

Graphical Model

Politeness group

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Let N sentences be given containing words w_{n1}, \dots, w_{nM_n} for $n = 1, \dots, N$. Each word w_{nm} is generated from a distribution of words ϕ_z , with the possibilities background (neutral), polite or impolite. These ϕ_z are Dirichlet distributions with hyperparameter β . In order to see which distribution a word is generated from, we attach a (latent) variable z_{nm} to each word. Furthermore, a sentence as a whole can be either polite or impolite, which we store in the (observed) variable y_n .

We make the assumption that polite sentences only contain words that were generated from the polite distribution or the background distribution, where the distribution over both distributions is specified by μ . Similarly, μ is used for impolite sentences to give the distribution over impolite words and backgrounds words. The distribution given by μ is a Beta distributions with hyperparameter $\alpha = (\alpha_1, \alpha_2)$. The generation of a topic z_{nm} for word w_{nm} is sampled from some μ , where y_n picks either the polite or the impolite distribution.

In order to visualize which words are polite, which are impolite and which are background, we want to sample the topics z_i for the words w_i of a new sentence. For this purpose, the sentence first needs to be classified as either polite or impolite (which gives the value for y) and then we need to sample from $p(z_i|W, y, \Phi, z_{-i}, \mu)$, where W consists of all words in the sentence, z_{-i} are the other topics and $\Phi = \phi_1, \phi_2, \phi_3 = \phi_{background}, \phi_{polite}, \phi_{impolite}$.

We see that

$$p(Z, W, Y, \mu, \Phi | \alpha, \beta) = p(\mu | \alpha) \prod_{i=1}^3 p(\phi_i | \beta) \prod_{n=1}^N \prod_{m=1}^{M_n} p(w_{nm} | \phi_{z_{nm}}) p(z_{nm} | \mu, y_n),$$

hence

$$p(Z, W | \alpha, \beta) = \int p(Z, W, Y, \mu, \Phi | \alpha, \beta) d\Phi d\mu = \left(\int p(\mu | \alpha) \prod_{n=1}^N \prod_{m=1}^{M_n} p(z_{nm} | \mu, y_n) d\mu \right) \left(\int \prod_{i=1}^3 p(\phi_i | \beta) \prod_{n=1}^N \prod_{m=1}^{M_n} p(w_{nm} | \phi_{z_{nm}}) d\Phi \right).$$

Both parts will be worked out separately.

$$\begin{aligned} & \int p(\mu | \alpha) \prod_{n=1}^N \prod_{m=1}^{M_n} p(z_{nm} | \mu, y_n) d\mu = \\ & \int \frac{\Gamma(\alpha_1 + \alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)} \mu^{\alpha_1-1} (1-\mu)^{\alpha_2-1} \prod_{i=1}^2 \prod_{\{n: y_n=i\}} \prod_{m=1}^{M_n} p(z_{nm} | \mu, y_n) d\mu = \end{aligned}$$

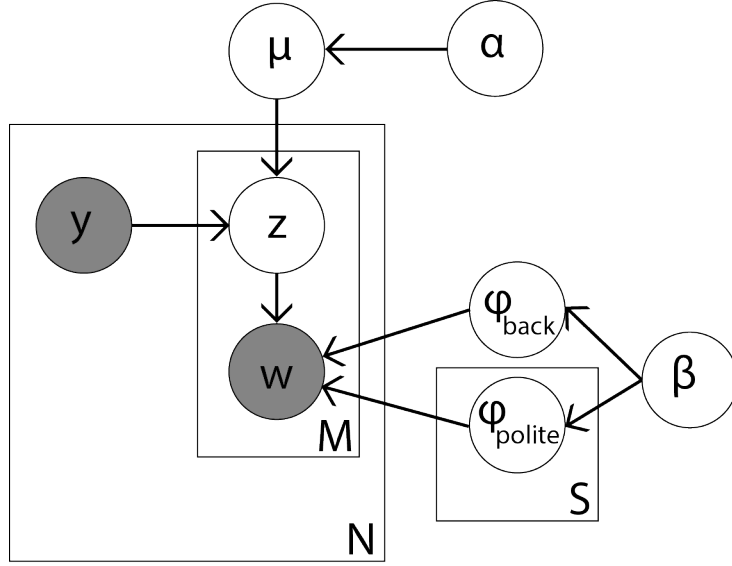


Figure 1: Graphical model for our topic model.

$$\frac{\Gamma(\alpha_1 + \alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)} \int \mu^{\alpha_1-1} (1-\mu)^{\alpha_2-1} \prod_{i=1}^2 \prod_{\{n:y_n=i\}} \mu^{C(0,n)} (1-\mu)^{C(1,n)} d\mu$$

where $C(0,n), C(1,n)$ denotes the number of background or (im)polite words in sentence n respectively. We rewrite this expression further:

$$\begin{aligned} & \frac{\Gamma(\alpha_1 + \alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)} \int \mu^{\alpha_1-1} (1-\mu)^{\alpha_2-1} \mu^{\sum_{i=1}^2 \sum_{\{n:y_n=i\}} C(0,n)} (1-\mu)^{\sum_{i=1}^2 \sum_{\{n:y_n=i\}} C(1,n)} d\mu = \\ & \frac{\Gamma(\alpha_1 + \alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)} \int \mu^{\alpha_1-1+C(0)} (1-\mu)^{\alpha_2-1+C(1)} d\mu = \\ & \frac{\Gamma(\alpha_1 + \alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)} \frac{\Gamma(\alpha_1 + C(0))\Gamma(\alpha_2 + C(1))}{\Gamma(\alpha_1 + \alpha_2 + C(0) + C(1))} \propto \frac{\Gamma(\alpha_1 + C(0))\Gamma(\alpha_2 + C(1))}{\Gamma(\alpha_1 + \alpha_2 + C(0) + C(1))} \end{aligned}$$

for $C(0)$ the total number of background tags, and $C(1)$ the total number of (im)polite tags. Before rewriting the second integral, note that we assume a fixed vocabulary of some size V_i of possible words that the ϕ_i can generate.

$$\begin{aligned} & \int \prod_{i=1}^3 p(\phi_i|\beta) \prod_{n=1}^N \prod_{m=1}^M p(w_{nm}|\phi_{z_{nm}}) d\Phi \propto \\ & \int \prod_{i=1}^3 \prod_{w=1}^{V_i} \phi_i(w)^{\beta-1} \prod_{i=1}^3 \prod_{w=1}^V \phi_i(w)^{C_i(w)} d\Phi = \\ & \prod_{i=1}^3 \int \prod_{w=1}^{V_i} \phi_i(w)^{\beta-1+C_i(w)} d\phi_i = \prod_{i=1}^3 \frac{\prod_{w=1}^{V_i} \Gamma(\beta + C_i(w))}{\Gamma(\sum_{w=1}^{V_i} \beta + C_i(w))} \end{aligned}$$

for $C_i(w)$ the number of (n, m) such that $w_{nm} = w$ and $z_{nm} = i$.

Combining the equations above gives

$$p(Z, W, Y, \mu, \Phi | \alpha, \beta) = \prod_{i=1}^3 \frac{\prod_{w=1}^{V_i} \Gamma(\beta + C_i(w))}{\Gamma(\sum_{w=1}^{V_i} \beta + C_i(w))} \times \frac{\Gamma(\alpha_1 + C(0))\Gamma(\alpha_2 + C(1))}{\Gamma(\alpha_1 + \alpha_2 + C(0) + C(1))}$$

such that

$$p(z_{nm} = i | Z_{-nm}, W_{-nm}, \Phi, \mu) = \frac{p(z_{nm} = i, Z_{-nm}, W_{-nm}, Y, \mu, \Phi | \alpha, \beta)}{p(Z_{-nm}, W_{-nm}, Y, \mu, \Phi | \alpha, \beta)} \propto$$

$$\frac{\Gamma(\alpha_1 + C(0))\Gamma(\alpha_2 + C(1))\Gamma(\alpha_1 + \alpha_2 + C(0) + C(1) - 1)}{\Gamma(\alpha_1 + \alpha_2 + C(0) + C(1))\Gamma(\alpha_1 + C(0) - \delta_{i,\text{back}})\Gamma(\alpha_2 + C(1) - \delta_{i,(\text{im})\text{polite}})} \times$$

$$\frac{\Gamma(\beta + C_i(w_{nm}))[\Gamma(\sum_{w=1}^{V_i} \beta + C_i(w) - \delta_{w,w_{nm}})]}{[\Gamma(\sum_{w=1}^{V_i} \beta + C_i(w))][\Gamma(\beta + C_i(w_{nm}) - 1)]}.$$

The equality $x - 1 = \frac{\Gamma(x)}{\Gamma(x-1)}$ and some simplifications give

$$\frac{\alpha_\delta + C(\delta) - 1}{\alpha_1 + \alpha_2 + C(0) + C(1) - 1} \times \frac{\beta + C_i(w_{nm}) - 1}{-1 + V_i\beta + \sum_{w=1}^{V_i} C_i(w)}$$

for $\delta = \delta_{i,(\text{im})\text{polite}}$, V_i the number of words in the vocabulary of ϕ_i , $C(0), C(1)$ the number of background respectively (im)polite words and $C_i(w) = \#\{(a, b) : w_{ab} = w \text{ and } z_{ab} = i\}$.