

# Poisson Tucker Decomposition version of the Interaction-pattern Partitioned Topic Model

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## 1 Generative Process

To maintain single interaction pattern assignments (instead of admixture form which adds huge complexity in network history calculations), we assume each document  $d \in [D]$  draws an interaction pattern  $c_d$  as below:

$$c_d \sim \text{Multinomial}(\boldsymbol{\psi}), \quad (1)$$

where

$$\boldsymbol{\psi} \sim \text{Dirichlet}\left(\xi, \left(\frac{1}{C}, \dots, \frac{1}{C}\right)\right). \quad (2)$$

Alternatively, following degree-corrected GPIRM we can use

$$c_d \sim \text{Multinomial}\left(\frac{\psi_1}{\sum_c \psi_c}, \dots, \frac{\psi_C}{\sum_c \psi_c}\right), \quad (3)$$

where

$$\psi_c \sim \Gamma\left(\frac{\gamma_0}{C}, \xi\right). \quad (4)$$

Next, we model the contents using Poisson Tucker Decomposition of Schein et al. (2016). First, each document  $d \in [D]$

$$\pi_{dc} = \begin{cases} \sim \Gamma(a_c, b) & \text{if } c_d = c \\ 0 & \text{if } c_d \neq c \end{cases} \quad (5)$$

Q: If we want this positive real numbers instead of indicator (such as degree-corrected GPIRM). Is this how you did? If so, how to derive the conditionals for Gibbs sampling of  $c_d$ ? If not, how to specify the prior for  $\pi_{dc}$  so as to achieve/enforce single membership constraints?

Then, each interaction pattern  $c \in [C]$  has the IP-specific topic distribution

$$\theta_{ck} \sim \Gamma(\epsilon_0, \epsilon_0), \quad (6)$$

and each topic  $k \in [K]$  has the topic-word distribution

$$\phi_{kv} \sim \Gamma(\epsilon_0, \epsilon_0). \quad (7)$$

Then, the number of tokens of type  $v$  in document  $d$  is

$$w_{dv} \sim \text{Poisson}\left(\sum_{c=1}^C \sum_{k=1}^K \pi_{dc} \theta_{ck} \phi_{kv}\right), \quad (8)$$

which is identical to  $w_{dv} \sim \text{Poisson}(\pi_{dc_d} \sum_{k=1}^K \theta_{c_d k} \phi_{kv})$ . Also note that  $\mathbf{w}_d = (w_{d1}, \dots, w_{dV})$  is a very sparse vector with  $\text{sum}(\mathbf{w}_d) = N_d$ .

## 2 Derivation

We first derive the sampling equation of  $\pi$ ,  $\theta$  and  $\phi$ , respectively. First, for  $c = c_d$ , we update  $\pi_{dc}$  as below.

$$\pi_{dc} | \text{rest} \sim \text{Gamma}(a_c + \mathbf{w}_{dc}, b + \sum_{v=1}^V \theta_{ck} \phi_{kv}), \quad (9)$$

where  $\mathbf{w}_{dc} = \sum_{k=1}^K \sum_{v=1}^V w_{dvck}$  with  $w_{dvck} \sim \text{Multinomial}(w_{dv}, \pi_{dc} \theta_{ck} \phi_{kv})$ .

$$\theta_{ck} | \text{rest} \sim \text{Gamma}(\epsilon_0 + \mathbf{w}_{ck}, \epsilon_0 + \sum_{d=1}^D \pi_{dc} \sum_{v=1}^V \phi_{kv}), \quad (10)$$

where  $\mathbf{w}_{ck} = \sum_{d=1}^D \sum_{v=1}^V w_{dvck}$  with  $w_{dvck} \sim \text{Multinomial}(w_{dv}, \pi_{dc} \theta_{ck} \phi_{kv})$ .

$$\phi_{kv} | \text{rest} \sim \text{Gamma}(\epsilon_0 + \mathbf{w}_{kv}, \epsilon_0 + \sum_{d=1}^D \pi_{dc} \theta_{ck}), \quad (11)$$

where  $\mathbf{w}_{kv} = \sum_{d=1}^D \sum_{c=1}^C w_{dvck}$  with  $w_{dvck} \sim \text{Multinomial}(w_{dv}, \pi_{dc} \theta_{ck} \phi_{kv})$ .

Then, we need to use Gibbs update of  $c_d$

$$\Pr(c_d = c | \text{rest}) = ? \quad (12)$$