Probabilistic Topic Models

Piyush Rai

Probabilistic Machine Learning (CS772A)

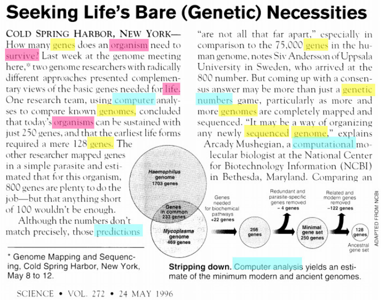
Oct 26, 2017

Remaining schedule..

- 6 more classes (+1 make up lecture for Diwali holiday; date TBD)
- Probabilistic Topic models (today)
- Deep Probabilistic Models (Bayesian neural nets, VAE, GAN)
- Models for sequential data (HMM, Linear Dynamical Systems)
- Probabilistic Graphical Models, Message Passing algorithms
- Other misc. topics
  - Semi-supervised Learning
  - Active Learning
  - Other suggestions.. ?

Topic Modeling

- Topic models is a way to model documents: assumes each document to be a mixture of topics



Seeking Life's Bare (Genetic) Necessities

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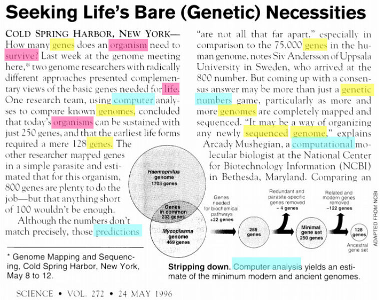

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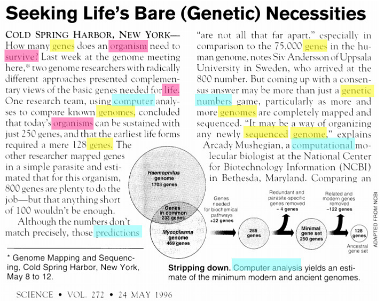

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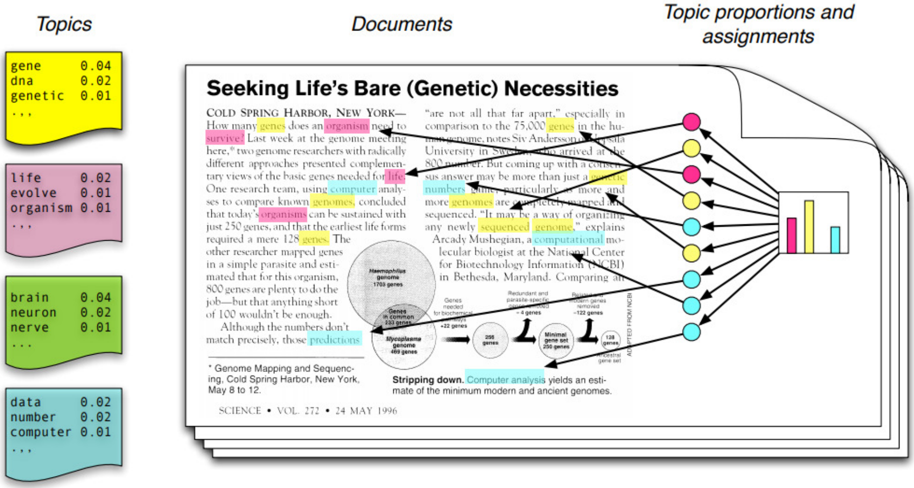
- The notion also applies for other type of data, not necessarily text (e.g., images as bag of "visual words" or speech data as phonemes) and a topic model makes sense for such data as well.

(Pic courtesy: David Blei)

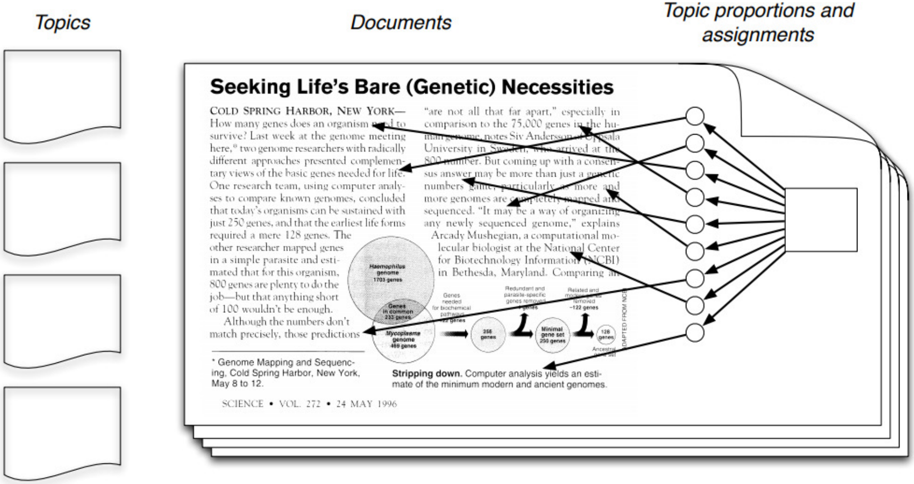
Topic Modeling

- Goal of topic modeling is to learn the topics that underlie the document collection, and represent each document in terms of these topics (fraction of various topics)



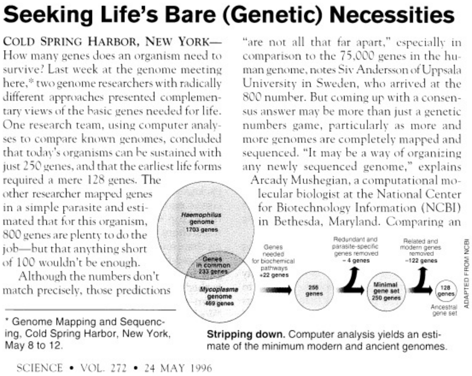
Topic Modeling

- The input for the topic modeling problem will be the raw contents of the documents and the goal is to infer all the unknowns of the model (topics, topic proportions for each document, etc.)



Applications of Topic Modeling

- Can be used to learn topic-based representation for each document
- These representation are compact (think dimensionality reduction) and semantically meaningful



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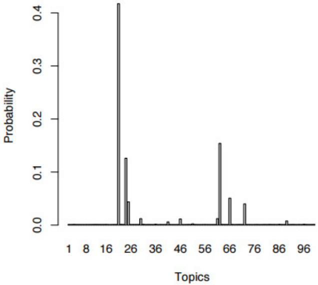

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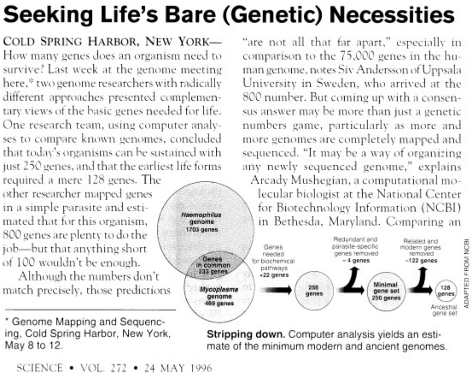

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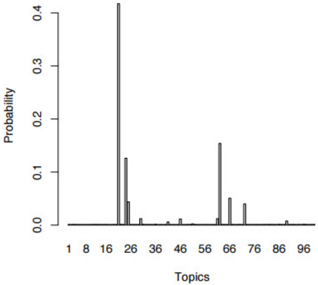

- Also makes it easy to cluster data naturally by (learned) topics

Topic Models: The Basic Idea

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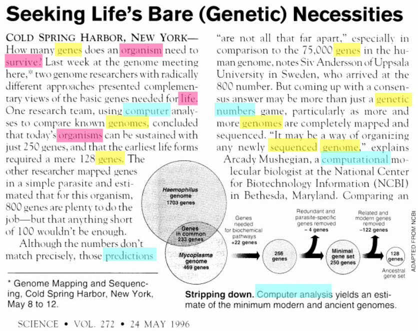
- Note: Different occurrences of the same word may be assigned to different topics



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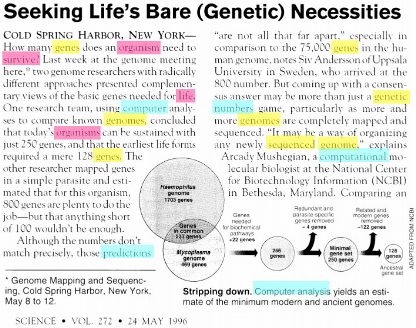

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- Note that word-level topic assignments can be aggregated to get the document's topic proportions

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- Suppose the vocabulary consists of V words
- Suppose there are K topics indexed by $k = 1, \ldots, K$

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Topic 247

word	prob.
DRUGS	.069
DRUG	.060
MEDICINE	.027
EFFECTS	.026
BODY	.023
MEDICINES	.019
PAIN	.016
PERSON	.016
MARIJUANA	.014
LABEL	.012
ALCOHOL	.012
DANGEROUS	.011
ABUSE	.009
EFFECT	.009
KNOWN	.008
PILLS	.008

Topic 5

word	prob.
RED	.202
BLUE	.099
GREEN	.096
YELLOW	.073
WHITE	.048
COLOR	.048
BRIGHT	.030
COLORS	.029
ORANGE	.027
BROWN	.027
PINK	.017
LOOK	.017
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Topic 43

word	prob.
MIND	.081
THOUGHT	.066
REMEMBER	.064
MEMORY	.037
THINKING	.030
PROFESSOR	.028
FELT	.025
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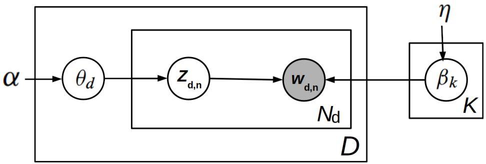
  - β_{kv} denotes the proability of word v in topic k and $\sum_{v=1}^{V} \beta_{kv} = 1$
  - High-probability words are representative of that topic

Latent Dirichlet Allocation (LDA)

Models data where each observation (document) consist of a set of discrete-valued tokens (words)



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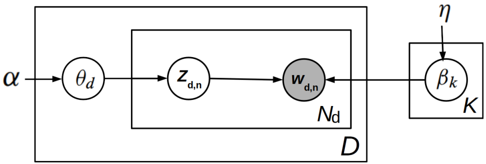

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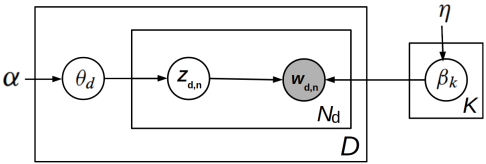

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$$\beta_k \sim \text{Dirichlet}(\eta, \ldots, \eta) \qquad k = 1, \ldots, K$$

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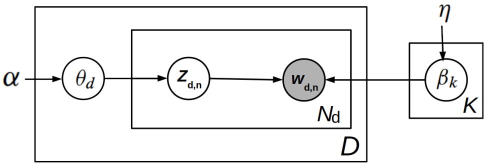

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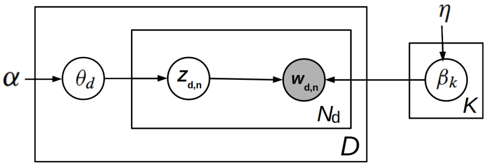

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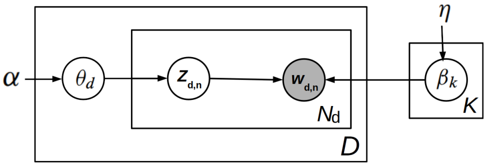

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  - For each word $n = 1, \ldots, N_d$ in document d

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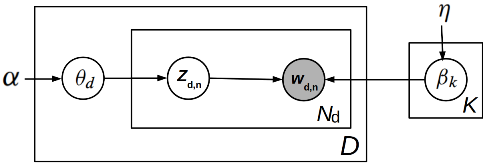

The LDA generative model (assuming α, η known) can be summarized as follows

- Draw K topics $\{\beta_k\}_{k=1}^{K}$ shared by all documents $d = 1, \ldots, D$

$$\beta_k \sim \text{Dirichlet}(\eta, \ldots, \eta) \qquad k = 1, \ldots, K$$

- For each document $d = 1, \ldots, D$
  - Draw its K-dim topic proportion vector $\theta_d \sim \text{Dirichlet}(\alpha, \ldots, \alpha)$
  - For each word $n = 1, \ldots, N_d$ in document d
    - First choose the topic for this word: $z_{d,n} \sim \text{multinoulli}(\theta_d)$

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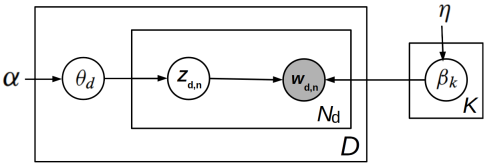

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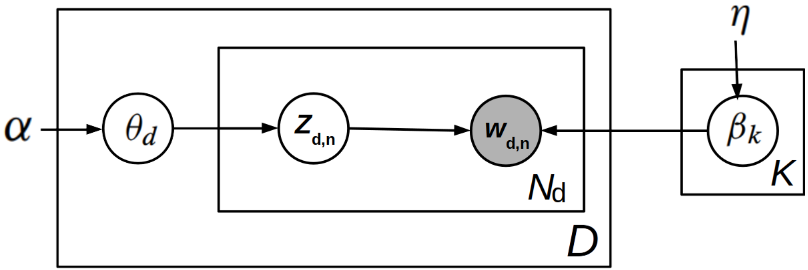
    - Now generate the word form the chosen topic: $\boldsymbol{w}_{d,n} \sim \text{multinoulli}(\beta_{z_{d,n}})$

What is LDA doing?

- Note that LDA is learning D many K-component mixture models (one for each document)



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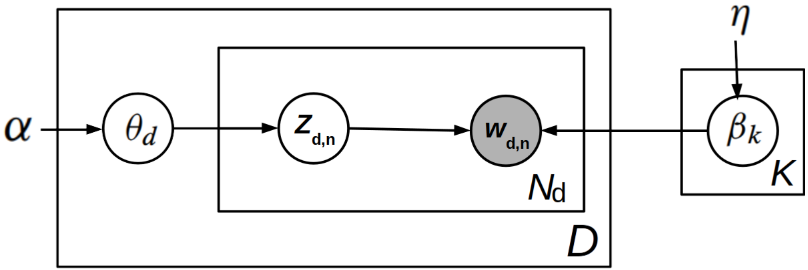

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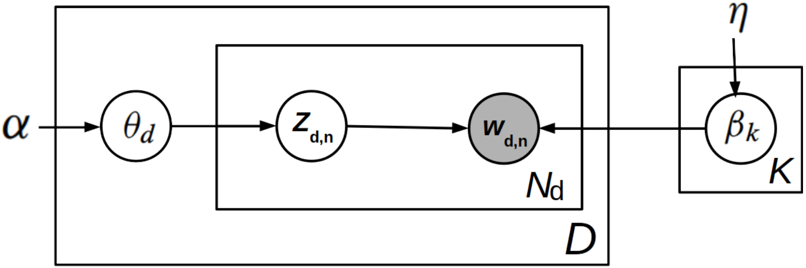
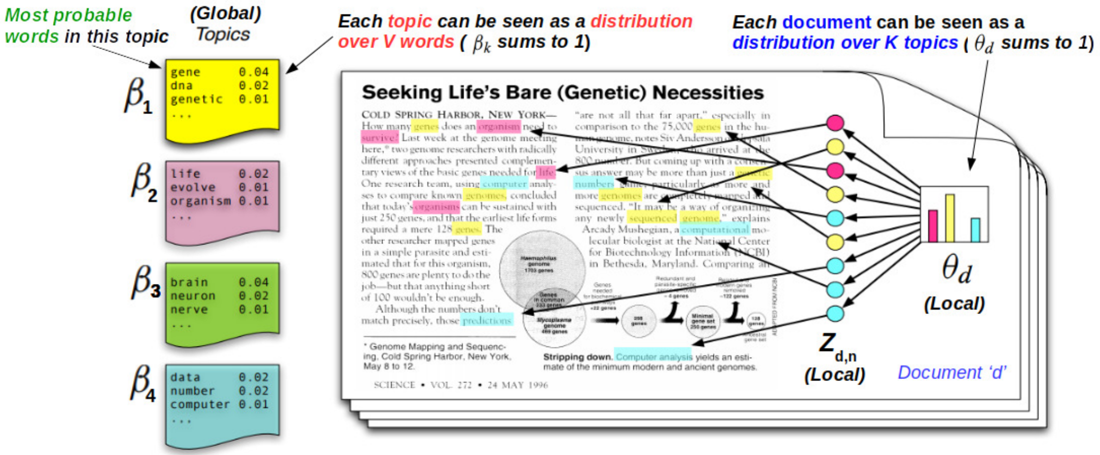


- These mixture models are "tied" together by the shared topics $\{\beta_k\}_{k=1}^K$ and hyperparams α, η
- Word co-occurrences (within/across document) influences the topics $\{\beta_k\}_{k=1}^K$ learned by the model

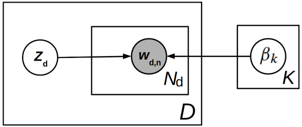
What LDA Output Looks Like, Qualitatively



(Figure: Modified from the original by David Blei)

Some LDA Precursors

- A naïve mixture model: Each document having a single topic, all words from that topic



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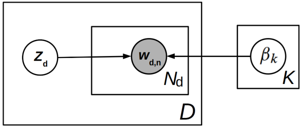

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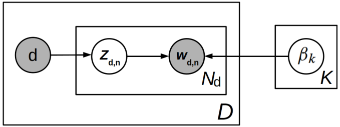

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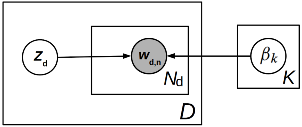

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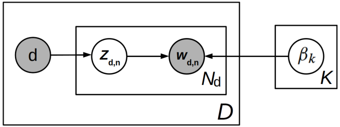

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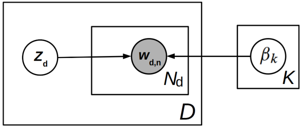

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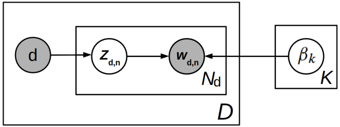

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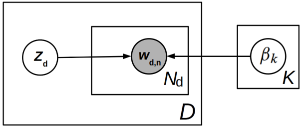

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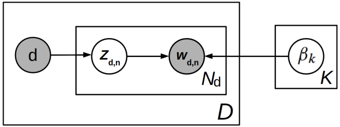

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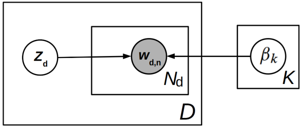

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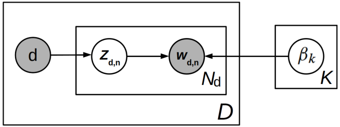

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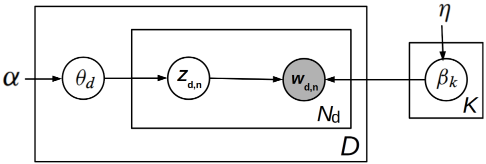
  - LDA however models $p(z=k|d)$ via random variables θ_d, not tied to only training data, so can extend to previously unseen documents unlike PLSA. A subtle but important difference (Blei et al, 2003)
- Also, unlike LDA, PLSA is not a Bayesian model

Inference for LDA



- The goal is to infer the posterior distribution over all the latent variables

$$p(\mathbf{Z}, \theta, \beta | \mathbf{W}, \alpha, \eta) = \frac{p(\mathbf{W}|\beta, \mathbf{Z})p(\mathbf{Z}|\theta)p(\beta|\eta)p(\theta|\alpha)}{p(\mathbf{W}|\alpha, \eta)} \qquad \text{(assuming hyperparams } \alpha, \eta \text{ are fixed)}$$

- $\mathbf{Z}$: Topic assignments of all words across all documents
- $\theta = \{\theta_1, \ldots, \theta_D\}$: Topic proportion vectors; each θ_d is a K-dim vector
- $\beta = \{\beta_1, \ldots, \beta_K\}$: The K topics; each β_k is a V-dim vector
- $\mathbf{W} = \{\boldsymbol{w}_{d,n}\}, d = 1, \ldots, D, n = 1, \ldots, N_d$: Collection of all words in all the documents

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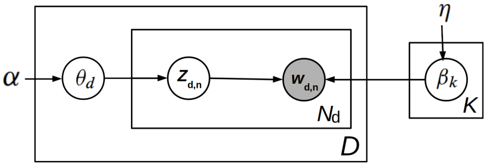

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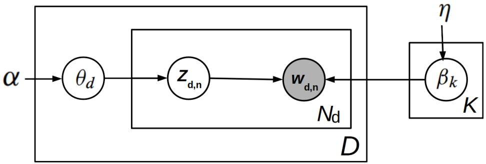

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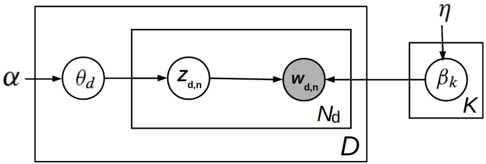

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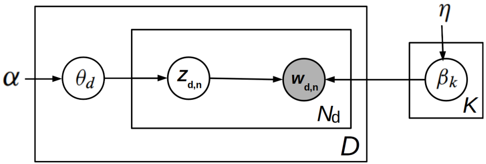

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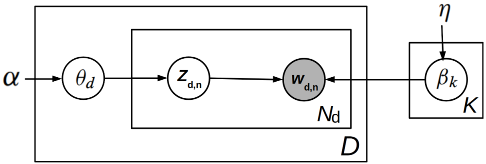

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- Note: Can even collapse some variables and do collapsed Gibbs or collapsed VB

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A Collapsed Gibbs Sampler for LDA

- Collapse θ_d's and β_k's (due to Dirichlet-multinomial conjugacy) and only infer $\mathbf{Z}$ as[†]

$$p(z_{d,n} = k|\mathbf{Z}_{-(d,n)}, \mathbf{W}) \propto \underbrace{p(z_{d,n} = k|\mathbf{Z}_{-(d,n)})}_{\text{collapsed prior for } z_{d,n}} \underbrace{p(\boldsymbol{w}_{d,n}|z_{d,n} = k, \mathbf{W}_{-(d,n)}, \mathbf{Z}_{-(d,n)})}_{\text{collapsed likelihood for } \boldsymbol{w}_{d,n}}$$

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- Note: Can compute the document topic proportions vector θ_d and topic β_k using the inferred $\mathbf{Z}$

$$\theta_{dk} = \frac{\sum_{n=1}^{N_d} 1[\boldsymbol{z}_{d,n} = k]}{N_d}$$

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- Note: Can compute the document topic proportions vector θ_d and topic β_k using the inferred $\mathbf{Z}$

$$\theta_{dk} = \frac{\sum_{n=1}^{N_d} 1[z_{d,n} = k]}{N_d} \qquad \text{and} \qquad \beta_{kv} = \frac{\sum_{d=1}^{D} \sum_{n=1}^{N_d} 1[z_{d,n} = k, \boldsymbol{w}_{d,n} = v]}{\sum_{d=1}^{D} N_d}$$

† Finding Scientific Topics (Griffiths and Steyvers, 2004)

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- A high average probability (low perplexity) implies a good fit to the data

LDA vs Matrix Factorization

- LDA is sort of equivalent to a non-negative matrix factorization model for discrete data
- Input: $V \times N$ word x document matrix $\mathbf{X}$ (of discrete values)

	Docs																			
Terms	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
data	1	1	0	0	2	0	0	0	0	0	1	2	1	1	1	0	1	0	0	0
examples	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
introduction	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
mining	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
network	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1
package	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

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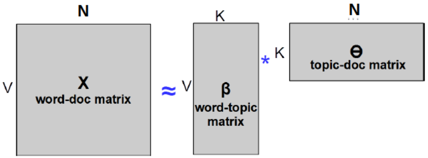
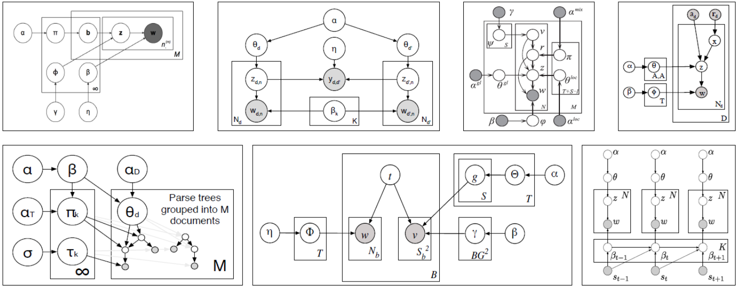
introduction	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
mining	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
network	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1
package	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

- Output: $V \times K$ word-topic matrix β, $K \times N$ topic-document matrix Θ



LDA is easy to extend



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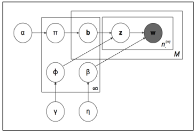

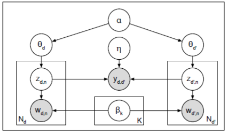

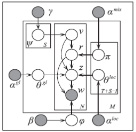

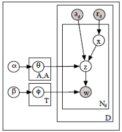

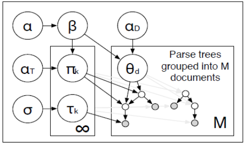

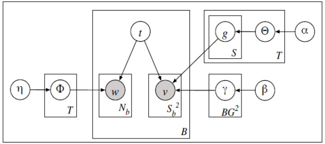

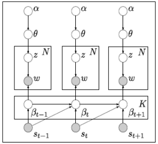

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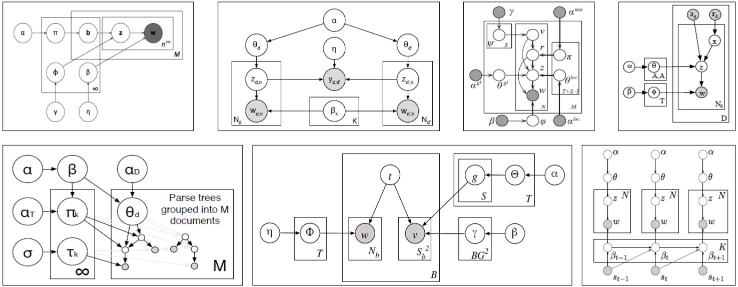

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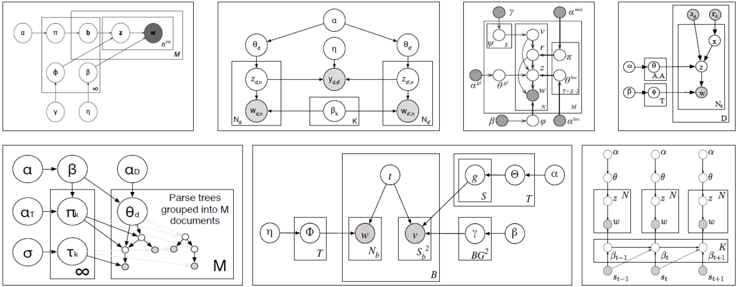

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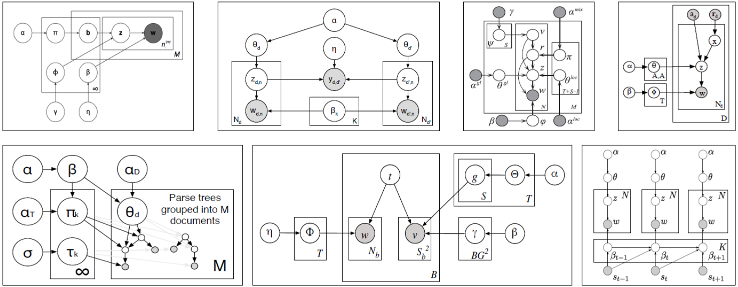

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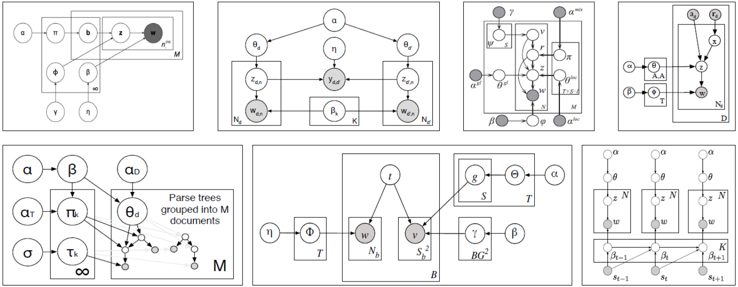

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- LDA with time-evolving topics
- LDA with HMM (takes into account word order), and many others..

Summary

- LDA is a simple but powerful model for discrete data (e.g., text documents)
- Easy to extend to more sophisticated models
- A variety of inference algorithms can be developed for doing inference for LDA based models
- Connections to matrix factorization methods, e.g., Poisson likelihood for the document-word count matrix with gamma priors on the latent factors (recall HW3 problem)
- Some recent work on "Deep Topic Models"