Topic Models

HSS 510: NLP for HSS

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Agenda

Things to be covered

- What is topic modeling
- Latent Dirichlet Allocation
- Extensions
  - Correlated Topic Model
  - Dynamic Topic Model
  - Structural Topic Model
- Model selection and interpretation
- Summary

What is Topic Model

Multi-membership, unsupervised algorithms to discover topics

- Offers an automated method to discover topics in a corpus of documents
  - Used to understand and organize large collections of documents according to the discovered topics
  - Either for exploration or for measurement
- Documents can contain multiple topics ($\Longleftrightarrow$ clustering algorithms)
- Unsupervised learning (no manual labeling of topics)

What is Topic Model

Multi-membership, unsupervised algorithms to discover topics

- Topic: what is being talked about/written about
  - Unclear what topic actually means in theoretical terms
  - Topic models assume an intuitive and abstract notion of a topic
- *"The meaning of a topic in an LDA topic model must be assessed empirically instead and defined against the background of substantive theoretical concepts, such as political issues or frames* (Maier et al. 2018)
  - See the labeling of topics in U.S. legislators' tweets at the end of the lecture

What is Topic Model

LDA and its extensions

- Latent Dirichlet Allocation (LDA) is one fundamental approach (Blei et al., 2003)
- Alternative approaches
  - Correlated Topic Model (CTM)
  - Structural Topic Model (STM)
  - Dynamic Topic Model (DTM)
  - Clustering of transformer-based embeddings (next lecture)

Topic Model in Context

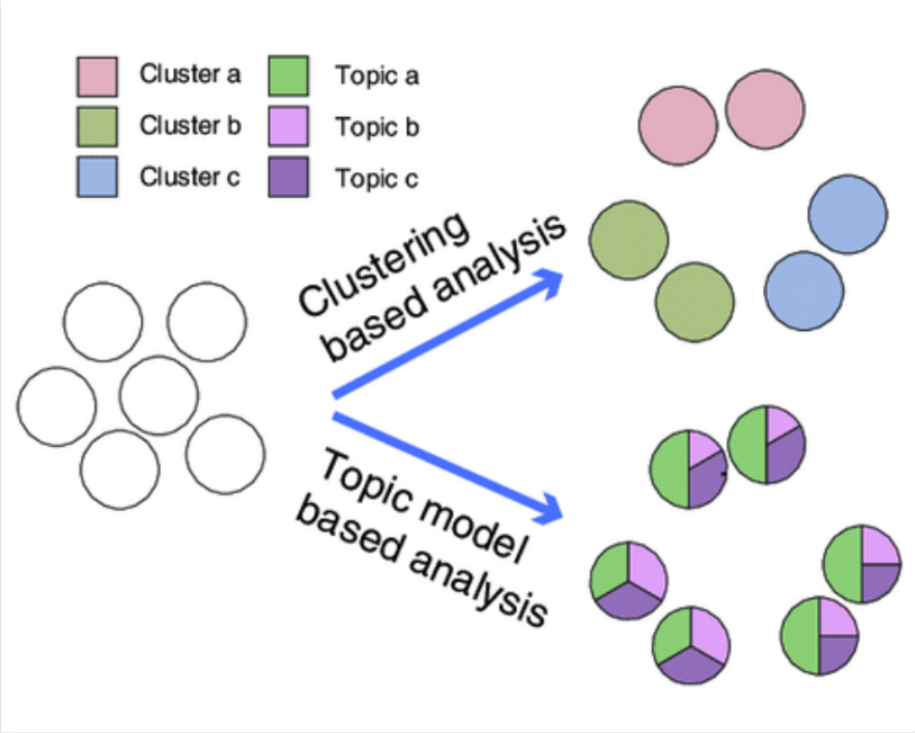
Supervised vs. Unsupervised

	Supervised	**Unsupervised**
Objective	Trained on a labeled data to learn a mapping from input to output	Find patterns or structures within data without labels
Outcome	Pre-defined categories	Not quite pre-defined
Model evaluation	Explicit metrics such as accuracy, precision, recall, or MSE	Can involve qualitative assessment
Examples	Classification/regression for texts	**Topic models**

Topic Model in Context

Clustering algorithms vs. Topic models

- Clustering (e.g., K-means) assumes that each document belongs to one cluster
- Documents can have more than one idea in them (e.g., political speeches, newspaper articles, novels)
- Click for figure source



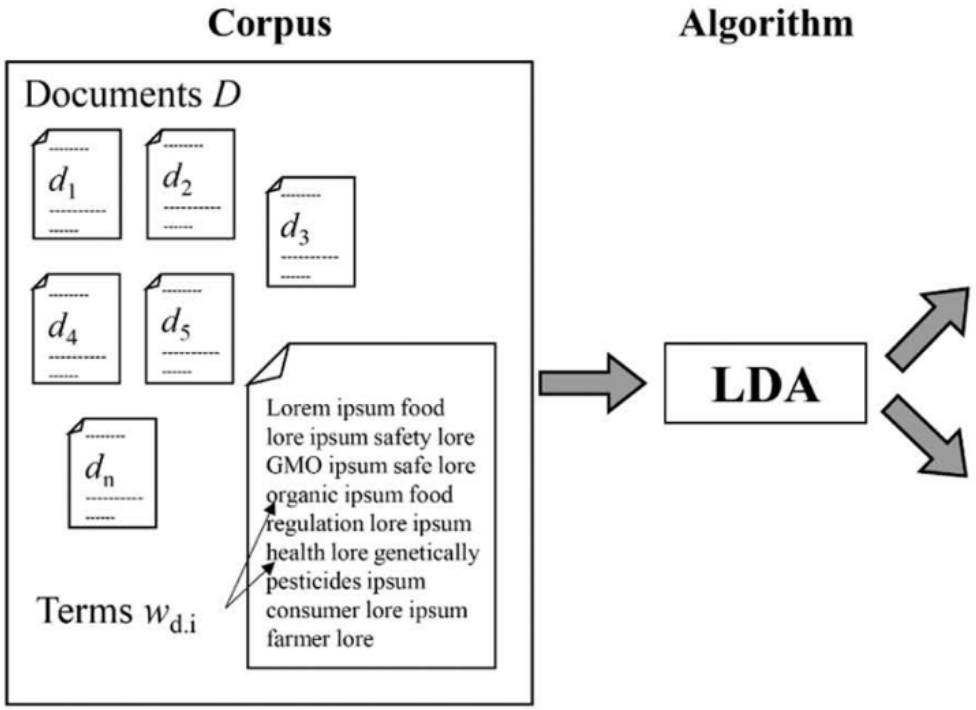
Latent Dirichlet Allocation (LDA)

Used to identify the latent topic structure within a corpus

- One of many statistical algorithms for topic modeling
- Most seminar and widely used model
- Estimated via Bayesian frameworks
- “Documents” are seen as “distributions over topics”
- “Topics” are seen as “distributions over words”
- Make use of the BoW (Bag of Words) assumption

Latent Dirichlet Allocation (LDA)

The framework of LDA (adaped from Maier et al. 2018)



Algorithm

LDA

Results

V	Topic$_1$	Topic$_2$	…	Topic$_K$
food	0.09	0.07	…	0.02
health	0.10	0.05	…	0.01
GMO	0.04	0.01	…	0.20
safety	0.03	0.03	…	0.05
farmer	0.01	0.10	…	0.07
…	…	…	…	…

D	Topic$_1$	Topic$_2$	…	Topic$_K$
d_1	0.10	0.04	…	0.02
d_2	0.05	0.03	…	0.02
d_3	0.02	0.03	…	0.09
d_4	0.07	0.05	…	0.01
…	…	…	…	…
d_D	0.08	0.01	…	0.10

LDA: Key Distributions

Multinomial distribution

- Generalization of binomial distribution (e.g., flipping a coin)
- Probabilities of different outcomes (not just two)
- E.g., rolling a (6-sided) dice
  - Each side (from 1 to 6): discrete outcome
  - The probabilities sum up to 1 ($\frac{1}{6} + \ldots + \frac{1}{6} = 1$)
- E.g., allocating a pie to one of 3 people
  - Each person: discrete outcome
  - The probabilities sum up to 1 ($\frac{1}{4} + \frac{1}{4} + \frac{1}{2} = 1$)

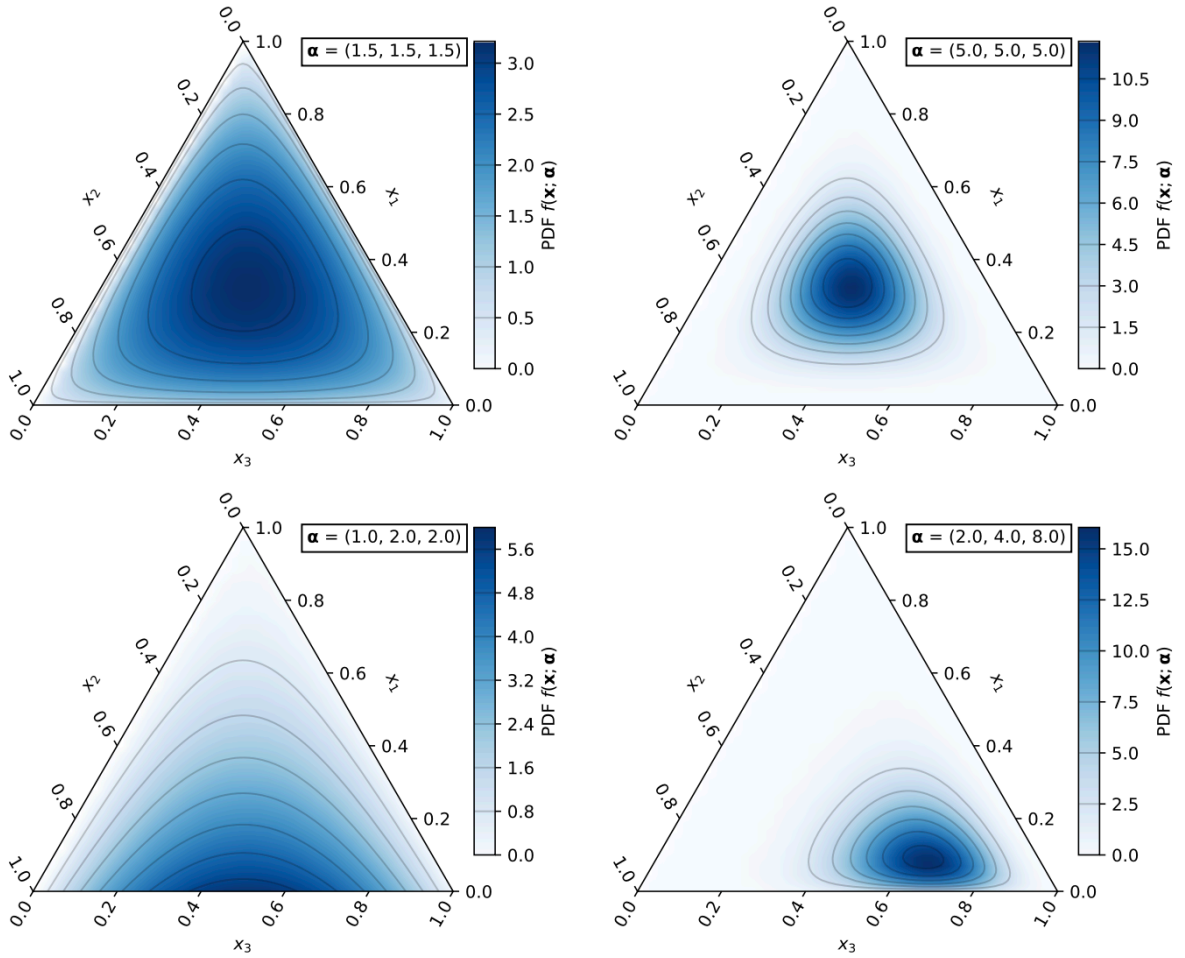
LDA: Key Distributions

Dirichlet distribution

- Provides a way to randomly generate *multinomial distributions*
- The pie split example
  - Imagine if you did not decide ahead of time exactly how to slice the pie
  - Instead, we specify a random process to decide how likely each person gets the pie
  - Equal chances among the three people, or perhaps it's more likely that one person gets it than the others
  - E.g., `[0, 0, 1]`, `[1/3, 1/3, 1/3]`, `[1/2, 1/4, 1/4]`, etc.

LDA: Key Distributions

$Dir(x = 3; \alpha)$



LDA: Generative process

Consider a corpus of D documents, each with N_d words

- Assume a statistical model that generated our documents, then estimate the model and recover latent (unobserved) topics
- **Each document** is seen as **a multinomial distribution over topics**
- **Each topic** is seen as **a multinomial distribution over words**
- E.g., a stylized corpus with D = 5, N = 8 per document (and also 8 unique words in the corpus in total), and K = 3

LDA: Generative process

E.g., $D = 5$, $K = 3$, $N = 8$

- θ_d ~ Dir(α): for each d, its **topic distribution** is drawn from a Dirichlet distribution (e.g., θ_1 = [0.1, 0.7, 0.2])
- β_k ~ Dir(η): for each k, its **word distribution** is drawn from another Dirichlet distribution (e.g., β_2 = [0, 0, 0.2, 0.1, 0, 0, 0.3, 0.4])
- $z_{d,n}$ ~ Multinomial(θ_d): for each document-word position, its topic is drawn from θ_d (i.e., Topic 1 can be drawn)
- $w_{d,n}$ ~ Multinomial($\beta_{z_{d,n}}$): for each document-word position, its word is drawn from the corresponding topic distribution (i.e., Word 8 can be drawn)

LDA: Generative process

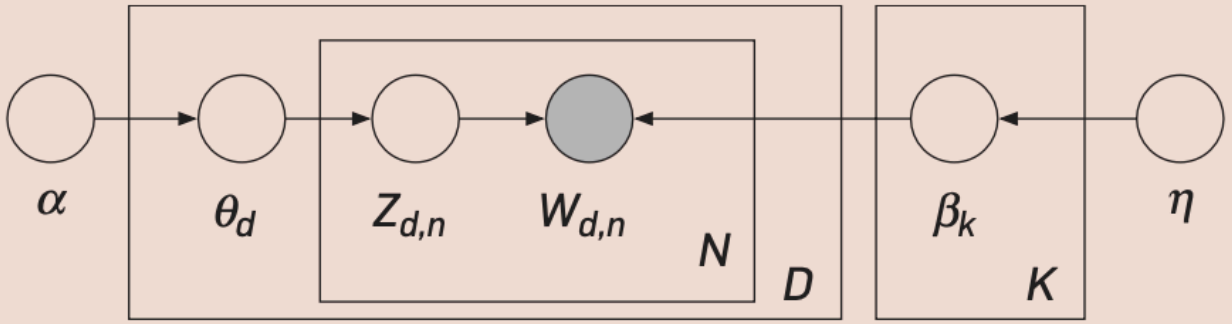
In summary, the joint probability is the following

- θ_d ~ Dir(α) for $d \in \{1, \ldots, D\}$
- β_k ~ Dir(η) for $k \in \{1, \ldots, K\}$
- $z_{d,n}$ ~ Multinomial(θ_d)
- $w_{d,n}$ ~ Multinomial($\beta_{z_{d,n}}$)

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n} | \theta_d) p(w_{d,n} | \beta_{1:K}, z_{d,n}) \right)$$

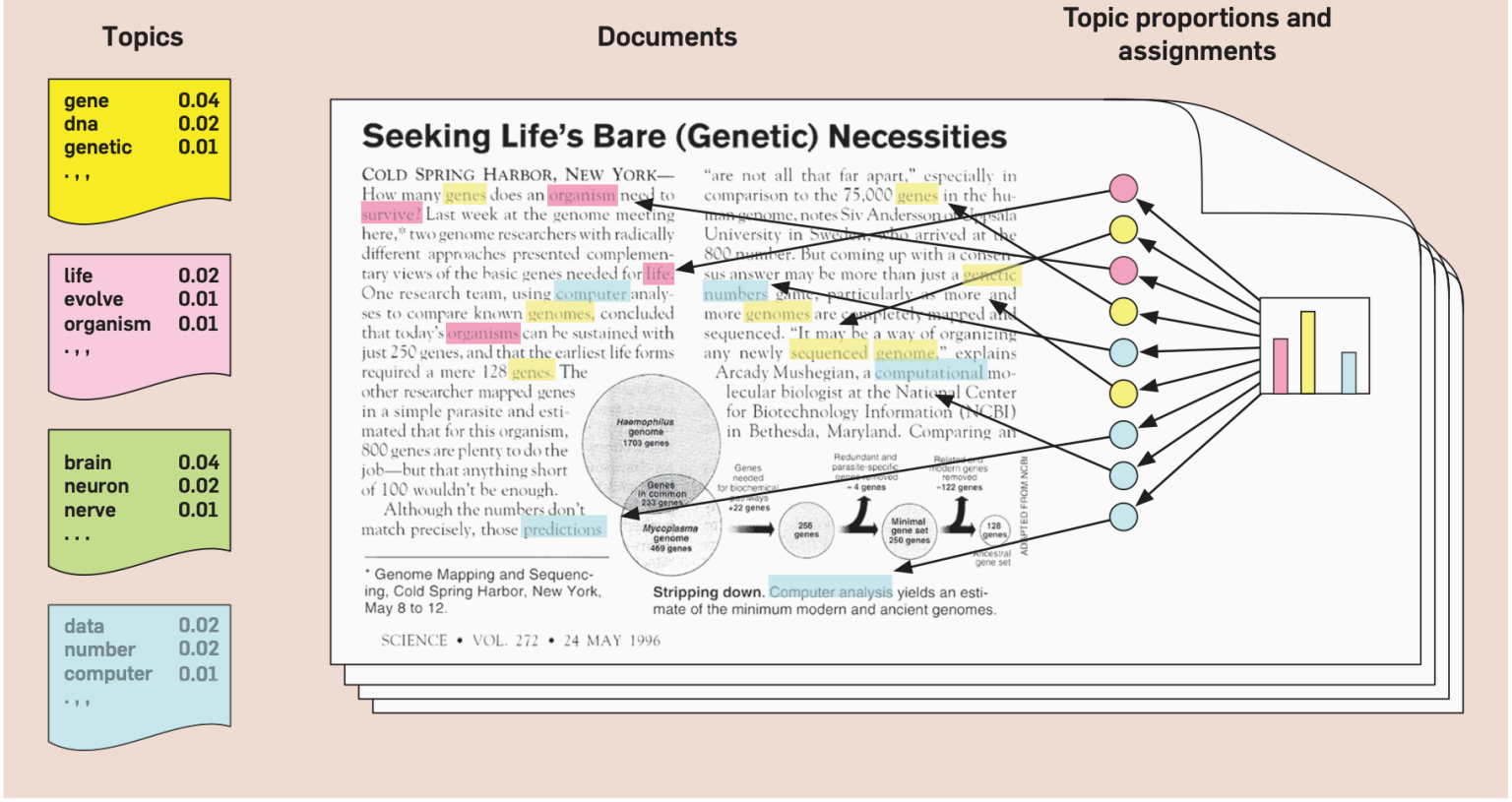
LDA: Generative process

Figure 4. The graphical model for latent Dirichlet allocation. Each node is a random variable and is labeled according to its role in the generative process (see Figure 1). The hidden nodes—the topic proportions, assignments, and topics—are unshaded. The observed nodes—the words of the documents—are shaded. The rectangles are "plate" notation, which denotes replication. The *N* plate denotes the collection words within documents; the *D* plate denotes the collection of documents within the collection.



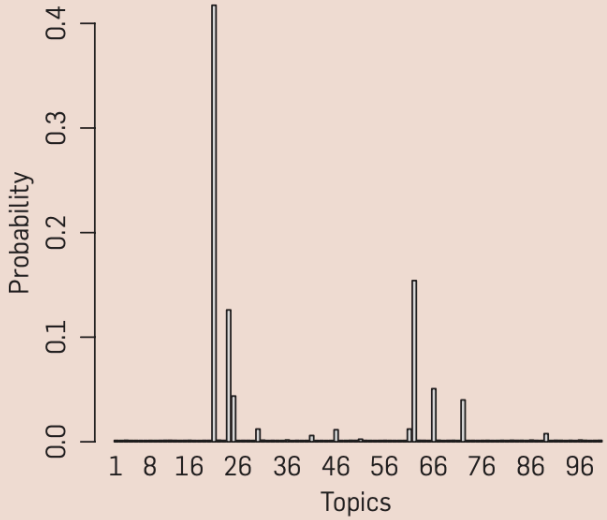
LDA: Generative process

Figure 1. The intuitions behind latent Dirichlet allocation. We assume that some number of "topics," which are distributions over words, exist for the whole collection (far left). Each document is assumed to be generated as follows. First choose a distribution over the topics (the histogram at right); then, for each word, choose a topic assignment (the colored coins) and choose the word from the corresponding topic. The topics and topic assignments in this figure are illustrative—they are not fit from real data. See Figure 2 for topics fit from data.



LDA: Generative process

Figure 2. Real inference with LDA. We fit a 100-topic LDA model to 17,000 articles from the journal *Science*. At left are the inferred topic proportions for the example article in Figure 1. At right are the top 15 most frequent words from the most frequent topics found in this article.



"Genetics"	"Evolution"	"Disease"	"Computers"
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

LDA: Estimation

E.g., with D = 1000, V = 10000, and K = 3

- LDA estimates θ (distributions over topics) and β (distributions over vocabularly)

$$\theta = \underbrace{\begin{pmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} \\ \theta_{2,1} & \theta_{2,2} & \theta_{2,3} \\ \dots & \dots & \dots \\ \theta_{1000,1} & \theta_{1000,2} & \theta_{1000,3} \end{pmatrix}}_{1000 \times 3} = \underbrace{\begin{pmatrix} 0.7 & 0.2 & 0.1 \\ 0.3 & 0.1 & 0.6 \\ \dots & \dots & \dots \\ 0.1 & 0.8 & 0.1 \end{pmatrix}}_{1000 \times 3}$$

$$\beta = \underbrace{\begin{pmatrix} \beta_{1,1} & \beta_{1,2} & \dots & \beta_{1,10000} \\ \beta_{2,1} & \beta_{2,2} & \dots & \beta_{2,10000} \\ \beta_{3,1} & \beta_{3,2} & \dots & \beta_{3,10000} \end{pmatrix}}_{3 \times 10000} = \underbrace{\begin{pmatrix} 0.04 & 0.01 & \dots & 0.0001 \\ 0.00002 & 0.001 & \dots & 0.05 \\ 0.00001 & 0.03 & \dots & 0.0001 \end{pmatrix}}_{3 \times 10000}$$

LDA: Estimation

Estimation is done in a Bayesian framework

- Dir(α) and Dir(η) are the so called "prior distributions" of θ and β (`Pr(B)`)
- With Bayes' rule (likelihood: `Pr(A|B)`; evidence: (`Pr(A)`)), we update these prior distributions to obtain "posterior distributions for θ and β (`Pr(B|A)`)
- Estimation methods (see Blei (2012) for more discussions)
  - Gibbs sampling methods
  - Variational approximations

Model Selection

Determining hyperparameters: K (and α, η)

- A combination of quantitative metrics and human judgement
- The Dirichlet priors;
  α (the topic distribution prior) and
  η (the word distribution prior)
  - Often set asymmetric (e.g., [0.1, 0.1, 0.1] for K = 3)
  - Typically both are set at 0.1 or 0.01 (the smaller, the fewer topics/words dominate) but this *can be tuned and affect* model performance
  - See (Maier et al. 2018) for more discussions

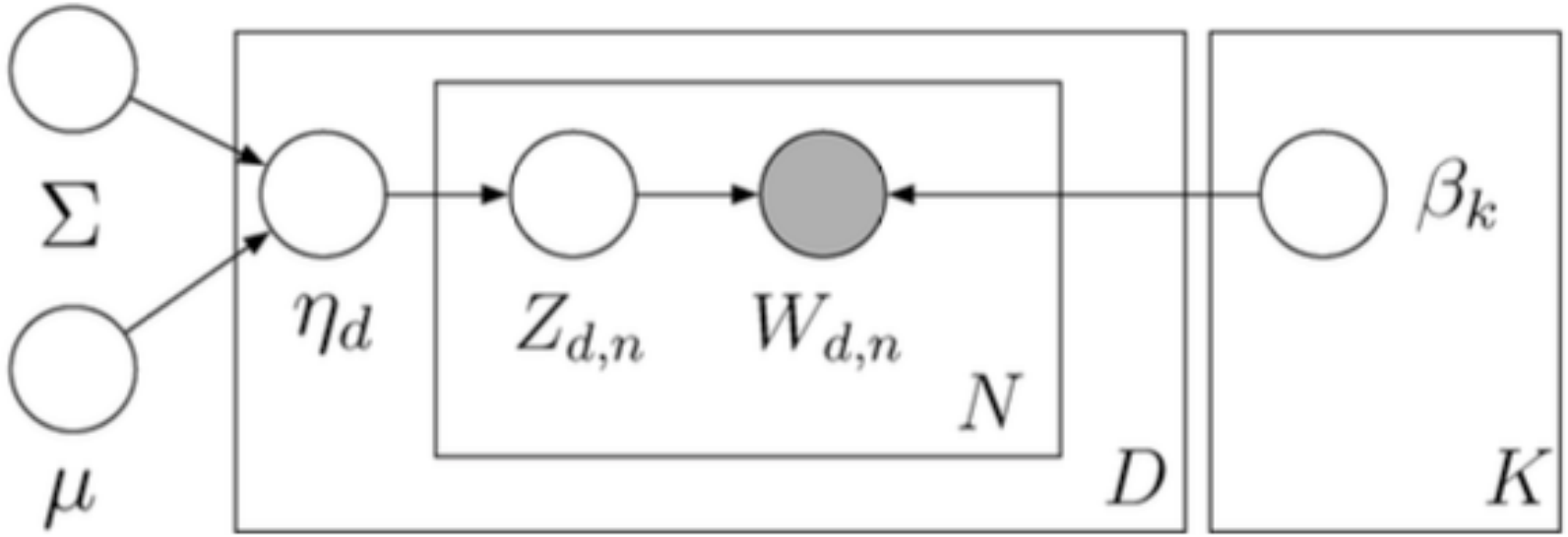
Extensions

Correlated Topic Model (CTM)

- Blei and Lafferty (2005) and (2007)
- A limitation of LDA is the inability to model topic correlation
- “A document about genetics is more likely to also be about disease than X-ray astronomy” (Blei and Lafferty (2007))
- CTM relies on logistic normal distribution, which allows for modeling correlations between topics through a covariance matrix
- The authors report that this can lead to a better model fit (what the model fit means will be discussed soon)

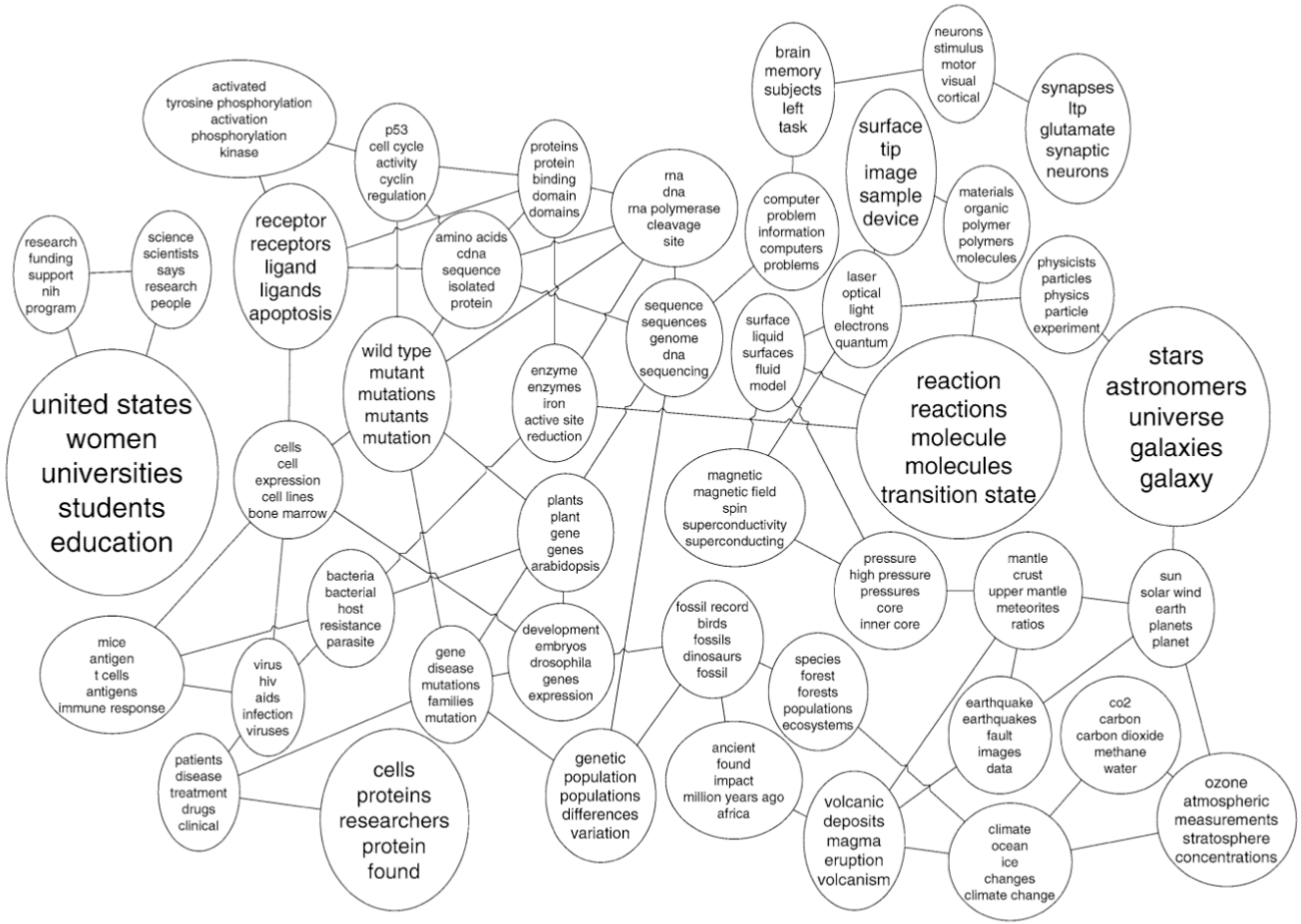
Extensions

Correlated Topic Model (CTM)



Extensions

Correlated Topic Model (CTM)



Extensions

Correlated Topic Model (CTM)

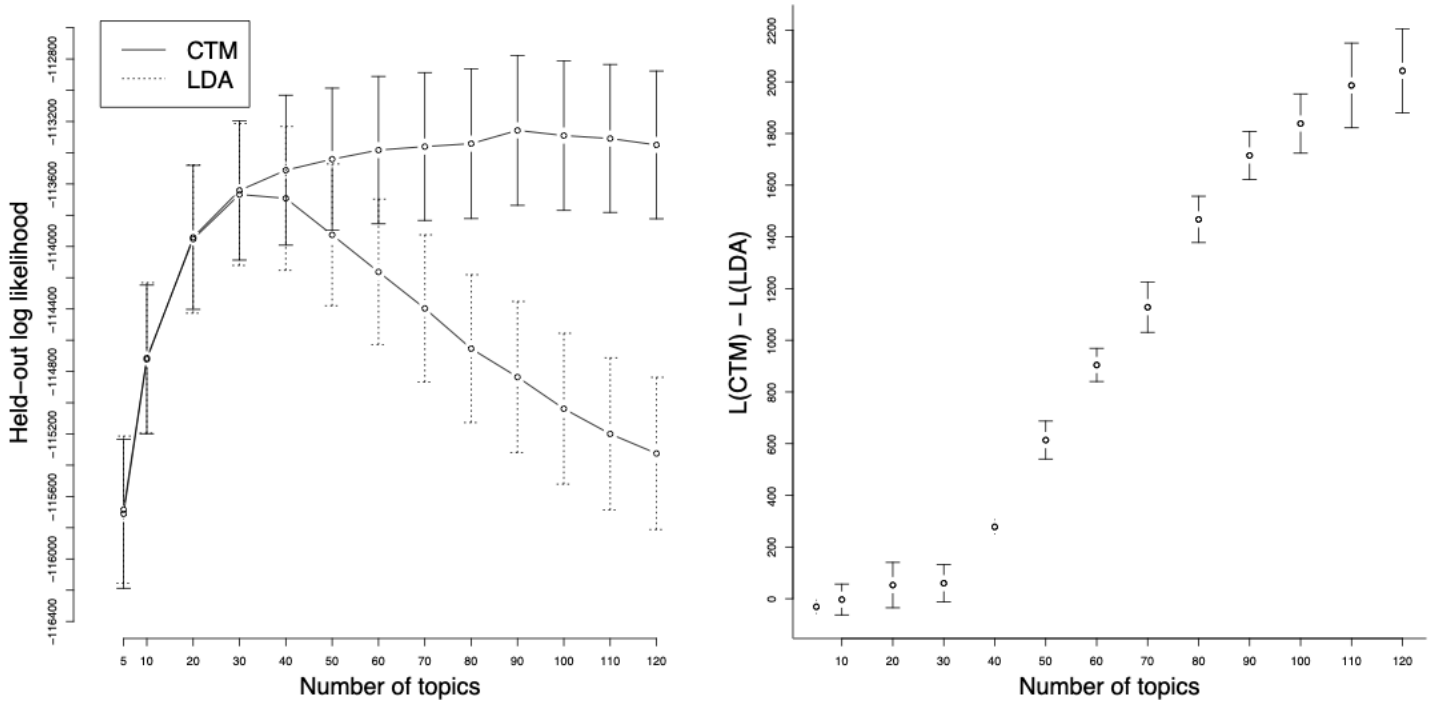


Figure 3: (L) The average held-out probability; CTM supports more topics than LDA. See figure at right for the standard error of the difference. (R) The log odds ratio of the held-out probability. Positive numbers indicate a better fit by the correlated topic model.

Extensions

Dynamic Topic Model (DTM)

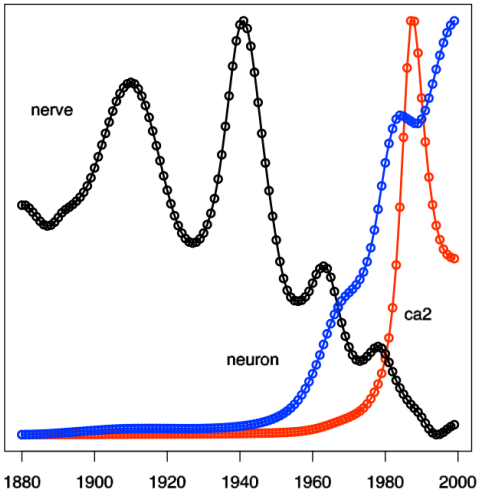
- Blei and Lafferty (2006) and Blei (2012)
- LDA assumes that the temporal order of documents does not matter
- This can be unrealistic when analyzing long-running collections
- Instead of a single distribution over words, a topic is now a sequence of distribution over words

Extensions

Dynamic Topic Model (DTM)

1881	1890	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000
brain	movement	brain	movement	movement	stimulate	record	respons	response	respons	cell	cell	neuron
movement	eye	eye	brain	sound	muscle	nerve	record	stimulate	cell	neuron	channel	active
action	right	movement	sound	muscle	sound	stimulate	stimulate	record	potential	response	neuron	brain
right	hand	right	nerve	active	movement	response	nerve	condition	stimul	active	ca2	cell
eye	brain	left	active	nerve	response	muscle	muscle	active	neuron	brain	active	fig
hand	left	hand	muscle	stimulate	nerve	electrode	active	potential	active	stimul	brain	response
left	action	nerve	left	fiber	frequency	active	frequency	stimulus	nerve	muscle	receptor	channel
muscle	muscle	vision	eye	reaction	fiber	brain	electrode	nerve	eye	system	muscle	receptor
nerve	sound	sound	right	brain	active	fiber	potential	subject	record	nerve	respons	synapse
sound	experiment	muscle	nervous	response	brain	potential	study	eye	abstract	receptor	current	signal

"Neuroscience"



1887 Mental Science
1900 Hemianopsia in Migraine
1912 A Defence of the ``New Phrenology''
1921 The Synchronal Flashing of Fireflies
1932 Myoesthesis and Imageless Thought
1943 Acetylcholine and the Physiology of the Nervous System
1952 Brain Waves and Unit Discharge in Cerebral Cortex
1963 Errorless Discrimination Learning in the Pigeon
1974 Temporal Summation of Light by a Vertebrate Visual Receptor
1983 Hysteresis in the Force-Calcium Relation in Muscle
1993 GABA-Activated Chloride Channels in Secretory Nerve Endings

Extensions

Structural Topic Model (STM)

- Roberts et al. (2013) and Roberts et al. (2014)
- Key motivation: short documents do not provide the opportunity to observe the correlations between words—key information used to estimate topics
- "Structure": how document-level covariates drives topics
  - E.g., group, time, etc.
- Covariates can be modeled to estimate **a) topic prevalence** and **b) topic content**
- Without any covariates, the model reduces to CTM

Extensions

Structural Topic Model (STM)

- Topic prevalence
  - Documents which have similar covariates will tend to talk about the same topics
  - Topic proportions within documents can vary through covariates
  - E.g., social media posts by Republican politicians might have different topic proportions than those posted by Democrats

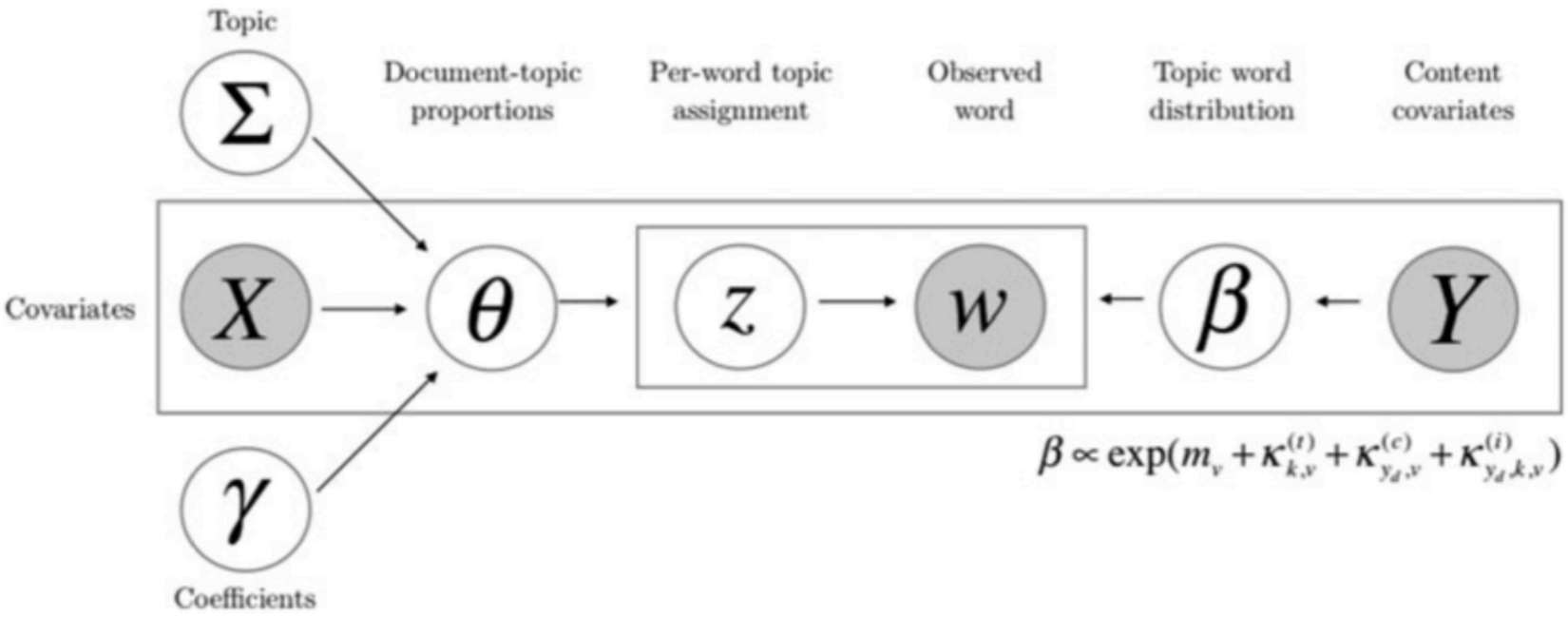
Extensions

Structural Topic Model (STM)

- Topic content
  - Word proportions within topics can vary through covariates
  - Documents which have similar covariates will tend to talk about topics in a similar way
  - E.g. when talking about a health care topic, Republican politicians might use different words than Democrats

Extensions

Structural Topic Model (STM)



Model Selection and Interpretation

Quantitative + qualitative approaches

- Quantitative
  - Perplexity (or held-out likelihood): for some held-out documents, how likely would the model have generated/predicted these documents?
    - Evaluation of predictive power ≠ coherent topics
    - For how they differ, see Chang et al.(2009) and/or this video)
  - Semantic coherence: how likely do the most common words for a topic co-occur in the same documents?
  - Exclusivity: do words with high probability in one topic have low probabilities in others?

Model Selection and Interpretation

Quantitative + qualitative approaches

- Qualitative
  - Careful reading of exemplar texts
    - Select a small subset of the documents with the highest proportion of the document assigned to the particular category under consideration
    - Read those documents to assess their common facets and interrogate whether a particular organization makes sense
  - Examine words that are indicative of a particular topic
    - The most straightforward method for obtaining these words is to select the highest probability words in each topic

Model Selection and Interpretation

Quantitative + qualitative approaches

- No quantitative metric can replace human judgement
- *"The most effective method for assessing model fit is to carefully read documents that are closely associated with particular topics to verify that the semantic concept covered by the topic is reflected in the text."* (Roberts et al. 2016)

Summary

- Topic models help us explore or explicitly measure the thematic structure of a large collection of documents
- Select an algorithm that suits your goal
- Experiment with hyper-parameters, including the number of topics
- Quantitative measures for model selection is useful
- Manual reading plays a crucial role in model seletion and labeling

Guided Coding

- Guided Coding for LDA: LDA with SOTU address data in R
- Materials for STM
  - Official documentation of `stm` package
    - Short demonstration
  - Tutorial with Facebook posts data