

## A MODEL AND PARAMETER DETAILS

### A.1 Preferential Attachment Preference (IBP)

The IBP model with parameters  $\alpha > 0$ ,  $\sigma \in [0, 1)$ , and  $c > -\sigma$  is defined as follows [21]:

- (1) The first user likes  $\text{Poisson}(\alpha)$  items.
- (2) User  $(n + 1)$  likes previously-known item  $i$  with probability  $\frac{m_i - \sigma}{n + c}$  (where  $m_i$  is the number of users who like item  $i$ ) and likes  $\text{Poisson}(\alpha \frac{\Gamma(1+c)\Gamma(n+c+\sigma)}{\Gamma(n+1+c)\Gamma(c+\sigma)})$  new items.

$c$  controls how likely the user is to rate new vs. old items.  $\sigma$  governs the power-law behavior of the generated preference matrix;  $\sigma = 0$  yields a traditional IBP, with larger values yielding stronger power-law distributions of item popularity.  $\alpha$  controls the density of the generated preference matrix. When  $\sigma > 0$ , the process generates on average  $\alpha|U|^\sigma$  items; when  $\sigma = 0$  and  $c = 1$ , it generates approximately  $\alpha(\log|U| + \gamma)$  items on average [21], where  $\gamma$  is Euler's constant [12].

### A.2 Correlated Preference (LDA)

The LDA generation process [4] with  $K$  latent features operates as follows:

- (1) Draw  $K$  feature-item vectors  $\vec{\phi}_k \in [0, 1]^{|I|}$  from  $\text{Dirichlet}(\beta)$ .
- (2) For each user:
  - (a) Draw a latent feature vector  $\vec{\theta}_u \in [0, 1]^K$  from  $\text{Dirichlet}(\alpha)$ .
  - (b) Draw  $n_u$  (the number of items) from  $\text{Poisson}(\lambda)$ .
  - (c) Draw items  $i_1, \dots, i_{n_u}$  liked by user  $u$  by drawing feature  $k_x \sim \text{Multinomial}(\vec{\theta}_u)$  and  $i_x$  from  $\text{Multinomial}(\vec{\phi}_{k_x})$ .
- (3) De-duplicate user-item pairs to produce implicit user preference samples.

To reduce the number of parameters for fitting efficiency, we use symmetric LDA, where  $\alpha$  is a constant vector with all values equal to  $a > 0$ , and likewise  $\beta$  is constant  $b > 0$ . These parameters  $a$  and  $b$  control the breadth of user preferences; when  $a < 1$ , the values of  $\vec{\theta}_u$  concentrate on a few of the  $K$  dimensions, making the user's preferences concentrate on a few items if  $b < 1$ . The parameter  $\lambda$  controls the average number of items each user likes. The parameter  $K$  controls the size of the latent feature space, affecting the diversity of user-item preference patterns in the whole true preference data.