Latent Dirichlet Allocation

CPSC 503 - Pedagogical Project Final Presentation

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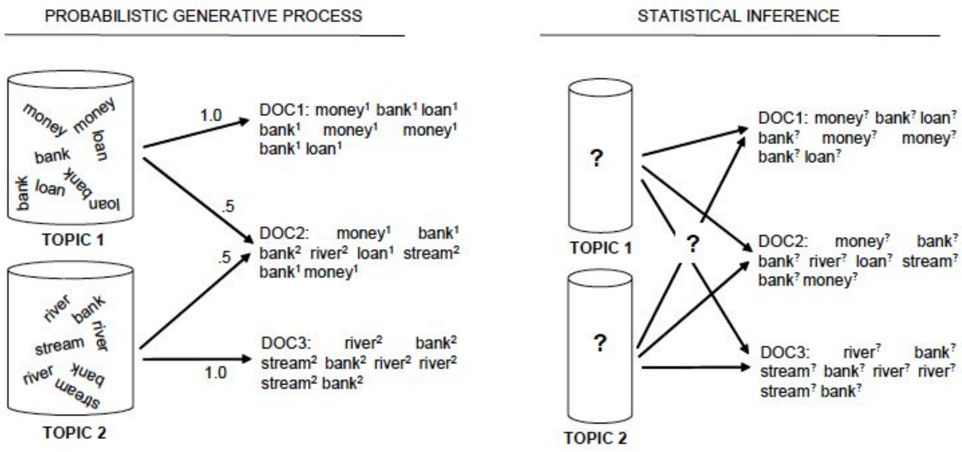
Motivation

- We can use topic models for
  - Data exploration
  - Information Retrieval
  - Classification (or prediction)
  - searching for relevant documents
- LDA is the most widely used topic modelling method
- **Latent Dirichlet Allocation** by Blei et al.(2003) is one of the most cited machine learning papers

Probabilistic Topic Modelling

1. Treat data as observations that arise from a generative process that includes hidden variables
2. Infer the hidden structure using posterior inference
3. Situate new data into the estimated model



Source: Steyvers, M., & Griffiths, T. (2006). Probabilistic Topic Models. In Latent Semantic Analysis: A Road to Meaning (p. 15).

History building up to LDA

- Latent Semantic Indexing (LSI) → not a generative model
  - Summarize each document by its TF-IDF values
  - Run Singular Value Decomposition (SVD) on TF-IDF matrix to reduce dimension
  - Treat the principal components as the “topics”
- Probabilistic LSI (Aspect Model)
  - Introduced as an alternative to LSI
  - Each word w as a sample from a mixture model

$$P(w \mid d) = \sum_{z \in Z} P(w \mid z) P(z \mid d)$$

  - Mixture components are multinomial random variables z that can be viewed as "topics"
  - No probabilistic model at the level of documents

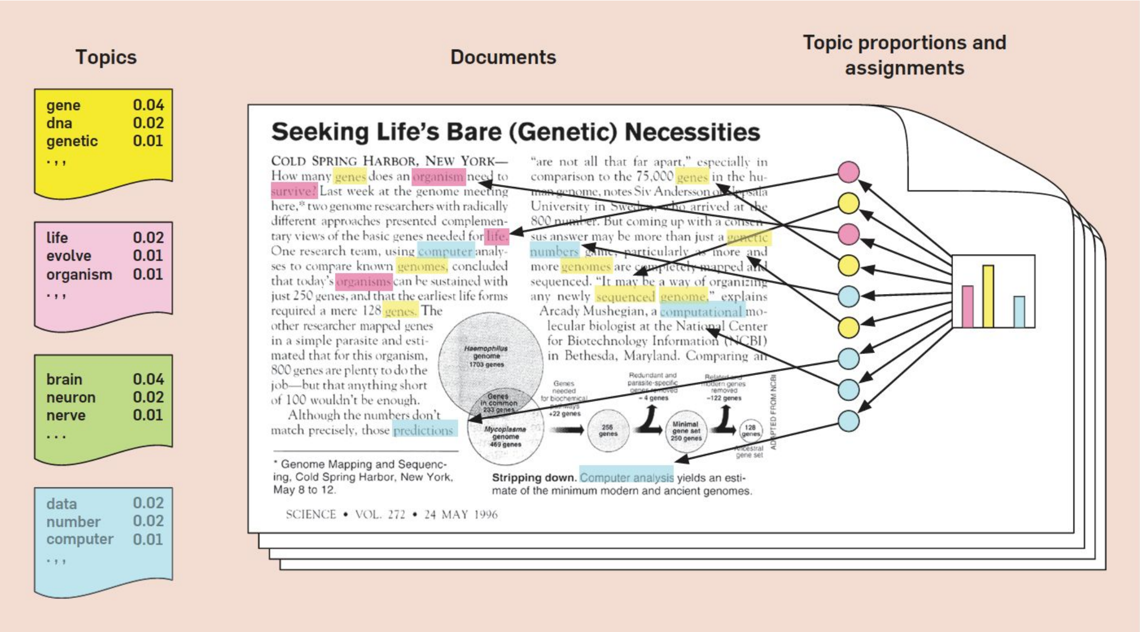
Latent Dirichlet Allocation (LDA)

An **extension of pLSI** bringing a solution to the computation of per-document topic distributions (θ)

A **hierarchical Bayesian model** of **each word in a document**

- Puts a prior on θ → conjugate prior is the Dirichlet distribution

The intuition behind LDA

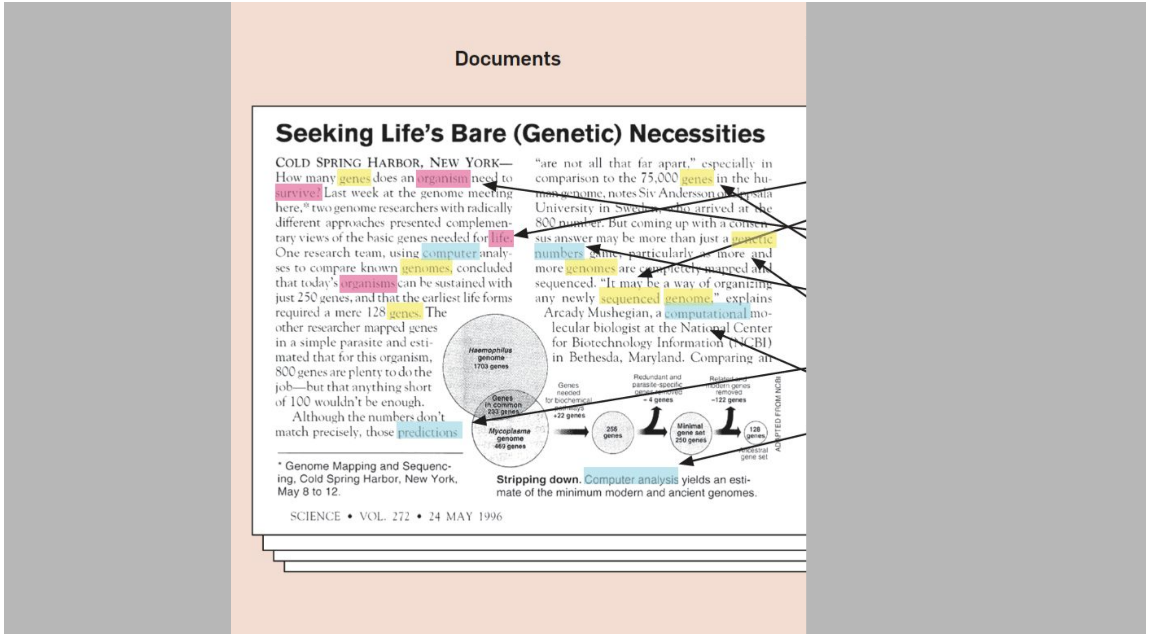


Each document is a random mixture of corpus-wide topics.

Each word is drawn from one of those topics.

Source: Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77. https://doi.org/10.1145/2133806.2133826

The intuition behind LDA



In **reality**,

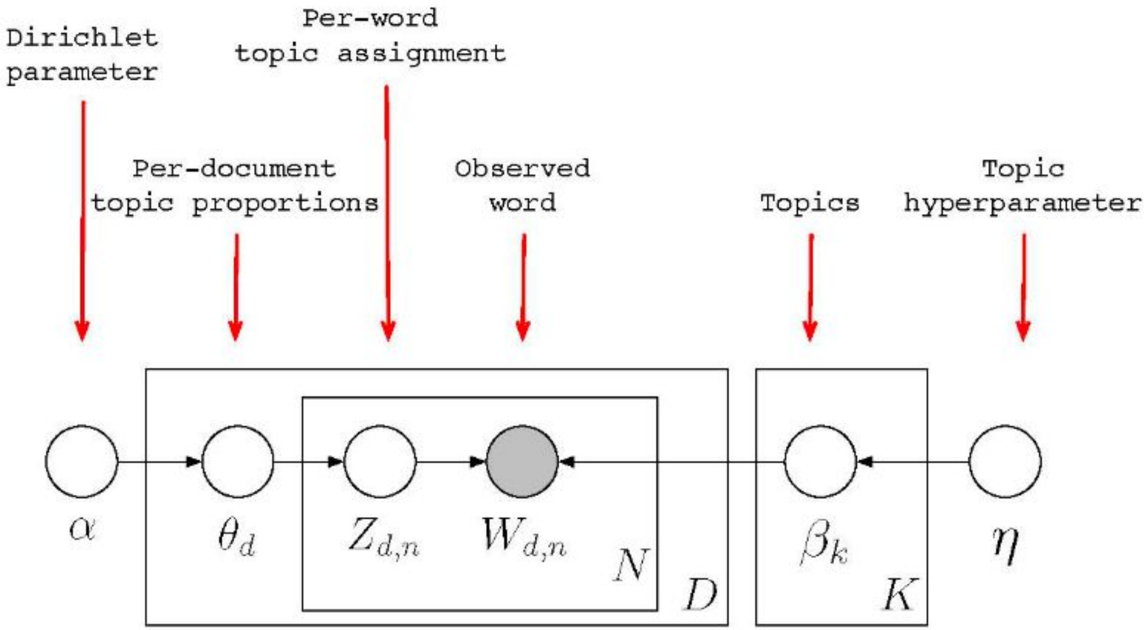
we only <u>observe the documents</u>

and

aim to <u>infer the topic structure</u>.

<u>Source:</u> Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77. https://doi.org/10.1145/2133806.2133826

Latent Dirichlet Allocation (LDA)



Source: Topic Model lecture by David Blei on http://videolectures.net/mlss09uk_blei_tm/

Approximate Posterior Inference

Given observations (words in documents), we want to **infer the hidden structure (topics)** from the posterior distribution.

$$p(\underbrace{Z}_{\text{topics}}, \underbrace{\pi}_{\text{word prob.}}, \overbrace{\theta}^{\text{topic prop.}} \mid \underbrace{X}_{\substack{\text{data} \\ \text{(words)}}}, \underbrace{\alpha}_{\substack{\text{prior} \\ \text{on topic} \\ \text{proportions}}}, \underbrace{\beta}_{\substack{\text{prior on} \\ \text{word} \\ \text{probabilities}}}) = \left[\prod_{i=1}^{n} \underbrace{p(\theta^i \mid \alpha)}_{\substack{\text{topic proportion} \\ \text{probability} \\ \text{(document 'i')}}} \prod_{j=1}^{d} \underbrace{p(z_j^i \mid \theta^i)}_{\substack{\text{topic probability} \\ \text{(topic at position} \\ \text{'j' in document 'i')}}} \underbrace{p(x_j^i \mid z_j^i, \pi_j)}_{\substack{\text{word probability} \\ \text{(word at position} \\ \text{'j' in document 'i')}}}\right] \left[\prod_{c=1}^{k} \underbrace{p(\pi_c \mid \beta)}_{\substack{\text{word probability} \\ \text{parameters} \\ \text{(topic 'c')}}}\right]$$

Source: CPSC 540 slides by Mark Schmidt at https://www.cs.ubc.ca/~schmidtm/Courses/540-W18/L33.pdf

Posterior probability is **computationally intractable** → approximate inference

- Sampling-based algorithms → MCMC (Markov Chain Monte Carlo)
  - Gibbs sampling
- Variational algorithms → optimization
  - Variational EM algorithm

Approximate inference with MCMC

With Gibbs sampling we alternate between:

- Sampling topics given word probabilities and topic proportions.
- Sampling topic proportions given topics and prior parameters α.
- Sampling word probabilities given topics, words, and prior parameters β.

Have a burn-in period, use thinning, try to monitor convergence, etc.

Finally we use posterior samples to do inference:

- Distribution of topic proportions for sample ‘i’ is frequency in samples.
- To see if words come from same topic, check frequency in samples.

Evaluation: Perplexity

Applications in Informations Systems (IS)

References

- Blei, D. M., Ng, A. Y., and Jordan, M. I. 2003. "Latent Dirichlet Allocation," Journal of Machine Learning Research (3), pp. 993-1022.
- CPSC 540: Machine Learning slides by Mark Schmidt on Topic Models
- University of Waterloo lecture slides