

A Generating a CRT random variable

Lemma A.1. *A CRT random variable $l \sim \text{CRT}(m, r)$ can be generated with the summation of independent Bernoulli random variables as*

$$l = \sum_{n=1}^m b_n, \quad b_n \sim \text{Bernoulli}\left(\frac{r}{n-1+r}\right). \quad (20)$$

Proof. Since l is the summation of independent Bernoulli random variables, its PGF becomes

$$C_L(z) = \prod_{n=1}^m \left(\frac{n-1}{n-1+r} + \frac{r}{n-1+r} z \right) = \frac{\Gamma(r)}{\Gamma(m+r)} \sum_{k=0}^m |s(m, k)| (rz)^k.$$

Thus we have $f_L(l|m, r) = \frac{C_L^{(l)}(0)}{l!} = \frac{\Gamma(r)}{\Gamma(m+r)} |s(m, l)| r^l$, $l = 0, 1, \dots, m$. \square

B Dir-PFA and LDA

The Dirichlet Poisson factor analysis (Dir-PFA) model [5] is constructed as

$$\begin{aligned} x_{ji} &\sim F(\omega_{z_{ji}}), \quad \omega_k \sim \text{Dir}(\eta, \dots, \eta) \\ N_j &= \sum_{k=1}^K n_{jk}, \quad n_{jk} \sim \text{Pois}(\tilde{\lambda}_{jk}), \quad \tilde{\lambda}_j \sim \text{Dir}(50/K, \dots, 50/K) \end{aligned} \quad (21)$$

where η is the Dirichlet smoothing parameter for the topic's distribution over the vocabulary, $n_{jk} = \sum_{i=1}^{N_j} \delta(z_{ji} = k)$, and the data likelihood $F(x_{ji}; \omega_k)$ in topic modeling is $\omega_{v_{ji}k}$, the probability of the i th word in j th document under topic ω_k .

The Dir-PFA has the same block Gibbs sampling as LDA [34], expressed as

$$\begin{aligned} \Pr(z_{ji} = k | -) &\propto F(x_{ji}; \omega_k) \tilde{\lambda}_{jk} \\ (\omega_k | -) &\sim \text{Dir} \left(\eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = 1), \dots, \eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = V) \right) \\ (\tilde{\lambda}_j | -) &\sim \text{Dir}(50/K + n_{j1}, \dots, 50/K + n_{jK}). \end{aligned} \quad (22)$$

C CRF-HDP

The CRF-HDP model [7, 26] is constructed as

$$\begin{aligned} x_{ji} &\sim F(\omega_{z_{ji}}), \quad \omega_k \sim \text{Dir}(\eta, \dots, \eta), \quad z_{ji} \sim \text{Discrete}(\tilde{\lambda}_j) \\ \tilde{\lambda}_j &\sim \text{Dir}(\alpha \tilde{\mathbf{r}}), \quad \alpha \sim \text{Gamma}(a_0, 1/b_0), \quad \tilde{\mathbf{r}} \sim \text{Dir}(\gamma_0/K, \dots, \gamma_0/K). \end{aligned} \quad (23)$$

Under the CRF metaphor, denote n_{jk} as the number of customers eating dish k in restaurant j and l_{jk} as the number of tables serving dish k in restaurant j , the direct assignment block Gibbs sampling

can be expressed as

$$\begin{aligned}
\Pr(z_{ji} = k | -) &\propto F(x_{ji}; \omega_k) \tilde{\lambda}_{jk} \\
(l_{jk} | -) &\sim \text{CRT}(n_{jk}, \alpha \tilde{r}_k), \quad w_j \sim \text{Beta}(\alpha + 1, N_j), \quad s_j \sim \text{Bernoulli}\left(\frac{N_j}{N_j + \alpha}\right) \\
\alpha &\sim \text{Gamma}\left(a_0 + \sum_{j=1}^J \sum_{k=1}^K l_{jk} - \sum_{j=1}^J s_j, \frac{1}{b_0 - \sum_j \ln w_j}\right) \\
(\tilde{\mathbf{r}} | -) &\sim \text{Dir}\left(\gamma_0/K + \sum_{j=1}^J l_{j1}, \dots, \gamma_0/K + \sum_{j=1}^J l_{jK}\right) \\
(\tilde{\lambda}_j | -) &\sim \text{Dir}(\alpha \tilde{r}_1 + n_{j1}, \dots, \alpha \tilde{r}_K + n_{jK}) \\
(\omega_k | -) &\sim \text{Dir}\left(\eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = 1), \dots, \eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = V)\right). \quad (24)
\end{aligned}$$

When $K \rightarrow \infty$, the concentration parameter γ_0 can be sampled as

$$\begin{aligned}
w_0 &\sim \text{Beta}\left(\gamma_0 + 1, \sum_{j=1}^J \sum_{k=1}^{\infty} l_{jk}\right), \quad \pi_0 = \frac{e_0 + K^+ - 1}{e_0 + K^+ - 1 + (f_0 - \ln w_0) \sum_{j=1}^J \sum_{k=1}^{\infty} l_{jk}} \\
\gamma_0 &\sim \pi_0 \text{Gamma}\left(e_0 + K^+, \frac{1}{f_0 - \ln w_0}\right) + (1 - \pi_0) \text{Gamma}\left(e_0 + K^+ - 1, \frac{1}{f_0 - \ln w_0}\right) \quad (25)
\end{aligned}$$

where K^+ is the number of used atoms. Since it is infeasible in practice to let $K \rightarrow \infty$, directly using this method to sample γ_0 is only approximately correct, which may result in a biased estimate especially if K is not set large enough. Thus in the experiments, γ_0 is not sampled and is fixed as one. Note that for implementation convenience, it is also common to fix the concentration parameter α as one [25]. We find through experiments that learning this parameter usually results in obviously lower per-word perplexity for held out words, thus we allow the learning of α using the data augmentation method proposed in [7], which is modified from the one proposed in [24].

D NB-LDA

The NB-LDA model is constructed as

$$\begin{aligned}
x_{ji} &\sim F(\omega_{z_{ji}}), \quad \omega_k \sim \text{Dir}(\eta, \dots, \eta) \\
N_j &= \sum_{k=1}^K n_{jk}, \quad n_{jk} \sim \text{Pois}(\lambda_{jk}), \quad \lambda_{jk} \sim \text{Gamma}(r_j, p_j/(1 - p_j)) \\
r_j &\sim \text{Gamma}(\gamma_0, 1/c), \quad p_j \sim \text{Beta}(a_0, b_0), \quad \gamma_0 \sim \text{Gamma}(e_0, 1/f_0) \quad (26)
\end{aligned}$$

Note that letting $r_j \sim \text{Gamma}(\gamma_0, 1/c)$, $\gamma_0 \sim \text{Gamma}(e_0, 1/f_0)$ allows different documents to share statistical strength for inferring their NB dispersion parameters.

The block Gibbs sampling can be expressed as

$$\begin{aligned}
\Pr(z_{ji} = k | -) &\propto F(x_{ji}; \omega_k) \lambda_{jk} \\
(p_j | -) &\sim \text{Beta}(a_0 + N_j, b_0 + K r_j), \quad p'_j = \frac{-K \ln(1 - p_j)}{c - K \ln(1 - p_j)} \\
(l_{jk} | -) &\sim \text{CRT}(n_{jk}, r_j), \quad l'_j \sim \text{CRT}\left(\sum_{k=1}^K l_{jk}, \gamma_0\right), \quad \gamma_0 \sim \text{Gamma}\left(e_0 + \sum_{j=1}^J l'_j, \frac{1}{f_0 - \sum_{j=1}^J \ln(1 - p'_j)}\right) \\
(r_j | -) &\sim \text{Gamma}\left(\gamma_0 + \sum_{k=1}^K l_{jk}, \frac{1}{c - K \ln(1 - p_j)}\right), \quad (\lambda_{jk} | -) \sim \text{Gamma}(r_j + n_{jk}, p_j) \\
(\omega_k | -) &\sim \text{Dir}\left(\eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = 1), \dots, \eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = V)\right). \quad (27)
\end{aligned}$$

E NB-HDP

The NB-HDP model is a special case of the Gamma-NB process model with $p_j = 0.5$. The hierarchical model and inference for the Gamma-NB process are shown in (16) and (18) of the main paper, respectively.

F NB-FTM

The NB-FTM model is a special case of zero-inflated NB process with $p_j = 0.5$, which is constructed as

$$\begin{aligned}
x_{ji} &\sim F(\omega_{z_{ji}}), \quad \omega_k \sim \text{Dir}(\eta, \dots, \eta) \\
N_j &= \sum_{k=1}^K n_{jk}, \quad n_{jk} \sim \text{Pois}(\lambda_{jk}) \\
\lambda_{jk} &\sim \text{Gamma}(r_k b_{jk}, 0.5/(1 - 0.5)) \\
r_k &\sim \text{Gamma}(\gamma_0, 1/c), \quad \gamma_0 \sim \text{Gamma}(e_0, 1/f_0) \\
b_{jk} &\sim \text{Bernoulli}(\pi_k), \quad \pi_k \sim \text{Beta}(c/K, c(1 - 1/K)). \quad (28)
\end{aligned}$$

The block Gibbs sampling can be expressed as

$$\begin{aligned}
& \Pr(z_{ji} = k | -) \propto F(x_{ji}; \omega_k) \lambda_{jk} \\
& b_{jk} \sim \delta(n_{jk} = 0) \text{Bernoulli} \left(\frac{\pi_k (1 - 0.5)^{r_k}}{\pi_k (1 - 0.5)^{r_k} + (1 - \pi_k)} \right) + \delta(n_{jk} > 0) \\
& \pi_k \sim \text{Beta} \left(c/K + \sum_{j=1}^J b_{jk}, c(1 - 1/K) + J - \sum_{j=1}^J b_{jk} \right), \quad p'_k = \frac{-\sum_j b_{jk} \ln(1 - 0.5)}{c - \sum_j b_{jk} \ln(1 - 0.5)} \\
& (l_{jk} | -) \sim \text{CRT}(n_{jk}, r_k b_{jk}), \quad (l'_k | -) \sim \text{CRT} \left(\sum_{j=1}^J l_{jk}, \gamma_0 \right) \\
& (\gamma_0 | -) \sim \text{Gamma} \left(e_0 + \sum_{k=1}^K l'_k, \frac{1}{f_0 - \sum_{k=1}^K \ln(1 - p'_k)} \right) \\
& (r_k | -) \sim \text{Gamma} \left(\gamma_0 + \sum_{j=1}^J l_{jk}, \frac{1}{c - \sum_{j=1}^J b_{jk} \ln(1 - 0.5)} \right) \\
& (\lambda_{jk} | -) \sim \text{Gamma}(r_k b_{jk} + n_{jk}, 0.5) \\
& (\omega_k | -) \sim \text{Dir} \left(\eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = 1), \dots, \eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = V) \right). \quad (29)
\end{aligned}$$

G Beta-NB

The beta-NB process model is constructed as

$$\begin{aligned}
& x_{ji} \sim F(\omega_{z_{ji}}), \quad \omega_k \sim \text{Dir}(\eta, \dots, \eta) \\
& N_j = \sum_{k=1}^K n_{jk}, \quad n_{jk} \sim \text{Pois}(\lambda_{jk}), \quad \lambda_{jk} \sim \text{Gamma}(r_j, p_k / (1 - p_k)) \\
& r_j \sim \text{Gamma}(e_0, 1/f_0), \quad p_k \sim \text{Beta}(c/K, c(1 - K)) \quad (30)
\end{aligned}$$

The block Gibbs sampling can be expressed as

$$\begin{aligned}
& \Pr(z_{ji} = k | -) \propto F(x_{ji}; \omega_k) \lambda_{jk} \\
& (p_k | -) \sim \text{Beta} \left(c/K + \sum_{j=1}^J n_{jk}, c(1 - 1/K) + \sum_{j=1}^J r_j \right), \quad l_{jk} \sim \text{CRT}(n_{jk}, r_j) \\
& (r_j | -) \sim \text{Gamma} \left(e_0 + \sum_{k=1}^K l_{jk}, \frac{1}{f_0 - \sum_{k=1}^K \ln(1 - p_k)} \right) \\
& (\lambda_{jk} | -) \sim \text{Gamma}(r_j + n_{jk}, p_k) \\
& (\omega_k | -) \sim \text{Dir} \left(\eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = 1), \dots, \eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = V) \right). \quad (31)
\end{aligned}$$

H Marked-Beta-NB

The Marked-Beta-NB process model is constructed as

$$\begin{aligned}
& x_{ji} \sim F(\omega_{z_{ji}}), \quad \omega_k \sim \text{Dir}(\eta, \dots, \eta) \\
& N_j = \sum_{k=1}^K n_{jk}, \quad n_{jk} \sim \text{Pois}(\lambda_{jk}), \quad \lambda_{jk} \sim \text{Gamma}(r_k, p_k / (1 - p_k)) \\
& r_k \sim \text{Gamma}(e_0, 1/f_0), \quad p_k \sim \text{Beta}(c/K, c(1 - K)) \quad (32)
\end{aligned}$$

The block Gibbs sampling can be expressed as

$$\begin{aligned}
& \Pr(z_{ji} = k | -) \propto F(x_{ji}; \omega_k) \lambda_{jk} \\
& p_k \sim \text{Beta} \left(c/K + \sum_{j=1}^J n_{jk}, c(1 - 1/K) + Jr_k \right), \quad l_{jk} \sim \text{CRT}(n_{jk}, r_k) \\
& (r_k | -) \sim \text{Gamma} \left(e_0 + \sum_{j=1}^J l_{jk}, \frac{1}{f_0 - J \ln(1 - p_k)} \right) \\
& (\lambda_{jk} | -) \sim \text{Gamma}(r_k + n_{jk}, p_k) \\
& (\omega_k | -) \sim \text{Dir} \left(\eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = 1), \dots, \eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = V) \right). \quad (33)
\end{aligned}$$

I Marked-Gamma-NB

The Marked-Gamma-NB process model is constructed as

$$\begin{aligned}
& x_{ji} \sim F(\omega_{z_{ji}}), \quad \omega_k \sim \text{Dir}(\eta, \dots, \eta) \\
& N_j = \sum_{k=1}^K n_{jk}, \quad n_{jk} \sim \text{Pois}(\lambda_{jk}), \quad \lambda_{jk} \sim \text{Gamma}(r_k, p_k / (1 - p_k)) \\
& r_k \sim \text{Gamma}(\gamma_0 / K, 1/c), \quad p_k \sim \text{Beta}(a_0, b_0), \quad \gamma_0 \sim \text{Gamma}(e_0, 1/f_0). \quad (34)
\end{aligned}$$

The block Gibbs sampling can be expressed as

$$\begin{aligned}
& \Pr(z_{ji} = k | -) \propto F(x_{ji}; \omega_k) \lambda_{jk} \\
& p_k \sim \text{Beta} \left(a_0 + \sum_{j=1}^J n_{jk}, b_0 + Jr_k \right), \quad p'_k = \frac{-J \ln(1 - p_k)}{c - J \ln(1 - p_k)} \\
& l_{jk} \sim \text{CRT}(n_{jk}, r_k), \quad l'_k \sim \text{CRT}(\sum_{j=1}^J l_{jk}, \gamma_0 / K), \quad \gamma_0 \sim \text{Gamma} \left(e_0 + \sum_{k=1}^K l'_k, \frac{1}{f_0 - \sum_{k=1}^K \ln(1 - p'_k) / K} \right) \\
& (r_k | -) \sim \text{Gamma} \left(\gamma_0 / K + \sum_{j=1}^J l_{jk}, \frac{1}{c - J \ln(1 - p_k)} \right), \quad (\lambda_{jk} | -) \sim \text{Gamma}(r_k + n_{jk}, p_k) \\
& (\omega_k | -) \sim \text{Dir} \left(\eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = 1), \dots, \eta + \sum_{j=1}^J \sum_{i=1}^{N_j} \delta(z_{ji} = k, v_{ji} = V) \right). \quad (35)
\end{aligned}$$