

# ExplicitAndImplicitFeedback

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## 1 Original EM Derivation

### 1.1 E-step

### 1.2 M-step

the updates of the parameters  $\{u, v, \theta\}$  as follow:

$$u_k = \frac{\sum_{u(d)=u} \gamma(d, k, \Theta^t)}{\sum_{s=1}^K \sum_{u(d)=u} \gamma(d, s, \Theta^t)} \quad (1)$$

## 2 Stochastic EM Derivation

### 2.1 E-step

$$\begin{aligned} p(g|d, \Theta^t) &\propto p(g|u, \Theta^t) p(d|g, \Theta^t) \\ p(g_k = 1|d, \Theta^t) &\propto u_k^t \frac{w_k^t}{w_k^t + \theta^t l_k^t} \prod_{k' \neq k} \left[ \frac{\theta^t w_{k'}^t}{l_{k'}^t + \theta^t w_{k'}^t} \right] \end{aligned} \quad (2)$$

then simply add an S-step after the E-step, the value of  $g$  for each session  $d$  is

### 2.2 S-step

$$k \sim u_k^t \frac{w_k^t}{w_k^t + \theta^t l_k^t} \prod_{k' \neq k} \left[ \frac{\theta^t w_{k'}^t}{l_{k'}^t + \theta^t w_{k'}^t} \right] \quad (3)$$

In the E-step of  $t$ -th EM round, compute the expectation  $Q(\Theta^t) = E_G \ln p(D, G|\Theta)$

$$\begin{aligned} E_G \ln p(D, G|\Theta) &= \sum_d \ln p(d, g|\Theta) \\ &= \sum_d \{ \ln u_k + \sum_{w \in W_d, v \in V_d} \left[ \ln \frac{w_k}{w_k + \theta v_k} + \sum_{k' \neq k} \ln \frac{\theta w_{k'}}{v_{k'} + \theta w_{k'}} \right] \} \end{aligned}$$

### 2.3 M-step

In the M-step, for the :

$$\ln \frac{y}{x} \geq 1 - \frac{x}{y}$$

we can derive a lower bound for the log-likelihood over the complete data, given the parameters learnt from previous round. hence, we obtain a minorization function of  $\tilde{Q}(\Theta^t)$ .

$$\begin{aligned} \tilde{Q}(\Theta^t) = & \sum_d \sum_{w \in W_d, v \in L_d} \{ [\ln w_k + 1 - \ln(w_k^t + \theta^t v_k^t) - \frac{w_k + \theta v_k}{w_k^t + \theta^t v_k^t}] + \\ & \sum_{k' \neq k} [\ln(\theta w_{k'}) + 1 - \ln(v_{k'}^t + \theta^t w_{k'}^t) - \frac{v_{k'} + \theta w_{k'}}{v_{k'}^t + \theta^t w_{k'}^t}] \} \end{aligned}$$

$\tilde{Q}(\Theta^t)$  can be separated for each item  $v$ . Considering only the  $k$ -th component  $v_k$ ,  $\tilde{Q}(v_k, \Theta^t)$  involves two terms, one of which is relevant to observations  $d \in W(v)$  where  $v$  acts as skyline object, the other is relevant to observations  $d \in L(v)$  where  $v$  acts as comparisons,  $\tilde{Q}(v_k, \Theta^t) = \tilde{Q}^1(v_k, \Theta^t) + \tilde{Q}^2(v_k, \Theta^t)$ . Removing all constants and irrelevant terms for  $v_k$ , we have the following minorizing function:

$$\begin{aligned} \tilde{Q}^1(v_k, \Theta^t) = & \sum_{d \in W(v)} |L_d| \ln v_k - v_k \sum_{d \in W(v)} \sum_{v' \in L_d} \left[ \frac{1}{\alpha(v, v', k, \Theta^t)} + \sum_{k' \neq k} \frac{\theta^t}{\alpha(v', v, k, \Theta^t)} \right] \\ \tilde{Q}^2(v_k, \Theta^t) = & -v_k \sum_{d \in L(v)} \sum_{v' \in W_d} \left[ \frac{\theta^t}{\alpha(v', v, k, \Theta^t)} + \sum_{k' \neq k} \frac{1}{\alpha(v, v', k, \Theta^t)} \right] \end{aligned}$$

where:

$|L_d|$  is the number of objects being dominated in  $d$ ,  
 $\alpha(v, v', k, \Theta^t) = v_k^t + \theta^t v_{k'}^t$ .

(1) By setting the partial derivative of  $\frac{\partial \tilde{Q}(v_k, \Theta^t)}{\partial v_k} = 0$ , we have:

$$\begin{aligned} \frac{1}{v_k} = & \frac{\sum_{d \in W(v)} \sum_{v' \in L_d} \left[ \frac{1}{\alpha(v, v', k, \Theta^t)} + \sum_{k' \neq k} \frac{\theta^t}{\alpha(v', v, k, \Theta^t)} \right]}{\sum_{d \in W(v)} |L_d|} \\ & + \frac{\sum_{d \in L(v)} \sum_{v' \in W_d} \left[ \frac{\theta^t}{\alpha(v', v, k, \Theta^t)} + \sum_{k' \neq k} \frac{1}{\alpha(v, v', k, \Theta^t)} \right]}{\sum_{d \in W(v)} |L_d|} \end{aligned}$$

(2) Fix  $u, v$ , update  $\theta$  by:

Fix  $v \in V$  and  $u \in U$ , rearranging *Equ.9*, we have the solution for  $\frac{\partial \tilde{Q}(\Theta^t)}{\partial \theta} = 0$  as:

$$\theta = \frac{(K-1) \sum_d |W_d| |L_d|}{\sum_d \sum_{w, v} \left[ \frac{v_k}{\alpha(w, v, k, \Theta^t)} + \sum_{k' \neq k} \frac{w_{k'}}{\alpha(v, w, k', \Theta^t)} \right]} \quad (4)$$