Statistical Topic Modeling

Hanna M. Wallach

University of Massachusetts Amherst wallach@cs.umass.edu

Text as Data

Home > Press Room > Press Release Kerry to Address U.S. Policy Toward United States FOR IMMEDIATE RELEASE: Tuesday, March 15, 2011 Arnold, et a

Method for il WASHINGTON, D.C. - Tomorrow, Senator John Kerry, Chairman the Carnegie Endowment for International Peace in Washington, policy in the Middle East. Marwan Muasher, vice president for stu the event.

Inventors:	Arnold; Todd W. (Charlo Kurt S. (Roskilde, DK), K DK)		
ways or with	WHEN:	Wednesday,	
interface (AI that provide		Speech on M	
cryptograph key manager	mer	Senator John	
A method, ai	CLIC.		

A mothod artic

2541

Abstract natural evaluation metric pic models is the probabil: ocuments given a trained 1 cact computation of this pr actable, several estimators bility have been used in the ig literature, including the 1 ethod and empirical likeliho is paper, we demonstrate at commonly-used methods ccurately estimate the prob out documents, and propose t methods that are both accurat

1. Introduction

OUTLINE I. Military actions against North Vietnam and In Laos A. Present program

1 B. Options for increased military programs 2 I. Destroy modern industry 3 SANITIZED - Thermal power (7-plant grid) ? E.O. 12356, Sec. 3.4 - Steel and cement NU 90-192 - Machine tool plant By man, MARA, Date O - Other

- Structured and formal: e.g., publications, patents, press releases
- Messy and unstructured: e.g., chat logs, OCRed documents, transcripts

 \Rightarrow Large scale, robust methods for analyzing text

Topic Modeling

- Three fundamental assumptions:
 - Documents have latent semantic structure ("topics")
 - We can infer topics from word-document co-occurrences
 - Can simulate this inference algorithmically
- Given a data set, the goal is to
 - Learn the composition of the topics that best represent it
 - Learn which topics are used in each document

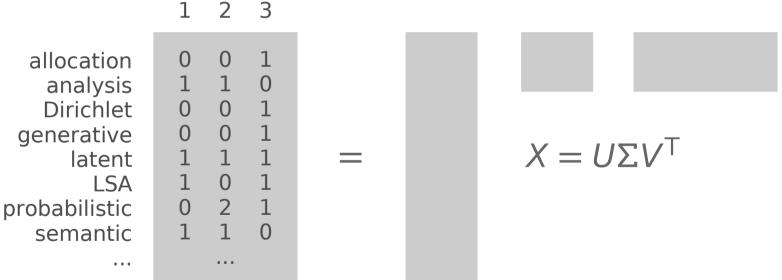
Latent Semantic Analysis (LSA)

(Deerwester et al., 1990)

- Based on ideas from linear algebra
- Form sparse term-document co-occurrence matrix X
 - Raw counts or (more likely) TF-IDF weights
- Use SVD to decompose *X* into 3 matrices:
 - *U* relates terms to "concepts"
 - *V* relates "concepts" to documents
 - Σ is a diagonal matrix of singular values

Singular Value Decomposition

- 1. Latent semantic analysis (LSA) is a theory and method for ...
- 2. Probabilistic latent semantic analysis is a probabilistic ...
- 3. Latent Dirichlet allocation, a generative probabilistic model ...



1

Generative Statistical Modeling

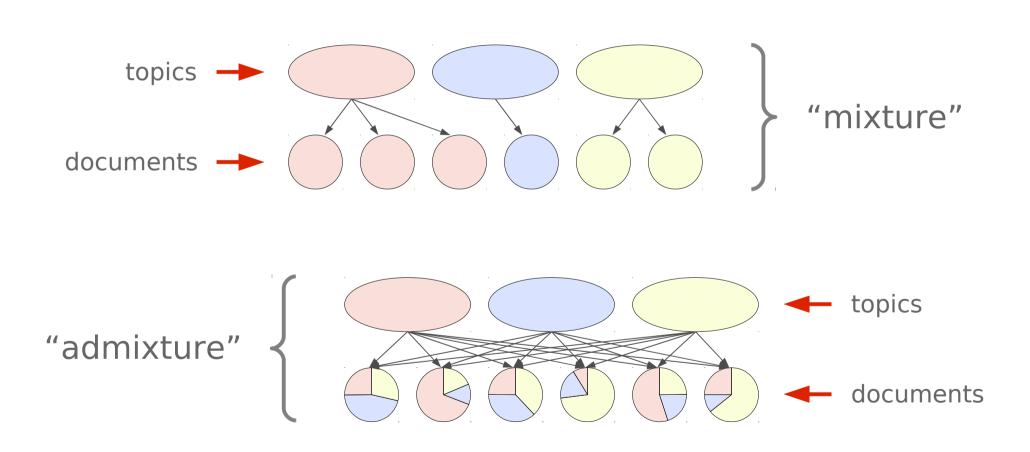
- Assume data was generated by a probabilistic model:
 - Model may have hidden structure (latent variables)
 - Model defines a joint distribution over all variables
 - Model parameters are unknown
- Infer hidden structure and model parameters from data
- Situate new data in estimated model

Topics and Words

	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

probability

Mixtures vs. Admixtures



Documents and Topics

Seeking Life's Bare (Genetic) Necessities

Haemophilus

genome

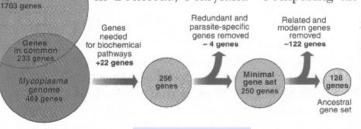
COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known 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

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12. "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 mo-

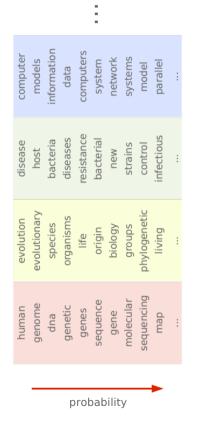
lecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



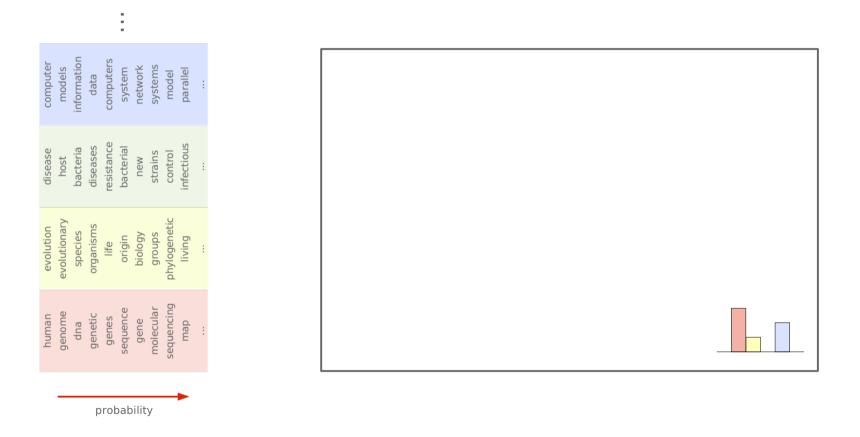
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

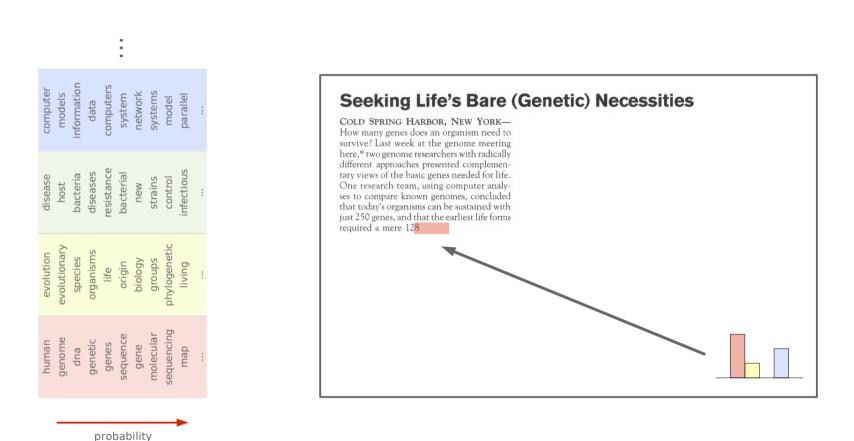
Generative Process



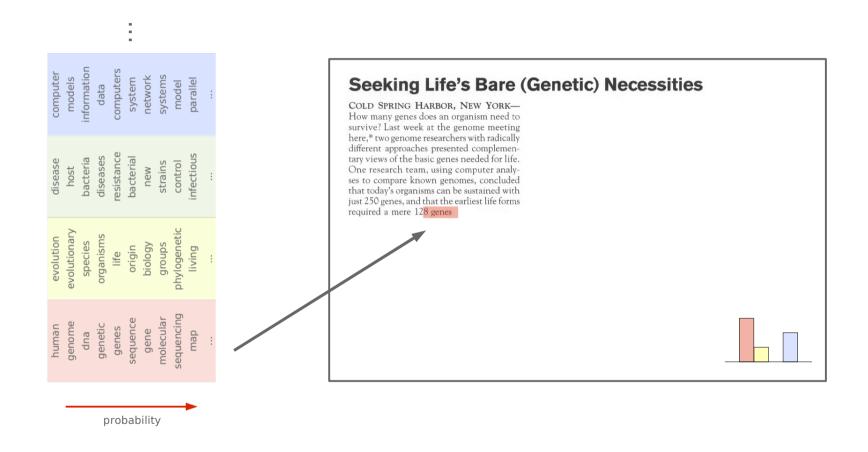
Choose a Distribution Over Topics



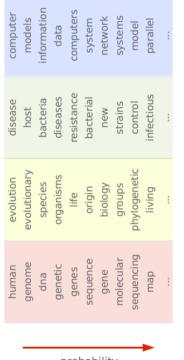
Choose a Topic



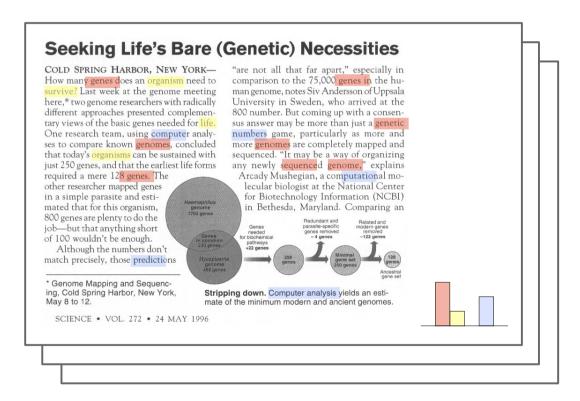
Choose a Word



... And So On



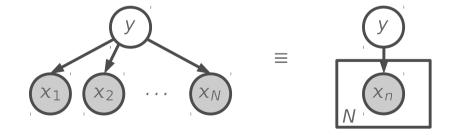
probability



Directed Graphical Models

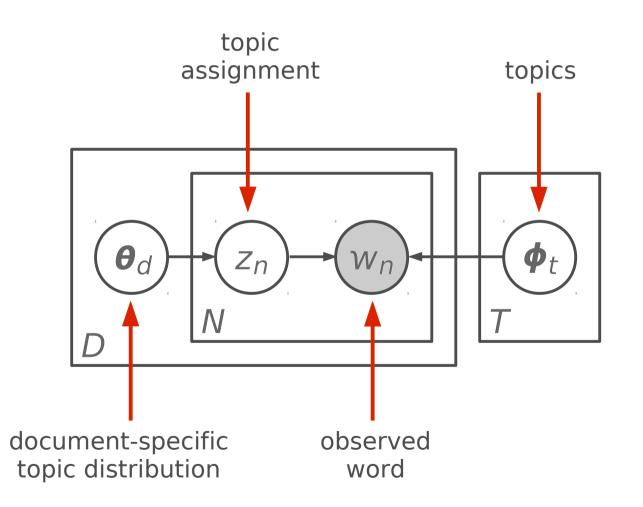
$$P(y, x_1, ..., x_N) = P(y) \prod_{n=1}^N P(x_n | y)$$

- Nodes: random variables (latent or observed)
- Edges: probabilistic dependencies between variables
- Plates: "macros" that allow subgraphs to be replicated



Probabilistic LSA

[Hofmann, '99]

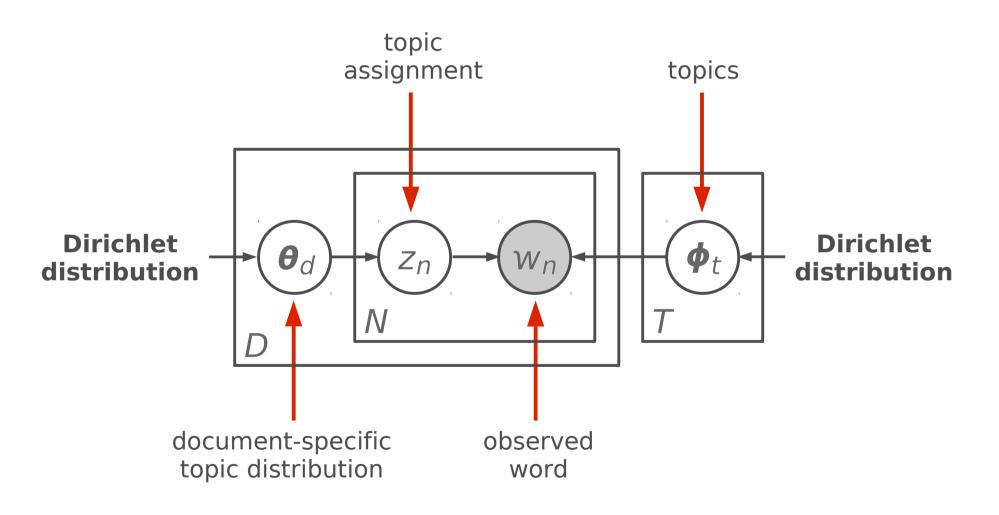


Strengths and Weaknesses

- Probabilistic graphical model: can be extended and embedded into other more complicated models
- X Not a well-defined generative model: no way of generalizing to new, unseen documents
- **x** Many free parameters: linear in # training documents
- **x** Prone to overfitting: have to be careful when training

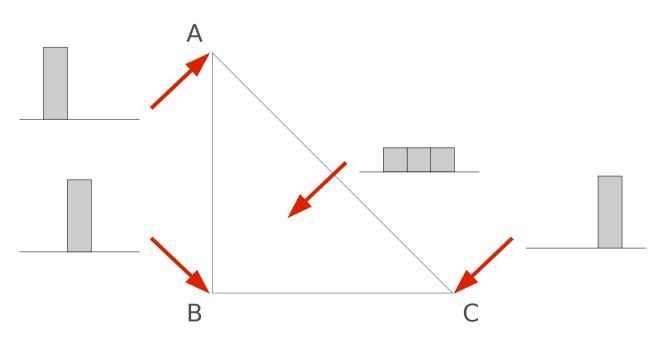
Latent Dirichlet Allocation (LDA)

[Blei, Ng & Jordan, '03]



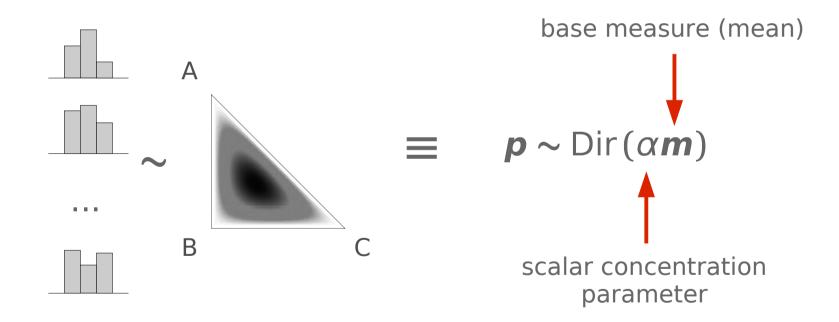
Discrete Probability Distributions

• 3-dimensional discrete probability distributions can be visually represented in 2-dimensional space:

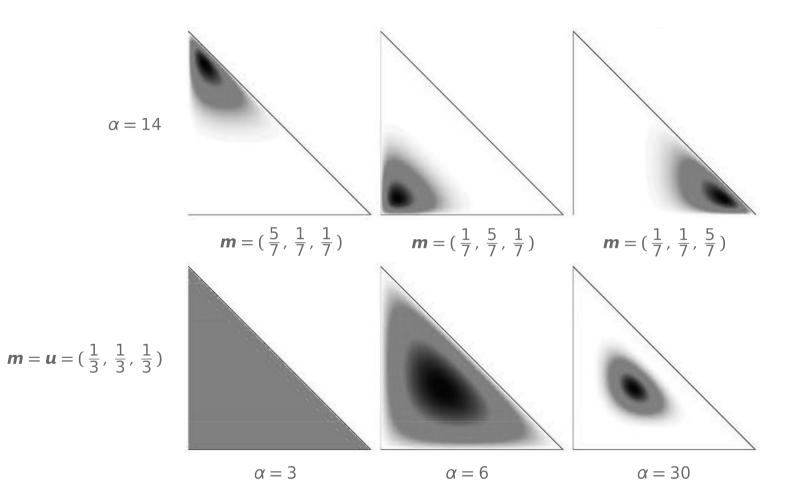


Dirichlet Distribution

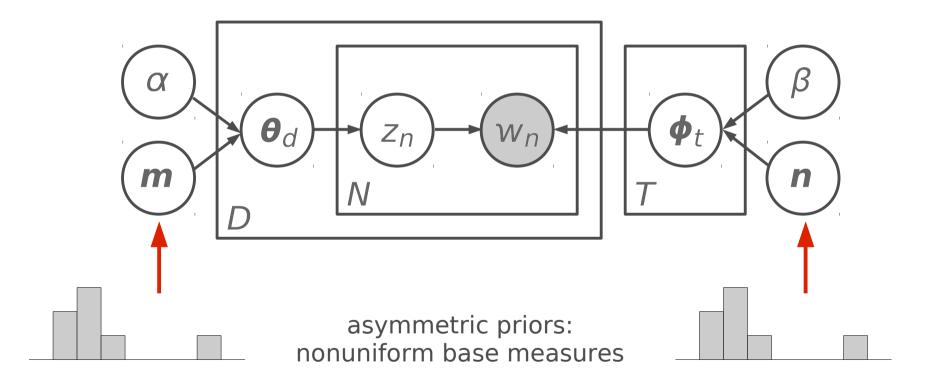
• Distribution over discrete probability distributions:



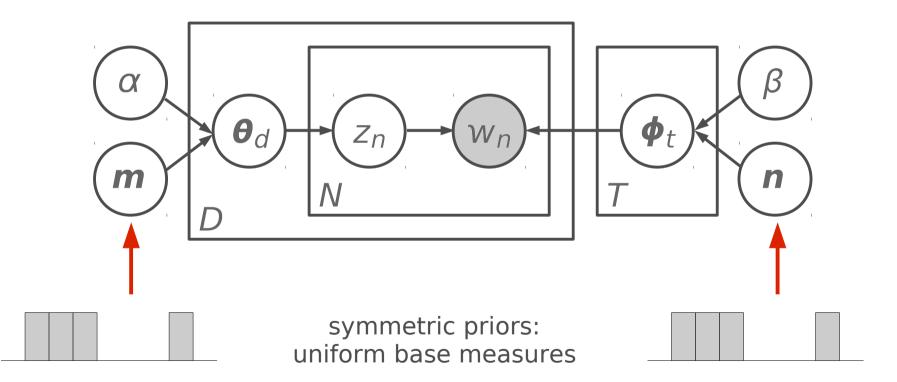
Dirichlet Parameters



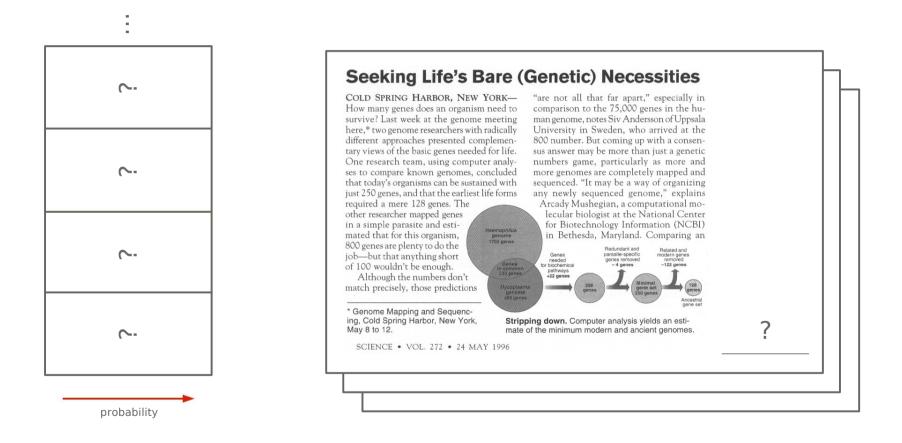
Dirichlet Priors for LDA



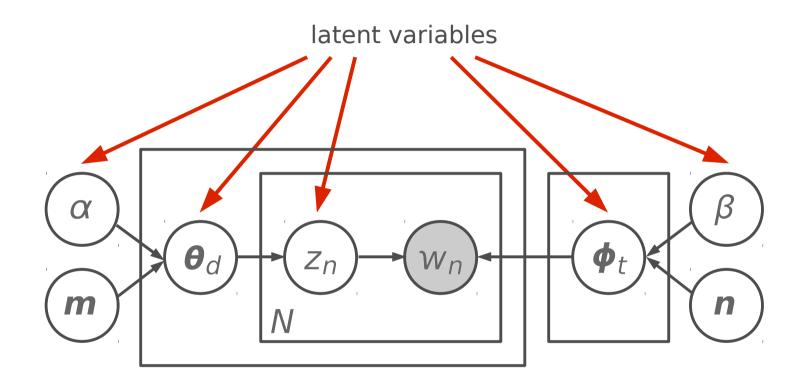
Dirichlet Priors for LDA



Real Data: Statistical Inference

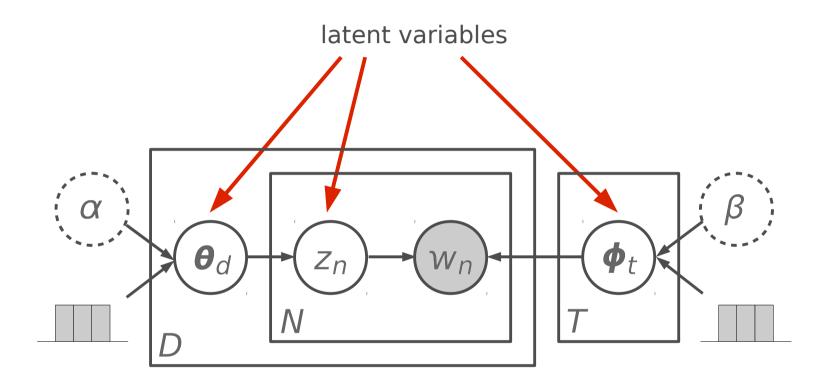


Posterior Inference



• Infer or integrate out all latent variables, given tokens

Posterior Inference

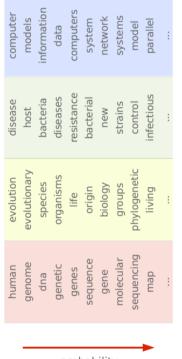


 $P(\Theta, \Phi, \boldsymbol{z}, \boldsymbol{w} | \alpha, \beta)$

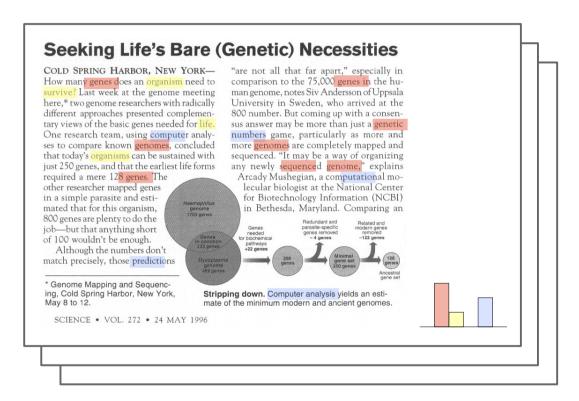
Inference Algorithms

- Exact inference in LDA is not tractable
- Approximate inference algorithms:
 - Mean field variational inference (Blei et al., 2001; 2003)
 - Expectation propagation (Minka & Lafferty, 2002)
 - Collapsed Gibbs sampling (Griffiths & Steyvers, 2002)
 - Collapsed variational inference (Teh et al., 2006)
- Each method has advantages and disadvantages

The End Result...



probability



Evaluating LDA

- Unsupervised nature of LDA makes evaluation hard
- Compute probability of held-out documents:
 - Classic way of evaluating generative models
 - Often used to evaluate topic models
- Problem: have to approximate an intractable sum

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

Computing Log Probability

(Wallach et al., 2009)

- Simple importance sampling methods
- The "harmonic mean" method (Newton & Raftery, 1994)
 - Known to overestimate, used anyway
- Annealed importance sampling (Neal, 2001)
 - Prohibitively slow for large collections of documents
- Chib-style method (Murray & Salakhutdinov, 2009)
- "Left-to-Right" method (Wallach, 2008)

Thanks!

wallach@cs.umass.edu http://www.cs.umass.edu/~wallach/