

Latent Dirichlet Allocation

Jérôme DOCKÈS (jerome@dockes.org), Pascal LU (pascal.lu@centraliens.net)

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Objectives

We consider the problem of modeling text corpora. The goal is to find short descriptions of the members of a collection. Our work is mainly based on:

[1] David M. Blei, Andrew Y. Ng, and Michael I. Jordan.
Latent dirichlet allocation.
The Journal of Machine Learning Research, 3:993–1022, 2003.

Notations

- $\mathcal{D} = \{d_1, d_2, \dots, d_M\}$ is a corpus.
- \mathcal{V} is the vocabulary of size V .
- k is the number of topics.

For a document $d \in \mathcal{D}$,

- $d = (w_1^{(d)}, \dots, w_{N_d}^{(d)})$ represents the document d , where the $w_i^{(d)}$ are all distinct. N_d is the number of **distinct** words in the document d .
- $w^{(d)}$ (**word_incidences**) is a matrix containing the number of times each word in the vocabulary appears in the document. Size of $w^{(d)} = N_d \times V$.
- $\theta^{(d)}$ is an array of size k , representing a probability density.
- $z^{(d)}$ is the set of topics : $z_{ni}^{(d)} = 1$ if the word n is linked with the topic i . Size of $z^{(d)} = N_d \times k$.

Presentation of the model

Latent Dirichlet allocation (LDA) is a generative probabilistic model of a corpus.

- Documents = random mixtures over latent topics,
- Topic = a distribution over words.

Input: corpus \mathcal{D}

- 1: **for** each document $d \in \mathcal{D}$ **do**
- 2: Choose $N \sim \text{Poisson}(\xi)$
- 3: Choose $\theta^{(d)} \sim \text{Dir}(\alpha)$
- 4: **for** each of the N words $w_n^{(d)}$ **do**
- 5: Choose a topic $z_n^{(d)} \sim \text{Multinomial}(\theta^{(d)})$
- 6: Choose a word w_n from $p(w_n | z_n^{(d)}, \beta)$, a multinomial probability conditioned on $z_n^{(d)}$.
- 7: **end for**
- 8: **end for**

We have:

$$\begin{aligned} p(d|\alpha, \beta) &= \int p(\theta^{(d)}|\alpha) \left(\prod_{n=1}^{N_d} p(w_n^{(d)}|\theta^{(d)}, \beta) \right) d\theta \\ &= \int p(\theta^{(d)}|\alpha) \left(\prod_{n=1}^{N_d} \sum_{z_n^{(d)}} p(z_n^{(d)}|\theta^{(d)}) p(w_n^{(d)}|z_n^{(d)}, \beta) \right) d\theta \end{aligned}$$

Generative model

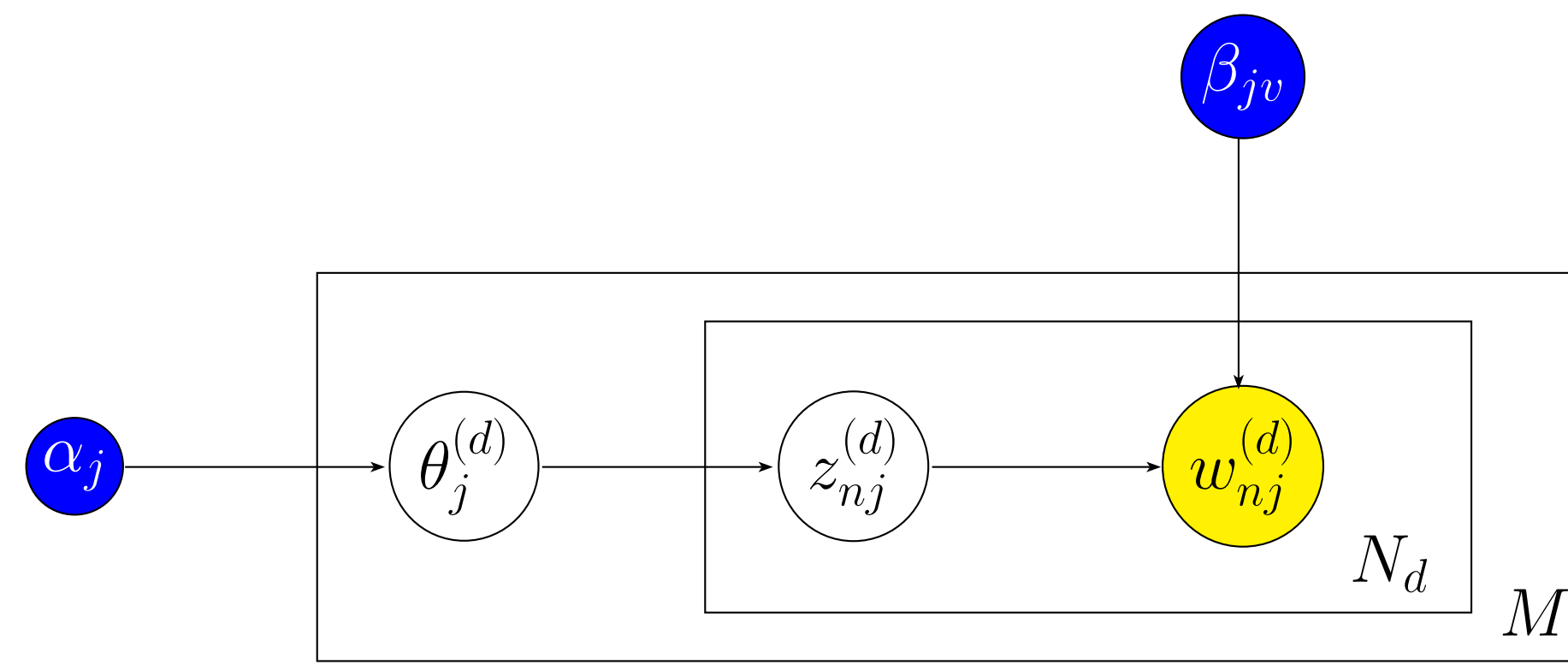
The goal is to determine:

- α is an estimate of the parameter of the Dirichlet distribution which generates the parameter for the (multinomial) probability distribution over topics in the document. Size of $\alpha = k$.

Exchangeable Dirichlet distribution assumption:

$$\forall i \in \{1, \dots, k\}, \quad \alpha_i = \alpha$$

- β is a matrix of size $k \times V$ which gives the estimated probability that a given topic will generate a certain word: $\beta_{ij} = p(w^j = 1 | z^i = 1)$.



Variational inference

We need to compute the posterior distribution of the hidden variables given a document d :

$$p(\theta^{(d)}, z^{(d)} | d, \alpha, \beta) = \frac{p(\theta^{(d)}, z^{(d)}, d | \alpha, \beta)}{p(d | \alpha, \beta)}$$

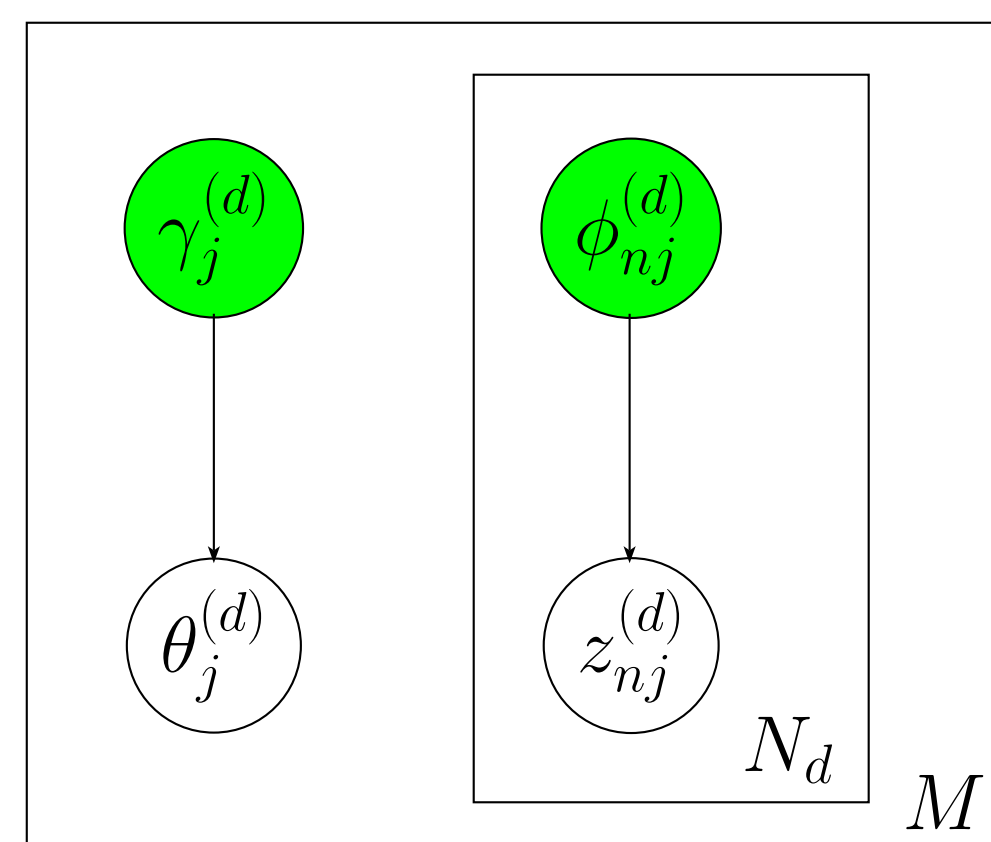
For a document $d \in \mathcal{D}$:

- $\gamma^{(d)}$ is the variational parameter for the Dirichlet distribution. Size of $\gamma^{(d)} = k$.
- $\phi^{(d)}$ is the variational parameter for the multinomial distribution. Size of $\phi^{(d)} = N_d \times k$. $\phi_{ni}^{(d)}$ depends on the relation between the word in position n of the document and the topic i of the list of topics.

$$q(\theta^{(d)}, z^{(d)} | \gamma^{(d)}, \phi^{(d)}) = q(\theta^{(d)} | \gamma^{(d)}) \prod_{n=1}^{N_d} q(z_n^{(d)} | \phi_n^{(d)})$$

\Rightarrow Estimate $\gamma^{(d)}, \phi_n^{(d)}$ instead of $\theta^{(d)}$ and $z_n^{(d)}$.

$$(\gamma^{(d)}, \phi^{(d)}) = \underset{(\gamma, \phi)}{\text{argmin}} D \left(q(\theta^{(d)}, z^{(d)} | \gamma, \phi) \parallel p(\theta^{(d)}, z^{(d)} | d, \alpha, \beta) \right)$$



Variational Inference Procedure (E-step for a document d)

Input: a document d defined by its $w^{(d)}$, α, β

Output: $\gamma^{(d)}, \phi^{(d)}$

- 1: Initialize $\phi_{ni}^{(d)} = \frac{1}{k}$ for all i and n .
- 2: Initialize $\gamma_i^{(d)} = \alpha + \frac{1}{k} \sum_{n=1}^{N_d} w_n^{(d)}$ for all i .
- 3: **while** the expected log-likelihood $L(\gamma^{(d)}, \phi^{(d)}, \alpha, \beta)$ for the document d has not converged **do**
- 4: **for** $n = 1 \dots N_d$ **do**
- 5: **for** $i = 1 \dots k$ **do**
- 6: $\phi_{ni}^{(d)} = \beta_{i w_n^{(d)}} \exp(\Psi(\gamma_i^{(d)}))$
- 7: **end for**
- 8: Normalize $\phi_n^{(d)}$ to sum to 1.
- 9: **end for**
- 10: $\gamma^{(d)} = \alpha + \sum_{n=1}^{N_d} w_n^{(d)} \phi_n^{(d)}$
- 11: Update $L(\gamma^{(d)}, \phi^{(d)}, \alpha, \beta)$
- 12: **end while**

EM-algorithm

Input: corpus \mathcal{D} , number of topics k

Output: α, β

- 1: **for** each $d \in \mathcal{D}$ **do**
- 2: Compute $w^{(d)}$.
- 3: **end for**
- 4: Initialize α and β .
- 5: **while** the expected log-likelihood $L(\alpha, \beta)$ has not converged **do**
- 6: Initialize $\Sigma_\gamma = 0$, $\beta_{\text{new}} = 0$ and $L(\alpha, \beta) = 0$.
- 7: **for** each $d \in \mathcal{D}$ **do**
- 8: $(\gamma^{(d)}, \phi^{(d)}) = \text{variational-inference}(w^{(d)}, \alpha, \beta)$
- 9: $\beta_{\text{new}} \leftarrow \beta_{\text{new}} + (\phi^{(d)})^\top w^{(d)}$
- 10: $\Sigma_\gamma \leftarrow \Sigma_\gamma + \sum_{i=1}^k \Psi(\gamma_i^{(d)}) - \Psi\left(\sum_{j=1}^k \gamma_j^{(d)}\right)$
- 11: $L(\alpha, \beta) \leftarrow L(\alpha, \beta) + L(\gamma^{(d)}, \phi^{(d)}, \alpha, \beta)$
- 12: **end for**
- 13: Normalize β_{new} and set $\beta = \beta_{\text{new}}$
- 14: **while** α has not converged **do**
- 15: $\frac{\partial L}{\partial \alpha}(\alpha) = |\mathcal{D}|k [\Psi(k\alpha) - \Psi(\alpha)] + \Sigma_\gamma$
- 16: $\frac{\partial^2 L}{\partial \alpha^2}(\alpha) = |\mathcal{D}|k [k\Psi'(k\alpha) - \Psi'(\alpha)]$
- 17: $\alpha \leftarrow \alpha - \frac{\frac{\partial L}{\partial \alpha}(\alpha)}{\frac{\partial^2 L}{\partial \alpha^2}(\alpha)}$
- 18: **end while**
- 19: **end while**

Implementation issues

- Document and vocabulary preprocessing : remove redundant words.
- $\alpha > 0$ and β were initialized randomly.
- Under the exchangeable Dirichlet distribution assumption, the computation of α becomes much simpler.

Results

We tested our LDA on real data from the Reuters21578 database (**reut2-000.sgm**).

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
devices	prolonged	zestril	seasons	withdrawn
disk	council	anesthetic	hotels	expiration
megabyte	forum	hypertension	VMS	clearances
expandable	dissident	oth	Biltmore	expire
megabytes	flying	stail	Marriott	Willemijn
equipped	sparks	diabetic	rename	BV
monochrome	talks	complications	hotel	Rotterdam
peripheral	outweighed	Barbara	228	licensed
color	accomplishments	definitive	DH	NCR

Table 1: Results for 5 topics ($k = 20$)

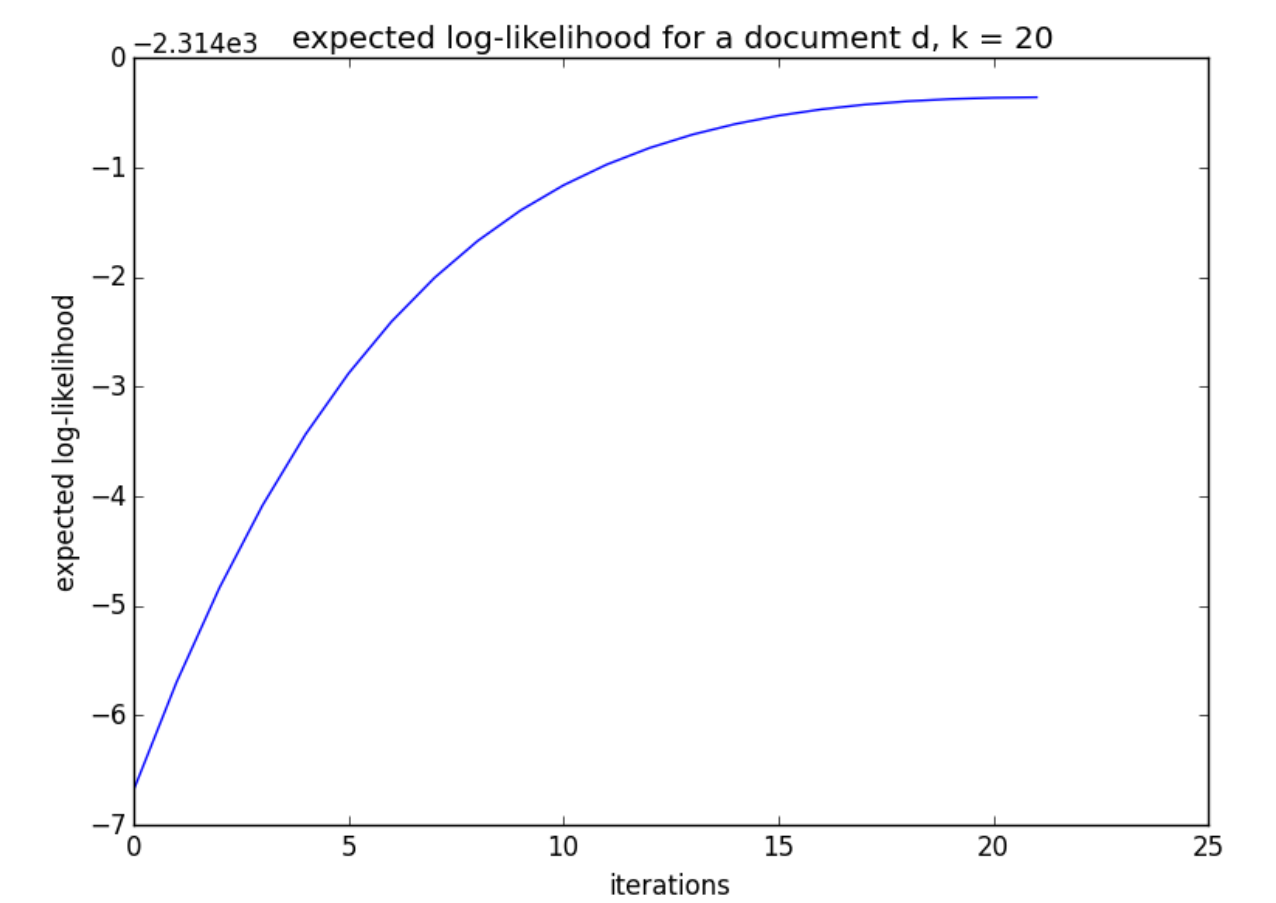


Figure 1: Expected log-likelihood for a document ($k = 20$)

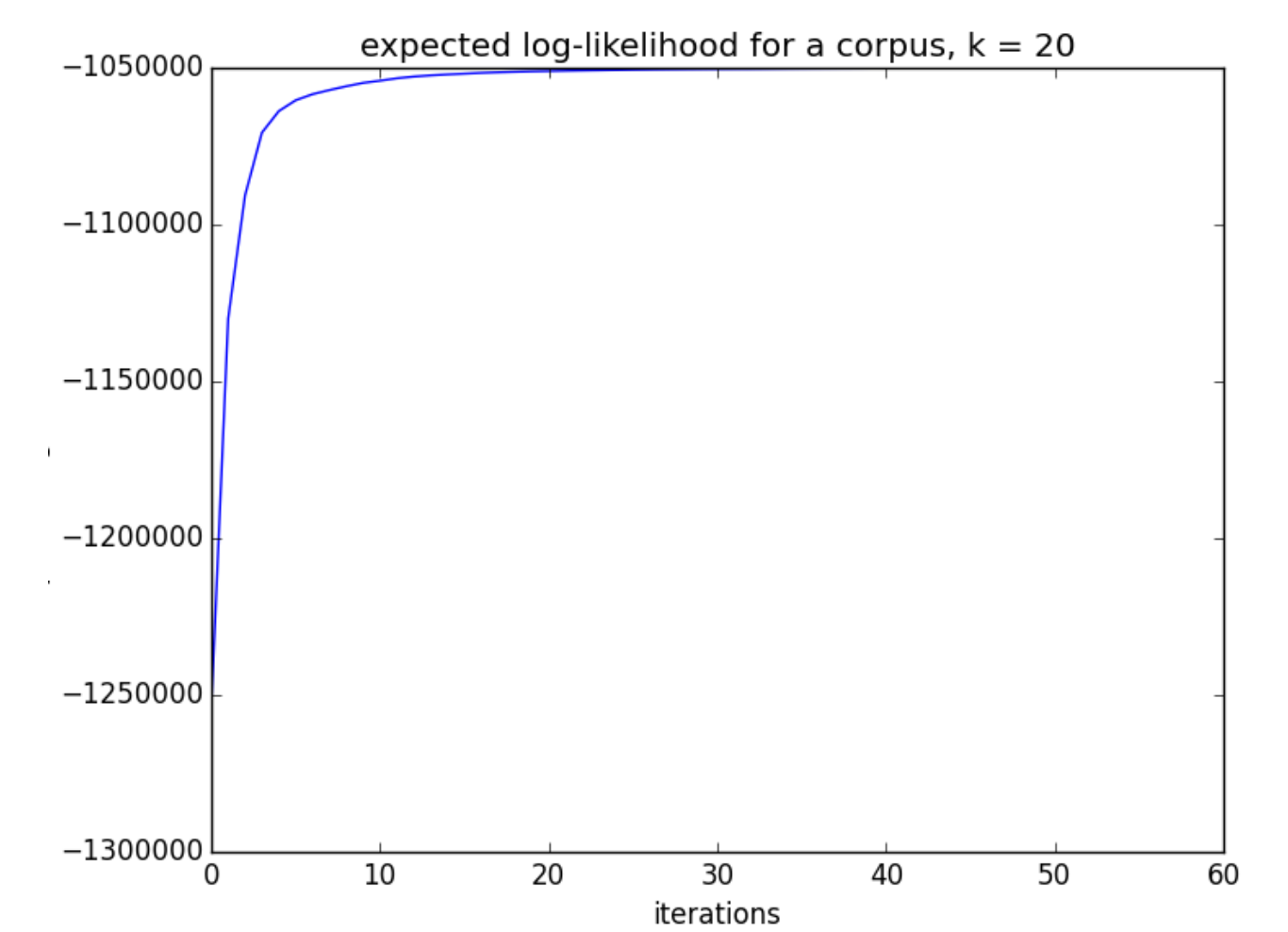


Figure 2: Expected log-likelihood for the corpus ($k = 20$)

Conclusion

- LDA = a way to apply graphical models to information retrieval = group words in the same categories.
- Key idea = variational inference.
- LDA is a non-convex optimization problem: estimates for α, β depend on their initialization.
- Other interesting applications: biology (DNA sequence), content-based image retrieval. . .