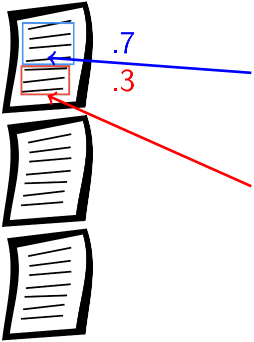

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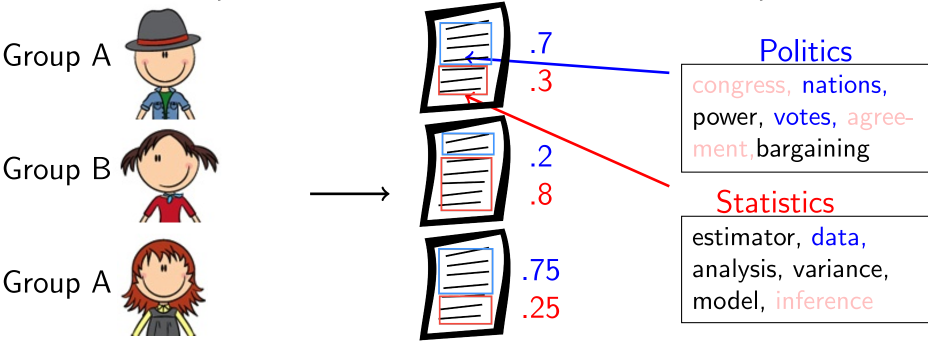

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More formal terminology:

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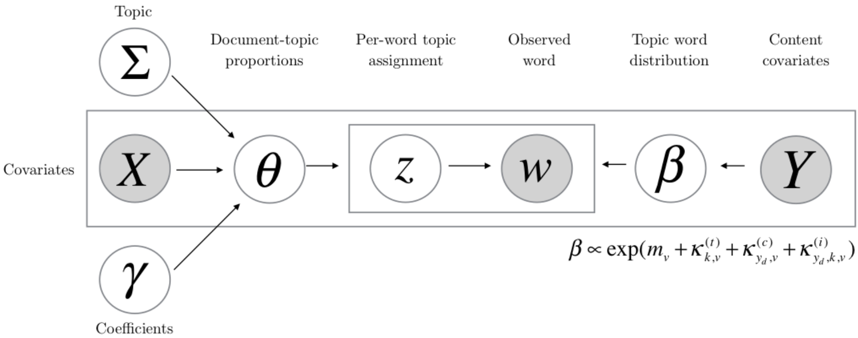

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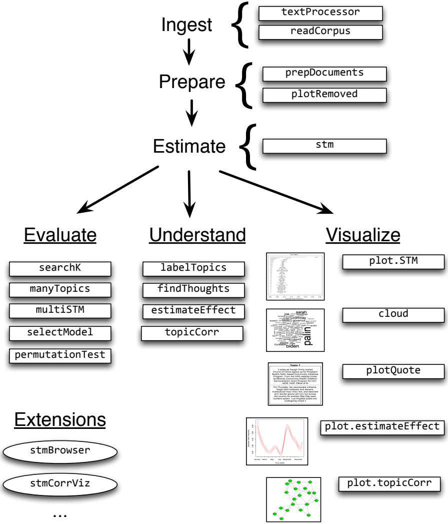
You can do this with your data!

stm is Full of Functions to Help You!



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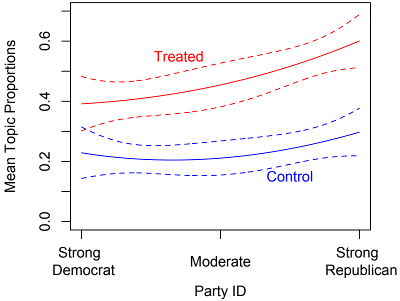

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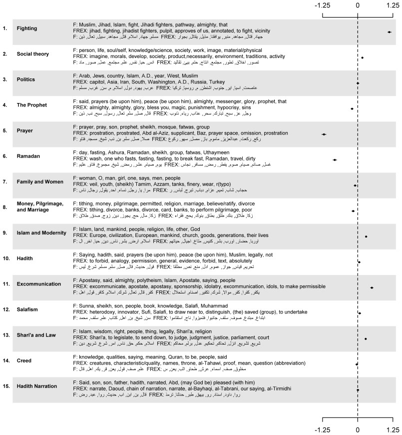

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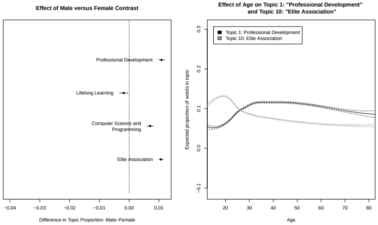

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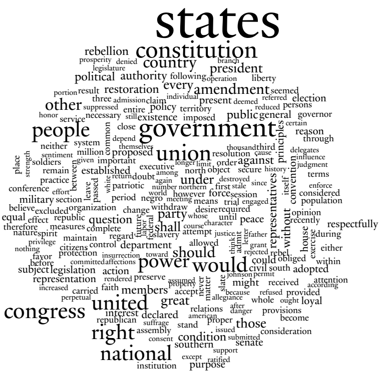

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- Talk has necessarily skipped over many, many important details- be sure to read more!

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" *NIPS*
- 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