Structural Topic Models

Margaret Roberts

UC San Diego

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Thanks to Justin Grimmer, Brandon Stewart, and Dustin Tingley from whom many of these slides were derived.

Topic models

- Methods of unsupervised text analysis

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- Describe main themes of a corpus

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- Many variants of topic models
- Today: Latent Dirichlet Allocation and Structural Topic Model

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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.

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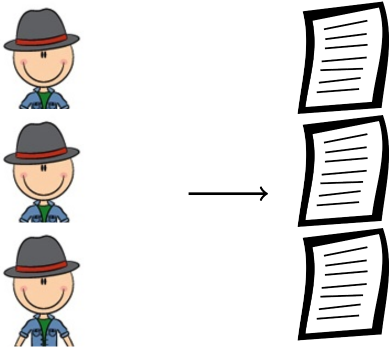
Each writes
some texts



What this means in pictures

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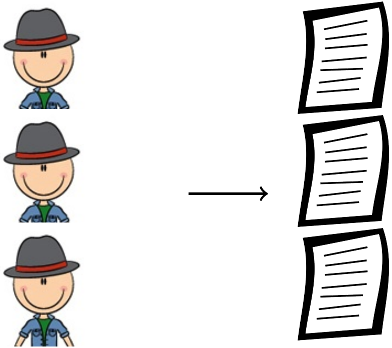

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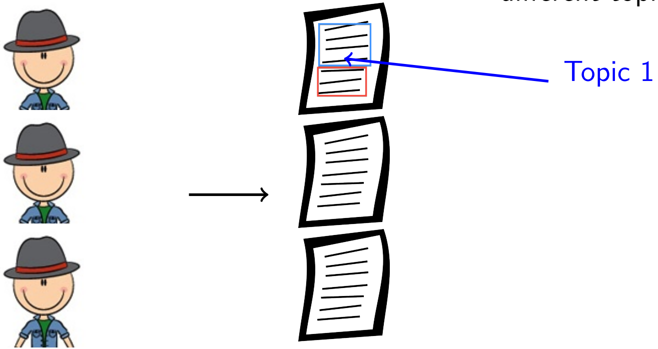

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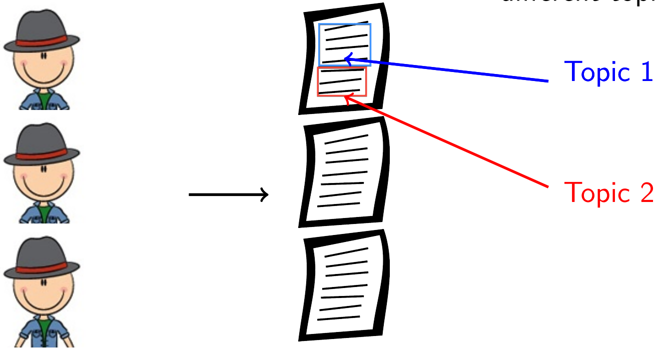

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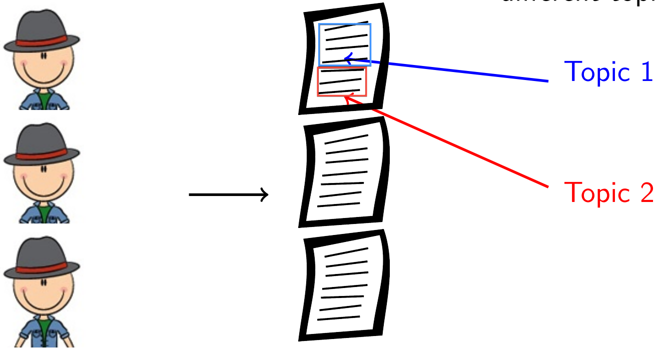

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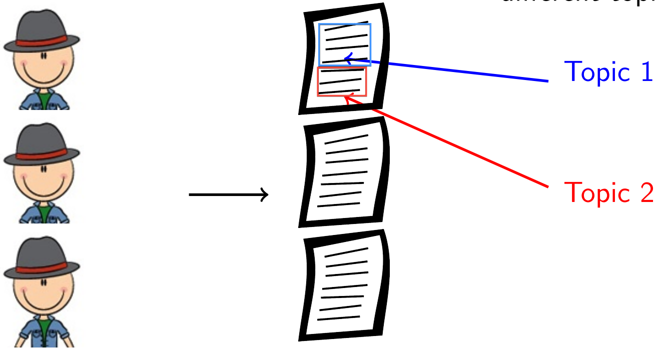

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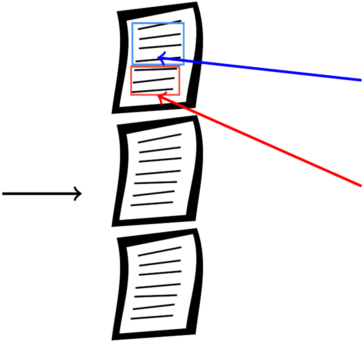

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congress, nations, power, votes, agreement, bargaining

estimator, data, analysis, variance, model, inference

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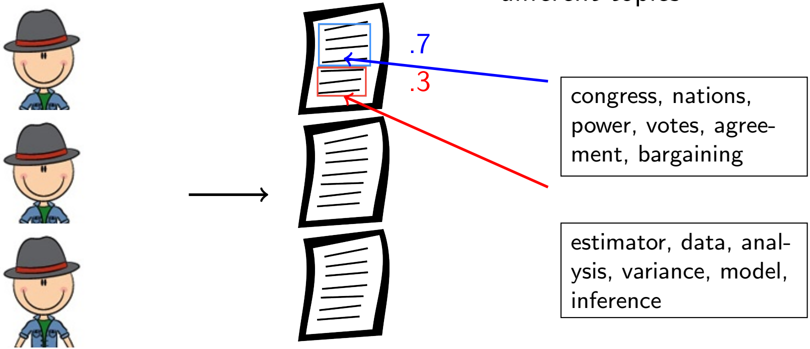

The Latent Dirichlet Allocation estimates:

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

Topic and Mixed Membership Models

Clustering

Document $\rightsquigarrow$ One Cluster

Doc 1	
	Cluster 1
Doc 2	
	Cluster 2
Doc 3	
	$\vdots$
$\vdots$	
	Cluster K
Doc N	

Topic and Mixed Membership Models

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Topic and Mixed Membership Models

Topic Models (Mixed Membership)

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	Cluster 1
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Topic and Mixed Membership Models

Topic Models (Mixed Membership)

Document $\rightsquigarrow$ Many clusters

Doc 1 → Cluster 1, Cluster 2, Cluster K

Doc 2

Doc 3

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Doc N

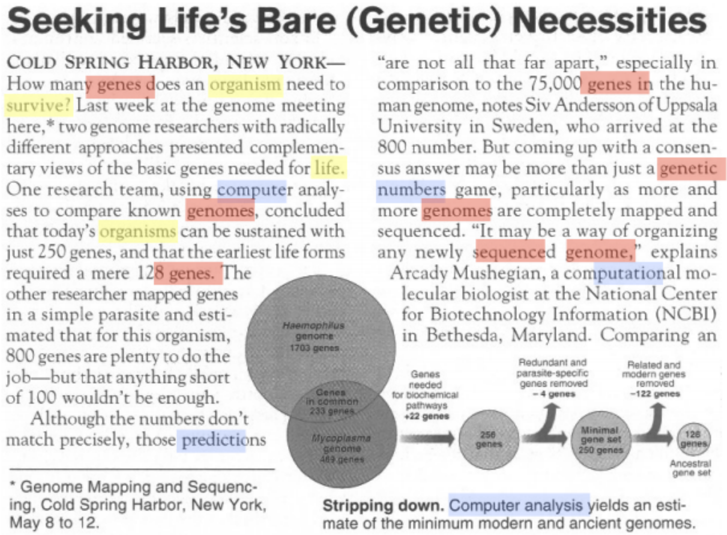
Cluster 1

Cluster 2

$\vdots$

Cluster K

A Statistical Highlighter (With Many Colors)



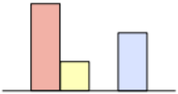
Seeking Life's Bare (Genetic) Necessities

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.



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1) Topical Prevalence Matrix (DxK)

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$$\theta = \left[\begin{array}{c|cccc} & Topic1 & Topic2 & \dots & TopicK \\ \hline Doc1 & .2 & .1 & \dots & 0.05 \\ Doc2 & .2 & .1 & \dots & .3 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ DocD & 0 & 0 & \dots & .5 \end{array}\right]$$

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2) Topical Content Matrix (VxK)

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Two primary matrices of interest: $X \approx \theta\beta$

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2) Topical Content Matrix (VxK)

$$\boldsymbol{\beta^T} = \left[\begin{array}{c|cccc} & Topic1 & Topic2 & \dots & TopicK \\ \hline \text{``}text\text{''} & .02 & .001 & \dots & 0.001 \\ \text{``}data\text{''} & .001 & .02 & \dots & 0.001 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \text{``}analysis\text{''} & .01 & .01 & \dots & 0.0005 \end{array}\right]$$

Vanilla Latent Dirichlet Allocation $\rightsquigarrow$ Objective Function

- Consider document i, $(i = 1, 2, \ldots, N)$.

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- Consider document i, $(i = 1, 2, \ldots, N)$.
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$$\begin{aligned} \boldsymbol{\theta}_i | \boldsymbol{\alpha} &\sim \text{Dirichlet}(\boldsymbol{\alpha}) \\ \boldsymbol{z}_{im} | \boldsymbol{\theta}_i &\sim \text{Multinomial}(1, \boldsymbol{\theta}_i) \end{aligned}$$

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Optimization:

- Variational Approximation $\rightsquigarrow$ Find "closest" distribution
- Gibbs sampling $\rightsquigarrow$ MCMC algorithm to approximate posterior

Example: Japanese Campaign Manifestos (Catalinac 2016)

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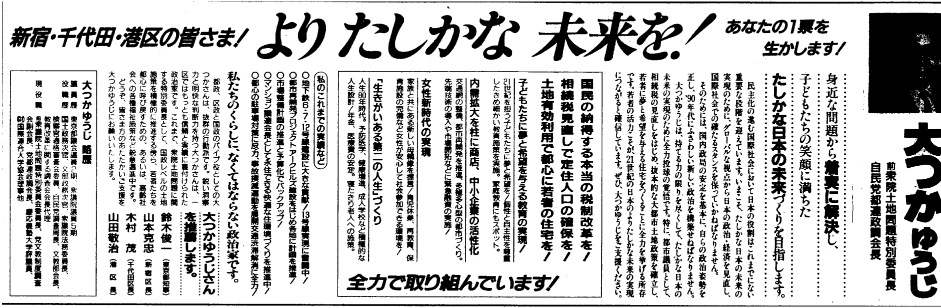
Typical Manifesto:



新宿・千代田・港区の皆さま！　よりたしかな未来を！　あなたの1票を生かします！

大つかゆうじ

前衆院土地問題特別委員長
自民党都連政調会長

身近な問題から着実に解決し、
子どもたちの笑顔に満ちた
たしかな日本の未来づくりを目指します。

民主化の進む国際社会において日本の役割はこれまでにない重要な段階を迎えています。いまこそ、たしかな日本の未来の実現のために、グローバルな視点から日本の政治・経済を見直し、国際社会での確たるスタンスを保っていかねばなりません。

そのためには、国内政局の安定を基本に、自らの政治姿勢を正し、'90年代にふさわしい新しい政治を構築せねばなりません。

大つかゆうじは、持てる力の限りを尽くして、たしかな日本の未来の実現のために全力投球の覚悟です。特に、都市議員として、相続税の見直しをはじめ、抜本的な大都市土地政策を確立し、若者に夢と希望を与える住宅をつくることに全力を挙げる所存です。若者の活力こそが、21世紀の日本のよりたしかな未来の実現につながると確信しています。ぜひ、大つかゆうじをご支援ください。

国民の納得する本当の税制改革を！

相続税見直しで定住人口の確保を！

土地有効利用で都心に若者の住宅を！

子どもたちに夢と希望を与える教育の実現！

21世紀を担う子どもたちに夢と希望を／個性と自主性を尊重したきめ細かい教育施策を実施。家庭教育にもスポット。

内需拡大を柱に商店、中小企業の活性化

交通網の整備、都市再開発を推進、多極多心型の都市づくり。先端技術の導入や市場開拓などに緊急融資の実施／

女性新時代の実現

家族と共にある新しい母親像を提言／育児休業、再教育、保育施設の完備など女性が安心して社会参加できる環境を／

「生きがいある第二の人生」づくり

人生80年時代。予防医学、健康増進、成人学校など積極的な人生設計／年金、医療費の安定。寝たきり老人への施策。

全力で取り組んでいます！

私のこれまでの実績など

○地下鉄6・7・12号線建設に大きな貢献／13号線実現に奮闘中／
○都市再開発プロジェクトアークヒルズ建設をはじめ各地に計画を推進／
○市場整備計画の推進と予算化でバックアップ／
○マンション議連会長として永住できる快適な住環境づくりを推進中／
○都心の駐車場対策に尽力、事故撲滅運動を展開交通渋滞解消に全力／

私たちのくらしに、なくてはならない政治家です。

都政、区政と国政のパイプ役としての大つかさんは、抜群の行動派です。鋭い洞察力と明快な判断力を持つ大つかさんは、一区ではもっとも信頼と実績に裏付けられた政治家です。これまで、衆院土地問題に関する特別委員長として、国政レベルの土地施策を積極的に推進する傍ら、若者たちを都心に呼び戻すための、あるいは、高齢社会への各種福祉施策など鋭意邁進中です。

どうぞ、皆さま方のあたたかいご支援を大つかゆうじにお願いいたします。

大つかゆうじさんを推薦します。

鈴木俊一（東京都知事）
山本克忠（新宿区長）
木村　茂（千代田区長）
山田敬治（港区長）

大つかゆうじ　略歴

議員歴　東京都議会議員2期、衆議院議員5期
役職歴　国土政務次官、文部政務次官、衆議院法務委員長、検察官適格審査会委員、自民党調査局長、文教部会長、教育改革に関する調査会会長代理
現役職　前衆議院土地問題特別委員会委員長、党文教制度調査会副会長、党都連政調会長、慶応義塾大学評議員、(財)国際連合大学協会理事他

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- Election Administration Commission runs elections $\rightarrow$ district level
- Required to submit manifestos for all candidates to National Diet
- Collected from 1950- 2009
  - Available only at district level

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- Harder for Japanese

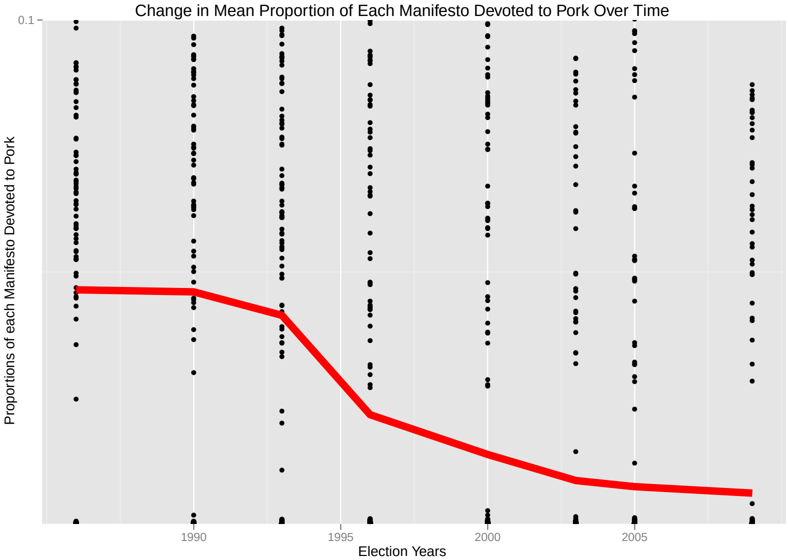
Example: Japanese Campaign Manifestos (Catalinac 2016)

- Applies Vanilla LDA
- Output: topics (with Japanese characters)

Example: Japanese Campaign Manifestos (Catalinac 2016)

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6
改革	年金	推進	区	政治	日本
郵政	円	整備	政策	改革	国
民営	廃止	図る	地域	国民	外交
小泉	改革	つとめる	まち	企業	国家
構造	兆	社会	鹿児島	自民党	社会
政府	実現	対策	全力	日本	国民
官	無駄	振興	選挙	共産党	保障
推進	日本	充実	国政	献金	安全
民	増税	促進	作り	金権	地域
自民党	削減	安定	横浜	党	拉致
日本	一元化	確立	対策	選挙	経済
制度	政権	企業	中小	禁止	守る
民間	子供	実現	発電	憲法	問題
年金	地域	中小	推進	腐敗	北朝鮮
実現	ひと	育成	エネルギー	団体	教育
進める	サラリーマン	制度	企業	区	責任
断行	制度	政治	声	ソ連	力
地方	議員	地域	実現	守る	創る
止める	金	福祉	活性	平和	安心
保障	民主党	事業	自民党	円	目指す
財政	年間	改革	地方	反対	誇り
作る	一掃	確保	尽くす	真	憲法
賛成	郵政	強化	商店	是正	可能
社会	道路	教育	いかす	一掃	道
国民	交代	施設	全国	悪政	未来
公務員	社会保険庁	生活	政党	抜本	ひと
力	月額	支援	ひと	定数	再生
経済	手当	環境	支援	政党	将来
国	談合	発展	経済	金丸	解決
安心	支援	施策	福祉	改悪	基本
Postal privatization	Reducing Wasteful Public Spending	Pork for the District	Policies for the district	Political Reform	National Security Policy

Example: Japanese Campaign Manifestos (Catalinac 2011)



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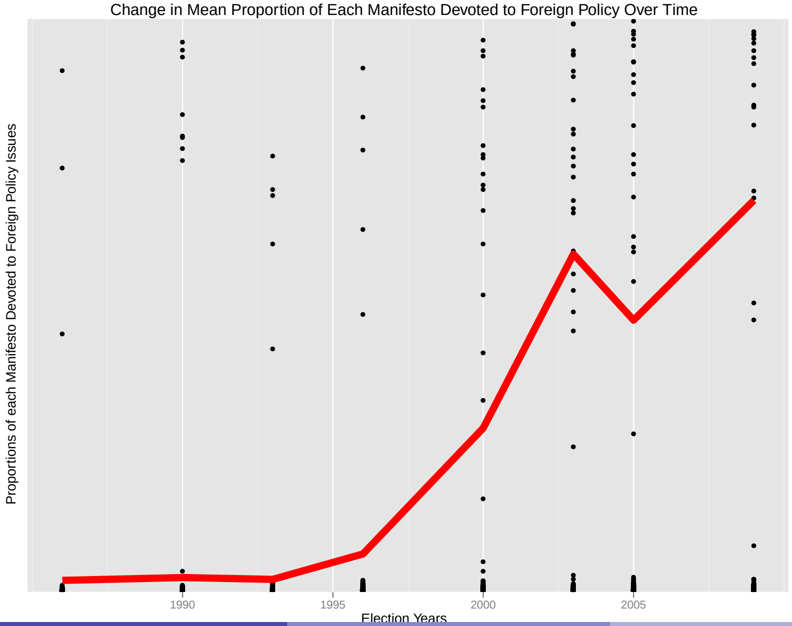

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$$\text{Perplexity} \quad = \quad \exp\left(-\log p(\boldsymbol{x}^{*}_{\text{out}} | \boldsymbol{\mu}, \boldsymbol{\pi})\right)$$

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How do we Choose K?

Generate many candidate models

1) Assess Cohesiveness/Exclusivity, select models on frontier
2) Use experiments
3) Read
4) Final decision $\rightsquigarrow$ combination

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- Integrated with support tools (visualization/uncertainty calculation/model selection)
- See structuraltopicmodel.com

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  - two uses of metadata: topic prevalence and topical content

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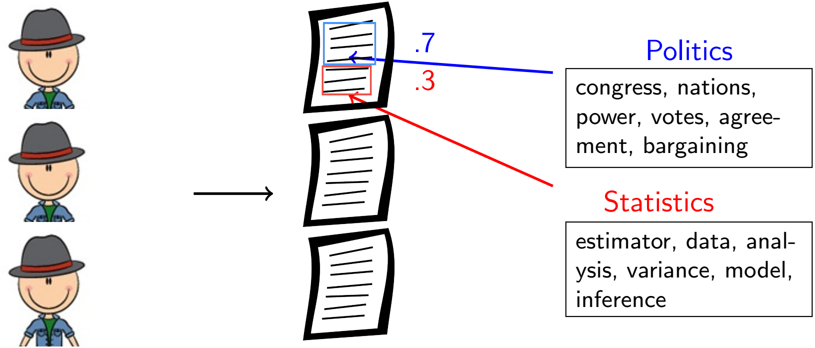
    - e.g. Democrats are less likely to use the word “life” when talking about abortion than Republicans
- Including context improves the model:
  - more accurate estimation
  - better qualitative interpretability

STM: What this means in pictures

Say you have
a lot of people.

Each writes
some text

that discuss a few
different topics



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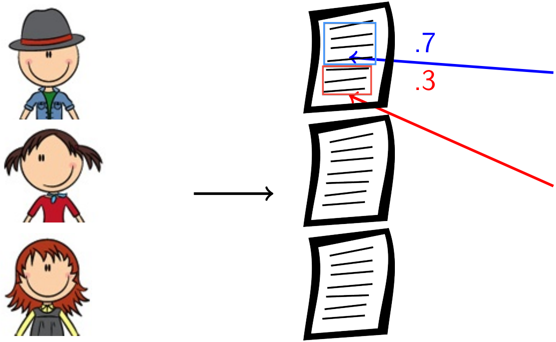

Politics

congress, nations, power, votes, agreement, bargaining

Statistics

estimator, data, analysis, variance, model, inference

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Group B

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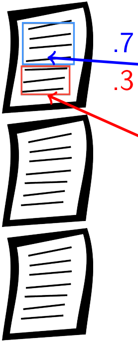

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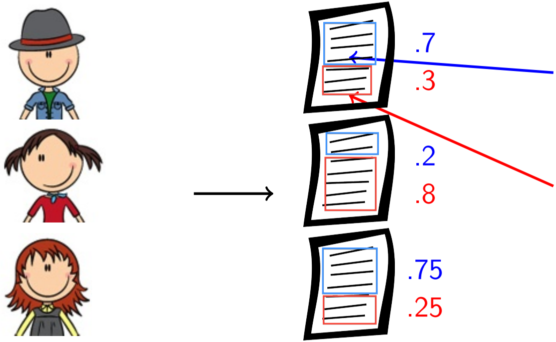

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Mixed-Membership Topic Models

More formal terminology:

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  - $\vec{\beta}_{k,\cdot} \propto \exp\left(m + \kappa^{(\text{topic})} + \kappa^{(\text{cov})} + \kappa^{(\text{int})}\right)$
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  - "border control, certain illegal immigrants tolerated, and others immediately deported."

Effects on Topic 1

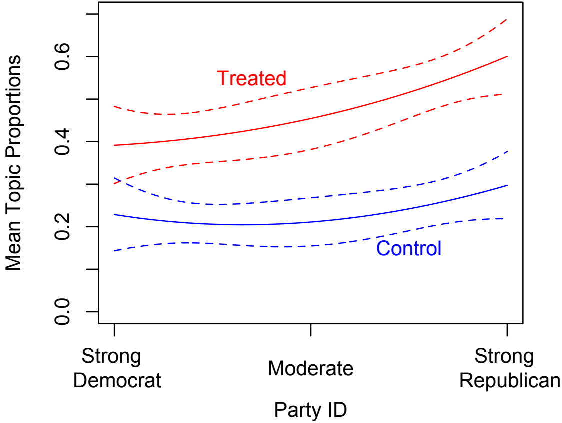
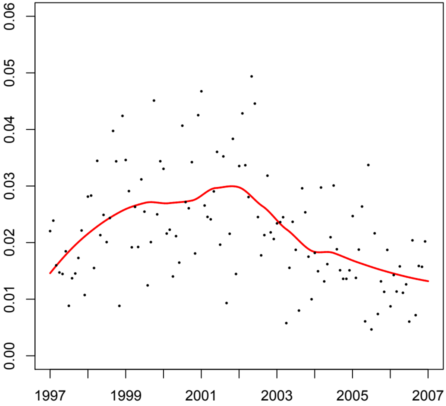


Figure: Topic 1.

Different Newspapers, Different Perspectives (Roberts, Stewart, Airoldi 2017)



Associated Press

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wang crackdown activist
movement sentenc center squar
china demonstr zhang
tiananmen dissid investig

Xinhua

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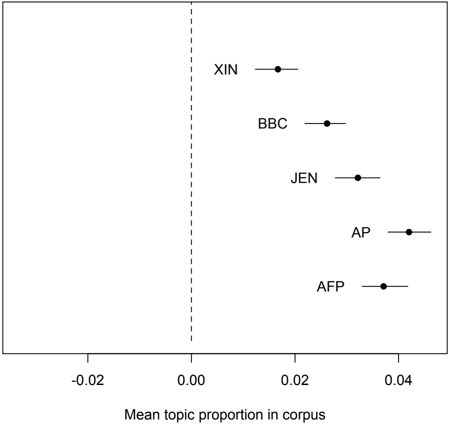


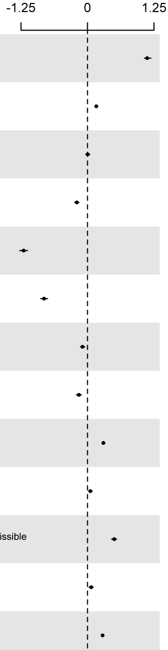
Fatwas (Lucas et al 2015 and Nielsen 2014)

fatwas: Islamic legal rulings on any virtually any aspect of human behavior, ranging from sex and dietary restrictions to violent Jihad.

We combine expert assessments 33 clerics (20 Jihadists and 13 non-Jihadists) with their Fatwas, giving us 11,045 texts.

Estimate STM with Jihadi vs. non-Jihadi classification as a topic prevalence parameter.

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



Jihad

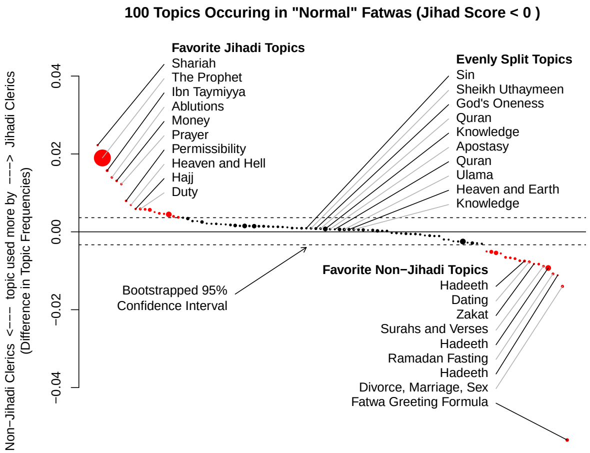


Figure: Estimated topic proportions by fighting the west and excommunication topics, separated out by jihadist versus jihadist coding.

Jihad

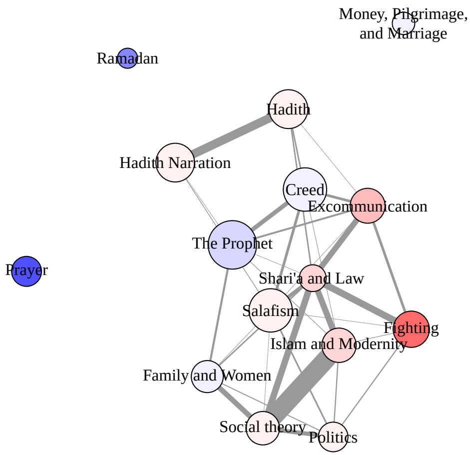
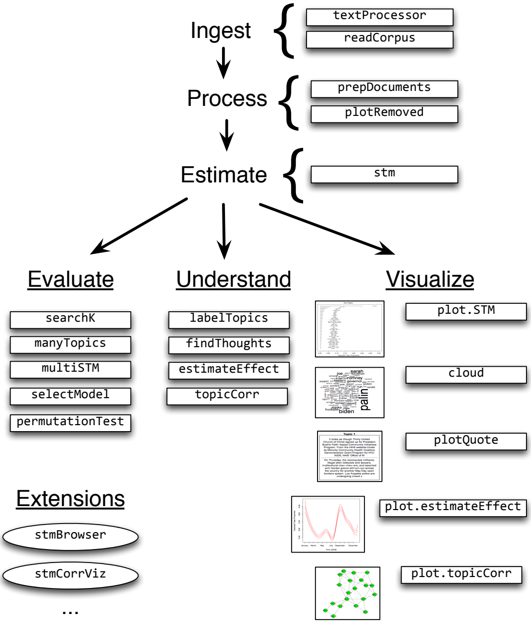


Figure: The network of correlated topics for a 15-topic Structural Topic Model with Jihadi/not-Jihadi as the predictor of topics in Arab Muslim cleric writings.

stm Packag


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

`stm` Package in R

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Available at structuraltopicmodel.com – example data/code:
https://goo.gl/j6T42I

Lots of quantities of interest

1. Label topics (4 styles of most informative words) (`summary`, `labelTopics`)
2. Plot predicted topic/covariate relationships and CI's with uncertainty (`plot`)
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New Functionality: stmBrowser

http:
//pages.ucsd.edu/~meroberts/stm-online-example/index.html