Unsupervised Clustering

Digging into Data: Jordan Boyd-Graber

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April 8, 2013

COLLEGE OF INFORMATION STUDIES

Outline

1. Topic Model Introduction

Why topic models?

- Suppose you have a huge number of documents
- Want to know what's going on
- Can't read them all (e.g. every New York Times article from the 90's)
- Topic models offer a way to get a corpus-level view of major themes

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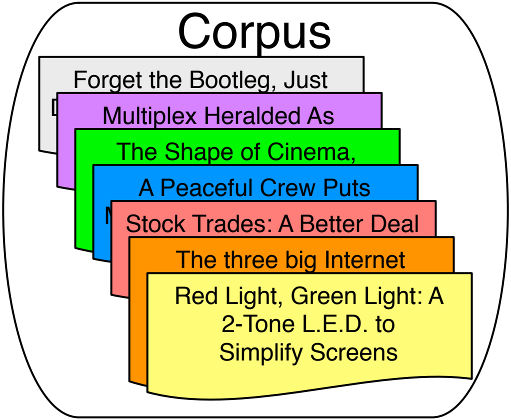
- Unsupervised

Conceptual Approach

From an **input corpus** and number of topics K → words to topics



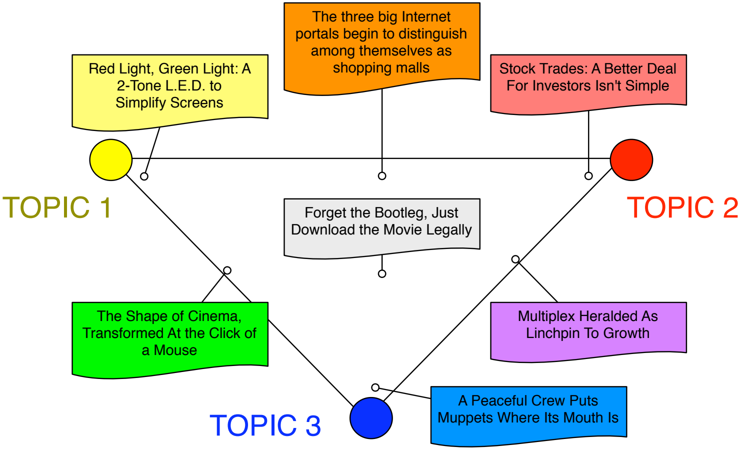
Conceptual Approach

From an input corpus and number of topics K $\longrightarrow$ **words to topics**

TOPIC 1	TOPIC 2	TOPIC 3
computer, technology, system, service, site, phone, internet, machine	sell, sale, store, product, business, advertising, market, consumer	play, film, movie, theater, production, star, director, stage

Conceptual Approach

- For each document, what topics are expressed by that document?



Topics from *Science*

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

Why should you care?

- Neat way to explore / understand corpus collections
  - E-discovery
  - Social media
  - Scientific data
- NLP Applications
  - POS Tagging [9]
  - Word Sense Disambiguation [2]
  - Word Sense Induction [3]
  - Discourse Segmentation [8]
- Psychology [5]: word meaning, polysemy
- Inference is (relatively) simple

Matrix Factorization Approach

$$\underbrace{\begin{bmatrix} M \times K \end{bmatrix}}_{\text{Topic Assignment}} \times \underbrace{\begin{bmatrix} \quad K \times V \quad \end{bmatrix}}_{\text{Topics}} \approx \underbrace{\begin{bmatrix} \quad M \times V \quad \end{bmatrix}}_{\text{Dataset}}$$

- **K** Number of topics
- **M** Number of documents
- **V** Size of vocabulary

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K Number of topics
M Number of documents
V Size of vocabulary

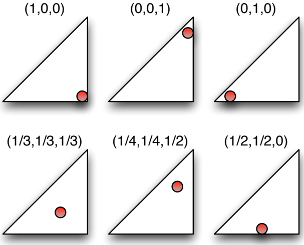
- If you use singular value decomposition (SVD), this technique is called latent semantic analysis.
- Popular in information retrieval.

Alternative: Generative Model

- How your data came to be
- Sequence of Probabilistic Steps
- Posterior Inference

Multinomial Distribution

- Distribution over discrete outcomes
- Represented by non-negative vector that sums to one
- Picture representation



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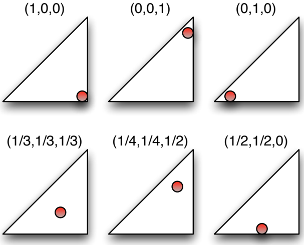

- Come from a Dirichlet distribution

Dirichlet Distribution

$$P(\boldsymbol{p} \,|\, \alpha \boldsymbol{m}) = \frac{\Gamma(\sum_k \alpha m_k)}{\prod_k \Gamma(\alpha m_k)} \prod_k p_k^{\alpha m_k - 1}$$

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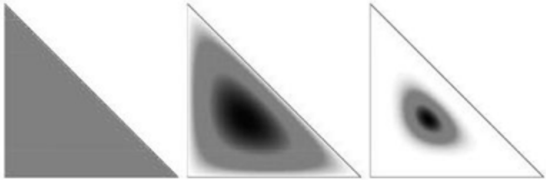

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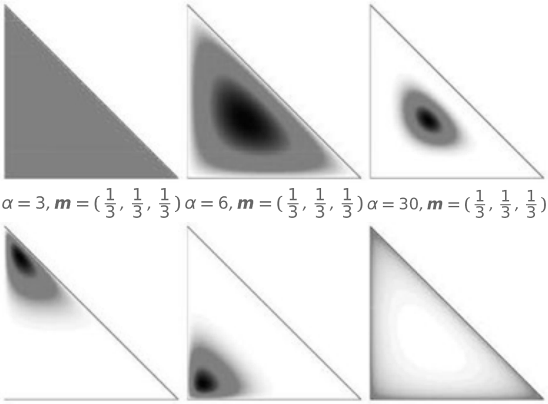

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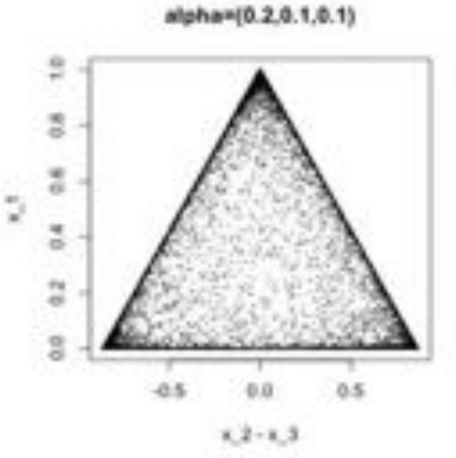

Dirichlet Distribution

- If $\phi \sim \text{Dir}(()\alpha)$, $\boldsymbol{w} \sim \text{Mult}(()\phi)$, and $n_k = |\{w_i : w_i = k\}|$ then

$$
\begin{aligned}
p(\phi|\alpha,\boldsymbol{w}) &\propto p(\boldsymbol{w}|\phi)p(\phi|\alpha) && (1)\\
&\propto \prod_k \phi^{n_k} \prod_k \phi^{\alpha_k - 1} && (2)\\
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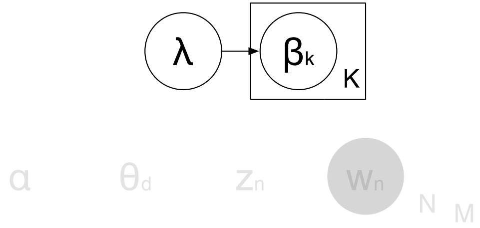
Generative Model Approach



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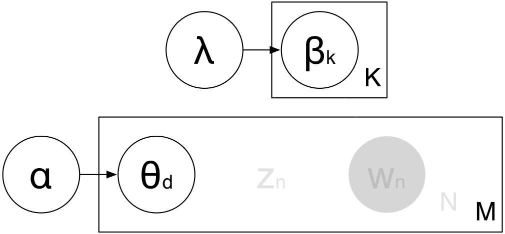

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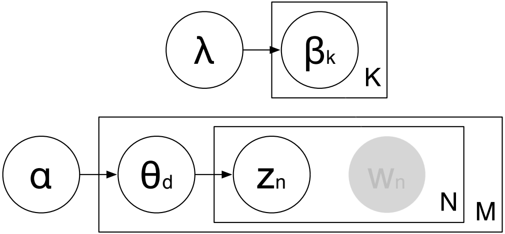

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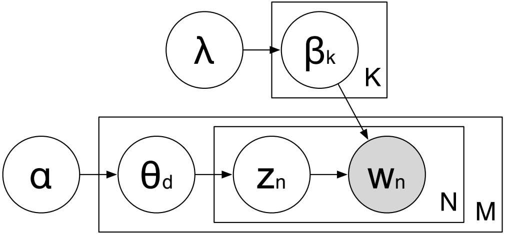

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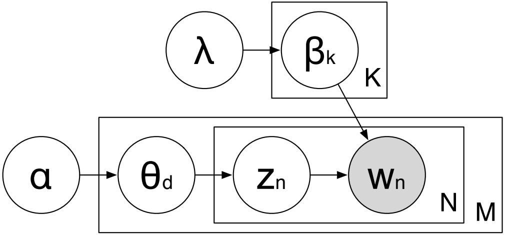

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We use statistical inference to uncover the most likely unobserved variables given observed data.

Topic Models: What's Important

- Topic models
  - Topics to words—multinomial distribution
  - Documents to topics—multinomial distribution
- Focus in this talk: statistical methods
  - Model: story of how your data came to be
  - Latent variables: missing pieces of your story
  - Statistical inference: filling in those missing pieces
- We use latent Dirichlet allocation (LDA) [1], a fully Bayesian version of pLSI [6], probabilistic version of LSA [7]

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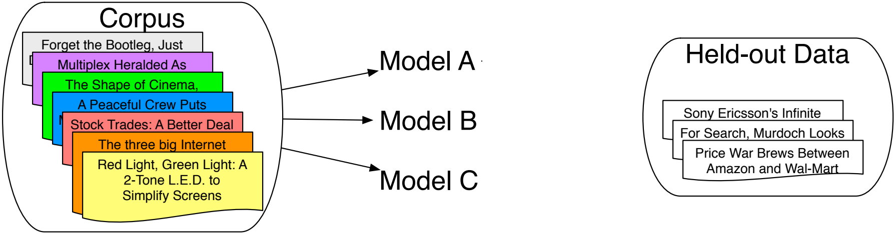
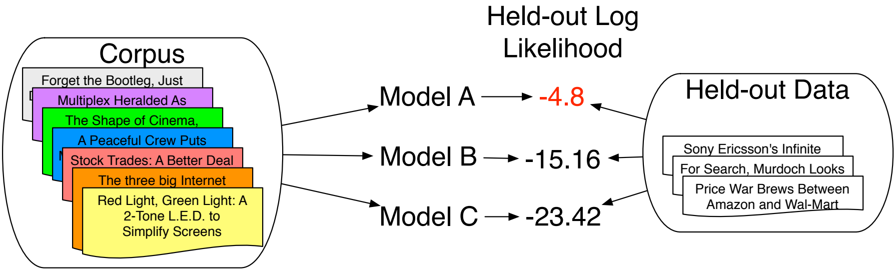
Evaluation



$$P(\mathbf{w} \mid \mathbf{w}', \mathbf{z}', \alpha\mathbf{m}, \beta\mathbf{u}) = \sum_{\mathbf{z}} P(\mathbf{w}, \mathbf{z} \mid \mathbf{w}', \mathbf{z}', \alpha\mathbf{m}, \beta\mathbf{u})$$

How you compute it is important too [10]

Evaluation



Measures predictive power, not what the topics are

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Word Intrusion

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Word Intrusion

1. Take the highest probability words from a topic

Original Topic

dog, cat, horse, pig, cow

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3. We ask users to find the word that doesn't belong

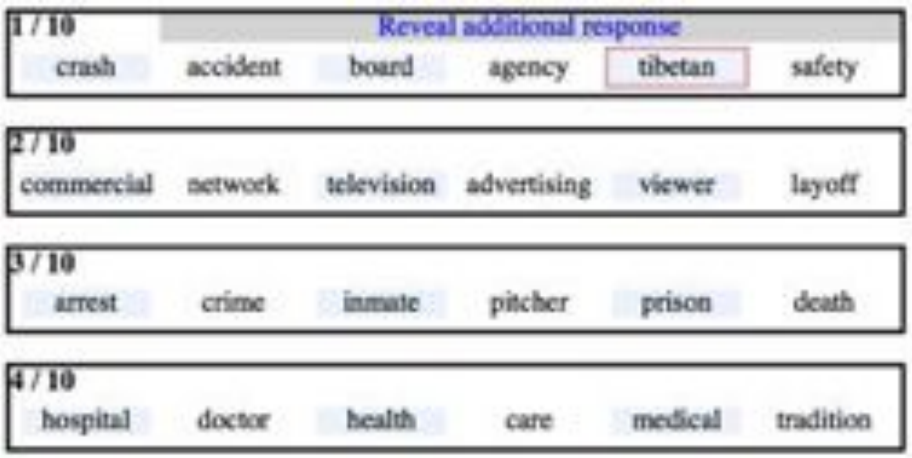
Hypothesis

If the topics are interpretable, users will consistently choose true intruder

Word Intrusion

1 / 10	crash	accident	board	agency	tibetan	safety
2 / 10	commercial	network	television	advertising	viewer	layoff
3 / 10	arrest	crime	inmate	pitcher	prison	death
4 / 10	hospital	doctor	health	care	medical	tradition

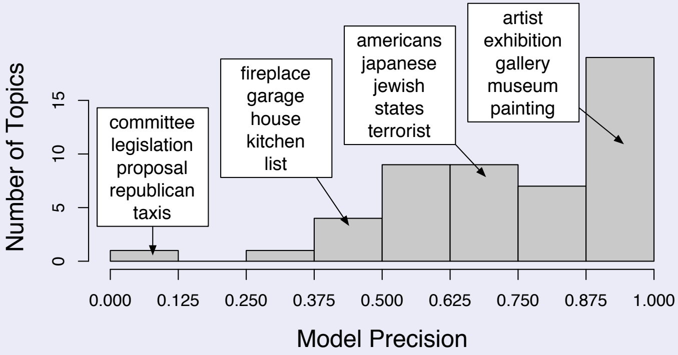
Word Intrusion



- Order of words was shuffled
- Which intruder was selected varied
- Model precision: percentage of users who clicked on intruder

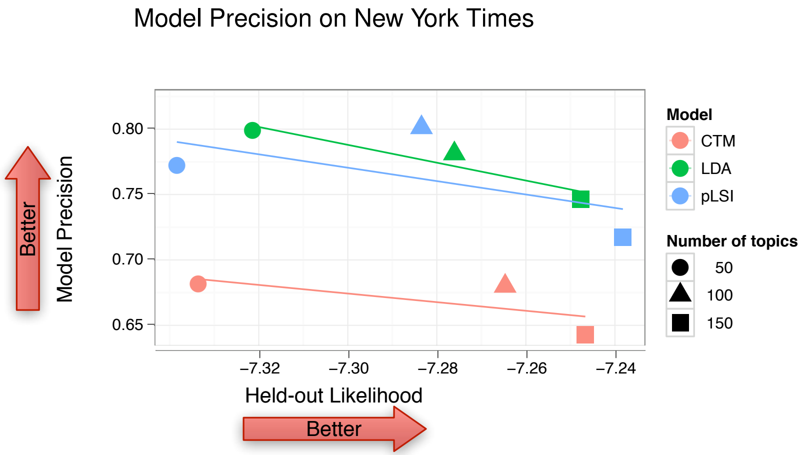
Word Intrusion: Which Topics are Interpretable?

New York Times, 50 LDA Topics



Model Precision: percentage of correct intruders found

Interpretability and Likelihood



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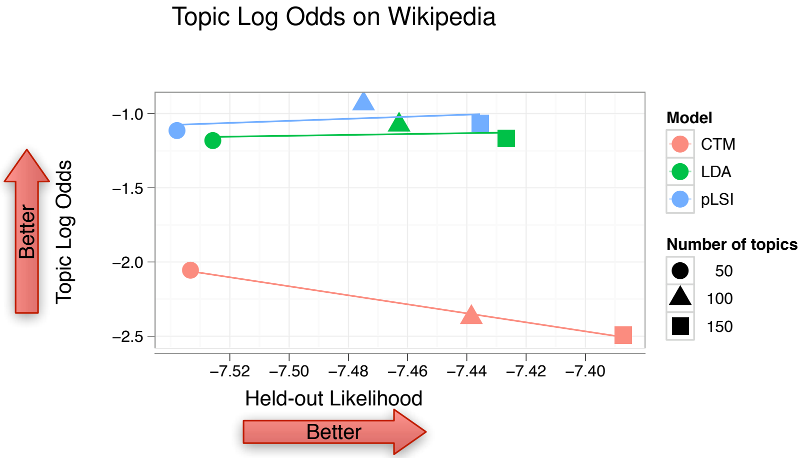

across models, higher likelihood $\neq$ higher interpretability

Evaluation Takeaway

- Measure what you care about [4]
- If you care about prediction, likelihood is good
- If you care about a particular task, measure that

Gibbs Sampling

- A way to go from random topics (i.e., bad) to good topics (i.e., ones that make sense)
- We do this by changing the topic assignment of a word $z_{d,n}$
- Given a state $\{z_1, \dots z_N\}$, drawing $z_n \sim p(n_n | z_1, \dots z_{n-1}, z_{n+1}, \dots z_N, X, \Theta)$ for all n (repeatedly) results in the distribution of topics **given documents.**
- For notational convenience, call $\boldsymbol{z}$ with $z_{d,n}$ removed $\boldsymbol{z}_{-d,n}$

Inference

computer, technology, system, service, site, phone, internet, machine

sell, sale, store, product, business, advertising, market, consumer

play, film, movie, theater, production, star, director, stage

Hollywood studios are preparing to let people download and buy electronic copies of movies over the Internet, much as record labels now sell songs for 99 cents through Apple Computer's iTunes music store and other online services ...

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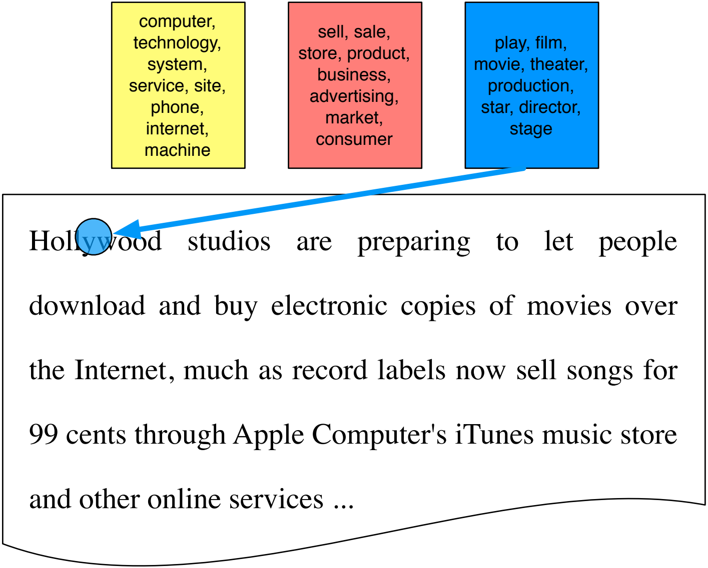
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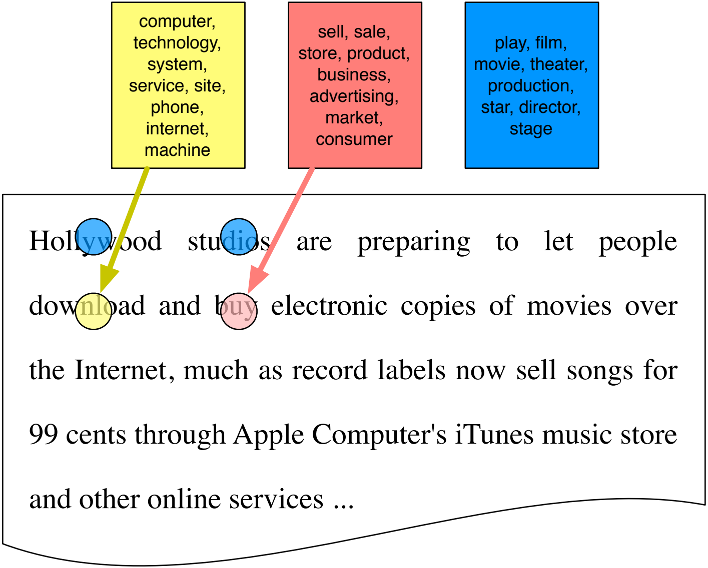
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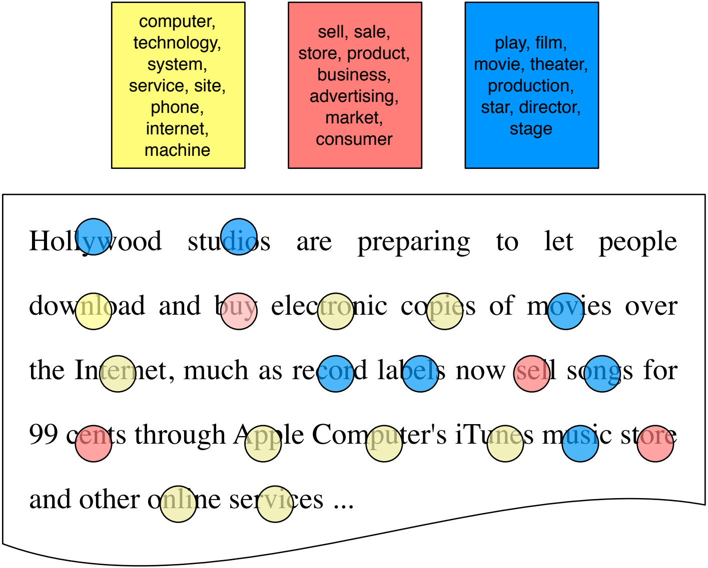
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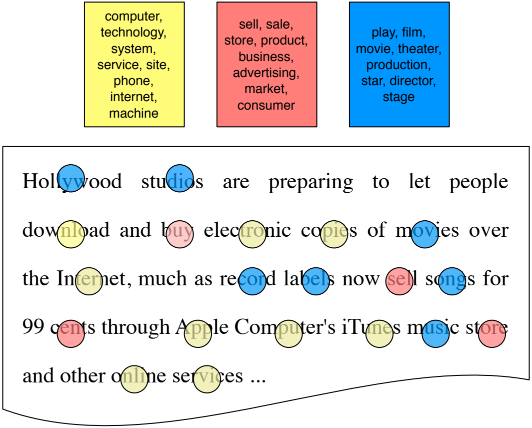

And repeat, conditioning $z_{d,n}$ on all of the other assignments

Gibbs Sampling

- For LDA, we will sample the topic assignments
- The topics and per-document topic proportions are integrated out / marginalized / Rao-Blackwellized
- Thus, we want:

$$p(z_{d,n} = k | \boldsymbol{z}_{-d,n}, \boldsymbol{w}, \alpha, \lambda) = \frac{p(z_{d,n} = k, \boldsymbol{z}_{-d,n} | \boldsymbol{w}, \alpha, \lambda)}{p(\boldsymbol{z}_{-d,n} | \boldsymbol{w}, \alpha, \lambda)}$$

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- Let $n_{d,i}$ be the number of words taking topic i in document d. Let $v_{k,w}$ be the number of times word w is used in topic k.

$$= \frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$

Sample Document

Etruscan	trade	price	temple	market

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Randomly Assign Topics

3	2	1	3	1
Etruscan	trade	price	temple	market

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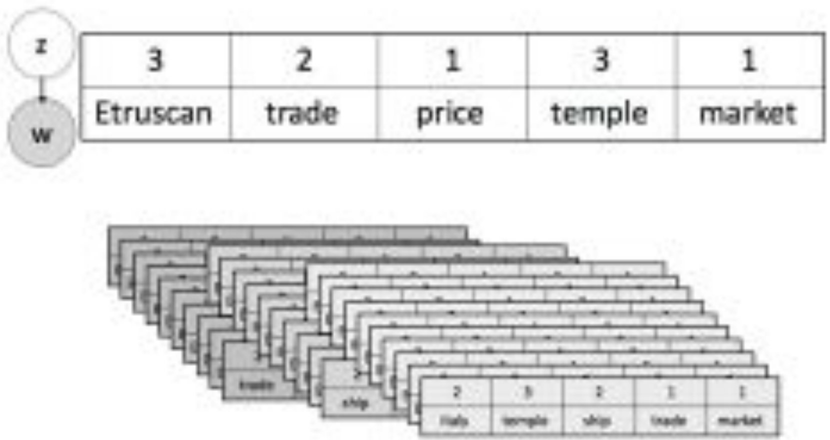

Total Topic Counts

3	2	1	3	1
Etruscan	trade	price	temple	market

Total counts from all docs

	1	2	3
Etruscan	1	0	35
market	50	0	1
price	42	1	0
temple	0	0	20
trade	10	8	1
...			

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Sampling Equation

$$\frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$

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We want to sample this word . . .

3	**2**	1	3	1
Etruscan	trade	price	temple	market

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Decrement its count

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Etruscan	trade	price	temple	market

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Etruscan	1	0	35
market	50	0	1
price	42	1	0
temple	0	0	20
trade	10	7	1
...			

What is the conditional distribution for this topic?

3	?	1	3	1
Etruscan	trade	price	temple	market

Part 1: How much does this document like each topic?

3	?	1	3	1
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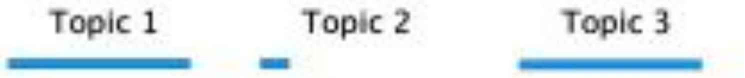

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Part 2: How much does each topic like the word?

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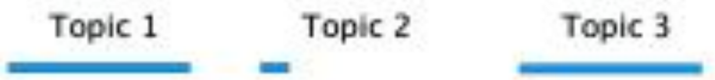
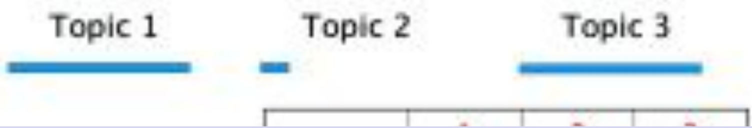


	1	2	3
trade	10	7	1

3	?	1	3	1
Etruscan	trade	price	temple	market

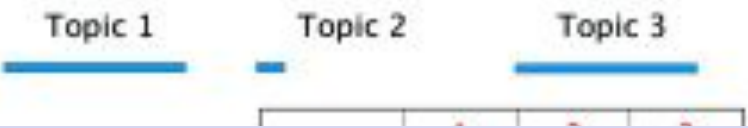


Sampling Equation

$$\frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$

Part 2: How much does each topic like the word?

3	?	1	3	1
Etruscan	trade	price	temple	market

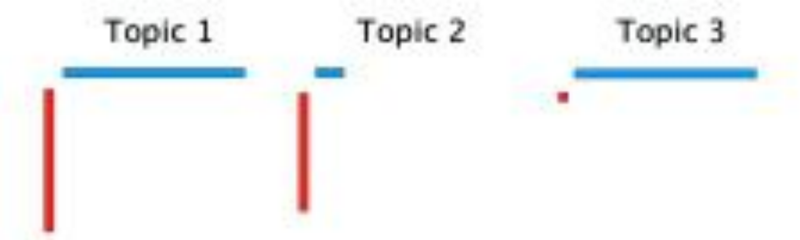


Sampling Equation

$$\frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$

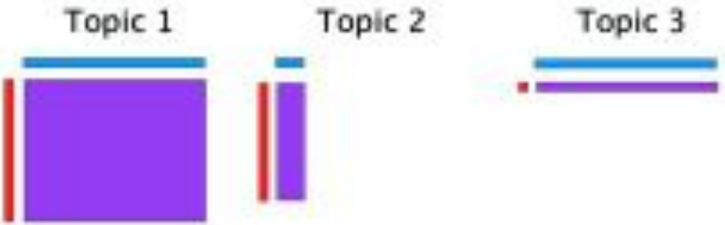
Geometric interpretation

3	?	1	3	1
Etruscan	trade	price	temple	market



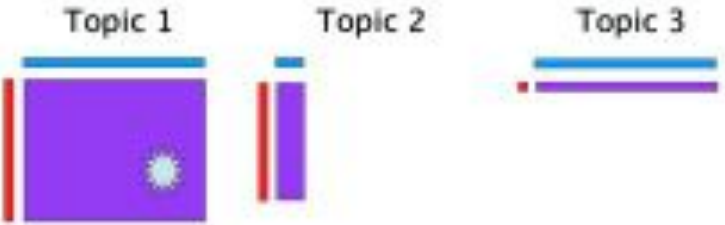
Geometric interpretation

3	?	1	3	1
Etruscan	trade	price	temple	market



Geometric interpretation

3	?	1	3	1
Etruscan	trade	price	temple	market



Update counts

3	?	1	3	1
Etruscan	trade	price	temple	market

	1	2	3
Etruscan	1	0	35
market	50	0	1
price	42	1	0
temple	0	0	20
trade	**10**	7	1
...			

Update counts

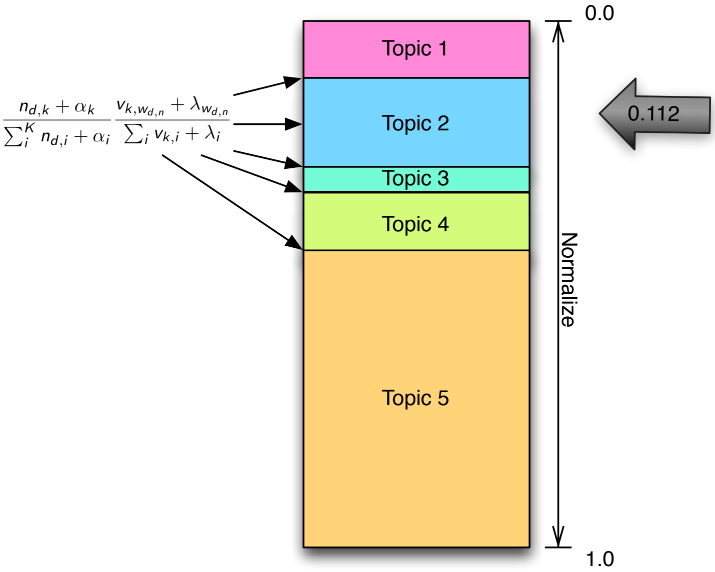
3	1	1	3	1
Etruscan	trade	price	temple	market

	1	2	3
Etruscan	1	0	35
market	50	0	1
price	42	1	0
temple	0	0	20
trade	11	7	1
...			

Update counts

3	1	1	3	1
Etruscan	trade	price	temple	market

Details: how to sample from a distribution



Algorithm

1. For each iteration i:
   1. For each document d and word n currently assigned to z_{old}:
      1. Decrement $n_{d,z_{old}}$ and $v_{z_{old},w_{d,n}}$
      2. Sample $z_{new} = k$ with probability proportional to $\frac{n_{d,k}+\alpha_k}{\sum_i^K n_{d,i}+\alpha_i} \frac{v_{k,w_{d,n}}+\lambda_{w_{d,n}}}{\sum_i v_{k,i}+\lambda_i}$
      3. Increment $n_{d,z_{new}}$ and $v_{z_{new},w_{d,n}}$

Implementation

Algorithm

1. For each iteration i:
   1. For each document d and word n currently assigned to z_{old}:
      1. Decrement $n_{d,z_{old}}$ and $v_{z_{old},w_{d,n}}$
      2. Sample $z_{new} = k$ with probability proportional to $\frac{n_{d,k}+\alpha_k}{\sum_i^K n_{d,i}+\alpha_i} \frac{v_{k,w_{d,n}}+\lambda_{w_{d,n}}}{\sum_i v_{k,i}+\lambda_i}$
      3. Increment $n_{d,z_{new}}$ and $v_{z_{new},w_{d,n}}$

Desiderata

- Hyperparameters: Sample them too (slice sampling)
- Initialization: Random
- Sampling: Until likelihood converges
- Lag / burn-in: Difference of opinion on this
- Number of chains: Should do more than one

Available implementations

- Mallet (http://mallet.cs.umass.edu)
- LDAC (http://www.cs.princeton.edu/ blei/lda-c)
- Topicmod (http://code.google.com/p/topicmod)
- LDA R pakcage (http://cran.r-project.org/web/packages/lda/lda.pdf)

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