Probabilistic Topic Models

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Topics in Probabilistic Modeling and Inference (CS698X)

March 13, 2019

Topic Models

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Pic courtesy: David Blei

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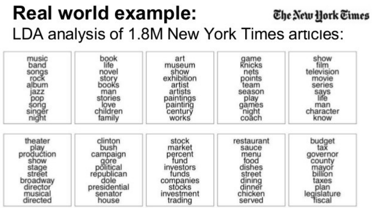

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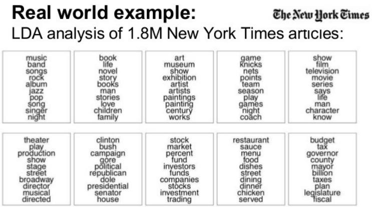

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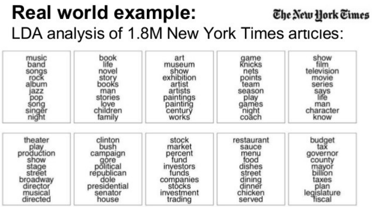

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  - Image collection: Each image is a "document" which is a bag of "visual words"

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Real world example: The New York Times

LDA analysis of 1.8M New York Times articles:

music band songs rock album jazz pop song singer night	book life novel story books man stories love children family	art museum show exhibition artist artists paintings painting century works	game knicks nets points team season play games night coach	show film television movie series says life man character know
theater play production show stage street broadway director musical directed	clinton bush campaign gore political republican dole presidential senator house	stock market percent fund investors funds companies stocks investment trading	restaurant sauce menu food dishes street dining dinner chicken served	budget tax governor county mayor billion taxes plan legislature fiscal

- Also applicable to other types of data, beyond text documents, e.g.,
  - Image collection: Each image is a "document" which is a bag of "visual words"
  - Customer-purchase data: Each customer is a "document" and items purchased are the "words"

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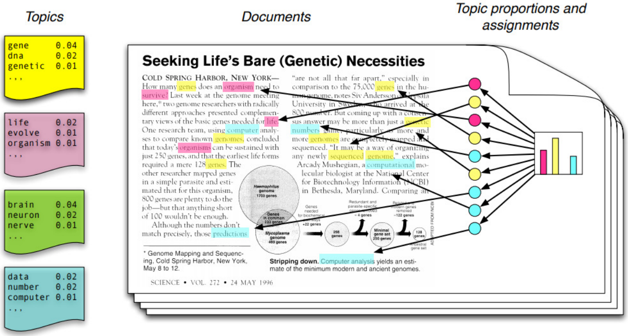

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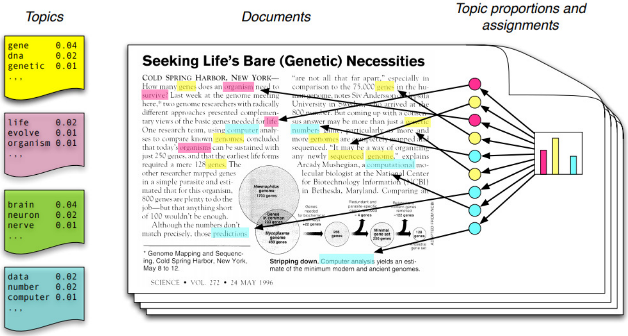
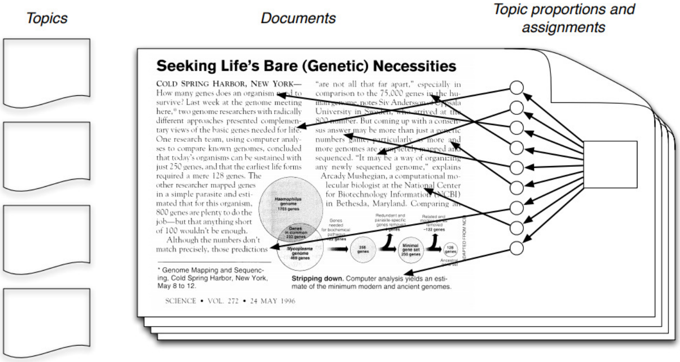


- Formally, a "topic" is a distribution over tokens (a prob. vector with length = # of unique tokens)

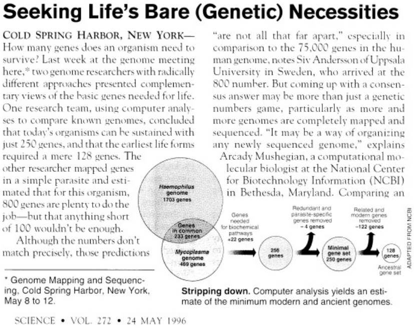
Topic Models

- 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 Models

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



Seeking Life's Bare (Genetic) Necessities

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

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

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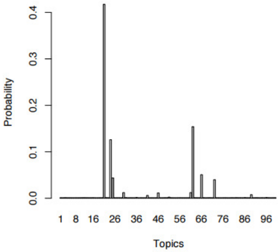

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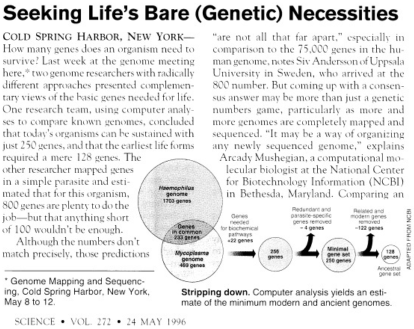

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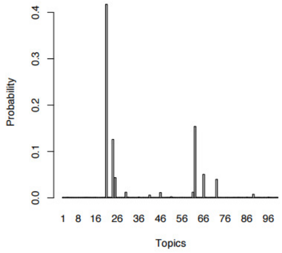

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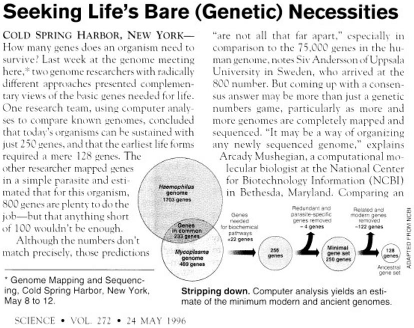

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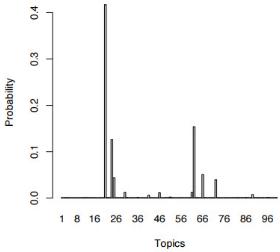
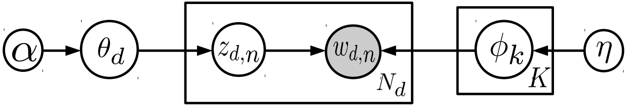


- Also makes it easy to cluster data naturally by (learned) topics
- Can also be used to understand evolution of a corpora (e.g., how topics drift over time - "Dynamic Topic Models" - e.g., word prominent in one topic now may not be so after 10 years later)

A Toy Mixture Model for Words in a Document

- Recall that topic modeling is like clustering the words of the documents
- Consider a toy K component multinoulli mixture model for the words of a single document



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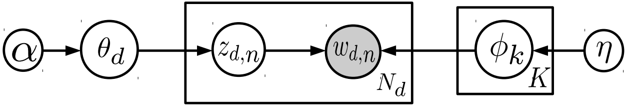

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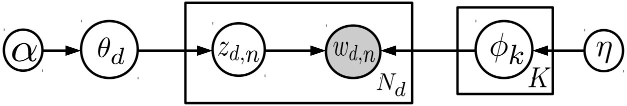

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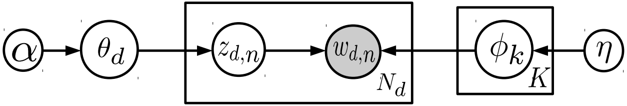

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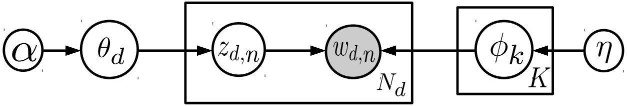

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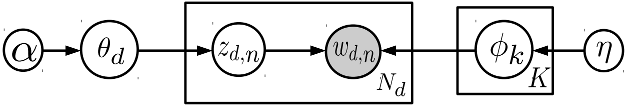

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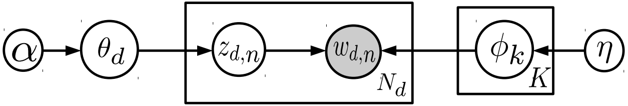

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- In a Bayesian version, θ_d and ϕ_k will have priors with hyperparams α and η, respectively

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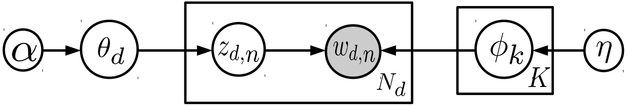

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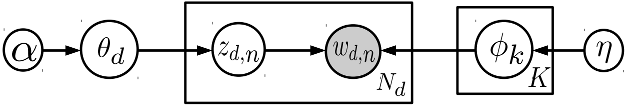

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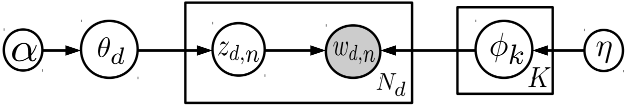

- The generative story will be
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$$\phi_k \sim \text{Dirichlet}(\eta, \ldots, \eta) \qquad k = 1, \ldots, K$$

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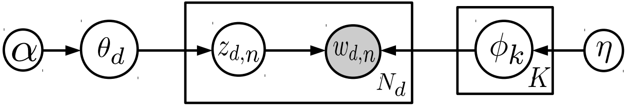

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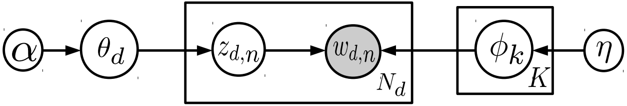

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  - For each word $w_{d,n}$, $n = 1, \ldots, N_d$

$$\begin{aligned} z_{d,n} &\sim \text{multinoulli}(\theta_d) \\ w_{d,n} &\sim \text{multinoulli}(\phi_{z_{d,n}}) \end{aligned}$$

Latent Dirichlet Allocation (LDA)

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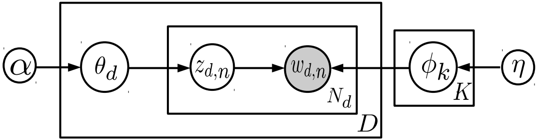
- The previous toy model can be extended easily to handle this



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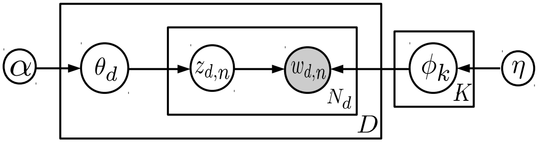

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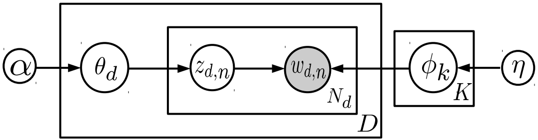

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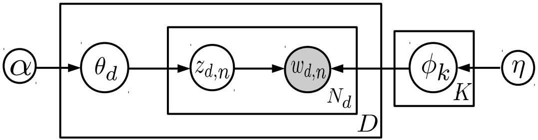

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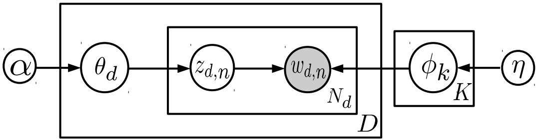

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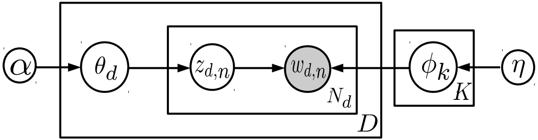

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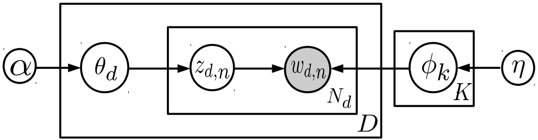

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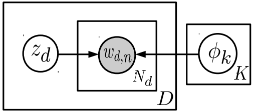
- This is basically the Latent Dirichlet Allocation (LDA) model (Blei *et al*, 2003)
- Generative story is identical to the single doc. toy example but now θ_d for each doc.

Some LDA Precursors

- **Mixture of unigrams models:** Each document having a single topic, all words from that topic



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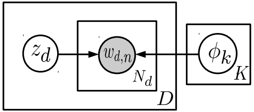

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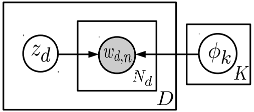

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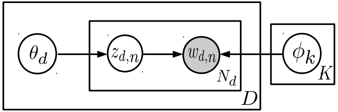
- **Probabilistic Latent Semantic Analysis:** Like LDA, each word in a doc has its own topic



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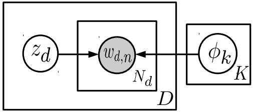

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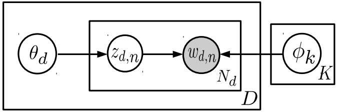

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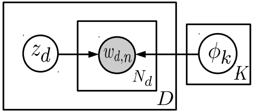

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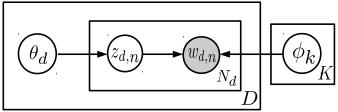

- However, unlike LDA, PLSA (Hofmann (2001) is not a Bayesian model
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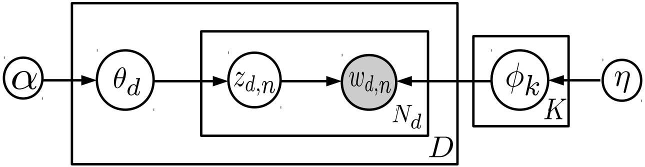

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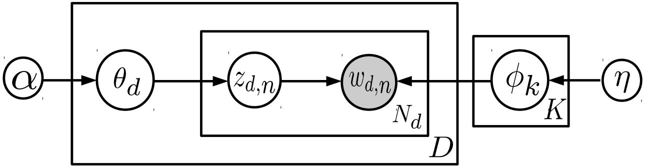

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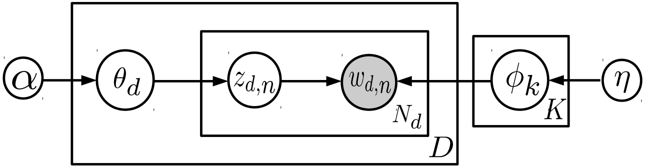

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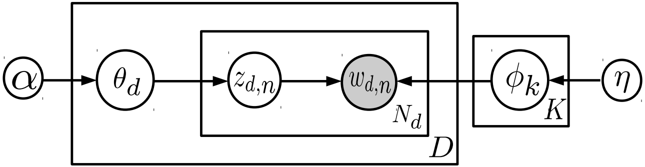

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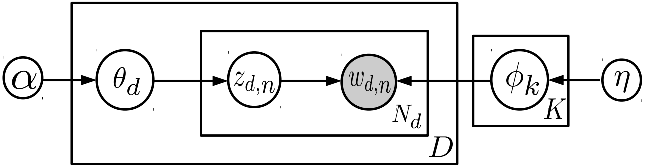

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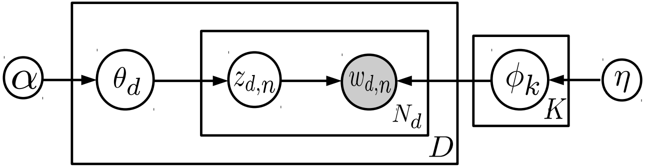

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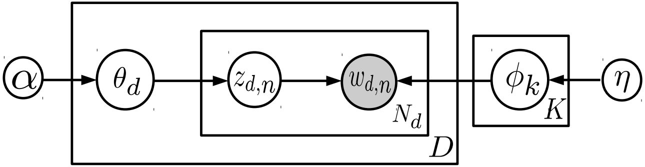

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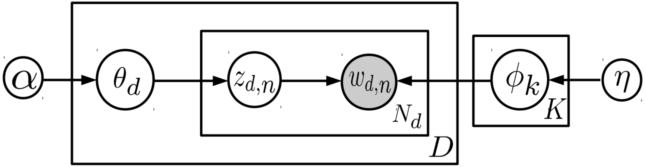

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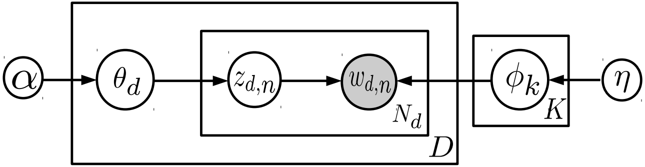

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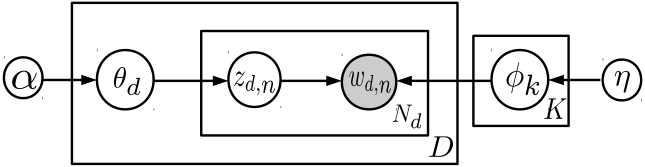

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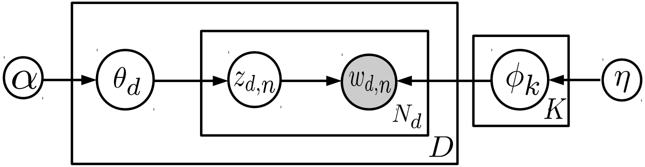

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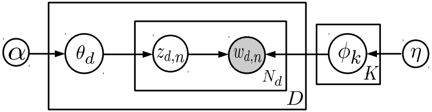
LDA as (Bayesian) Non-negative/Poisson Matrix Factorization



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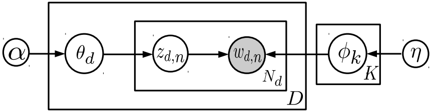

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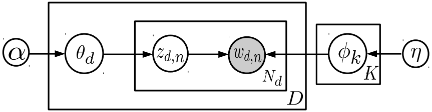

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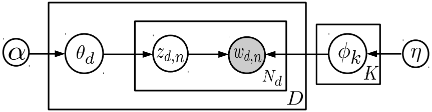

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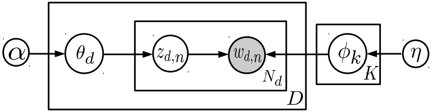

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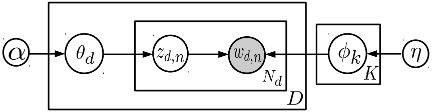

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- Note: Even if priors on ϕ_k and θ_d are not Dirichlet (e.g., each entry of vectors ϕ_k and/or θ_d has some other non-neg prior[†], such as gamma, the Bayesian Poisson NMF equivalence still holds)

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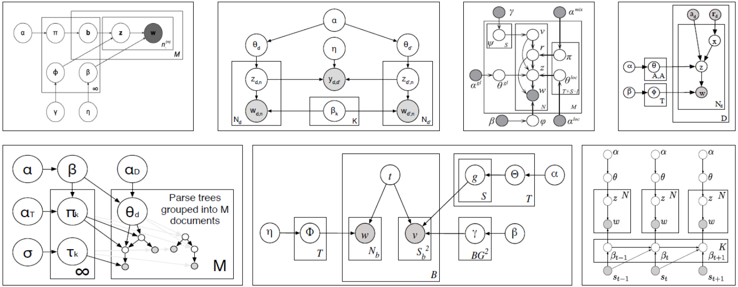

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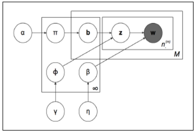

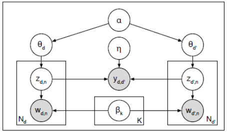

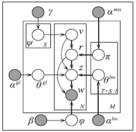

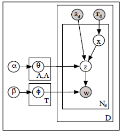

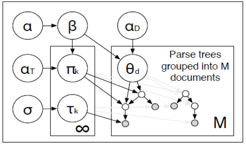

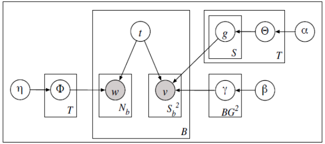

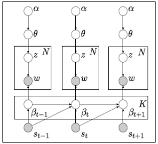

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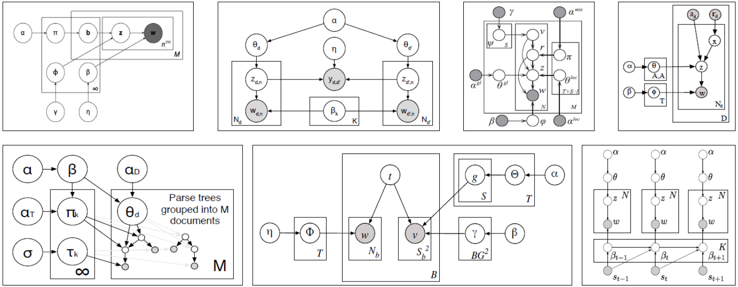

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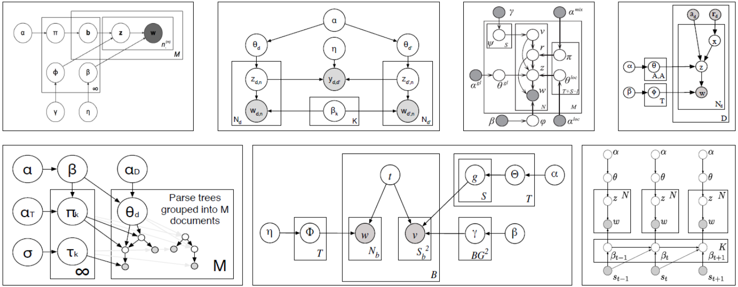

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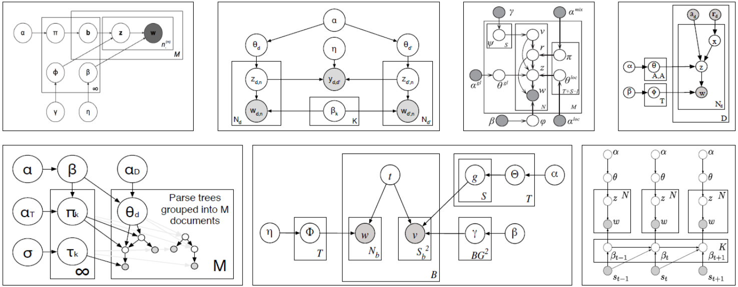

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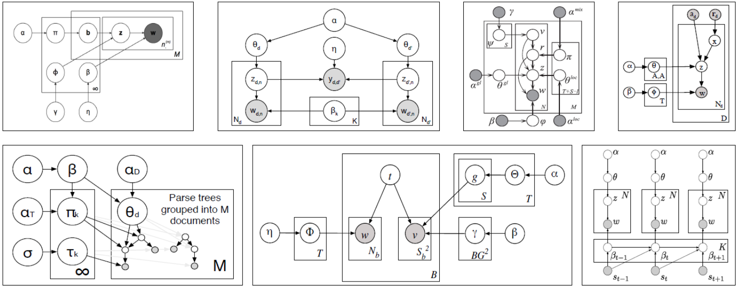

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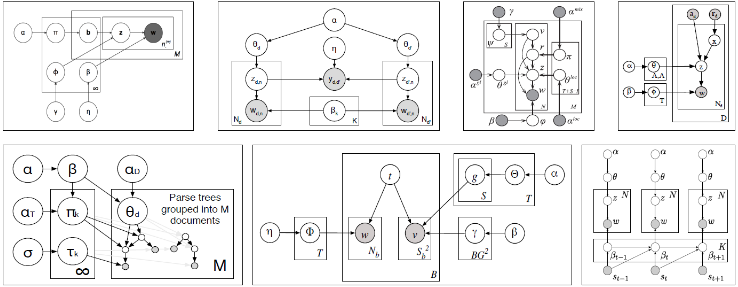

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