

Day 9: Topic Models

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Introduction to Data Science and Big Data Analytics

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Day 9 Outline

Topic models

Latent Dirichlet allocation (LDA)

Beyond Latent Dirichlet Allocation

Correlated and Dynamic Topic Models

Structural Topic Model

Topic models

Intro

- ▶ Topic models are algorithms for discovering the main “themes” in an unstructured corpus
- ▶ They require no prior information, training set, or labelling of texts before estimation
- ▶ They allows us to automatically organise, understand, and summarise large archives of text data.
 - ▶ Uncover hidden themes.
 - ▶ Annotate the documents according to themes.
 - ▶ Organise the collection using annotations.

What is a topic?

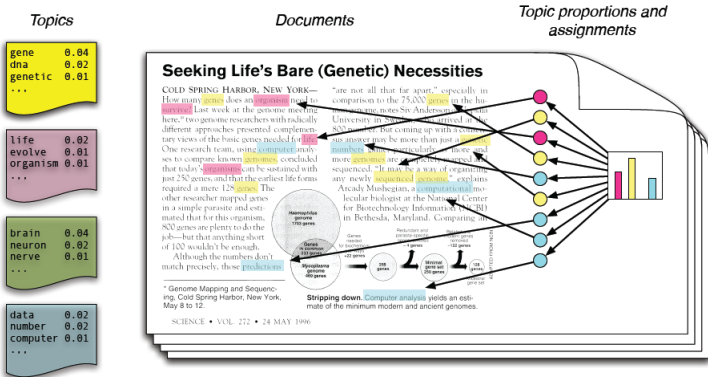
- ▶ Google: “a matter dealt with in a text, discourse, or conversation; a subject.”
- ▶ Topic models: a probability distribution over a fixed vocabulary
 - ▶ If you are speaking about the topic “police”:
 - ▶ you will probably use the word “police”
 - ▶ you will also probably use the words “jail” & “criminal”
 - ▶ you probably won’t use the word “kitten”.
 - ▶ If you are speaking about the topic “pets”
 - ▶ you will probably use the word “kitten”
 - ▶ you will also probably use the words “dog” & “hamster”
 - ▶ you probably won’t use the word “police”.

A motivating example

- ▶ Data: UK House of Commons' debates (PMQs)
 - ▶ ≈ 30000 parliamentary speeches from 1997 to 2015
 - ▶ ≈ 3000 unique words
 - ▶ $\approx 2m$ total words
- ▶ Note that I have already made a number of sample selection decisions
 - ▶ Only PMQs ($\approx 3\%$ of total speeches)
 - ▶ Removed frequently occurring & very rare words
 - ▶ All words have been 'stemmed'
- ▶ Results of a 30-topic model: [▶ Link](#)

Latent Dirichlet allocation (LDA)

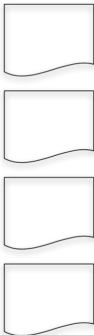
Latent Dirichlet allocation (LDA)



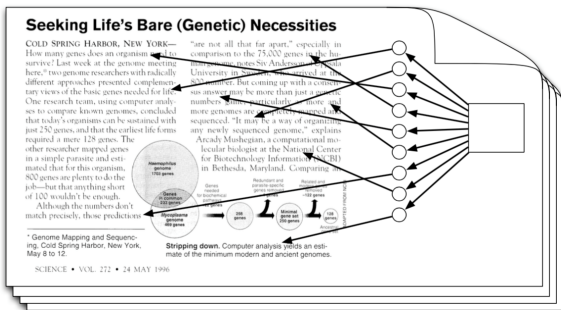
- ▶ Each **topic** is a distribution over words
- ▶ Each **document** is a mixture of corpus-wide topics
- ▶ Each **word** is drawn from one of those topics

Latent Dirichlet allocation (LDA)

Topics

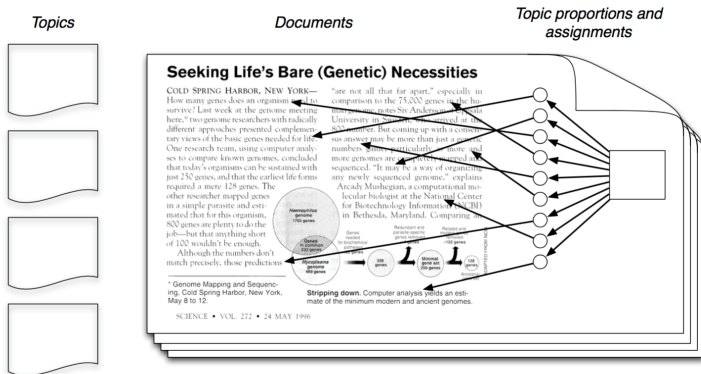


Documents



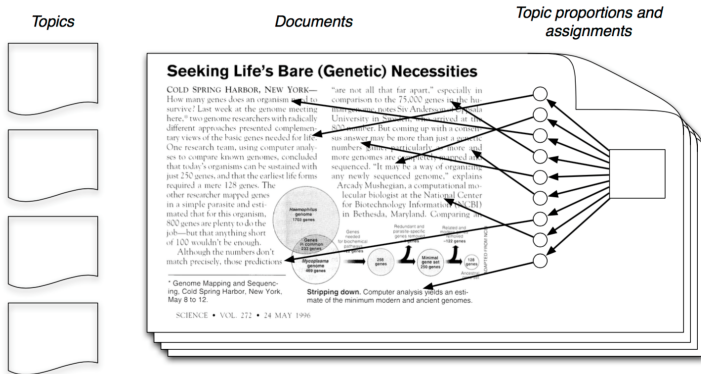
Topic proportions and assignments

Latent Dirichlet allocation (LDA)



- ▶ In reality, we only observe the documents
- ▶ The other structure are **hidden variables**

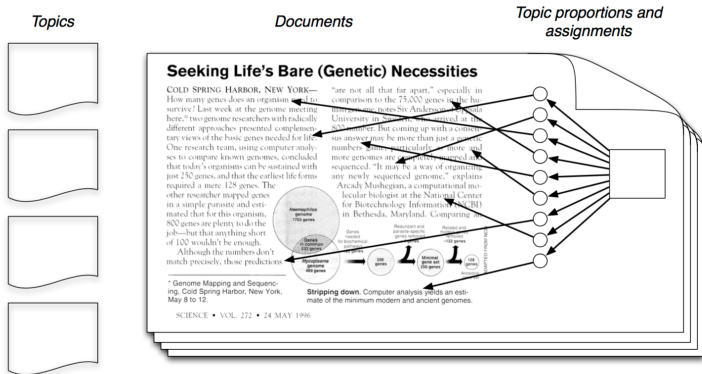
Latent Dirichlet allocation (LDA)



- ▶ Our goal is to **infer** the hidden variables
- ▶ I.e., compute their distribution conditioned on the documents

$$p(\text{topics, proportions, assignments} | \text{documents})$$

Latent Dirichlet allocation (LDA)



- Topic modelling allows us to extrapolate backwards from a collection of documents to infer the “topics” that could have generated them.

Latent Dirichlet Allocation

- ▶ The LDA model is a Bayesian mixture model for discrete data where topics are assumed to be uncorrelated
- ▶ LDA provides a generative model that describes how the documents in a dataset were created
- ▶ Each of the K topics is a distribution over a fixed vocabulary
- ▶ Each document is a collection of words, generated according to a multinomial distribution, one for each of K topics
- ▶ Inference consists of estimating a posterior distribution from a joint distribution based on the probability model from a combination of what is observed (words in documents) and what is hidden (topic and word parameters)

Latent Dirichlet Allocation: Details

- ▶ For each document, the LDA generative process is:
 1. randomly choose a distribution over topics (a multinomial of length K)
 2. for each word in the document
 - 2.1 Probabilistically draw one of the K topics from the distribution over topics obtained in (a), say topic β_k (each document contains topics in different proportions)
 - 2.2 Probabilistically draw one of the V words from β_k (each individual word in the document is drawn from one of the K topics in proportion to the document's distribution over topics as determined in previous step)
- ▶ The goal of inference in LDA is to discover the topics from the collection of documents, and to estimate the relationship of words to these, *assuming this generative process*

LDA generative model

How to generate

1. Term distribution β for each topic is drawn:

$$\beta \sim \text{Dirichlet}(\eta)$$

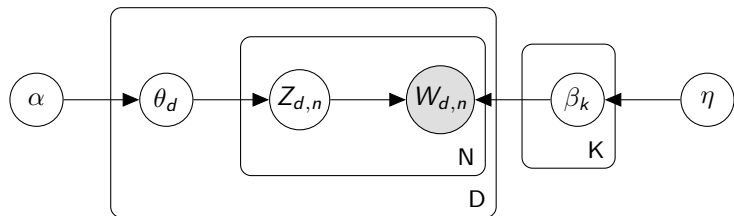
β is the term distribution of topics and contains the probability of a word occurring in a given topic

2. proportions θ of the topic distribution for the document are drawn by

$$\theta \sim \text{Dirichlet}(\alpha)$$

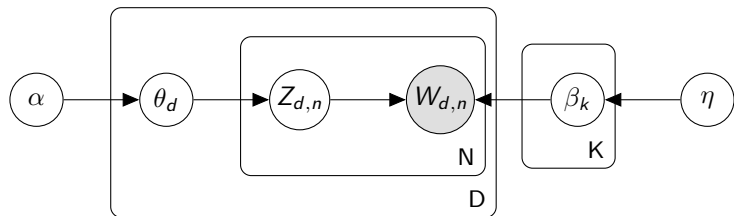
3. For each of the N words in each document
 - ▶ choose a topic $z_i \sim \text{Multinomial}(\theta)$
 - ▶ choose a word $w_i \sim \text{Multinomial}(p(w_i|z_i, \beta))$

LDA as a graphical model



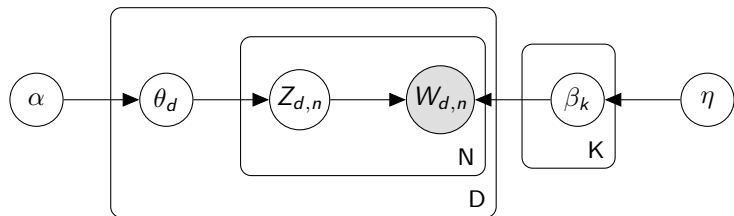
- ▶ Encodes **assumptions**
- ▶ Defines a **factorization** of the joint distribution
- ▶ Connects to **algorithms** for computing with data

LDA as a graphical model



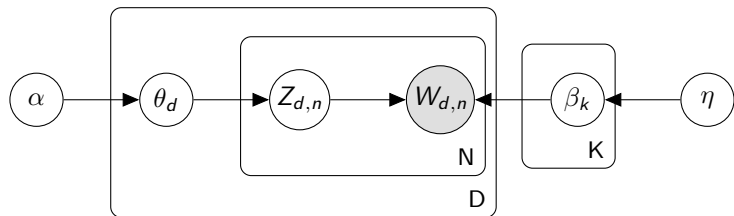
- ▶ Nodes are random variables; edges indicate dependence.
- ▶ Shaded nodes are observed; unshaded nodes are hidden.
- ▶ Plates indicate replicated variables.

LDA as a graphical model



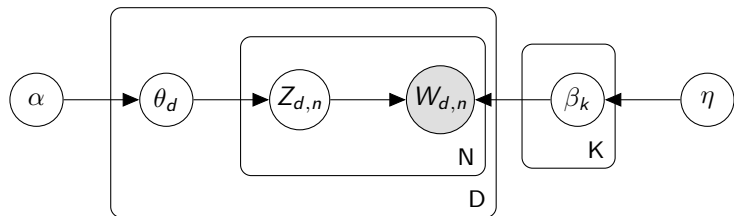
- ▶ α proportions parameter (corpus level)
- ▶ η topic parameter (corpus level)
- ▶ β_k probability distribution over words (topic level)
- ▶ θ_d topic proportions (document level)
- ▶ $Z_{d,n}$ topic assignment (word level)
- ▶ $W_{d,n}$ observed word (word level)

LDA as a graphical model



- ▶ $\beta_k \sim \text{Dirichlet}(\eta)$
- ▶ $\theta_d \sim \text{Dirichlet}(\alpha)$
- ▶ $Z_{d,n} \sim \text{Multinomial}(\theta_d)$
- ▶ $W_{d,n} \sim \text{Multinomial}(p(w_i|z_i, \beta_k))$

LDA as a graphical model

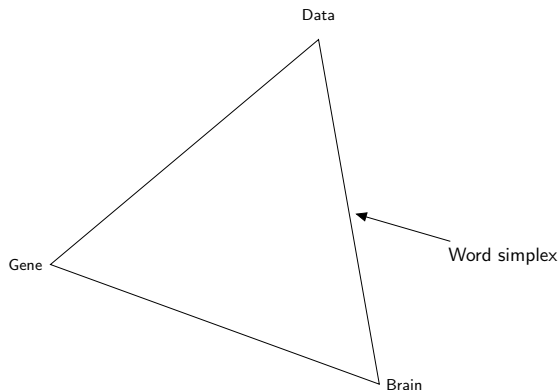


- ▶ This joint defines a posterior, $p(\theta, z, \beta | w)$.
- ▶ From a collection of documents, infer
 - ▶ Per-word topic assignment $z_{d,n}$
 - ▶ Per-document topic proportions θ_d
 - ▶ Per-corpus topic distributions β_k
- ▶ Then use posterior expectations to perform the task at hand: information retrieval, document similarity, exploration, and others.

The Dirichlet distribution

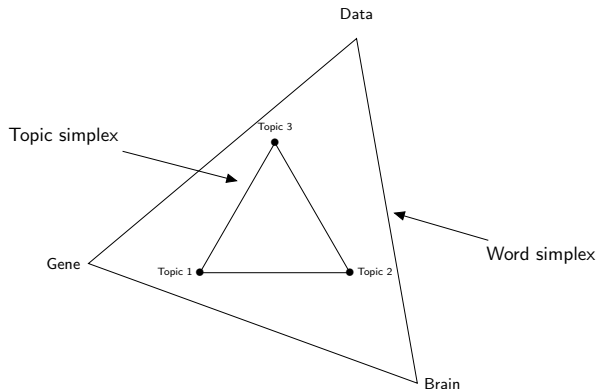
- ▶ The Dirichlet distribution is an exponential family distribution over the simplex, i.e., positive vectors that sum to one
- ▶ It is conjugate to the multinomial distribution, and is used in the Bayesian inference required to estimate the parameters.
- ▶ The Dirichlet is used twice in LDA:
 - ▶ The topic proportions (θ) are a K dimensional Dirichlet
 - ▶ The topics (β) are a V dimensional Dirichlet.
- ▶ Estimation is performed using collapsed Gibbs sampling and/or Variational Expectation-Maximization (VEM)
- ▶ Fortunately, for us these are easily implemented in R

Latent Dirichlet allocation (LDA)



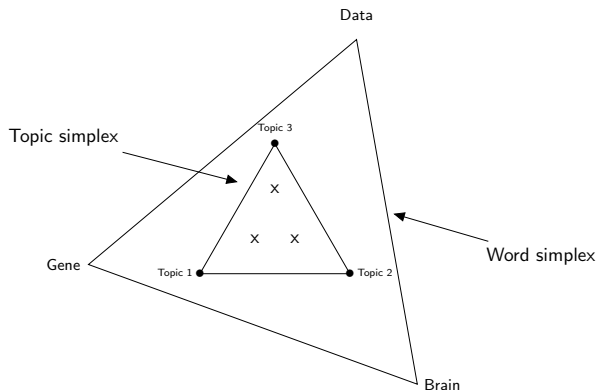
- ▶ Imagine a corpus consisting of only three words
- ▶ The word simplex describes the possible probabilities of the categorical distribution over these three words

Latent Dirichlet allocation (LDA)



- ▶ We can locate **topics** within the **word-simplex**
- ▶ Each topic represents a different distribution over words

Latent Dirichlet allocation (LDA)

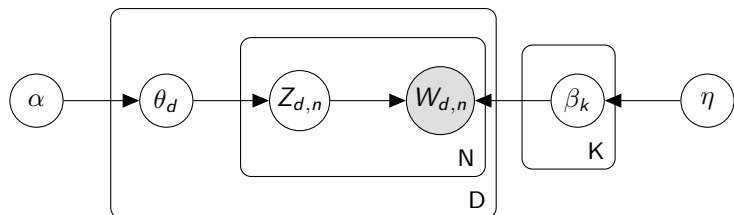


- ▶ The topic simplex describes the possible probabilities of the categorical distribution over these topics
- ▶ We can locate **documents** within the **topic-simplex**
- ▶ Each document is a mixture of topics

Why does LDA “work”?

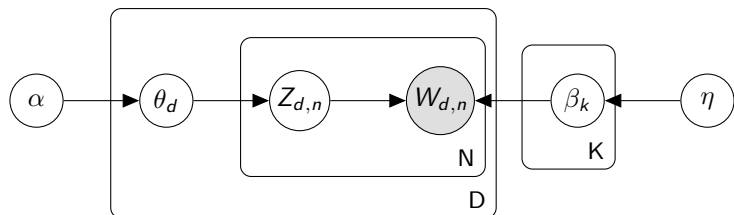
- ▶ LDA trades off two goals.
 1. For each document, allocate its words to as few topics as possible.
 2. For each topic, assign high probability to as few terms as possible.
- ▶ These goals are at odds.
 - ▶ Putting a document in a single topic makes (2) hard: All of its words must have probability under that topic.
 - ▶ Putting very few words in each topic makes (1) hard: To cover a document's words, it must assign many topics to it.
- ▶ Trading off these goals finds groups of tightly co-occurring words.

LDA summary



- ▶ LDA is a probabilistic model of text. It casts the problem of discovering themes in large document collections as a posterior inference problem.
- ▶ It lets us visualize the hidden thematic structure in large collections, and generalize new data to fit into that structure.

LDA summary



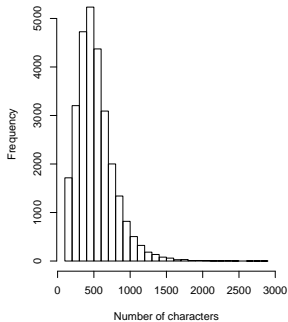
- ▶ LDA is a simple building block that enables many applications.
- ▶ It is popular because organizing and finding patterns in data has become important in the sciences, humanities, industry, and culture.
- ▶ Further, algorithmic improvements let us fit models to massive data.

LDA example

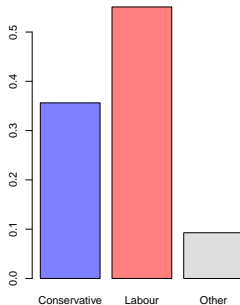
- ▶ Data: UK House of Commons' debates (PMQs)
 - ▶ ≈ 30000 parliamentary speeches from 1997 to 2015
 - ▶ ≈ 3000 unique words
 - ▶ $\approx 2m$ total words
- ▶ Note that I have already made a number of sample selection decisions
 - ▶ Only PMQs ($\approx 3\%$ of total speeches)
 - ▶ Removed frequently occurring & very rare words
 - ▶ All words have been 'stemmed'
- ▶ Estimate a range of topic models ($K \in \{20, 30, \dots, 100\}$) using the `topicmodels` package

LDA example

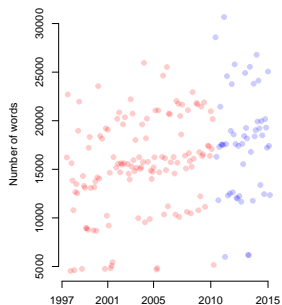
Speech length



Speeches by party



words by month



Implementation in R (via quanteda)

```
1 ## Create corpus
2 speechCorpus <- corpus(pmq$Speech, docvars = pmq)
3
4 ## Create DFM
5 speechDFM <- dfm(speechCorpus,
6   ignoredFeatures = stopwords("SMART"), stem = T)
7
8 ## Remove very infrequent words
9 speechDFM <- trim(speechDFM, minCount = 5)
10
11 ## Convert for usage in 'topicmodels' package
12 tmDFM <- convert(speechDFM, to = 'topicmodels')
13
14 ## Set topic count and estimate LDA using Gibbs sampling
15 K <- 60
16 ldaOut <- LDA(tmDFM, k = K, method = "Gibbs",
17   control = list(seed = 123))
18
19 ## Save (because it can take a long time to run again!)
20 save(ldaOut, file = paste0("ldaOut",K,".Rdata"))
```

LDA example

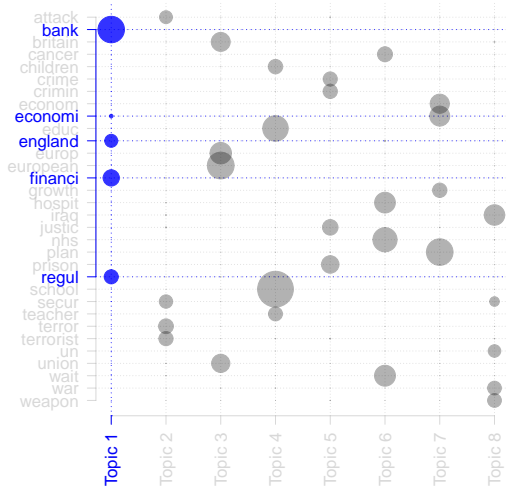
We will make use of the following score to visualise the posterior topics:

$$\text{term-score}_{k,v} = \hat{\beta}_{k,v} \log \left(\frac{\hat{\beta}_{k,v}}{(\prod_{j=1}^K \hat{\beta}_{j,v})^{\frac{1}{K}}} \right) \quad (1)$$

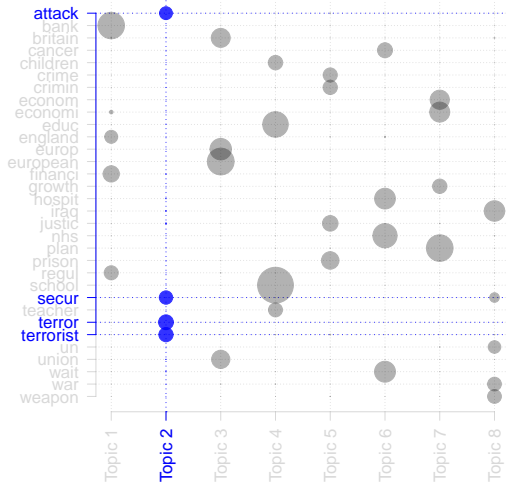
This formulation is similar to the TFIDF term score, where

- ▶ the first term, $\hat{\beta}_{k,v}$, is the probability of term v in topic k and is akin to the term frequency
- ▶ the second term is akin to the document frequency (i.e. it down-weights terms that have high probability under all topics)

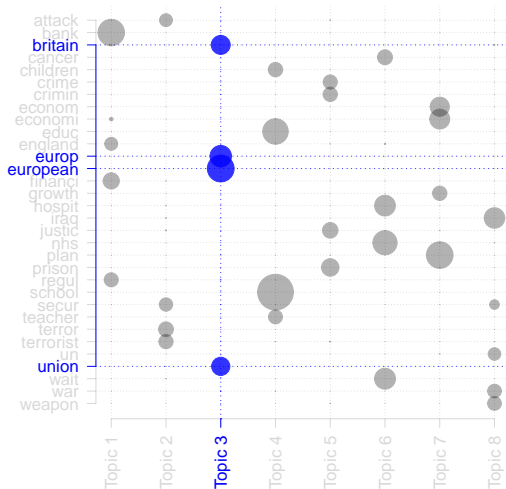
LDA example



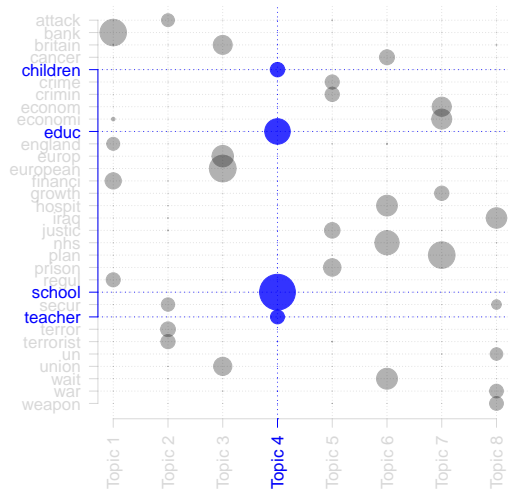
LDA example



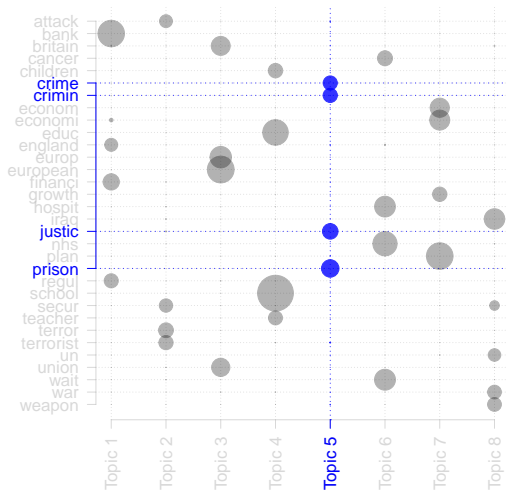
LDA example



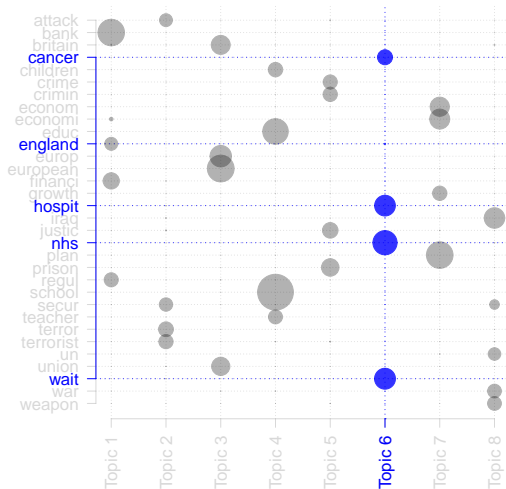
LDA example



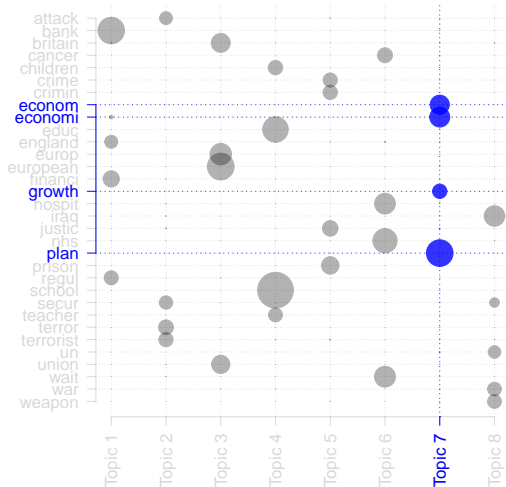
LDA example



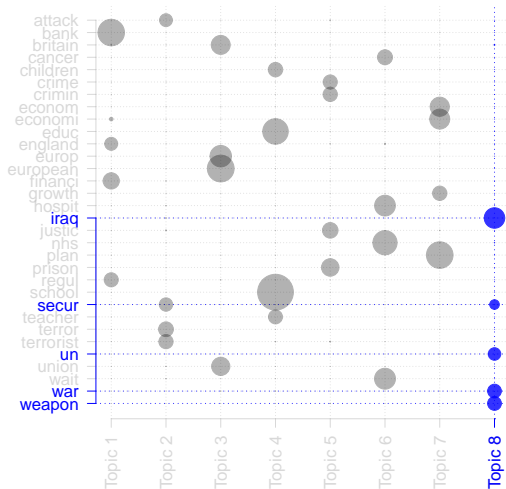
LDA example



LDA example



LDA example



LDA example

Topic 1

bank
financi
regul
england
crisi
fiscal
market

Topic 2

terror
terrorist
secur
attack
protect
agre
act

Topic 3

european
europ
britain
union
british
referendum
constitut

Topic 4

school
educ
children
teacher
pupil
class
parent

Topic 5

prison
justic
crimin
crime
releas
court
sentenc

Topic 6

nhs
wait
hospit
cancer
patient
list
health

Topic 7

plan
economi
econom
growth
grow
longterm
deliv

Topic 8

iraq
weapon
war
un
resolut
iraqi
saddam

Evaluating LDA performance

- ▶ How well does the model predict held-out data?

$$\text{perplexity}(w) = \exp \left\{ - \frac{\sum_{d=1}^M \log p(w_d)}{\sum_{d=1}^M N_d} \right\}$$

- ▶ Essentially we are asking which words the model believes will be in a given document and comparing this to the document's actual word composition
- ▶ Problems:
 - ▶ Prediction is not always important in exploratory or descriptive tasks. We may want models that capture other aspects of the data.
 - ▶ There tends to be a negative correlation between quantitative diagnostics such as these and human judgements of topic coherence!

Evaluating model performance

Chang, Jonathan et al. 2009. "Reading Tea Leaves: How Humans Interpret Topic Models." *Advances in neural information processing systems*.

Uses human evaluation of:

- ▶ whether a topic has (human-identifiable) semantic coherence: **word intrusion**, asking subjects to identify a spurious word inserted into a topic
- ▶ whether the association between a document and a topic makes sense: **topic intrusion**, asking subjects to identify a topic that was not associated with the document by the model

Evaluating LDA performance

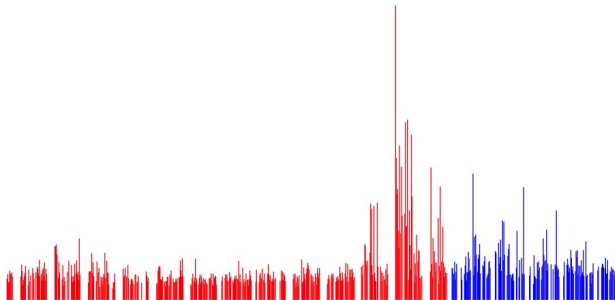
- ▶ *Semantic validity* – does a topic identify a coherent groups of texts that are internally homogenous but distinctive from other topics?
- ▶ *Predictive validity* – how well does variation in topic usage correspond to known events?
- ▶ *Construct validity* – how well does our measure correlate with other measures?

Here, we will focus on semantic and predictive validity. **Why?**

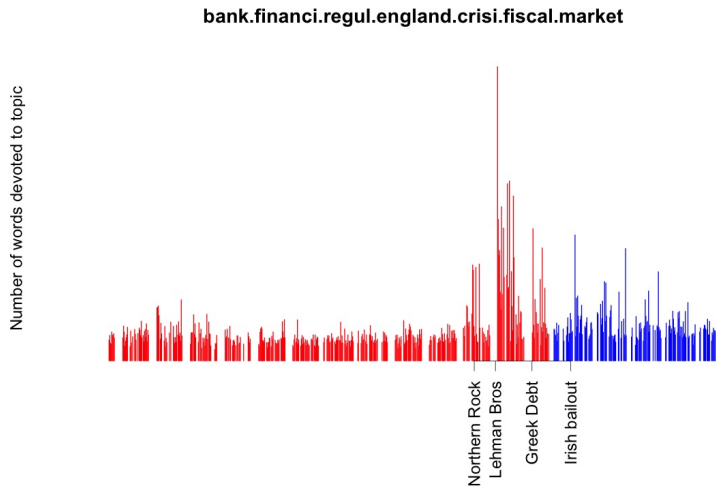
Predictive validity

bank.financi.regul.england.crisi.fiscal.market

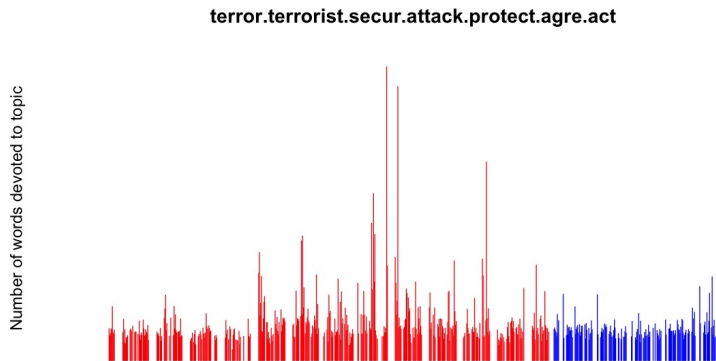
Number of words devoted to topic



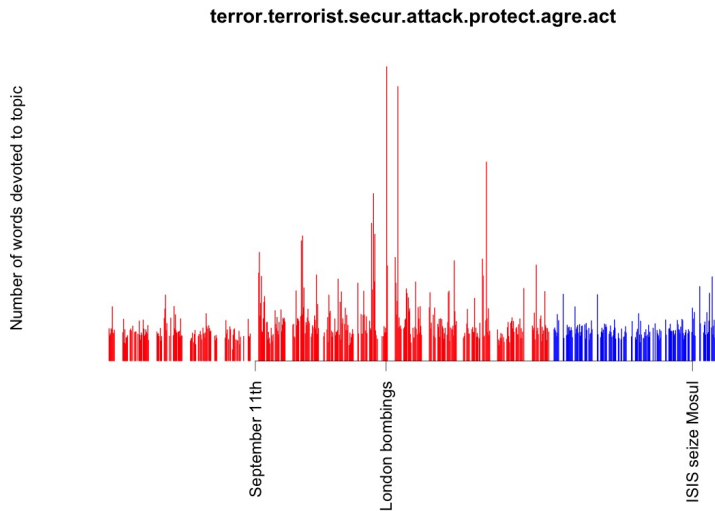
Predictive validity



Predictive validity



Predictive validity

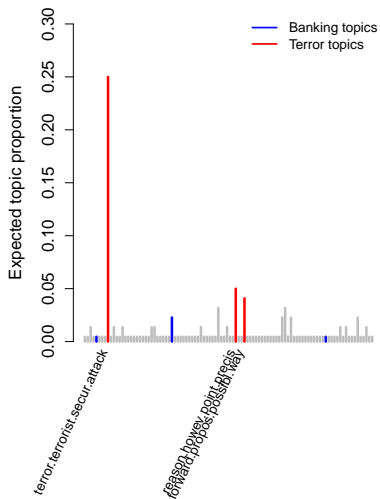
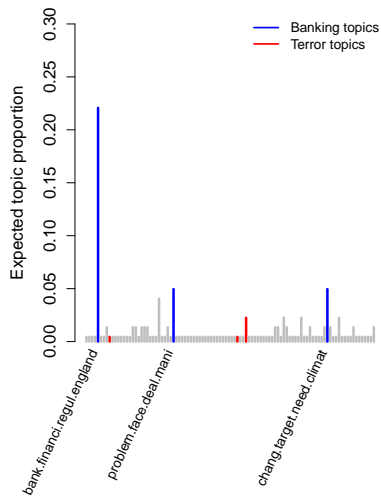


Semantic validity

The reforms that we are bringing into the banking system will include greater competition in banking. We will have a judgment from the European Commission soon, which we are supporting, that will allow more competition in British banking. As for the restructuring of the banking system and whether there should be investment banks on one side and retail-only banks on the other, the right hon. Gentleman must remember that Northern Rock was effectively a retail bank and it collapsed. Lehman Brothers was effectively an investment bank without a retail bank and it collapsed. The difference between retail and investment banks is not the cause of the problem. The cause of the problem is that banks have been insufficiently regulated at a global level and we have to set the standards for that for the future. We will be doing that at the G20 Finance Ministers summit in a few weeks' time.

The purpose of this coming before the House is for the Home Secretary to advise us that, in her view, there is an exceptional terrorist threat a grave terrorist threat that either has occurred or is occurring and that the need for action is urgent, but that it has not been possible to assemble the necessary evidence to lay charges within the 28 days. It will then be for the House to vote on the commencement order and agree that an exceptional terrorist incident has occurred. It is not the business of the House to interfere in the individual case, but it should be able to vote simply on whether an exceptional and grave terrorist threat has occurred. Given that the right hon. Gentleman and others have referred to the Civil Contingencies Act 2004 in discussing this issue, I would hope that he understands that this is exactly the same problem that has to be faced in respect of that Act.

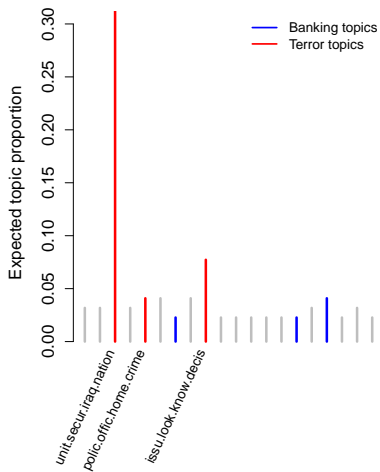
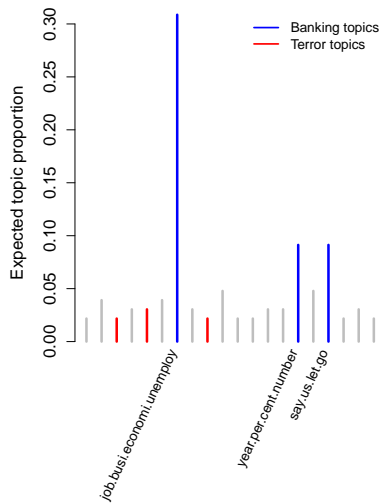
Semantic validity



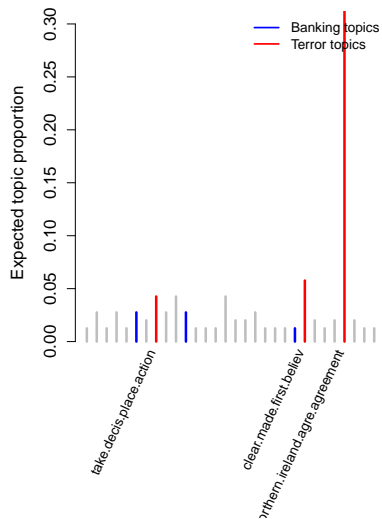
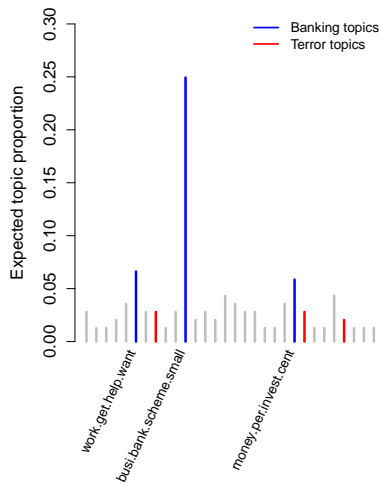
Semantic validity

- ▶ These plots suggest that our model is picking up at least some properties that we would intuitively expect to see in this particular corpus
- ▶ However, they do not help us to choose between the different models that we have estimated
- ▶ In other words, how should we pick K ?

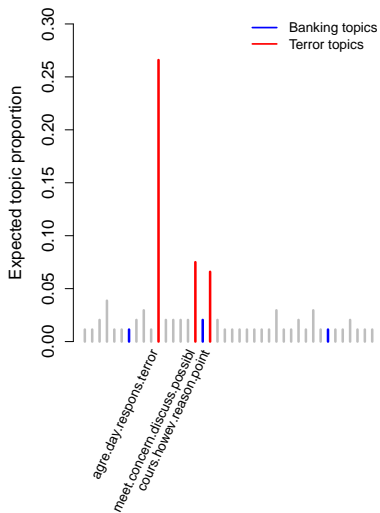
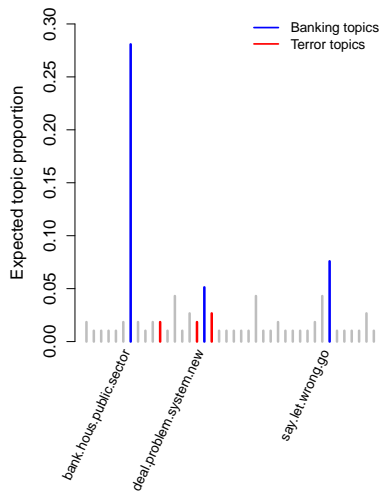
Which K? 20...



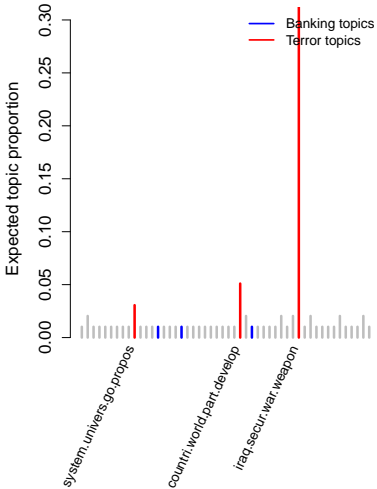
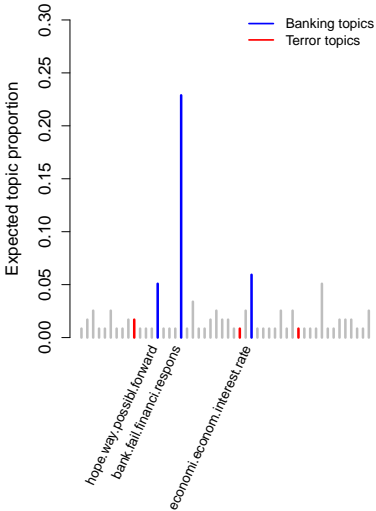
Which K? 30...



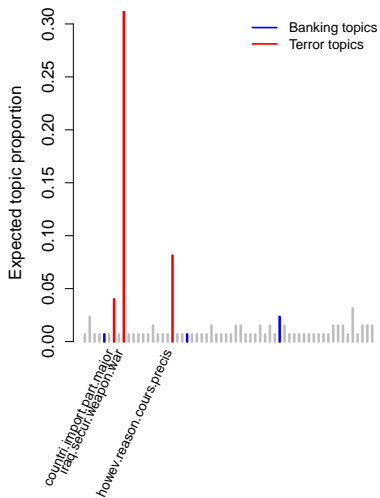
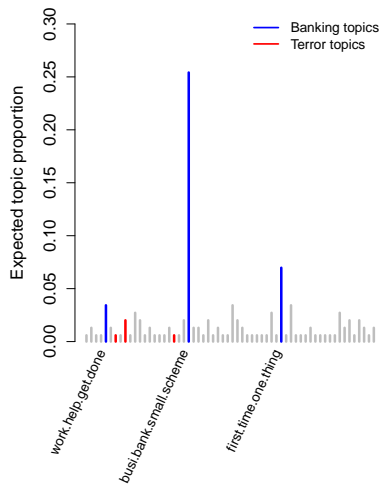
Which K? 40...



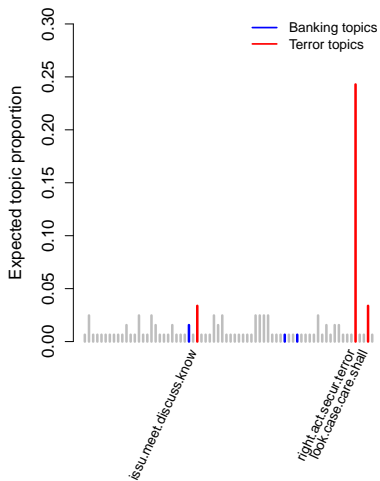
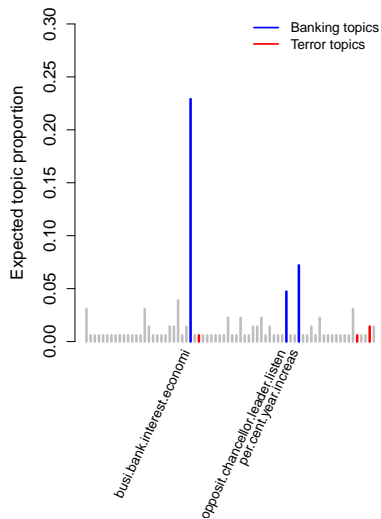
Which K? 50...



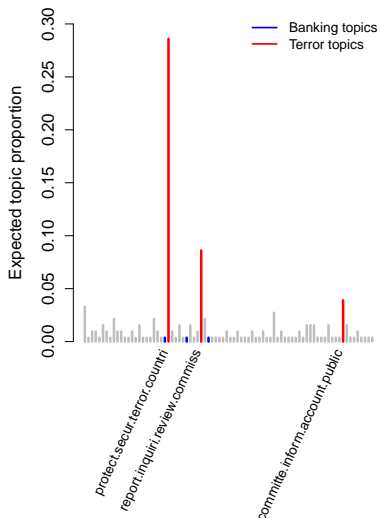
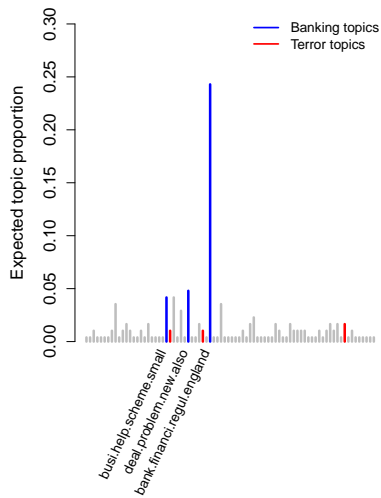
Which K? 60...



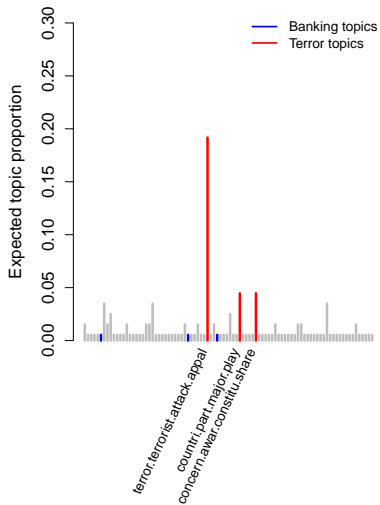
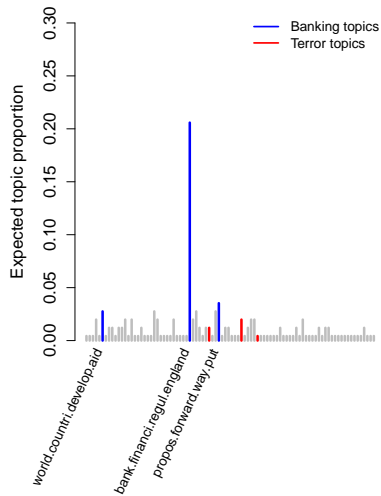
Which K? 70...



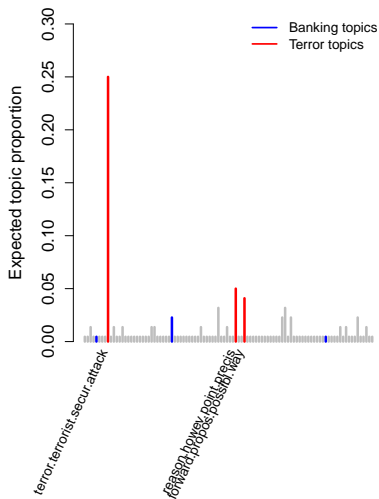
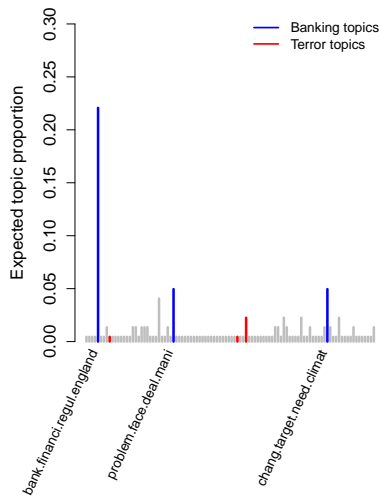
Which K? 80...



Which K? 90...



Which K? 100...



Semantic validity (revisited)

- ▶ Semantic validity requires that the topics are coherent and meaningful.
- ▶ We hope that texts assigned to a given topic are homogenous
- ▶ We hope that texts from different topics are distinctive
- ▶ This is a strong test of a topic model, but requires human input, which can be costly
- ▶ One option here would be to crowdsource the validation task to online workers
- ▶ Another option is to mercilessly exploit a class of participants by using crappy selective incentives (A PRIZE!!!!)

Semantic validity (revisited)

Related?

Unrelated ▼

NEXT COMPARISON.

Comparisons completed: 0

Text one:

That is total complacency about one month's figures when the Prime Minister has had five years of failure under this Government. Under this Prime Minister we are a country of food banks and bank bonuses; a country of tax cuts for millionaires while millions are paying more. Is not his biggest broken promise of all that we are all in it together?

Text two:

This is totally desperate stuff because the Prime Minister has nothing to say about the cost of living crisis. That is the reality, and his reshuffle had nothing to do with the country and everything to do with his party. After four years of this Government, we have a recovery that people cannot feel, a cost of living crisis that people cannot deny, and a Prime Minister whom people cannot believe.

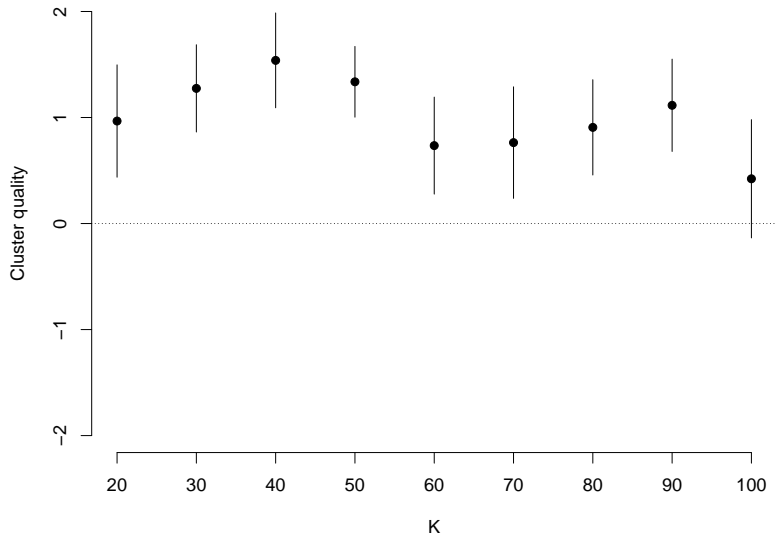
Semantic validity (revisited)

- ▶ Sample pairs of speeches from the posterior distribution
 - ▶ 5 pairs from the same topic, for each topic
 - ▶ 5 pairs from different topics, for each topic
- ▶ Randomly present to human coders, asking whether they are:
 - ▶ closely related (3)
 - ▶ loosely related (2)
 - ▶ unrelated (1)
- ▶ Calculate the 'Cluster Quality' for the topic by regressing

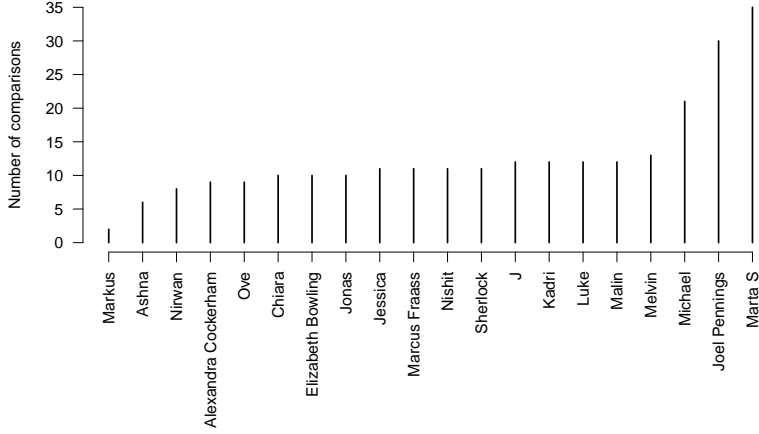
$$Related_{ik} = \alpha + \beta_k * SameTopic_{ik} + \gamma \quad (2)$$

- ▶ β_k is an estimate of the cluster quality of topic model k
 - ▶ i.e. the difference between relatedness of same-topic and different-topic pairs
- ▶ γ is a coder fixed-effect (Why?)
- ▶ Repeat for each value of K

Semantic validity (revisited)



Semantic validity (revisited)



An application

- ▶ Once we are happy with the topic model we have estimated, we can use the posterior distribution in various ways
 - ▶ Visualisation
 - ▶ Information retrieval
 - ▶ Corpus exploration
 - ▶ Similarity
 - ▶ Dimensionality reduction
- ▶ In this example, we can use the posterior distribution of document-topic proportions to ask: Which MPs are most active at asking questions in each topic?

$$MPAttention_{i,k} = \frac{MPWords_{i,k}}{\sum_1^K MPWords_{i,k}} \quad (3)$$

An application

bank.financi.regul

Christopher Gill
Malcolm Wicks
Tom Greatrex
Alasdair Morgan
Nick Herbert
Karl McCartney
Donald Gorrie
Justin Tomlinson
John Townend
Howard Flight
Derek Foster
Lindsay Roy

prison.justic.crimin

Jack Lopresti
Kevin McNamara
Alan Clark
Chris Skidmore
Charles Walker
Jeremy Wright
Tess Kingham
Sarah Champion
Philip Davies
Kali Mountford
Mike Wood
Lynda Waltho

terror.terrorist.secur

Shahid Malik
Parmjit Gill
George Mudie
Jonathan Djanogly
James Brokenshire
Tobias Ellwood
Brian Wilson
John Maples
Seamus Mallon
Ann Keen
Stephen Barclay
Pat McFadden

nhs.wait.hospit

Julia Goldsworthy
Seema Malhotra
Michael Penning
Nick Hurd
Virendra Sharma
Tim Farron
Bill Esterson
John Penrose
Malcolm Chisholm
Grant Shapps
Marion Roe
Mike Thornton

european.europ.britain

David Lock
William Cash
Alistair Darling
Denzil Davies
David Heathcoat-Amory
David Wilshire
David Davis
Giles Radice
Ann Winterton
Jenny Jones
Dale Campbell-Savours
Jacob Rees-Mogg

plan.economi.econom

Chloe Smith
Conor Burns
Donald Gorrie
Guy Opperman
Karen Bradley
Neil Carmichael
Wayne David
Michael Colvin
Michael Ellis
Anne Milton
John Stevenson
Sarah Newton

school.educ.children

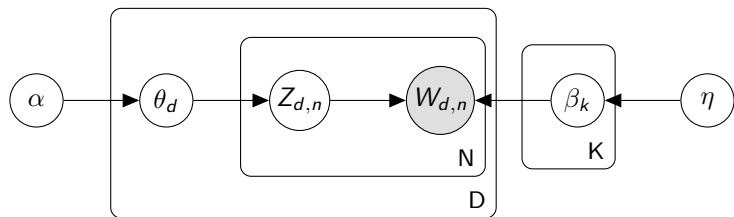
Christine Butler
Melanie Johnson
Julie Kirkbride
Sam Gyimah
Malcolm Moss
Paul Clark
Ian Liddell-Grainger
Michael Heseltine
Stephen Hammond
Chris Pond
Ivan Henderson
Derek Conway

iraq.weapon.war

Alan Howarth
Chris Smith
Tony Worthington
Terry Davis
George Foulkes
Jonathan Sayeed
Melanie Johnson
Denzil Davies
Paul Stinchcombe
Adam Price
Kevin Hughes
Tony Benn

Beyond Latent Dirichlet Allocation

LDA summary



- ▶ LDA is a simple topic model.
- ▶ It can be used to find topics that describe a corpus.
- ▶ Each document exhibits multiple topics.
- ▶ There are several ways to extend this model.

Extending LDA

- ▶ LDA can be **embedded in more complicate models**, embodying further intuitions about the structure of the texts.
- ▶ E.g., it can be used in models that account for syntax, authorship, word sense, dynamics, correlation, hierarchies, and other structure.
- ▶ The **data generating distribution** can be changed. We can apply mixed-membership assumptions to many kinds of data.
- ▶ E.g., we can build models of images, social networks, music, purchase histories, computer code, genetic data, and other types.
- ▶ The **posterior** can be used in creative ways.
- ▶ E.g., we can use inferences in information retrieval, recommendation, similarity, visualization, summarization, and other applications.

Extending LDA

- ▶ These different kinds of extensions can be combined.
- ▶ To give a sense of how LDA can be extended, we'll look at several examples of major extensions.
- ▶ We will discuss
 - ▶ Correlated topic models
 - ▶ Dynamic topic models
 - ▶ Structural topic models

Correlated and Dynamic Topic Models

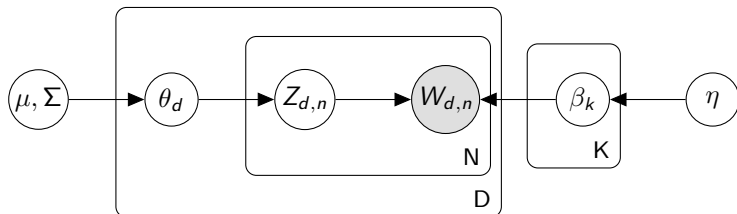
Correlated topic models

- ▶ The Dirichlet is a distribution on the simplex, positive vectors that sum to 1.
- ▶ It assumes that components are nearly independent.
- ▶ In real data, an article about fossil fuels is more likely to also be about geology than about genetics.
- ▶ The logistic normal is a distribution on the simplex that can model dependence between components (Aitchison, 1980).
- ▶ The log of the parameters of the multinomial are drawn from a multivariate Gaussian distribution,

$$X \sim N_k(\mu, \Sigma)$$

$$\theta_i \propto \exp\{x_i\}.$$

Correlated topic models

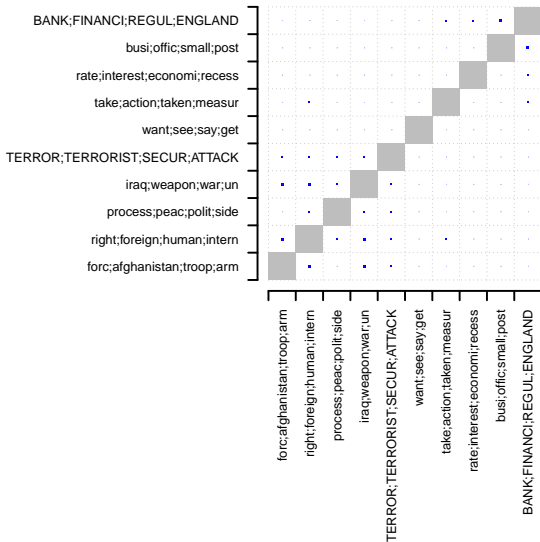


where the first node is logistic normal prior.

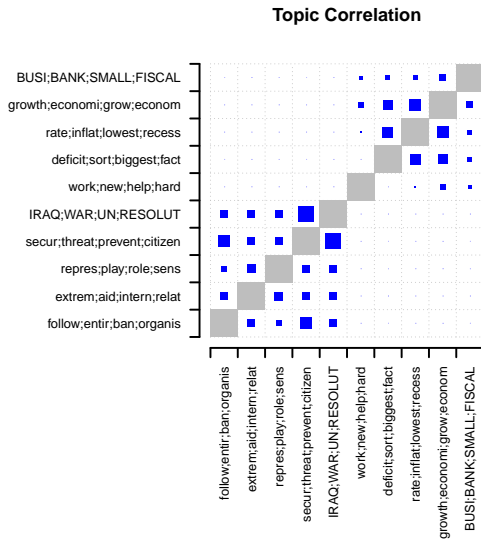
- ▶ Draw topic proportions from a logistic normal.
- ▶ This allows topic occurrences to exhibit correlation.
- ▶ Provides a “map” of topics and how they are related
- ▶ Provides a better fit to text data, but computation is more complex

LDA topic correlation

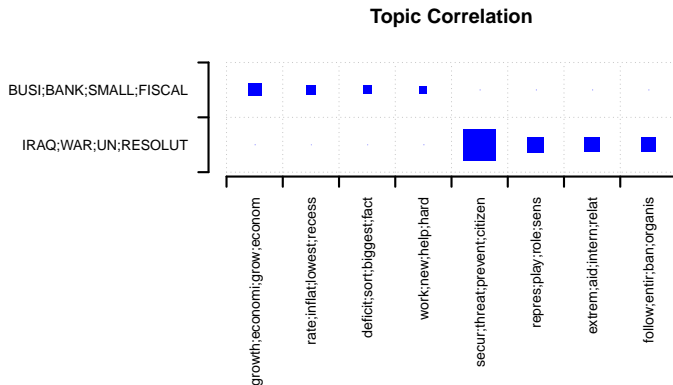
Topic Correlation



CTM topic correlation



CTM topic correlation



Dynamic topic models

- ▶ LDA assumes that the order of documents does not matter.
- ▶ Not appropriate for sequential corpora (e.g., that span hundreds of years)
- ▶ We may want to track how language changes over time.
 - ▶ How has the language used to describe neuroscience developed from “The Brain of Professor Laborde” (1903) to “Reshaping the Cortical Motor Map by Unmasking Latent Intracortical Connections” (1991)
 - ▶ How has the language used to describe love developed from “Pride and Prejudice” (1813) to “Eat, Pray, Love” (2006)
- ▶ Dynamic topic models let the topics drift in a sequence.

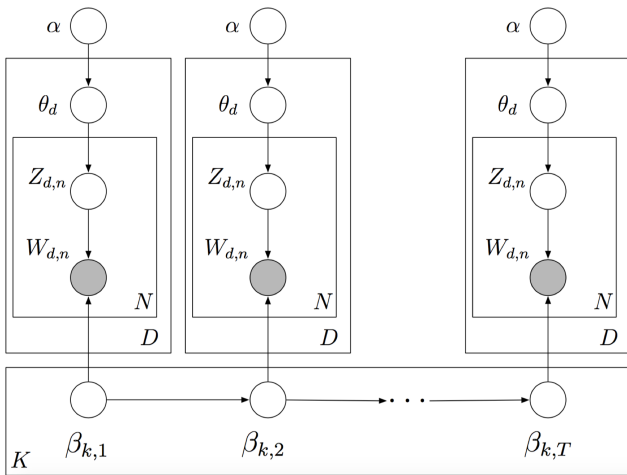
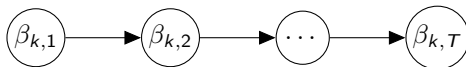


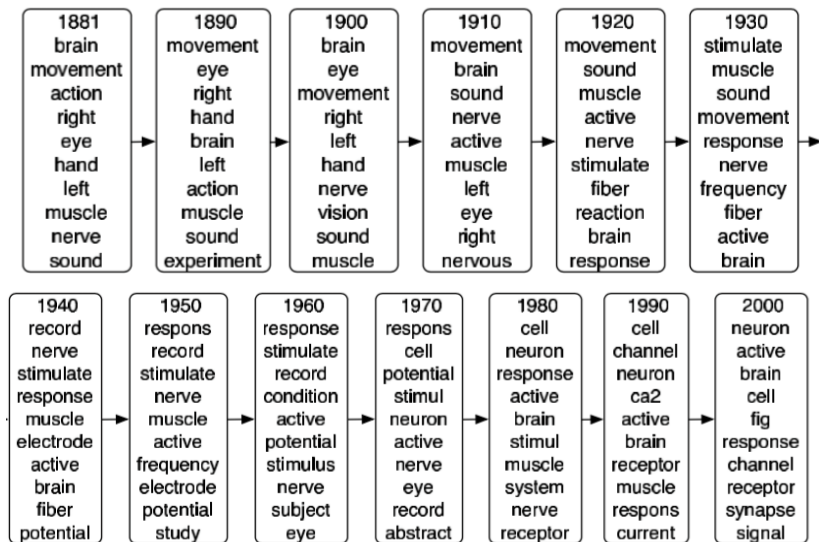
Plate (K) is topics drift through time.

Dynamic topic models



- ▶ Use a logistic normal distribution to model topics evolving over time.
 - ▶ The k th topic at time 2 has evolved smoothly from the k th topic at time 1
- ▶ As for CTMs, this makes computation more complex. But it lets us make inferences about sequences of documents.

Dynamic topic models



Summary: Correlated and dynamic topic models

- ▶ The Dirichlet assumption on topics and topic proportions makes strong conditional independence assumptions about the data.
- ▶ The **correlated topic model** uses a logistic normal on the topic proportions to find patterns in how topics tend to co-occur.
- ▶ The **dynamic topic model** uses a logistic normal in a linear dynamic model to capture how topics change over time.
- ▶ What's the catch? These models are harder to compute.

Structural Topic Model

Structural Topic Model

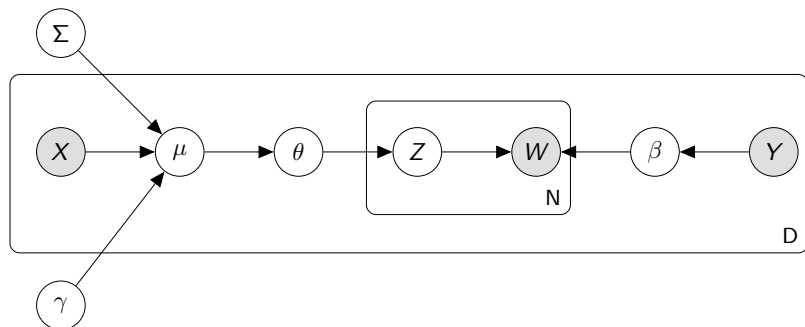
- ▶ Typically, when estimating topic models we are interested in how some covariate is associated with the prevalence of topic usage (Gender, date, political party, etc)
- ▶ The Structural Topic Model (STM) allows for the inclusion of arbitrary covariates of interest into the generative model
- ▶ The addition of covariates provides structure to the prior distributions
 1. Benefit 1: improves the estimation of the topics by allowing documents to share information according to the covariates (known as ‘partial pooling’ of parameters)
 2. Benefit 2: the relationship between covariates and latent topics is most frequently the estimand of interest, so we should include this in the estimation procedure

Structural Topic Model

How does it differ from LDA?

- ▶ As with the CTM, topics within the STM can be **correlated**
- ▶ **Topic prevalence** is allowed to vary according to the covariates X
 - ▶ Each document has its own prior distribution over topics, which is defined by its covariates, rather than sharing a global mean
- ▶ **Topical content** can also vary according to the covariates Y
 - ▶ Word use *within* a topic can differ for different groups of speakers/writers

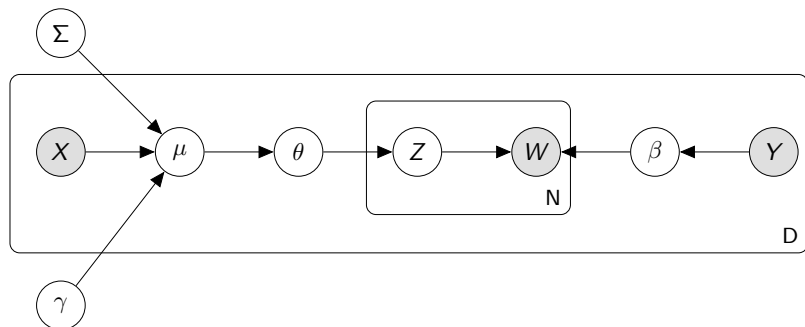
Structural topic model



Topic prevalence model:

- ▶ Draw topic proportions from a logistic normal generalised linear model based on covariates X
- ▶ This allows the expected document-topic proportions to vary by covariates, rather than from a single shared prior

Structural topic model



Topical content model:

- ▶ The β coefficients, which indicate the distribution over words for a given topic, are allowed to vary according to the covariates Y
- ▶ This allows us to estimate how different covariates affect the words used *within a given topic*

Structural Topic Model – example

- ▶ In the legislative domain, we might be interested in the degree to which MPs from different parties represent distinct interests in their parliamentary questions
- ▶ We can use the STM to analyse how topic prevalence varies by party

```
1 ## Convert DFM for usage in 'stm' package
2 stmTexts <- convert(speechDFM,
3                     to = 'stm',
4                     docvars = docvars(speechCorpus))
5
6 ## Set topic count and estimate LDA using Gibbs sampling
7 K <- 60
8 stmOut <- stm(stmTexts$documents,
9               stmTexts$vocab,
10               data= stmTexts$meta,
11               prevalence = ~party,
12               content = ~party,
13               K, seed = 123)
```

Structural Topic Model – example

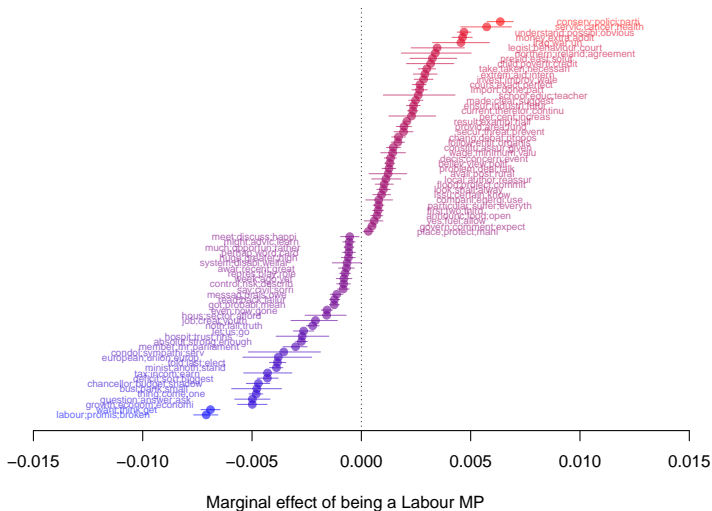
- ▶ Specify a linear model with:
 - ▶ the topic proportions of speech d , by legislator i as the outcome
 - ▶ the party of legislator i as the predictor

$$\theta_{dk} = \alpha + \gamma_{1k} * \text{labour}_{di} \quad (4)$$

- ▶ The γ_k coefficients give the estimated difference in topic proportions for Labour and Conservative legislators for each topic

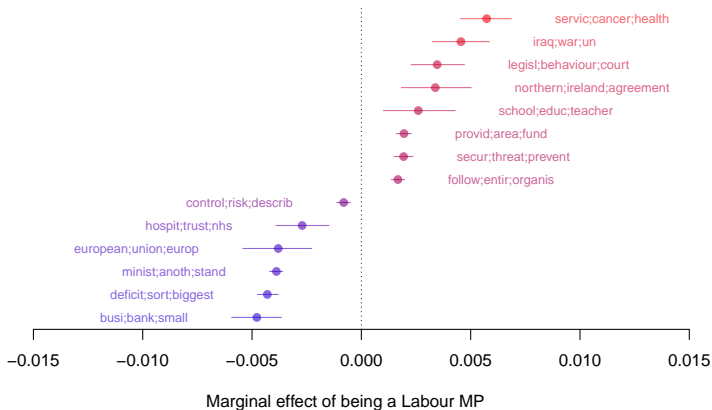
Topic prevalence

Labour vs Conservative topic differences

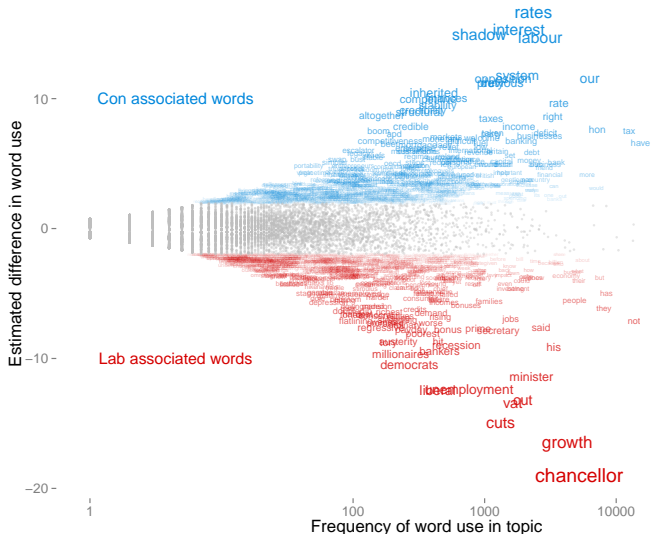


Topic prevalence

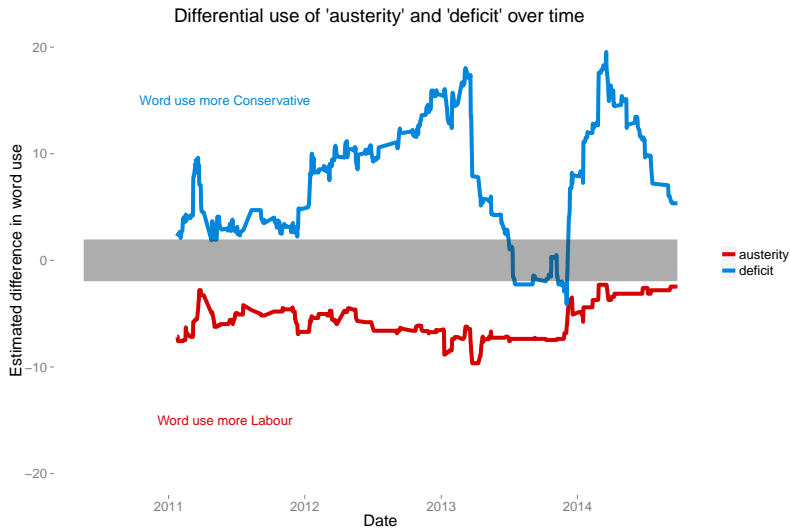
Labour vs Conservative topic differences



Topical content



Topical content



Summary

Topics

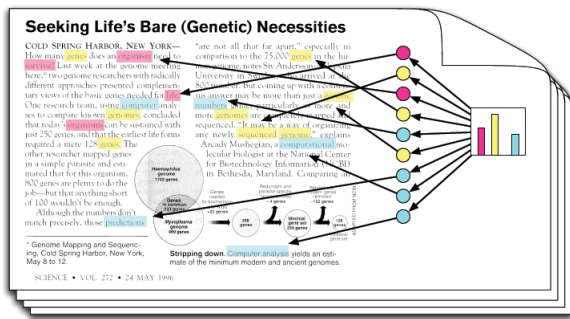
gene 0.04
dna 0.02
genetic 0.01
...

life 0.02
evolve 0.01
organism 0.01
...

brain 0.04
neuron 0.02
nerve 0.01
...

data 0.02
number 0.02
computer 0.01
...

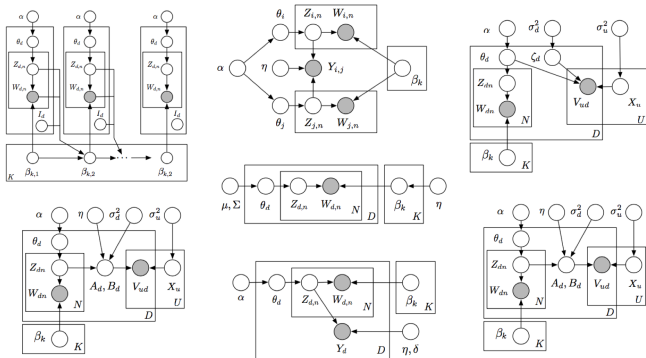
Documents



Topic proportions and assignments

- ▶ LDA assumes that there are K topics shared by the collection.
- ▶ Each document exhibits the topics with different proportions.
- ▶ Each word is drawn from one topic.
- ▶ We discover the structure that best explain a corpus.

Summary



Topic models can be adapted to many settings

- relax assumptions
- combine models
- model more complex data

Implementations of topic models in R

Incomplete list:

- ▶ `topicmodels`
- ▶ `lda`
- ▶ `stm`
- ▶ `mallet`