Topic Models

Advanced Machine Learning for NLP

Jordan Boyd-Graber

OVERVIEW

Low-Dimensional Space for Documents

- Last time: embedding space for words
- This time: embedding space for documents
- Generative story
- New inference techniques

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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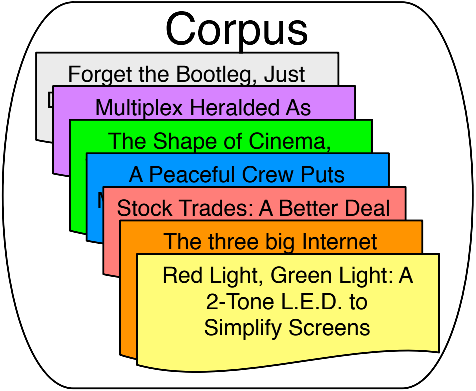
- Unsupervised

Roadmap

- What are topic models
- How to go from raw data to topics

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



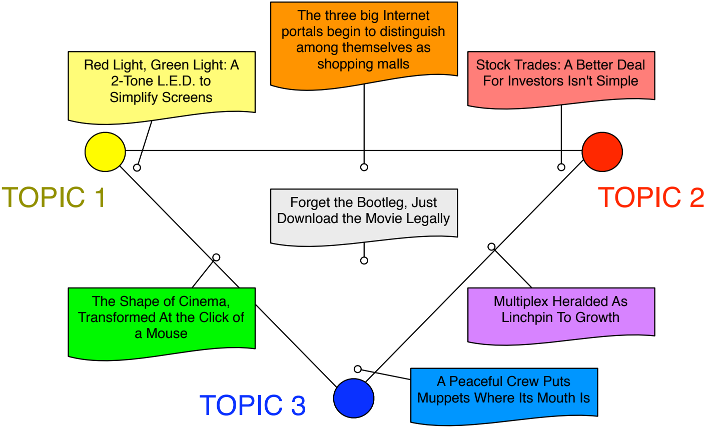
Embedding Space

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
  - Word Sense Disambiguation
  - Discourse Segmentation
  - Machine Translation
- Psychology: word meaning, polysemy
- Inference is (relatively) simple

Matrix Factorization Approach

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

K Number of topics

M Number of documents

V Size of vocabulary

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- 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

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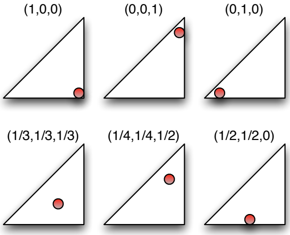
- Blei, Ng, Jordan. Latent **Dirichlet** Allocation. JMLR, 2003.

Multinomial Distribution

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



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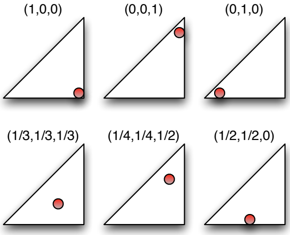

- Come from a Dirichlet distribution

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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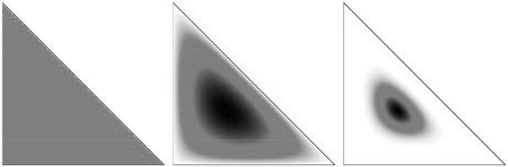

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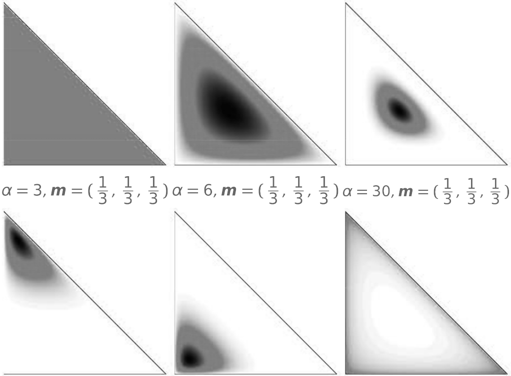

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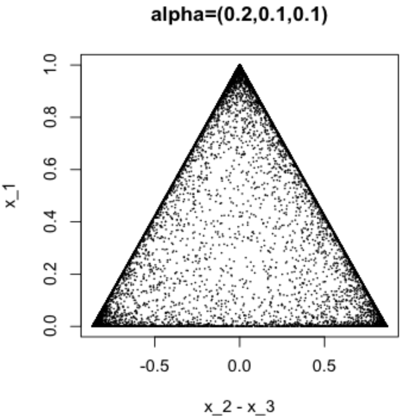

Dirichlet Distribution

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

$$p(\phi|\alpha, \boldsymbol{w}) \propto p(\boldsymbol{w}|\phi)p(\phi|\alpha) \tag{1}$$
$$\propto \prod_k \phi^{n_k} \prod_k \phi^{\alpha_k - 1} \tag{2}$$
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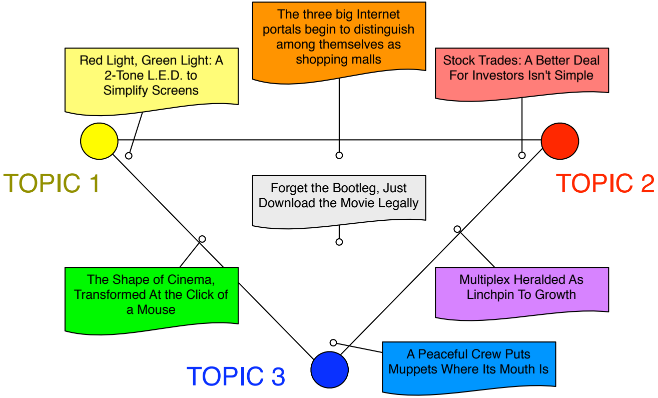

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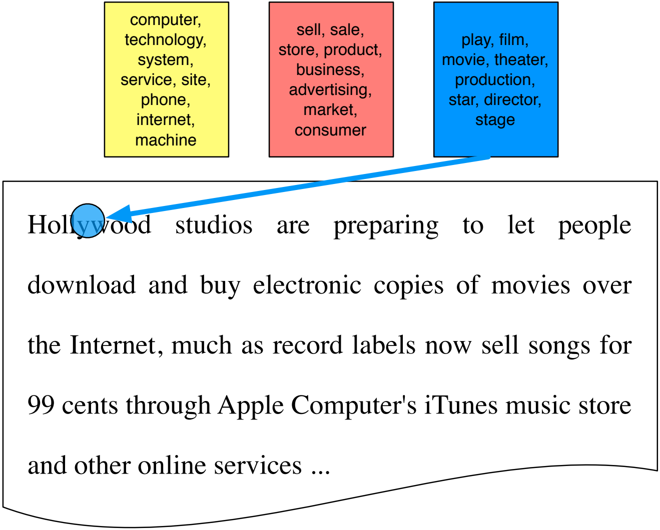
Generative Model



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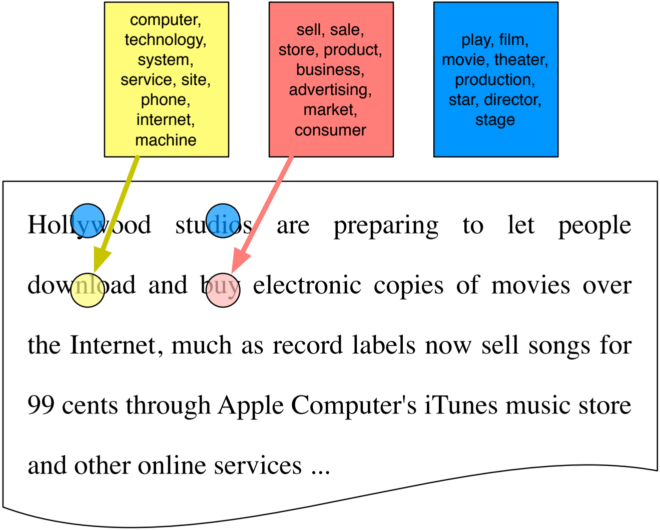

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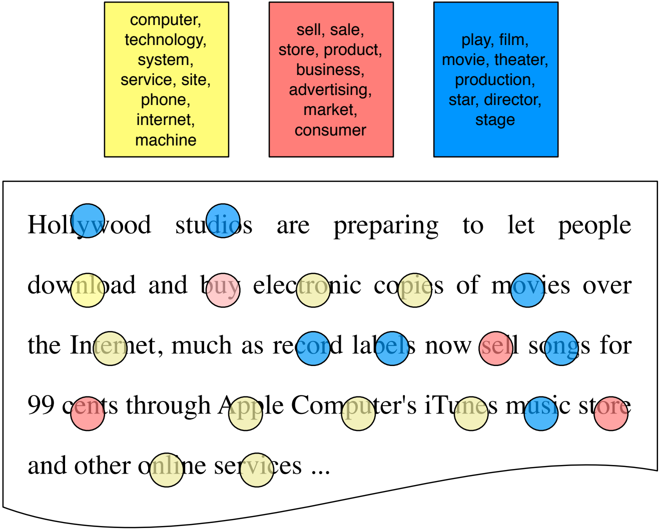
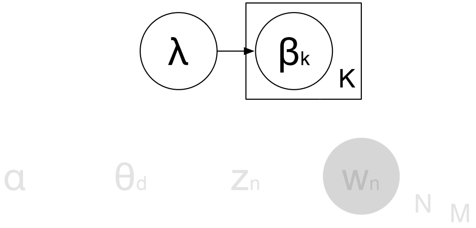


Generative Model Approach



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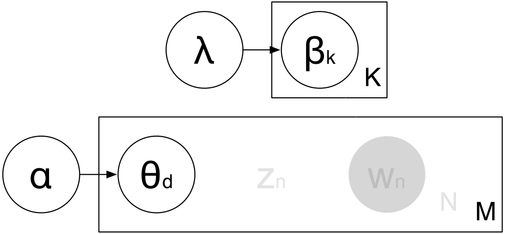

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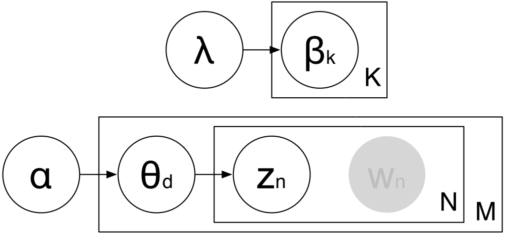

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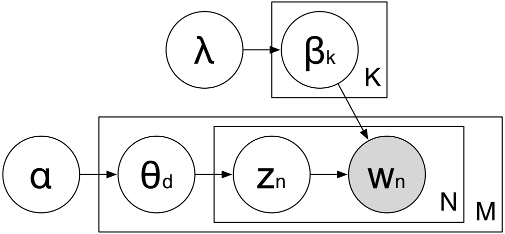

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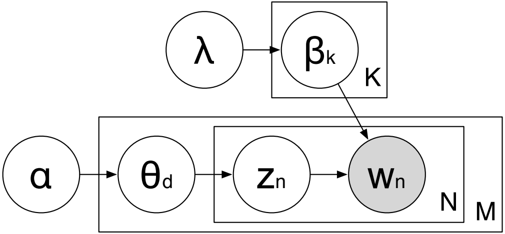

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Topic Models: What's Important

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  - 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
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