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## Abstract

# 1 Derivation

Variational Distribution

$$q(\phi, \pi, d, z | \lambda, \gamma, \eta, \varphi) = \prod_{k=1}^K q(\phi_k | \lambda) \prod_{m=1}^M q(\pi_m | \gamma) \prod_{n=1}^N q(d_n | \eta) q(z_n | \varphi) \quad (1)$$

where

$\phi_k \in R^V$  distribution over word of topic  $k$

$\pi_m \in R^K$  distribution over topics of document  $m$

$d_n \in R^M$  indicator vector where if  $d_{nm} = 1$  means word  $n$  belongs to document  $m$

$z_n \in R^K$  indicator vector where if  $z_{nk} = 1$  means word  $n$  is assigned to topic  $k$

Lower bound of log likelihood:

$$p(\mathbf{w}, \mathbf{c} | \alpha, \beta, \eta, \sigma) = \log \int_{\phi} \int_{\pi} \sum_d \sum_z p(\phi, \pi, d, z, \mathbf{w}, \mathbf{c} | \alpha, \beta, \eta, \sigma) \quad (2)$$

$$= \log \int_{\phi} \int_{\pi} \sum_d \sum_z q(\phi, \pi, d, z | \lambda, \gamma, \eta, \varphi) \frac{p(\phi, \pi, d, z, \mathbf{w} | \alpha, \beta, \eta, \sigma)}{q(\phi, \pi, d, z | \lambda, \gamma, \eta, \varphi)} d\phi d\pi dd dz \quad (3)$$

$$= \log E_q \frac{p(\phi, \pi, d, z, \mathbf{c}, \mathbf{w} | \alpha, \beta, \eta, \sigma)}{q(\phi, \pi, d, z | \lambda, \gamma, \eta, \varphi)} \quad (4)$$

$$\geq E_q \log p(\phi, \pi, d, z, \mathbf{c}, \mathbf{w} | \alpha, \beta, \eta, \sigma) - E_q \log q(\phi, \pi, d, z | \lambda, \gamma, \eta, \varphi) = L \quad (5)$$

where  $E_q \equiv E_{q(\phi, \pi, d, z | \lambda, \gamma, \eta, \varphi)}$

Instead of maximizing  $p$ , we estimate it by maximizing the lower bound  $L$

Consider the first term in  $L$

$$E_q[\log p(\phi, \pi, d, z, \mathbf{c}, \mathbf{w} | \alpha, \beta, \eta, \sigma)] = E_q[\log p(\phi | \beta) p(\pi | \alpha) p(d | \eta) p(\mathbf{c} | c_d^d, \sigma) p(z | \pi_d) p(\mathbf{w} | \phi_d)] \quad (6)$$

$$= E_q[\log p(\phi | \beta)] + E_q[p(\pi | \alpha)] + E_q[\log p(d | \eta)] \quad (7)$$

$$+ E_q[\log p(\mathbf{c} | c_d^d, \sigma)] + E_q[\log p(z | \pi_d)] + E_q[\log p(\mathbf{w} | \phi_z)] \quad (8)$$

$$(9)$$

$$E_q[\log p(\phi | \beta)] = E_q \log \prod_{k=1}^K p(\phi_k | \beta) \quad (10)$$

$$= \sum_{k=1}^K E_q [\log \Gamma(\sum_{v=1}^V \beta_v) - \sum_{v=1}^V \log \Gamma(\beta_v) + \sum_{v=1}^V (\beta_v - 1) \log(\phi_{kv})] \quad (11)$$

$$= \sum_{k=1}^K \log \Gamma(\sum_{v=1}^V \beta_v) - \sum_{v=1}^V \log \Gamma(\beta_v) + \sum_{v=1}^V (\beta_v - 1) (\Psi(\lambda_{kv}) - \Psi(\sum_{v'=1}^V \lambda_{kv'})) \quad (12)$$

$$E_q[\log p(\pi|\alpha)] = E_q[\log \prod_{m=1}^M p(\pi_m|\alpha)] \quad (13)$$

$$= \sum_{m=1}^M E_q \log(p(\pi_m|\alpha)) \quad (14)$$

$$= \sum_{m=1}^M E_q[\log(\Gamma(\sum_{k=1}^K \alpha_k)) - \sum_{k=1}^K \log(\Gamma(\alpha_k)) + \sum_{k=1}^K (\alpha_k - 1) \log(\pi_m k)] \quad (15)$$

$$= \sum_{m=1}^M \log(\Gamma(\sum_{k=1}^K \alpha_k)) - \sum_{k=1}^K \log(\Gamma(\alpha_k)) + \sum_{k=1}^K (\alpha_k - 1) (\Psi(\gamma_{mk}) - \Psi(\sum_{k'=1}^K \gamma_{mk'})) \quad (16)$$

Speed up things a little bit:

$$E_q[\log p(d|\eta)] = \sum_{n=1}^N E_q \log(p(d_n|\eta)) \quad (17)$$

$$= \sum_{n=1}^N E_q \sum_{m=1}^M d_n m \log(\eta) \quad (18)$$

$$= \sum_{n=1}^N \sum_{m=1}^M \eta \log(\eta) \quad (19)$$

$$= (N + M) \eta \log(\eta) \quad (20)$$

$$E_q[\log p(c|c_d^d, \sigma)] = \sum_{n=1}^N E_q \log p(c_n|c_{d_n}^d) \quad (21)$$

$$= \sum_{n=1}^N \sum_{m=1}^M E_q[d_{mn} \log p(c_n|c_{d_{mn}}^d)] \quad (22)$$

$$= \sum_{n=1}^N \sum_{m=1}^M \eta (\delta_{g_{d_{mn}}^d} - \frac{(x_{d_{mn}}^d - x_n)^2 + (y_{d_{mn}}^d - y_n)^2}{\sigma^2}) \quad (23)$$

$$(24)$$

$$E_q[\log p(z|\pi_d)] = \sum_{n=1}^N \sum_{m=1}^M E_q[d_{mn} \log(\pi_{mn})] \quad (25)$$

$$= \sum_{n=1}^N \sum_{m=1}^M \eta (\Psi(\gamma_{mn}) - \Psi(\sum_{m'=1}^M \gamma_{m'n})) \quad (26)$$

$$E_q[\log p(\mathbf{w}|\phi_z)] = \sum_n^N \sum_m^M \sum_k^K \sum_v^V E_q[d_{mn} z_{kn} \mathbf{w}_n^v \log(\phi_k v)] \quad (27)$$

$$= \sum_n^N \sum_m^M \sum_k^K \eta \phi_{kn} \mathbf{w}_n^v (\Psi(\lambda_{kv}) - \Psi(\sum_{k'}^K \lambda_{k'v})) \quad (28)$$

$$(29)$$