Supplementary Material for Co-Regularized Deep Multi-Network Embedding

Jingchao Ni¹, Shiyu Chang², Xiao Liu³, Wei Cheng⁴, Haifeng Chen⁴, Dongkuan Xu¹, and Xiang Zhang¹

¹College of Information Sciences and Technology, Pennsylvania State University ²IBM T. J. Watson Research Center

³Department of Biomedical Engineering, Pennsylvania State University, ⁴NEC Laboratories America ¹{jzn47, dux19, xzhang}@ist.psu.edu, ²shiyu.chang@ibm.com ³xxl213@engr.psu.edu, ⁴{weicheng, haifeng}@nec-labs.com

Here we prove Theorem 1 and Theorem 2 using the Auxiliary Function approach [2]. First, we introduce the definition of an auxiliary function as below.

DEFINITION 1. [2] A function $Z(h, \tilde{h})$ is an auxiliary function for a given function J(h) if the conditions $Z(h, \tilde{h}) \geq J(h)$ and Z(h, h) = J(h) are satisfied.

1. PROOF OF THEOREM 1

In this section, we provide the detailed proof of Theorem 1. We first introduce a generic matrix inequality proposed in [1].

LEMMA 1. [1] For any matrices $\mathbf{A} \in \mathbb{R}_{+}^{k \times k}$, $\mathbf{B} \in \mathbb{R}_{+}^{k \times k}$, $\mathbf{V} \in \mathbb{R}_{+}^{n \times k}$, $\tilde{\mathbf{V}} \in \mathbb{R}_{+}^{n \times k}$, and \mathbf{A} , \mathbf{B} are symmetric, the following inequality holds

$$Tr(\mathbf{V}^T \mathbf{A} \mathbf{V} \mathbf{B}) \leq \sum_{xp} \frac{(\mathbf{A} \tilde{\mathbf{V}} \mathbf{B})_{xp} \mathbf{V}_{xp}^2}{\tilde{\mathbf{V}}_{xp}}$$

In the following, we use $\mathbf{U}^{(\tau)}$ $(1 \le \tau \le g)$ to denote variable and $\tilde{\mathbf{U}}^{(\tau)}$ to denote current estimate (i.e., a constant).

PROOF. Using ED loss $\mathscr{L}_{ed}^{(ij)}$ in Eq. (12)¹, the sum of all terms in Eq. (12) that contains $\mathbf{U}^{(\tau)}$ is

$$\mathcal{L}_{ed}(\mathbf{U}^{(\tau)}) = \alpha \sum_{(\tau,j)\in\mathcal{I}} \|\mathbf{O}^{(\tau j)}\mathbf{U}^{(\tau)} - \tilde{\mathbf{S}}^{(\tau j)}\mathbf{U}^{(j)}\|_F^2$$
$$+ \beta \|\mathbf{U}^{(\tau)} - \mathbf{H}^{(\tau)}\|_F^2$$

which is equivalent to (after removing some constants)

$$\mathscr{L}_{ed}(\mathbf{U}^{(au)})$$

$$\begin{split} &= \alpha \sum_{(\tau,j) \in \mathcal{I}} \mathrm{Tr} \bigg((\mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)})^T \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} - 2 (\tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)})^T \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} \bigg) \\ &+ \alpha \sum_{(j,\tau) \in \mathcal{I}} \mathrm{Tr} \bigg((\tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} - 2 (\mathbf{O}^{(j\tau)} \mathbf{U}^{(j)})^T \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} \bigg) \\ &+ \beta \mathrm{Tr} \bigg((\mathbf{U}^{(\tau)})^T \mathbf{U}^{(\tau)} - 2 (\mathbf{H}^{(\tau)})^T \mathbf{U}^{(\tau)} \bigg) \end{split}$$

where $Tr(\cdot)$ is the trace function.

First, we derive a tight upper bound for $\mathcal{L}_{ed}(\mathbf{U}^{(\tau)})$. Using the inequality introduced in Lemma 1, substituting \mathbf{A} with

 $(\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)}$, **B** with an identity matrix, and **V** with $\mathbf{U}^{(\tau)}$, we can obtain an upper bound for the first term

$$\alpha \operatorname{Tr} \left((\mathbf{U}^{(\tau)})^T (\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} \right) \leq \sum_{n,n} (\mathbf{\Phi}_{xp}^{(\tau j)})' \frac{(\mathbf{U}_{xp}^{(\tau)})^2}{\tilde{\mathbf{U}}_{xp}^{(\tau)}}$$
(18)

where

$$(\mathbf{\Phi}^{(\tau j)})' = \alpha (\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)} \tilde{\mathbf{U}}^{(\tau)}$$

Similarly, substituting **A** with $(\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)}$, **B** with an identity matrix, and **V** with $\mathbf{U}^{(\tau)}$, we obtain an upper bound for the third term

$$\alpha \operatorname{Tr} \left((\mathbf{U}^{(\tau)})^T (\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} \right) \leq \sum_{xp} (\mathbf{\Pi}_{xp}^{(j\tau)})' \frac{(\mathbf{U}_{xp}^{(i)})^2}{\tilde{\mathbf{U}}_{xp}^{(\tau)}}$$
(19)

where

$$(\mathbf{\Pi}^{(j\tau)})' = \alpha (\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \tilde{\mathbf{U}}^{(\tau)}$$

Using the inequality $z > 1 + \log z$, which holds for z > 0, we have

$$\frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}} \ge 1 + \log \frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}} \tag{20}$$

Then we can derive an upper bound for the second term

$$-2\alpha \operatorname{Tr}\left(\left(\tilde{\mathbf{S}}^{(\tau j)}\mathbf{U}^{(j)}\right)^{T}\mathbf{O}^{(\tau j)}\mathbf{U}^{(\tau)}\right) = -2\sum_{xp} \left(\mathbf{\Theta}_{xp}^{(\tau j)}\right)' \mathbf{U}_{xp}^{(\tau)}$$

$$\leq -2\sum_{xp} \left(\mathbf{\Theta}_{xp}^{(\tau j)}\right)' \tilde{\mathbf{U}}_{xp}^{(\tau)} \left(1 + \log \frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}}\right)$$

$$(21)$$

where

$$(\mathbf{\Theta}^{(\tau j)})' = \alpha (\mathbf{O}^{(\tau j)})^T \tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)}$$

Similarly, we derive an upper bound for the fourth term

$$-2\alpha \operatorname{Tr}\left(\left(\mathbf{O}^{(j\tau)}\mathbf{U}^{(j)}\right)^{T}\tilde{\mathbf{S}}^{(j\tau)}\mathbf{U}^{(\tau)}\right) = -2\sum_{xp}(\mathbf{\Lambda}_{xp}^{(j\tau)})'\mathbf{U}_{xp}^{(\tau)}$$

$$\leq -2\sum_{xp}(\mathbf{\Lambda}_{xp}^{(j\tau)})'\tilde{\mathbf{U}}_{xp}^{(\tau)}(1+\log\frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}})$$
(22)

where

(17)

$$(\mathbf{\Lambda}^{(j\tau)})' = \alpha(\tilde{\mathbf{S}}^{(j\tau)})^T \mathbf{O}^{(j\tau)} \mathbf{U}^{(j)}$$

and also for the last term, we have

$$-2\beta \operatorname{Tr}\left(\left(\mathbf{H}^{(\tau)}\right)^{T} \mathbf{U}^{(\tau)}\right) = -2\beta \sum_{xp} \mathbf{H}_{xp}^{(\tau)} \mathbf{U}_{xp}^{(\tau)}$$

$$\leq -2\beta \sum_{xp} \mathbf{H}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{xp}^{(\tau)} (1 + \log \frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}})$$
(23)

¹The equation numbers in this supplementary material are consistent with those in the original paper.

The fifth term it is equivalent to

$$\beta \operatorname{Tr} \left((\mathbf{U}^{(\tau)})^T \mathbf{U}^{(\tau)} \right) = \beta \sum_{xx} (\mathbf{U}_{xp}^{(\tau)})^2$$
 (24)

Therefore, with the inequalities Eq. (18), (19), (21), (22), (23) and the equation Eq. (24), we can formulate an upper bound for $\mathcal{L}_{ed}(\mathbf{U}^{(\tau)})$ in Eq. (17) as below.

$$\begin{split} &Z_{ed}(\mathbf{U}^{(\tau)},\tilde{\mathbf{U}}^{(\tau)})\\ &=\sum_{(\tau,j)\in\mathcal{I}}\bigg(\sum_{xp}[(\boldsymbol{\Phi}_{xp}^{(\tau j)})'\frac{(\mathbf{U}_{xp}^{(\tau)})^2}{\tilde{\mathbf{U}}_{xp}^{(\tau)}}-2(\boldsymbol{\Theta}_{xp}^{(\tau j)})'\tilde{\mathbf{U}}_{xp}^{(\tau)}(1+\log\frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}})]\bigg)\\ &+\sum_{(j,\tau)\in\mathcal{I}}\bigg(\sum_{xp}[(\boldsymbol{\Pi}_{xp}^{(j\tau)})'\frac{(\mathbf{U}_{xp}^{(\tau)})^2}{\tilde{\mathbf{U}}_{xp}^{(\tau)}}-2(\boldsymbol{\Lambda}_{xp}^{(j\tau)})'\tilde{\mathbf{U}}_{xp}^{(\tau)}(1+\log\frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}})]\bigg)\\ &+\bigg(\sum_{xp}[\beta(\mathbf{U}_{xp}^{(\tau)})^2-2\beta\mathbf{H}_{xp}^{(\tau)}\tilde{\mathbf{U}}_{xp}^{(\tau)}(1+\log\frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}})]\bigg) \end{split}$$

We can verify that $Z_{ed}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ is a tight upper bound of $\mathcal{L}_{ed}(\mathbf{U}^{(\tau)})$. That is, it satisfies

$$Z_{ed}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)}) \ge \mathcal{L}_{ed}(\mathbf{U}^{(\tau)}), \quad Z_{ed}(\mathbf{U}^{(\tau)}, \mathbf{U}^{(\tau)}) = \mathcal{L}_{ed}(\mathbf{U}^{(\tau)})$$
(25)

Thus, according to Definition 1, $Z_{ed}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ is an auxiliary function of $\mathcal{L}_{ed}(\mathbf{U}^{(\tau)})$.

Next, we derive the minimal solution to $Z_{ed}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$. The gradient of $Z_{ed}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ w.r.t. $\mathbf{U}^{(\tau)}$ is

$$\begin{split} &\frac{\partial Z_{ed}(\mathbf{U}^{(\tau)},\tilde{\mathbf{U}}^{(\tau)})}{\partial \mathbf{U}_{xp}^{(\tau)}} = \sum_{(\tau,j)\in\mathcal{I}} \left(2(\mathbf{\Phi}_{xp}^{(\tau j)})' \frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}} - 2(\mathbf{\Theta}_{xp}^{(\tau j)})' \frac{\tilde{\mathbf{U}}_{xp}^{(\tau)}}{\mathbf{U}_{xp}^{(\tau)}} \right) \\ &+ \sum_{(j,\tau)\in\mathcal{I}} \left(2(\mathbf{\Pi}_{xp}^{(j\tau)})' \frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}} - 2(\mathbf{\Lambda}_{xp}^{(j\tau)})' \frac{\tilde{\mathbf{U}}_{xp}^{(\tau)}}{\mathbf{U}_{xp}^{(\tau)}} \right) \\ &+ \left(2\beta \mathbf{U}_{xp}^{(\tau)} - 2\beta \mathbf{H}_{xp}^{(\tau)} \frac{\tilde{\mathbf{U}}_{xp}^{(\tau)}}{\mathbf{U}_{xp}^{(\tau)}} \right) \end{split}$$

Then the global minimum of $Z_{ed}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ can be obtained by solving $\frac{\partial Z_{ed}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})}{\partial \mathbf{U}_{xp}^{(\tau)}} = 0$. This gives

$$\mathbf{U}_{xp}^{(\tau)} = \mathbf{U}_{xp}^{(\tau)} \left(\frac{\sum_{(\tau,j) \in \mathcal{I}} (\mathbf{\Theta}_{xp}^{(\tau j)})' + \sum_{(j,\tau) \in \mathcal{I}} (\mathbf{\Lambda}_{xp}^{(j\tau)})' + \beta \mathbf{H}_{xp}^{(\tau)}}{\sum_{(\tau,j) \in \mathcal{I}} (\mathbf{\Phi}_{xp}^{(\tau j)})' + \sum_{(j,\tau) \in \mathcal{I}} (\mathbf{\Pi}_{xp}^{(j\tau)})' + \beta \mathbf{U}_{xp}^{(\tau)}} \right)^{\frac{1}{2}}$$

which is consistent with the updating rule in Eq. (13).

Therefore, according to the properties of auxiliary function, i.e., Eq. (25), at any iteration $\kappa \geq 1$ when updating $\mathbf{U}^{(\tau)}$ using Eq. (13), we have

$$\begin{split} \mathscr{L}_{ed}((\mathbf{U}^{(\tau)})^{(\kappa)}) &= Z_{ed}((\mathbf{U}^{(\tau)})^{(\kappa)}, (\mathbf{U}^{(\tau)})^{(\kappa)}) \\ &\geq Z_{ed}((\mathbf{U}^{(\tau)})^{(\kappa+1)}, (\mathbf{U}^{(\tau)})^{(\kappa)}) \geq \mathscr{L}_{ed}((\mathbf{U}^{(\tau)})^{(\kappa+1)}) \end{split}$$

where $(\mathbf{U}^{(\tau)})^{(\kappa)}$ denotes the updated $\mathbf{U}^{(\tau)}$ at the κ -th iteration. Therefore, using ED loss, the objective value in Eq. (12) monotonically decreases. This completes the proof of Theorem 1. \square

2. PROOF OF THEOREM 2

In this section, we provide the detailed proof of Theorem 2. The idea is similar to the proof of Theorem 1. We first introduce a generic matrix inequality proposed in [3].

LEMMA 2. [3] For any matrices $\mathbf{A} \in \mathbb{R}_{+}^{k \times k}$, $\mathbf{B} \in \mathbb{R}_{+}^{k \times k}$, $\mathbf{V} \in \mathbb{R}_{+}^{n \times k}$, $\tilde{\mathbf{V}} \in \mathbb{R}_{+}^{n \times k}$, and \mathbf{A} , \mathbf{B} are symmetric, the following inequality holds

$$Tr(\mathbf{VAV}^T\mathbf{VBV}^T) \leq \sum_{xp} \left(\frac{\tilde{\mathbf{V}}\mathbf{A}\tilde{\mathbf{V}}^T\tilde{\mathbf{V}}\mathbf{B} + \tilde{\mathbf{V}}\mathbf{B}\tilde{\mathbf{V}}^T\tilde{\mathbf{V}}\mathbf{A}}{2}\right)_{xp} \frac{\mathbf{V}_{xp}^4}{\tilde{\mathbf{V}}_{xp}^3}$$

In the following, we use $\mathbf{U}^{(\tau)}$ $(1 \leq \tau \leq g)$ to denote variable and $\tilde{\mathbf{U}}^{(\tau)}$ to denote current estimate (i.e., a constant).

PROOF. Using PD loss $\mathscr{L}_{pd}^{(ij)}$ in Eq. (12), the sum of all terms in Eq. (12) that contains $\mathbf{U}^{(\tau)}$ is

$$\begin{split} & \mathscr{L}_{pd}(\mathbf{U}^{(\tau)}) \\ &= \alpha \sum_{(\tau,j) \in \mathcal{I}} \| (\mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)}) (\mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)})^T - (\tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)}) (\tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)})^T \|_F^2 \\ &+ \beta \| \mathbf{U}^{(\tau)} - \mathbf{H}^{(\tau)} \|_F^2 \end{split}$$

which is equivalent to (after removing some constants)

$$\mathcal{J}_{pd}(\mathbf{U}^{(\tau)}) = \alpha \sum_{(\tau,j)\in\mathcal{I}} \operatorname{Tr} \left(\mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} (\mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)})^T \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} (\mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)})^T \right) \\
- 2\tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)} (\tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)})^T \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} (\mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)})^T \right) \\
+ \alpha \sum_{(j,\tau)\in\mathcal{I}} \operatorname{Tr} \left(\tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} (\tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} (\tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)})^T \right) \\
- 2\mathbf{O}^{(j\tau)} \mathbf{U}^{(j)} (\mathbf{O}^{(j\tau)} \mathbf{U}^{(j)})^T \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} (\tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)})^T \right) \\
+ \beta \operatorname{Tr} \left((\mathbf{U}^{(\tau)})^T \mathbf{U}^{(\tau)} - 2(\mathbf{H}^{(\tau)})^T \mathbf{U}^{(\tau)} \right) \tag{26}$$

Next, we derive a tight upper bound for $\mathcal{L}_{pd}(\mathbf{U}^{(\tau)})$. Using the inequality introduced in Lemma 2, substituting both \mathbf{A} and \mathbf{B} with $(\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)}$, and \mathbf{V} with $(\mathbf{U}^{(\tau)})^T$, we can obtain an upper bound for the first term

$$\alpha \operatorname{Tr} \left((\mathbf{U}^{(\tau)})^T (\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} (\mathbf{U}^{(\tau)})^T (\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} \right)$$

$$\leq \sum_{xp} (\hat{\mathbf{\Phi}}_{xp}^{(\tau j)})' \frac{(\mathbf{U}_{xp}^{(\tau)})^4}{(\tilde{\mathbf{U}}_{xp}^{(\tau)})^3}$$
(27)

where

$$(\mathbf{\hat{\Phi}}^{(\tau j)})' = \alpha(\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)} \mathbf{\tilde{U}}^{(\tau)} (\mathbf{\tilde{U}}^{(\tau)})^T (\mathbf{O}^{(\tau j)})^T \mathbf{O}^{(\tau j)} \mathbf{\tilde{U}}^{(\tau)}$$

Similarly, substituting both **A** and **B** with $(\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)}$, and **V** with $(\mathbf{U}^{(\tau)})^T$, we can obtain an upper bound for the third term

$$\alpha \operatorname{Tr} \left((\mathbf{U}^{(\tau)})^T (\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} (\mathbf{U}^{(\tau)})^T (\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)} \right)$$

$$\leq \sum_{xp} (\hat{\mathbf{\Pi}}_{xp}^{(j\tau)})' \frac{(\mathbf{U}_{xp}^{(\tau)})^4}{(\tilde{\mathbf{U}}_{xp}^{(\tau)})^3}$$
(28)

where

$$(\hat{\mathbf{\Pi}}^{(j\tau)})' = \alpha(\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \tilde{\mathbf{U}}^{(\tau)} (\tilde{\mathbf{U}}^{(\tau)})^T (\tilde{\mathbf{S}}^{(j\tau)})^T \tilde{\mathbf{S}}^{(j\tau)} \tilde{\mathbf{U}}^{(\tau)}$$

Using the inequality $z > 1 + \log z$, which holds for z > 0, we have

$$\frac{\mathbf{U}_{xp}^{(\tau)}\mathbf{U}_{yp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}\tilde{\mathbf{U}}_{yp}^{(\tau)}} \geq 1 + \log \frac{\mathbf{U}_{xp}^{(\tau)}\mathbf{U}_{yp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}\tilde{\mathbf{U}}_{yp}^{(\tau)}}$$

Then we can derive an upper bound for the second term

$$-2\alpha \operatorname{Tr}\left((\mathbf{U}^{(\tau)})^{T} (\mathbf{O}^{(\tau j)})^{T} \tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)} (\tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)})^{T} \mathbf{O}^{(\tau j)} \mathbf{U}^{(\tau)} \right)$$

$$\leq -2 \sum_{xyp} (\hat{\mathbf{\Gamma}}_{xy}^{(\tau j)})' \tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)} \left(1 + \log \frac{\mathbf{U}_{xp}^{(\tau)} \mathbf{U}_{yp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)}} \right)$$
(29)

where

$$(\hat{\boldsymbol{\Gamma}}^{(\tau j)})' = \alpha (\mathbf{O}^{(\tau j)})^T \tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)} (\tilde{\mathbf{S}}^{(\tau j)} \mathbf{U}^{(j)})^T \mathbf{O}^{(\tau j)}$$

Similarly, we derive an upper bound for the fourth term

$$-2\alpha \operatorname{Tr}\left(\left(\mathbf{U}^{(\tau)}\right)^{T} \left(\tilde{\mathbf{S}}^{(j\tau)}\right)^{T} \mathbf{O}^{(j\tau)} \mathbf{U}^{(j)} \left(\mathbf{O}^{(j\tau)} \mathbf{U}^{(j)}\right)^{T} \tilde{\mathbf{S}}^{(j\tau)} \mathbf{U}^{(\tau)}\right)$$

$$\leq -2\sum_{xyp} (\hat{\mathbf{\Omega}}_{xy}^{(j\tau)})' \tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)} \left(1 + \log \frac{\mathbf{U}_{xp}^{(\tau)} \mathbf{U}_{yp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)}}\right)$$
(30)

where

$$(\mathbf{\hat{\Omega}}^{(j\tau)})' = \alpha(\mathbf{\tilde{S}}^{(j\tau)})^T \mathbf{O}^{(j\tau)} \mathbf{U}^{(j)} (\mathbf{O}^{(j\tau)} \mathbf{U}^{(j)})^T \mathbf{\tilde{S}}^{(j\tau)}$$

Using the inequality $2ab \le a^2 + b^2$, we can derive an upper bound for the fifth term

$$\beta \operatorname{Tr} \left((\mathbf{U}^{(\tau)})^T \mathbf{U}^{(\tau)} \right) = \beta \sum_{xp} (\mathbf{U}_{xp}^{(\tau)})^2 \le \beta \sum_{xp} \frac{(\mathbf{U}_{xp}^{(\tau)})^4 + (\tilde{\mathbf{U}}_{xp}^{(\tau)})^4}{2(\tilde{\mathbf{U}}_{xp}^{(\tau)})^2}$$
(3)

Using the inequality in Eq. (20), we obtain an upper bound for the last term

$$-2\beta \operatorname{Tr}\left((\mathbf{H}^{(\tau)})^T \mathbf{U}^{(\tau)} \right) \le -2\beta \sum_{xp} \mathbf{H}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{xp}^{(\tau)} (1 + \log \frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}}) \quad (32)$$

Therefore, with the inequalities Eq. (27), (28), (29), (30), (31) and (32), we can formulate an upper bound for $\mathcal{L}_{pd}(\mathbf{U}^{(\tau)})$ in Eq. (26) as below.

$$\begin{split} &Z_{pd}(\mathbf{U}^{(\tau)},\tilde{\mathbf{U}}^{(\tau)}) = \sum_{(\tau,j)\in\mathcal{I}} \bigg(\sum_{xp} (\hat{\mathbf{\Phi}}_{xp}^{(\tau j)})' \frac{(\mathbf{U}_{xp}^{(\tau)})^4}{(\tilde{\mathbf{U}}_{xp}^{(\tau)})^3} \\ &- 2\sum_{xyp} (\hat{\mathbf{\Gamma}}_{xy}^{(\tau j)})' \tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)} (1 + \log \frac{\mathbf{U}_{xp}^{(\tau)} \mathbf{U}_{yp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)}}) \bigg) \\ &+ \sum_{(j,\tau)\in\mathcal{I}} \bigg(\sum_{xp} (\hat{\mathbf{\Pi}}_{xp}^{(j\tau)})' \frac{(\mathbf{U}_{xp}^{(\tau)})^4}{(\tilde{\mathbf{U}}_{xp}^{(\tau)})^3} \\ &- 2\sum_{xyp} (\hat{\mathbf{\Omega}}_{xy}^{(j\tau)})' \tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)} (1 + \log \frac{\mathbf{U}_{xp}^{(\tau)} \mathbf{U}_{yp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{yp}^{(\tau)}}) \bigg) \\ &+ \sum_{xp} \bigg(\beta \frac{(\mathbf{U}_{xp}^{(\tau)})^4 + (\tilde{\mathbf{U}}_{xp}^{(\tau)})^4}{2(\tilde{\mathbf{U}}_{xp}^{(\tau)})^2} - 2\beta \mathbf{H}_{xp}^{(\tau)} \tilde{\mathbf{U}}_{xp}^{(\tau)} (1 + \log \frac{\mathbf{U}_{xp}^{(\tau)}}{\tilde{\mathbf{U}}_{xp}^{(\tau)}}) \bigg) \end{split}$$

We can verify that $Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ is a tight upper bound of $\mathcal{L}_{pd}(\mathbf{U}^{(\tau)})$. That is, it satisfies

$$Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)}) \ge \mathcal{L}_{pd}(\mathbf{U}^{(\tau)}), \quad Z_{pd}(\mathbf{U}^{(\tau)}, \mathbf{U}^{(\tau)}) = \mathcal{L}_{pd}(\mathbf{U}^{(\tau)})$$
(33

Thus, according to Definition 1, $Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ is an auxiliary function of $\mathcal{L}_{pd}(\mathbf{U}^{(\tau)})$.

Next, we derive the minimal solution to $Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$. The gradient of $Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ w.r.t. $\mathbf{U}^{(\tau)}$ is

$$\begin{split} &\frac{\partial Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})}{\partial \mathbf{U}_{xp}^{(\tau)}} \\ &= \sum_{(\tau, j) \in \mathcal{I}} \left(4(\hat{\mathbf{\Phi}}_{xp}^{(\tau j)})' \frac{(\mathbf{U}_{xp}^{(\tau)})^3}{(\tilde{\mathbf{U}}_{xp}^{(\tau)})^3} - 4(\hat{\mathbf{\Theta}}_{xp}^{(\tau j)})' \frac{\tilde{\mathbf{U}}_{xp}^{(\tau)}}{\mathbf{U}_{xp}^{(\tau)}} \right) \\ &+ \sum_{(j, \tau) \in \mathcal{I}} \left(4(\hat{\mathbf{\Pi}}_{xp}^{(j\tau)})' \frac{(\mathbf{U}_{xp}^{(\tau)})^3}{(\tilde{\mathbf{U}}_{xp}^{(\tau)})^3} - 4(\hat{\mathbf{\Lambda}}_{xp}^{(j\tau)})' \frac{\tilde{\mathbf{U}}_{xp}^{(\tau)}}{\mathbf{U}_{xp}^{(\tau)}} \right) \\ &+ (2\beta \frac{(\mathbf{U}_{xp}^{(\tau)})^3}{(\tilde{\mathbf{U}}_{xp}^{(\tau)})^2} - 2\beta \mathbf{H}_{xp}^{(\tau)} \frac{\tilde{\mathbf{U}}_{xp}^{(\tau)}}{\mathbf{U}_{xp}^{(\tau)}} \end{split}$$

where

$$(\hat{\boldsymbol{\Theta}}^{(\tau j)})' = (\hat{\boldsymbol{\Gamma}}^{(\tau j)})'\tilde{\mathbf{U}}^{(\tau)}, \quad (\hat{\boldsymbol{\Lambda}}^{(j\tau)})' = (\hat{\boldsymbol{\Omega}}^{(\tau j)})'\tilde{\mathbf{U}}^{(\tau)}$$

Then the global minimum of $Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})$ can be ob-

tained by solving $\frac{\partial Z_{pd}(\mathbf{U}^{(\tau)}, \tilde{\mathbf{U}}^{(\tau)})}{\partial \mathbf{U}_{xp}^{(\tau)}} = 0$. This gives

$$\mathbf{U}_{xp}^{(\tau)} = \mathbf{U}_{xp}^{(\tau)} \left(\frac{\sum_{(\tau,j) \in \mathcal{I}} 2(\hat{\mathbf{\Theta}}_{xp}^{(\tau j)})' + \sum_{(j,\tau) \in \mathcal{I}} 2(\hat{\mathbf{\Lambda}}_{xp}^{(j\tau)})' + \beta \mathbf{H}_{xp}^{(\tau)}}{\sum_{(\tau,j) \in \mathcal{I}} 2(\hat{\mathbf{\Phi}}_{xp}^{(\tau j)})' + \sum_{(j,\tau) \in \mathcal{I}} 2(\hat{\mathbf{\Pi}}_{xp}^{(j\tau)})' + \beta \tilde{\mathbf{U}}_{xp}^{(\tau)}} \right)^{\frac{1}{4}}$$

which is consistent with the updating rule in Eq. (14). Note the factor 2 before $(\hat{\boldsymbol{\Theta}}^{(\tau j)})'$, $(\hat{\boldsymbol{\Phi}}^{(\tau j)})'$, $(\hat{\boldsymbol{\Lambda}}^{(j\tau)})'$, $(\hat{\boldsymbol{\Pi}}^{(j\tau)})'$ in the above equation has been incorporated into $\hat{\boldsymbol{\Theta}}^{(\tau j)}$, $\hat{\boldsymbol{\Phi}}^{(\tau j)}$, $\hat{\boldsymbol{\Lambda}}^{(j\tau)}$, $\hat{\boldsymbol{\Pi}}^{(j\tau)}$ in Eq. (14).

Therefore, according to the properties of auxiliary function, i.e., Eq. (33), at any iteration $\kappa \geq 1$ when updating $\mathbf{U}^{(\tau)}$ using Eq. (14), we have

$$\mathcal{L}_{pd}((\mathbf{U}^{(\tau)})^{(\kappa)}) = Z_{pd}((\mathbf{U}^{(\tau)})^{(\kappa)}, (\mathbf{U}^{(\tau)})^{(\kappa)})$$

$$> Z_{pd}((\mathbf{U}^{(\tau)})^{(\kappa+1)}, (\mathbf{U}^{(\tau)})^{(\kappa)}) > \mathcal{L}_{pd}((\mathbf{U}^{(\tau)})^{(\kappa+1)})$$

which indicates that, using PD loss, the objective value in Eq. (12) monotonically decreases. This completes the proof of Theorem 2. \square

3. REFERENCES

- [1] C. H. Ding, T. Li, and M. I. Jordan. Convex and semi-nonnegative matrix factorizations. *IEEE Trans.* Pattern Anal. Mach. Intell., 32(1):45–55, 2010.
- [2] D. D. Lee and H. S. Seung. Algorithms for non-negative matrix factorization. In NIPS, 2001.
- [3] H. Wang, H. Huang, and C. Ding. Simultaneous clustering of multi-type relational data via symmetric nonnegative matrix tri-factorization. In *CIKM*, 2011.