Lecture 12: Graphical models for Text

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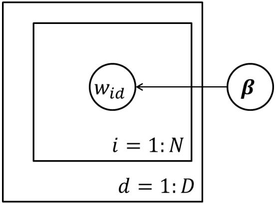
`http://mlg.eng.cam.ac.uk/teaching/4f13/`

A really simple document model

Consider a collection of D documents with a dictionary of M unique words.

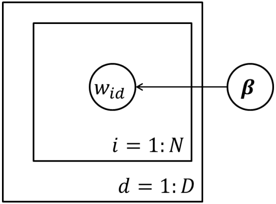
- N_d: number of (non-unique) words in document d.
- w_{id}: i-th word in document d ($w_{id} \in \{1 \dots M\}$).
- $w_{id} \sim \text{Cat}(\boldsymbol{\beta})$: each word is drawn from a discrete categorical distribution with parameters $\boldsymbol{\beta}$
- $\boldsymbol{\beta} = [\beta_1, \dots, \beta_M]^\top$: parameters of a categorical / multinomial distribution[1] over the dictionary of M unique words.



[1] It's a categorical distribution if we observe the sequence of words in the document, it's a multinomial if we only observe the counts.

A really simple document model

Modelling D documents from a dictionary of M unique words.



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- $w_{id} \sim \mathrm{Cat}(\boldsymbol{\beta})$: each word is drawn from a discrete categorical distribution with parameters $\boldsymbol{\beta}$

We can fit $\boldsymbol{\beta}$ by maximising the likelihood:

$$\hat{\boldsymbol{\beta}} = \mathrm{argmax}_{\boldsymbol{\beta}} \prod_{d=1}^{D} \mathrm{Mult}(c_{1d}, \ldots, c_{Md} | \boldsymbol{\beta}, N_d)$$

$$= \mathrm{argmax}_{\boldsymbol{\beta}} \mathrm{Mult}(c_1, \ldots, c_M | \boldsymbol{\beta}, N)$$

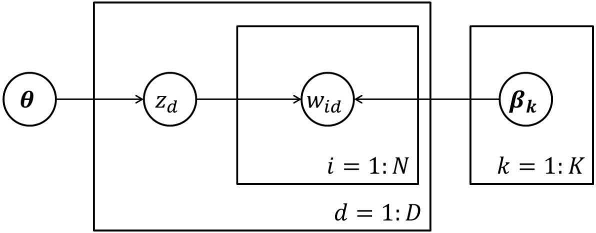
$$\hat{\beta}_j = \frac{c_j}{N} = \frac{c_j}{\sum_{l=1}^{M} c_l}$$

- $N = \sum_{d=1}^{D} N_d$: total number of (non-unique) words in the collection.
- $c_{jd} = \sum_{i=1}^{N_d} \mathbb{I}(w_{id} = j)$: count of unique word j in document d.
- $c_j = \sum_{d=1}^{D} c_{jd}$: count of total occurrences of unique word j in the collection.

Limitations of the really simple document model

- Document d is the result of sampling N_d words from the multinomial $\boldsymbol{\beta}$.
- $\boldsymbol{\beta}$ estimated by maximum likelihood reflects the aggregation of all documents.
- All documents are therefore modelled by the global word frequency distribution.
- This generative model does not specialise.
- It possible that different documents might be about different *topics*.

A mixture of multinomials model



$$z_d \sim \text{Cat}(\theta)$$
$$w_{id} | z_d \sim \text{Cat}(\beta_{z_d})$$

We want to allow for a mixture of K multinomials parametrised by $\beta_1, \ldots, \beta_K$. Each of those multinomials corresponds to a *document category*.

- $z_d \in \{1, \ldots, K\}$ assigns document d to one of the K categories.
- $\theta_k = p(z_d = k)$ is the probability any document d is assigned to category k.
- so $\theta = [\theta_1, \ldots, \theta_K]$ is the parameter of a multinomial over K categories.

We have introduced a new set of *hidden* variables z_d.

- How do we fit those variables? What do we do with them?
- Are these variables interesting? Or are we only interested in θ and β?

The Expectation Maximization (EM) algorithm

Given a set of observed (visible) variables V, a set of unobserved (hidden / latent / missing) variables H, and model parameters θ, optimize the log likelihood:

$$\mathcal{L}(\theta) = \log p(V|\theta) = \log \int p(H, V|\theta) dH, \qquad (1)$$

where we have written the marginal for the visibles in terms of an integral over the joint distribution for hidden and visible variables.

Using *Jensen's inequality* for any distribution of hidden states $q(H)$ we have:

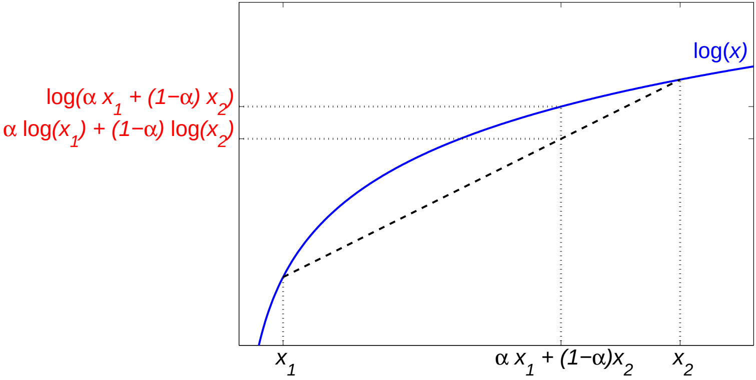
$$\mathcal{L}(\theta) = \log \int q(H) \frac{p(H, V|\theta)}{q(H)} dH \geqslant \int q(H) \log \frac{p(H, V|\theta)}{q(H)} dH = \mathcal{F}(q, \theta), \qquad (2)$$

defining the $\mathcal{F}(q, \theta)$ functional, which is a lower bound on the log likelihood.

In the EM algorithm, we alternately optimize $\mathcal{F}(q, \theta)$ wrt q and θ, and we can prove that this will never decrease $\mathcal{L}(\theta)$.

Jensen's Inequality

For any concave function, such as $\log(x)$



For $\alpha_i \geqslant 0$, $\sum_i \alpha_i = 1$ and any $\{x_i > 0\}$

$$\log\Big(\sum_i \alpha_i x_i\Big) \geqslant \sum_i \alpha_i \log(x_i)$$

Equality if and only if $\alpha_i = 1$ for some i (and therefore all others are 0).

The E and M steps of EM

The lower bound on the log likelihood:

$$\mathcal{F}(q,\theta) \;=\; \int q(H)\log\frac{p(H,V|\theta)}{q(H)}dH \;=\; \int q(H)\log p(H,V|\theta)dH + \mathcal{H}(q), \qquad (3)$$

where $\mathcal{H}(q) = -\int q(H)\log q(H)dH$ is the entropy of q. We iteratively alternate:

E step: maximize $\mathcal{F}(q,\theta)$ wrt the distribution over hidden variables given the parameters:

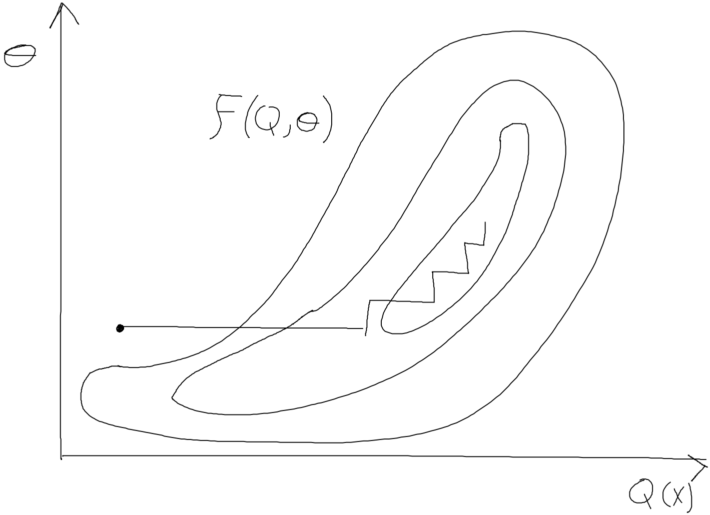
$$q^{(k)}(H) := \underset{q(H)}{\operatorname{argmax}}\; \mathcal{F}\big(q(H), \theta^{(k-1)}\big). \qquad (4)$$

M step: maximize $\mathcal{F}(q,\theta)$ wrt the parameters given the hidden distribution:

$$\theta^{(k)} := \underset{\theta}{\operatorname{argmax}}\; \mathcal{F}\big(q^{(k)}(H), \theta\big) = \underset{\theta}{\operatorname{argmax}}\; \int q^{(k)}(H)\log p(H,V|\theta)dH, \qquad (5)$$

which is equivalent to optimizing the expected complete-data likelihood $p(H,V|\theta)$, since the entropy of $q(H)$ does not depend on θ.

EM as Coordinate Ascent in $\mathcal{F}$



The EM algorithm never decreases the log likelihood

The difference between the objective functions:

$$\begin{aligned}
\mathcal{L}(\theta) - \mathcal{F}(q, \theta) &= \log p(V|\theta) - \int q(H) \log \frac{p(H, V|\theta)}{q(H)} dH \\
&= \log p(V|\theta) - \int q(H) \log \frac{p(H|V, \theta) p(V|\theta)}{q(H)} dH \\
&= -\int q(H) \log \frac{p(H|V, \theta)}{q(H)} dH \ = \ \mathcal{KL}\big(q(H), p(H|V, \theta)\big),
\end{aligned}$$

is called the Kullback-Liebler divergence; it is non-negative and zero if and only if $q(H) = p(H|V, \theta)$ (thus this is the E step). Although we are optimising a lower bound, $\mathcal{F}$, the likelihood $\mathcal{L}$ is still increased in every iteration:

$$\mathcal{L}\big(\theta^{(k-1)}\big) \underset{\text{E step}}{=} \mathcal{F}\big(q^{(k)}, \theta^{(k-1)}\big) \underset{\text{M step}}{\leqslant} \mathcal{F}\big(q^{(k)}, \theta^{(k)}\big) \underset{\text{Jensen}}{\leqslant} \mathcal{L}\big(\theta^{(k)}\big),$$

where the first equality holds because of the E step, and the first inequality comes from the M step and the final inequality from Jensen. Usually EM converges to a local optimum of $\mathcal{L}$ (although there are exceptions).

EM and Mixtures of Multinomials

In the mixture model for text, the latent variables are

$$z_d \in \{1, \ldots, K\}, \quad \text{where} \quad d = 1, \ldots, D$$

which for each document encodes which mixture component generated it.

E-step: for each document d, set q to the posterior

$$q_d(z_d = k) \;\propto\; p(z_d = k|\theta) \prod_{i=1}^{N_d} p(w_i|\beta_{w_i k}) \;=\; \theta_k \text{Mult}(c_{1d}, \ldots, c_{Md}|\boldsymbol{\beta}_k, N_d) \;\stackrel{\text{def}}{=}\; r_{kd}$$

M-step: Maximize

$$\begin{aligned}
\sum_{k=1}^{K} q_d(z_d = k) \log p(\{w_{id}\}, z_d) \;&=\; \sum_k r_{kd} \log \prod_{d=1}^{D} \left[\prod_{i=1}^{N_d} p(w_i|\beta_{w_i k}) \right] p(z_d = k) \\
&=\; \sum_k r_{kd} \Big(\sum_{d=1}^{D} \log \prod_{j=1}^{M} \beta_{jk}^{c_{jd}} + \log \theta_k \Big) \\
&=\; \sum_{k,d} r_{kd} \big(\sum_{j=1}^{M} c_{jd} \log \beta_{jk} + \log \theta_k \big) \;\stackrel{\text{def}}{=}\; F(R, \theta, \beta)
\end{aligned}$$

EM: M step for mixture model

$$F(R, \theta, \beta) = \sum_{k,d} r_{kd}\Big(\sum_{j=1}^{M} c_{jd} \log \beta_{jk} + \log \theta_k\Big)$$

Need Lagrange multipliers to constrain the maximization of F and ensure proper distributions.

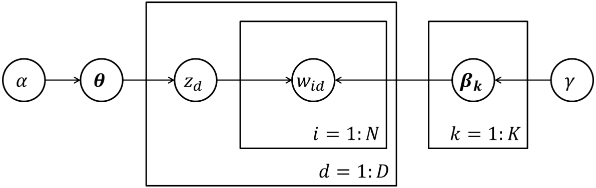
$$\hat{\theta}_k \leftarrow \text{argmax}_{\theta_k}\ F(R, \theta, \beta) + \lambda\Big(1 - \sum_{k'=1}^{K} \theta_{k'}\Big)$$

$$= \frac{\sum_{d=1}^{D} r_{kd}}{\sum_{k'=1}^{K} \sum_{d=1}^{D} r_{k'd}} = \frac{\sum_{d=1}^{D} r_{kd}}{D}$$

$$\hat{\beta}_{jk} \leftarrow \text{argmax}_{\beta_{jk}}\ F(R, \theta, \beta) + \sum_{k'=1}^{K} \lambda_{k'}\Big(1 - \sum_{j'=1}^{M} \beta_{j'k'}\Big)$$

$$= \frac{\sum_{d=1}^{D} r_{kd} c_{jd}}{\sum_{j'=1}^{M} \sum_{d=1}^{D} r_{kd} c_{j'd}}$$

A Bayesian mixture of Multinomials model



$$
\begin{aligned}
\theta &\sim \mathrm{Dir}(\alpha) \\
\beta_k &\sim \mathrm{Dir}(\gamma) \\
z_d|\theta &\sim \mathrm{Cat}(\theta) \\
w_{id}|z_d, \beta &\sim \mathrm{Cat}(\beta_{z_d})
\end{aligned}
$$

With the EM algorithm we have essentially estimated θ and β by maximum likelihood. An alternative, Bayesian treatment infers the parameters starting from priors:

- $\theta \sim \mathrm{Dir}(\alpha)$ is a symmetric Dirichlet over category probabilities.
- $\beta_k \sim \mathrm{Dir}(\gamma)$ is a symmetric Dirichlet over unique word probabilities.

What is different?

- We no longer want to compute a point estimate of θ or β.
- We are now interested in computing the *posterior* distributions.

Variational Bayesian Learning

Lower Bounding the Marginal Likelihood

Let the hidden latent variables be $\mathbf{x}$, data $\mathbf{y}$ and the parameters θ.

Lower bound the marginal likelihood (Bayesian model evidence) using Jensen's inequality:

$$\begin{aligned} \log P(\mathbf{y}) &= \log \int d\mathbf{x}\, d\theta\; P(\mathbf{y}, \mathbf{x}, \theta) \qquad |m \\ &= \log \int d\mathbf{x}\, d\theta\; Q(\mathbf{x}, \theta) \frac{P(\mathbf{y}, \mathbf{x}, \theta)}{Q(\mathbf{x}, \theta)} \\ &\geqslant \int d\mathbf{x}\, d\theta\; Q(\mathbf{x}, \theta) \log \frac{P(\mathbf{y}, \mathbf{x}, \theta)}{Q(\mathbf{x}, \theta)}. \end{aligned}$$

Use a simpler, factorised approximation to $Q(\mathbf{x}, \theta)$:

$$\begin{aligned} \log P(\mathbf{y}) &\geqslant \int d\mathbf{x}\, d\theta\; Q_{\mathbf{x}}(\mathbf{x}) Q_{\theta}(\theta) \log \frac{P(\mathbf{y}, \mathbf{x}, \theta)}{Q_{\mathbf{x}}(\mathbf{x}) Q_{\theta}(\theta)} \\ &= \mathcal{F}(Q_{\mathbf{x}}(\mathbf{x}), Q_{\theta}(\theta), \mathbf{y}). \end{aligned}$$

Maximize this lower bound.

Variational Bayesian Learning ...

Maximizing this lower bound, $\mathcal{F}$, leads to **EM-like** updates:

$$\begin{aligned} Q^*_{\mathbf{x}}(\mathbf{x}) &\propto \exp \langle \log P(\mathbf{x},\mathbf{y}|\theta) \rangle_{Q_\theta(\theta)} && \textit{E-like step} \\ Q^*_{\theta}(\theta) &\propto P(\theta) \exp \langle \log P(\mathbf{x},\mathbf{y}|\theta) \rangle_{Q_{\mathbf{x}}(\mathbf{x})} && \textit{M-like step} \end{aligned}$$

Maximizing $\mathcal{F}$ is equivalent to minimizing KL-divergence between the *approximate posterior*, $Q(\theta)Q(\mathbf{x})$ and the *true posterior*, $P(\theta, \mathbf{x}|\mathbf{y})$.

$$\begin{aligned} \log P(\mathbf{y}) - \mathcal{F}(Q_{\mathbf{x}}(\mathbf{x}), Q_\theta(\theta), \mathbf{y}) &= \\ \log P(\mathbf{y}) - \int d\mathbf{x}\, d\theta\; Q_{\mathbf{x}}(\mathbf{x}) Q_\theta(\theta) \log \frac{P(\mathbf{y},\mathbf{x},\theta)}{Q_{\mathbf{x}}(\mathbf{x}) Q_\theta(\theta)} &= \\ \int d\mathbf{x}\, d\theta\; Q_{\mathbf{x}}(\mathbf{x}) Q_\theta(\theta) \log \frac{Q_{\mathbf{x}}(\mathbf{x}) Q_\theta(\theta)}{P(\mathbf{x},\theta|\mathbf{y})} &= \mathrm{KL}(Q\|P) \end{aligned}$$