# 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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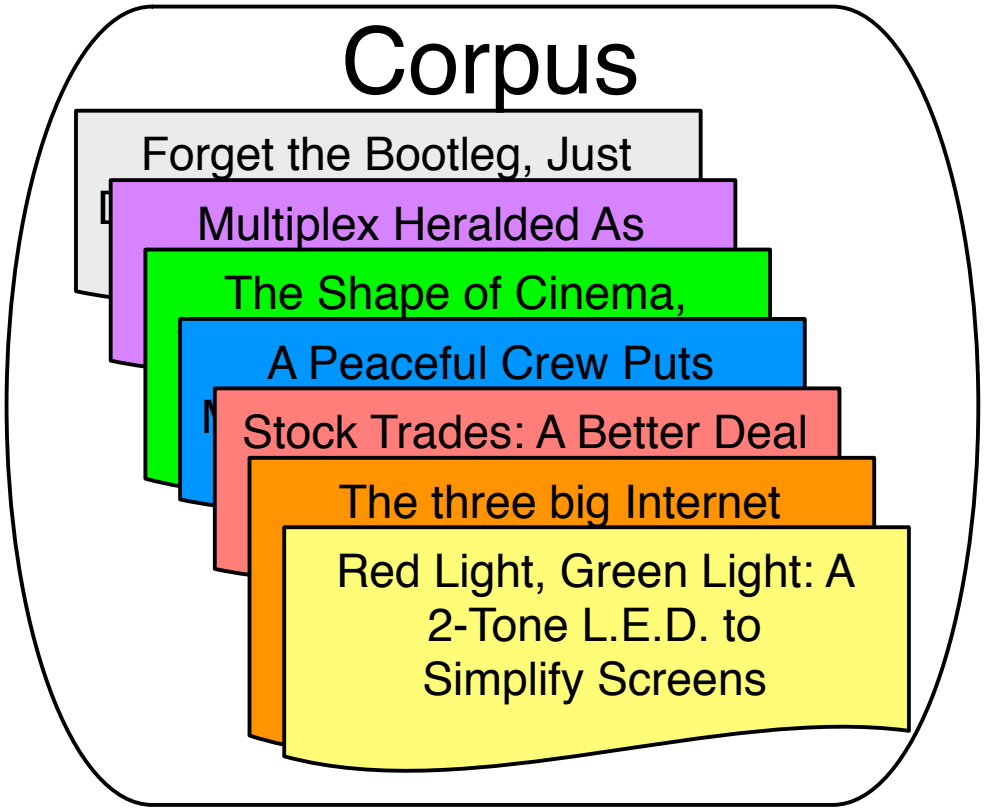
- Unsupervised

## Roadmap

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

## Embedding Space

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



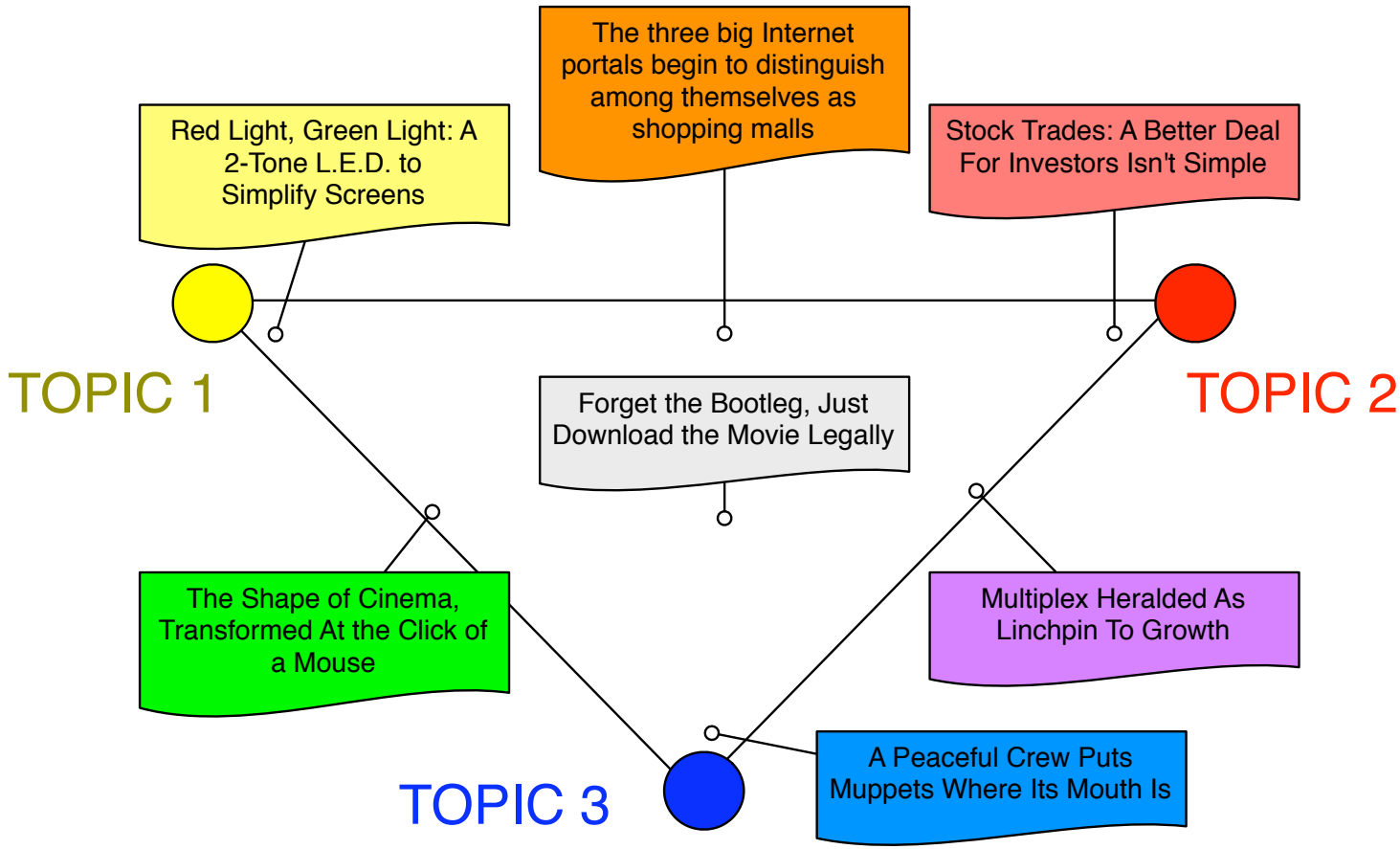
## Embedding Space

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



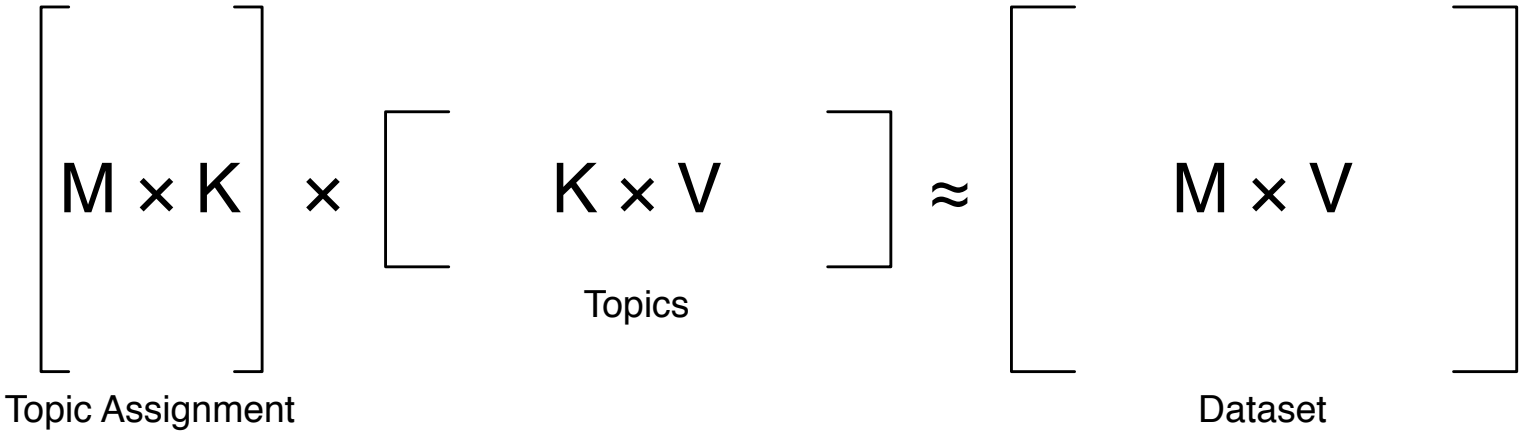
## Topics from *Science*

| | | | |
|---|---|---|---|
| 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




- **K** Number of topics
- **M** Number of documents
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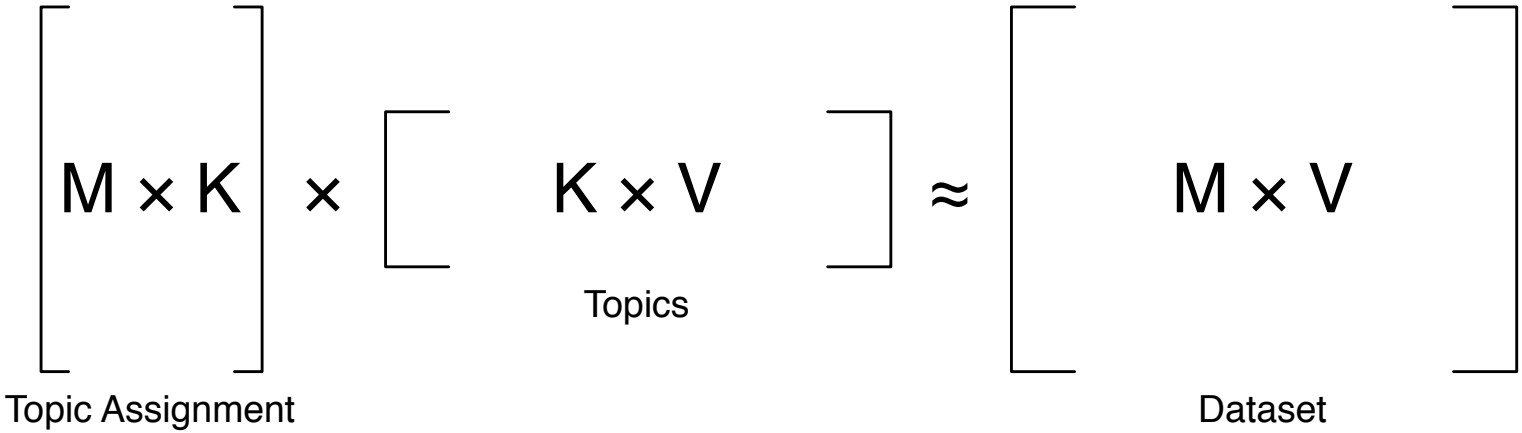


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- If you use singular value decomposition (SVD), this technique is called latent semantic analysis.
- Popular in information retrieval.

## Alternative: Generative Model

- How your data came to be
- Sequence of Probabilistic Steps
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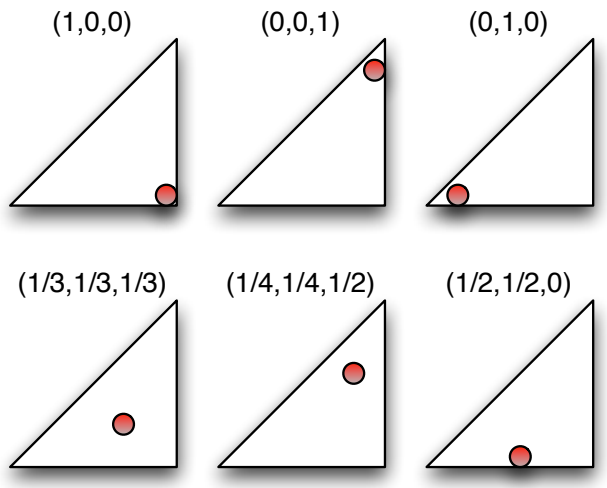
- Blei, Ng, Jordan. Latent **Dirichlet** Allocation. JMLR, 2003.

## Multinomial Distribution

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



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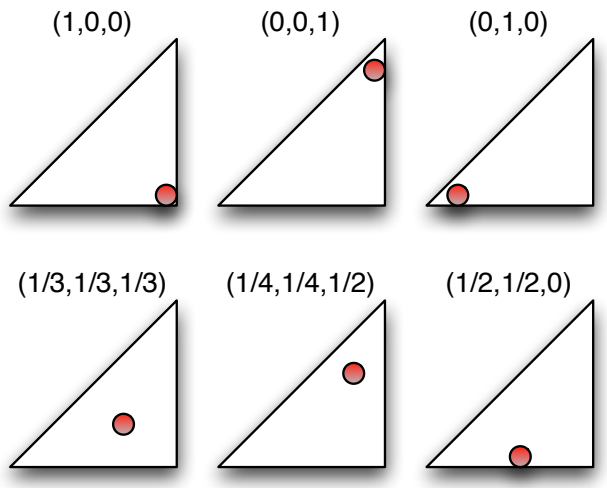


- Come from a Dirichlet distribution

## Dirichlet Distribution

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

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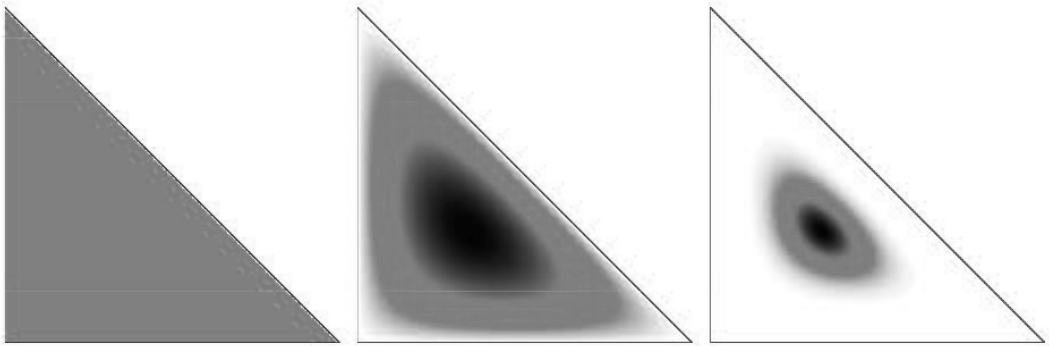

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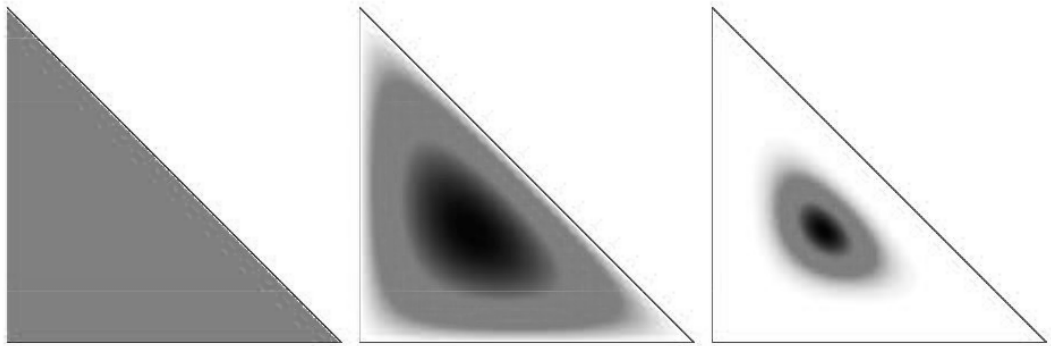

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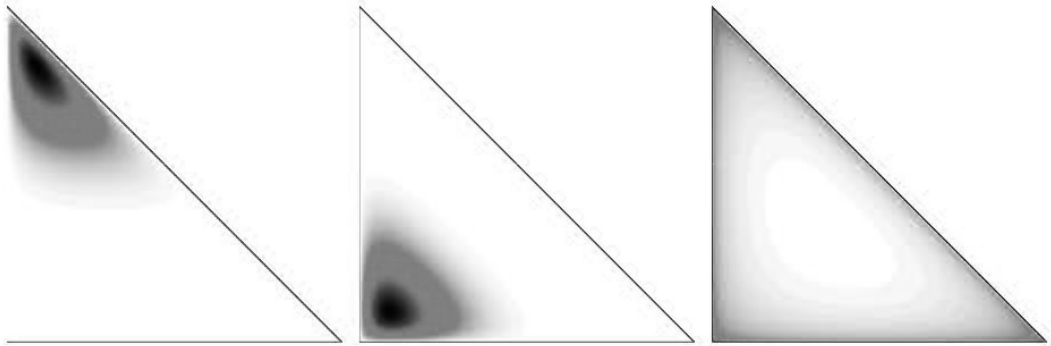

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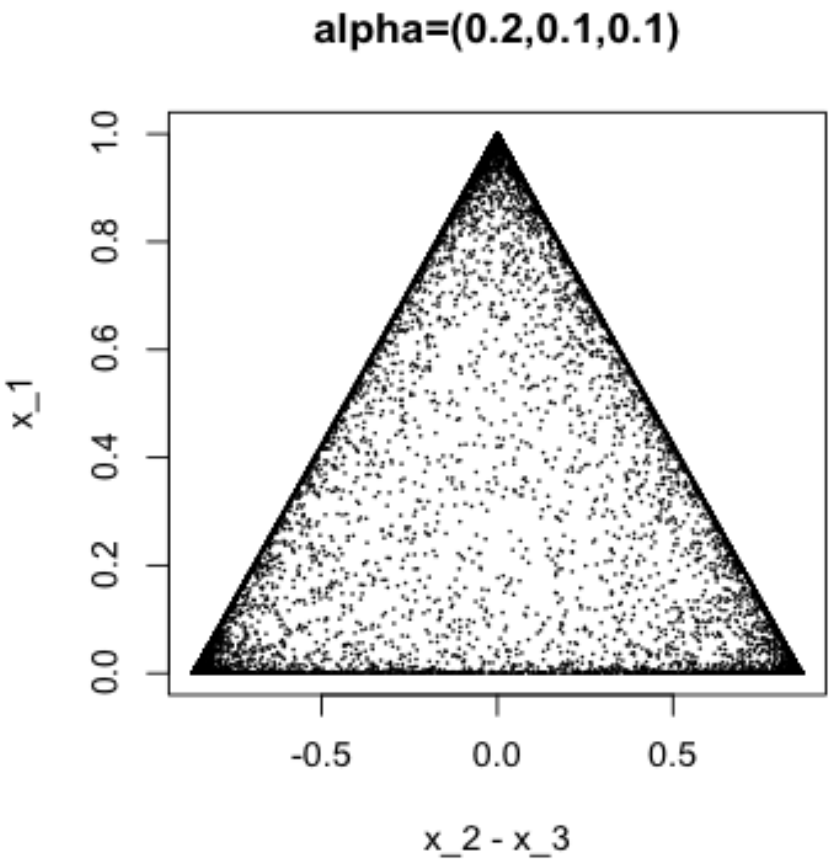

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- If $\boldsymbol{\phi} \sim \text{Dir}(()\alpha)$, $\boldsymbol{w} \sim \text{Mult}(()\boldsymbol{\phi})$, and $n_k = |\{w_i : w_i = k\}|$ then

$$p(\phi|\alpha, \boldsymbol{w}) \propto p(\boldsymbol{w}|\phi)p(\phi|\alpha) \tag{1}$$

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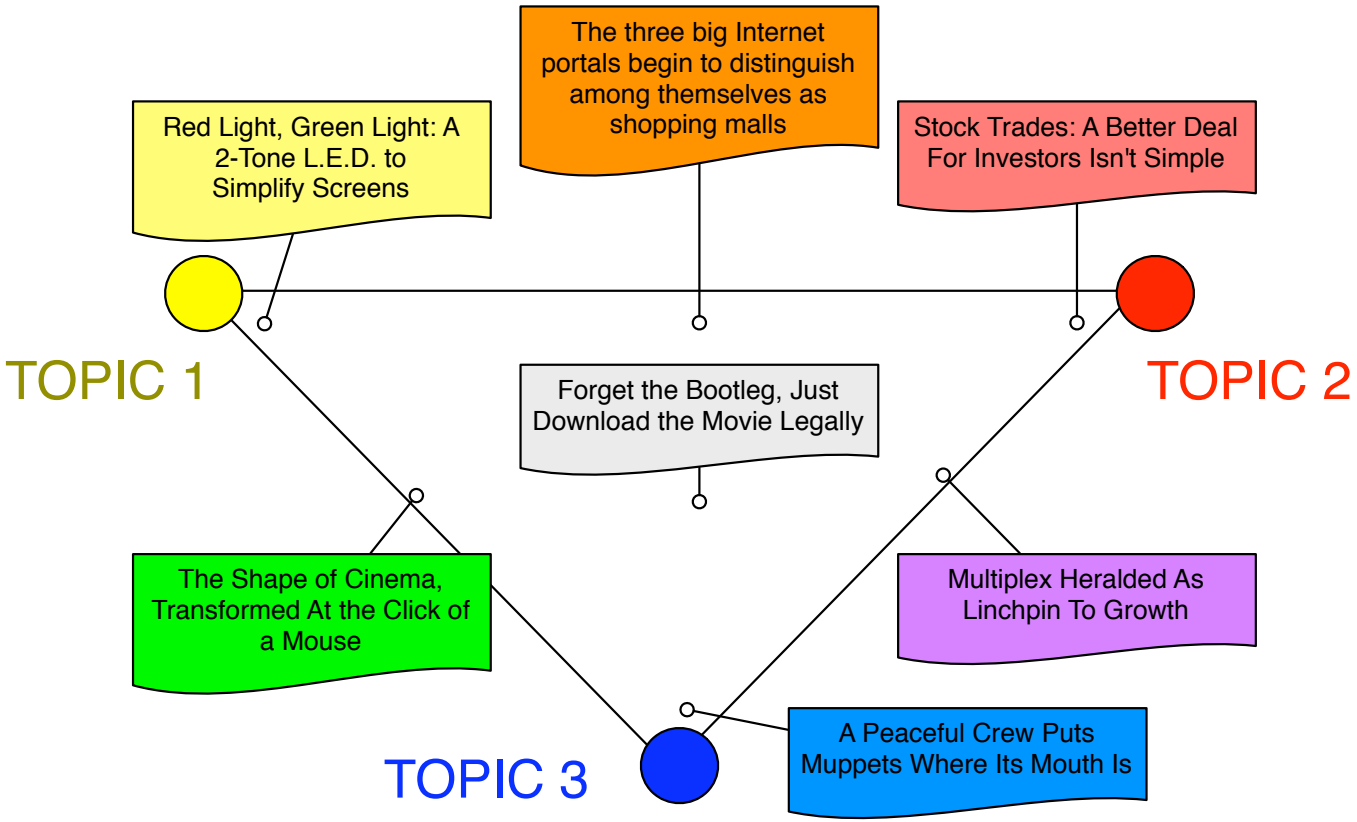

## Generative Model

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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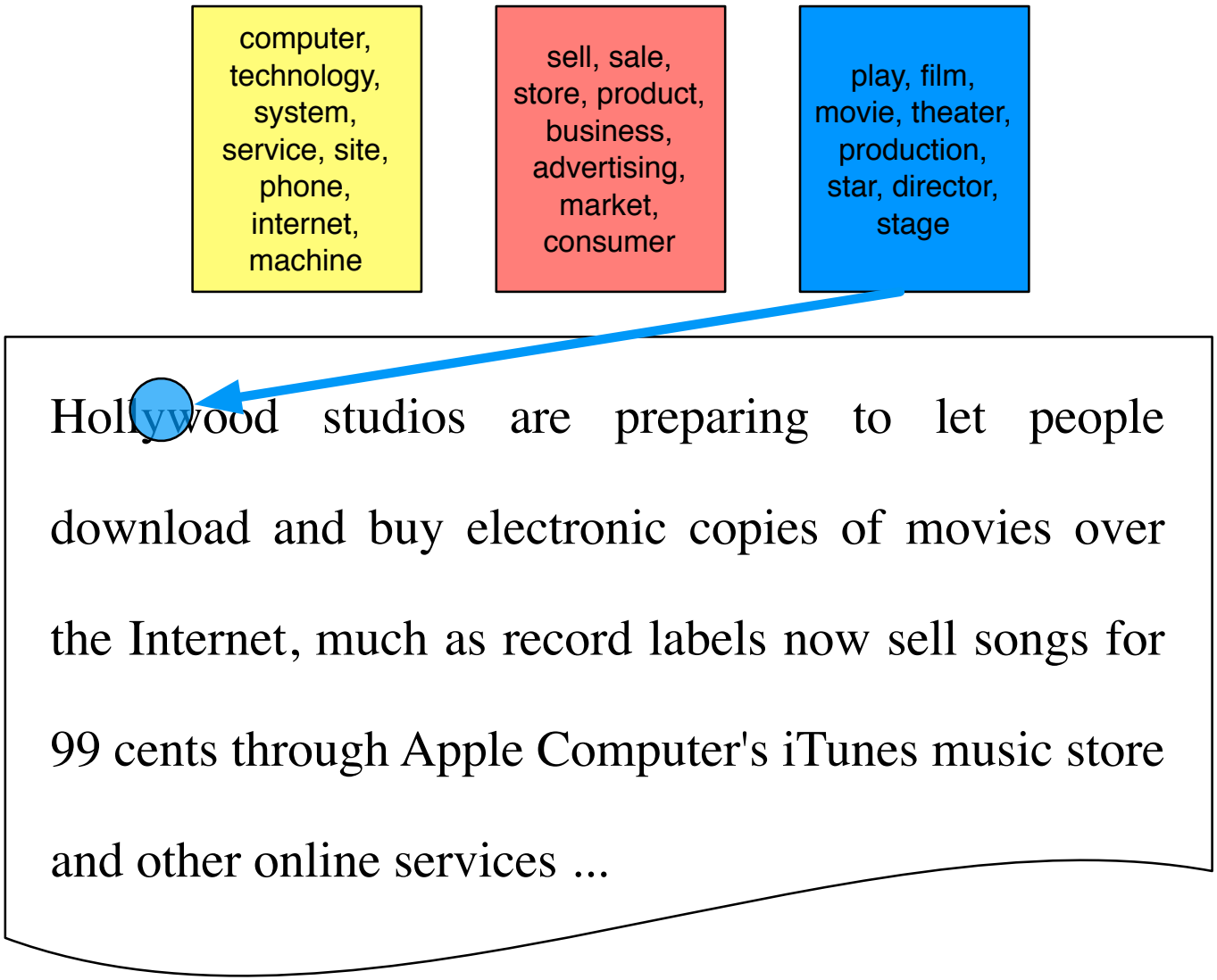

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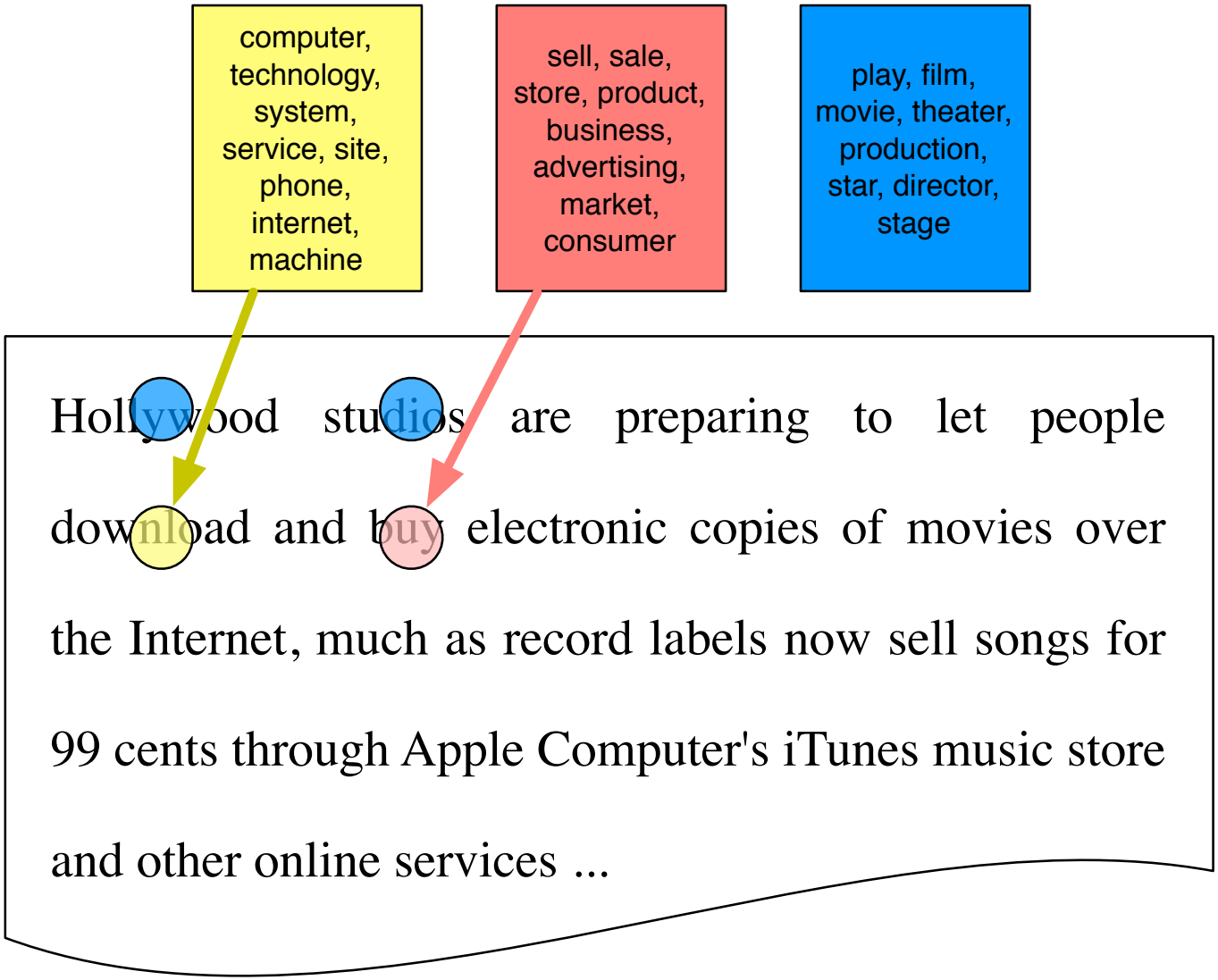

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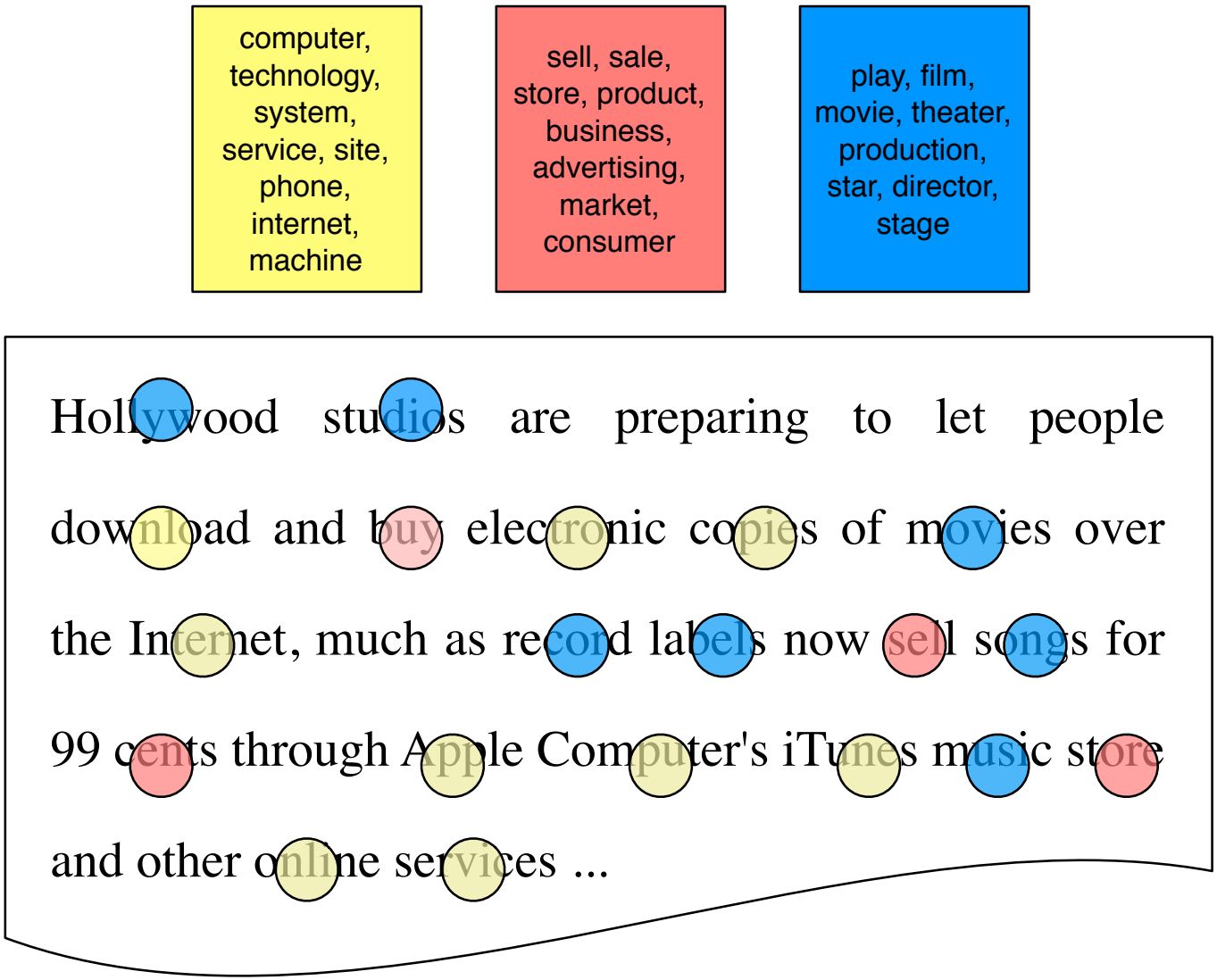

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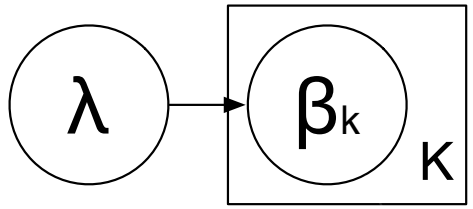

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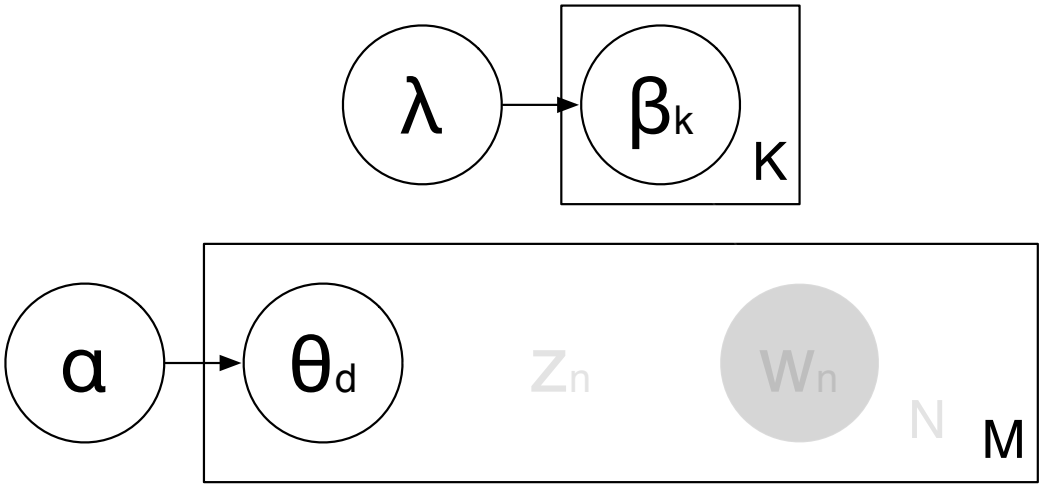


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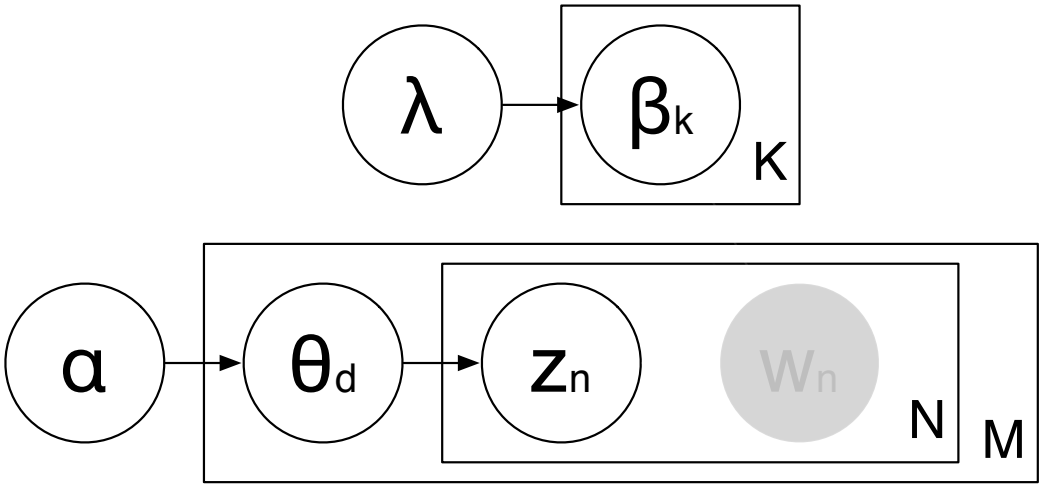


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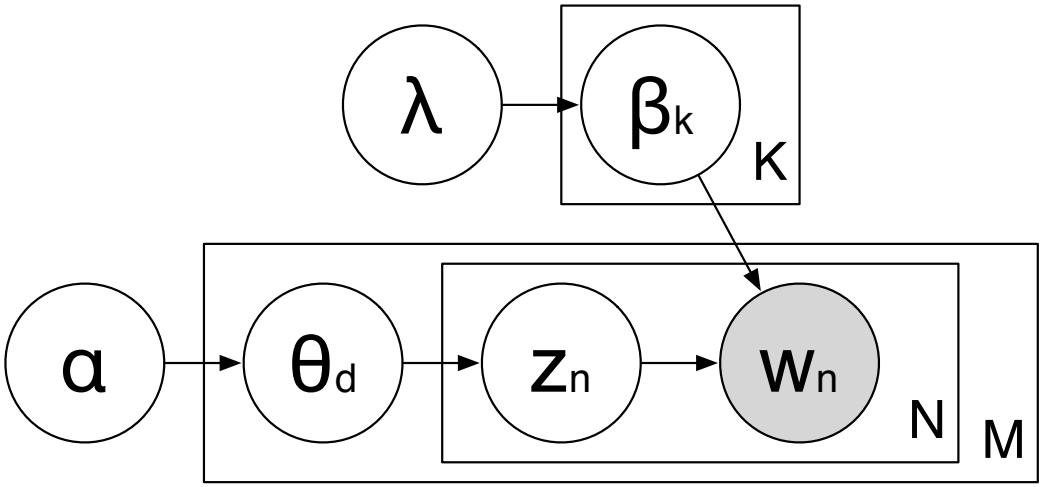


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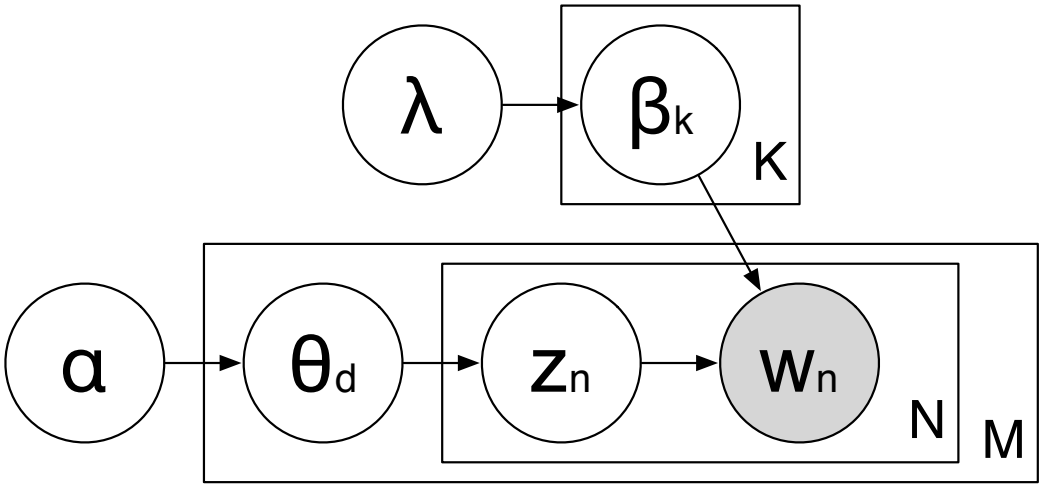


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## Topic Models: What's Important

- Topic models
  - Topics to word types—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
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