Dual Similarity Learning for Heterogeneous One-Class Collaborative Filtering

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Problem Definition

- **Problem:** In this paper, we study the heterogeneous one-class collaborative filtering (HOCCF) problem.

- **Input:** For a user $u \in \mathcal{U}$, we have a set of purchased items, i.e., $\mathcal{I}_u^p$, and a set of examined items, i.e., $\mathcal{I}_u^e$.

- **Goal:** Our goal is to exploit such two types of one-class feedback and recommend a ranked list of items for each user $u$. 

Challenges

1. The *sparsity* of target feedback.
2. The *ambiguity and noise* of auxiliary feedback.
Overall of Our Solution

Dual similarity learning model (DSLM):
- Learn the similarity $s_{ii'}$ between a target item $i$ and a purchased item $i'$, and the similarity $s_{ji}$ between a target item $i$ and an examined item $j$.
- Learn the similarity $s_{u'u}$ between a target user $u$ and a user $u'$ who purchased item $i$, and the similarity $s_{wu}$ between a target item $u$ and a user $w$ who examined item $i$. 
Advantages of Our Solution

- By introducing the auxiliary feedback, DSLM is able to alleviate the sparsity problem to some extent.
- DSLM learns not only the similarity among items, but also the similarity among users, which is useful to capture the correlations between users and items.
- DSLM strikes a good balance between the item-based similarity and user-based similarity.
### Notations

<table>
<thead>
<tr>
<th>Notation</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n$</td>
<td>number of users</td>
</tr>
<tr>
<td>$m$</td>
<td>number of items</td>
</tr>
<tr>
<td>$u, u', w \in {1, 2, \ldots, n}$</td>
<td>user ID</td>
</tr>
<tr>
<td>$i, i', j \in {1, 2, \ldots, m}$</td>
<td>item ID</td>
</tr>
<tr>
<td>$\mathcal{U} = {u},</td>
<td>\mathcal{U}</td>
</tr>
<tr>
<td>$\mathcal{I} = {i},</td>
<td>\mathcal{I}</td>
</tr>
<tr>
<td>$\mathcal{R}^P = {(u, i)}$</td>
<td>the whole set of purchases</td>
</tr>
<tr>
<td>$\mathcal{R}^E = {(u, i)}$</td>
<td>the whole set of examinations</td>
</tr>
<tr>
<td>$\mathcal{R}^A = {(u, i)}$</td>
<td>the set of absent pairs</td>
</tr>
<tr>
<td>$\mathcal{I}^P_u = {i</td>
<td>(u, i) \in \mathcal{R}^P}$</td>
</tr>
<tr>
<td>$\mathcal{I}^E_u = {i</td>
<td>(u, i) \in \mathcal{R}^E}$</td>
</tr>
<tr>
<td>$\mathcal{U}^P_i = {u</td>
<td>(u, i) \in \mathcal{R}^P}$</td>
</tr>
<tr>
<td>$\mathcal{U}^E_i = {u</td>
<td>(u, i) \in \mathcal{R}^E}$</td>
</tr>
<tr>
<td>$U_u, P_{u'}, E_w \in \mathbb{R}^{1 \times d}$</td>
<td>user’s latent vectors</td>
</tr>
<tr>
<td>$V_i, \tilde{P}_i, \tilde{E}_j \in \mathbb{R}^{1 \times d}$</td>
<td>item’s latent vectors</td>
</tr>
<tr>
<td>$b_u, b_i \in \mathbb{R}$</td>
<td>user bias and item bias</td>
</tr>
<tr>
<td>$d$</td>
<td>latent feature number</td>
</tr>
<tr>
<td>$\hat{r}_{ui}$</td>
<td>predicted preference of user $u$ on item $i$</td>
</tr>
<tr>
<td>$\rho$</td>
<td>sampling parameter</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>learning rate</td>
</tr>
<tr>
<td>$T, L, L_0$</td>
<td>iteration number</td>
</tr>
<tr>
<td>$\lambda_<em>, \alpha_</em>, \beta_*$</td>
<td>tradeoff parameters</td>
</tr>
</tbody>
</table>
Factored Item Similarity Model (FISM)

In FISM, we can estimate the preference of user $u$ towards item $i$ by aggregating the similarity between item $i$ and all of its neighbors (i.e., $\mathcal{I}_u \backslash \{i\}$), which is shown as follows,

$$
\hat{r}_{ui} = \frac{1}{\sqrt{|\mathcal{I}_u \backslash \{i\}|}} \sum_{i' \in \mathcal{I}_u \backslash \{i\}} \tilde{P}_{i'.V_i^T},
$$

(1)

where we can regard the term \( \frac{1}{\sqrt{|\mathcal{I}_u \backslash \{i\}|}} \sum_{i' \in \mathcal{I}_u \backslash \{i\}} \tilde{P}_{i'} \) as a certain virtual user profile w.r.t. the target feedback, denoting the distinct preference of user $u$. 

Transfer via Joint Similarity Learning (TJSL)

TJSL introduces a new similarity term in a similar way to that of FISM, through which the knowledge from the auxiliary feedback (e.g., examination actions) can be transferred. Then, the preference estimation of user $u$ towards item $i$ is as follows,

$$\sum_{i' \in I_u \setminus \{i\}} s_{i'i} + \sum_{j \in I_u^{\ell}} s_{ji}, \quad I_u^{\ell} \subseteq I_u,$$

(2)

where

$$\sum_{j \in I_u^{\ell}} s_{ji} = \frac{1}{\sqrt{|I_u^{\ell}|}} \sum_{j \in I_u^{\ell}} \tilde{E}_j. V_i^T,$$

and the term

$$\frac{1}{\sqrt{|I_u^{\ell}|}} \sum_{j \in I_u^{\ell}} \tilde{E}_j.$$ can be regarded as a virtual user profile w.r.t. the auxiliary feedback.
Dual Similarity Learning Model (DSLM)

In TJSL, two similarity among items are learned. Symmetrically, we define the similarity among users as follows,

$$\sum_{u' \in U_i^P \setminus \{u\}} s_{u'u} + \sum_{w \in U_i^{E(\ell)}} s_{wu}, \quad U_i^{E(\ell)} \subseteq U_i^E,$$

where

$$\sum_{u' \in U_i^P \setminus \{u\}} s_{u'u} = \frac{1}{\sqrt{|U_i^P \setminus \{u\}|}} \sum_{u' \in U_i^P \setminus \{u\}} P_{u'} U^T_{u'},$$

$$\sum_{w \in U_i^{E(\ell)}} s_{wu} = \frac{1}{\sqrt{|U_i^{E(\ell)}|}} \sum_{w \in U_i^{E(\ell)}} E_w U^T_{u'}. \quad \text{Intuitively, we can also regard the term}$$

$$\frac{1}{\sqrt{|U_i^P \setminus \{u\}|}} \sum_{u' \in U_i^P \setminus \{u\}} P_{u'} \text{ and } \frac{1}{\sqrt{|U_i^{E(\ell)}|}} \sum_{w \in U_i^{E(\ell)}} E_w$$

as the virtual item profiles w.r.t. the target feedback and auxiliary feedback, respectively.
The predicted preference of user $u$ on item $i$, 

$$
\hat{r}_{ui}^{(l)} = \sum_{i' \in \mathcal{I}_u^P \setminus \{i\}} s_{i'i} + \sum_{j \in \mathcal{I}_u^{(l)}} s_{ji} + b_u + b_i + \\
\sum_{u' \in \mathcal{U}_i^P \setminus \{u\}} s_{u'u} + \sum_{w \in \mathcal{U}_i^{(l)}} s_{wu}, \mathcal{I}_u^{(l)} \subseteq \mathcal{I}_u, \mathcal{U}_i^{(l)} \subseteq \mathcal{U}_i^{(l)}. 
$$  

(4)

where $\mathcal{I}_u^{(l)}$ is the set of likely-to-prefer items selected from $\mathcal{I}_u$, $\mathcal{U}_i^{(l)}$ is the set of potential users that are likely to purchase item $i$ selected from $\mathcal{U}_i$. 
The objective function of DSLM is as follows,

$$\min_{\Theta^{(\ell)}, I_u^{E^{(\ell)}} \subseteq I_u^{E}, U_i^{E^{(\ell)}} \subseteq U_i^{E}} \sum_{(u,i) \in \mathcal{R}^P \cup \mathcal{R}^A} f_{ui}^{(\ell)}$$

(5)

where $f_{ui}^{(\ell)} = \frac{1}{2} (r_{ui} - \hat{r}_{ui}^{(\ell)})^2 + \frac{\lambda_u}{2} \| U_u \|_F^2 + \frac{\lambda_p}{2} \sum_{u' \in U_i^P \setminus \{u\}} \| P_{u'} \|_F^2 + \frac{\lambda_e}{2} \sum_{w \in U_i^{E^{(\ell)}}} \| E_w \|_F^2 + \frac{\beta_u}{2} b_u^2 + \frac{\alpha_v}{2} \| V_i \|_F^2 + \frac{\alpha_p}{2} \sum_{i' \in I_i^P \setminus \{i\}} \| \tilde{P}_{i'} \|_F^2 + \frac{\alpha_e}{2} \sum_{j \in I_u^{E^{(\ell)}}} \| \tilde{E}_j \|_F^2 + \frac{\beta_v}{2} b_i^2$, and the model parameters are

$$\Theta^{(\ell)} = \{ U_u, P_{u'}, E_w, V_i, \tilde{P}_{i'}, \tilde{E}_j, b_u, b_i \}.$$  Note that $\mathcal{R}^A$ is the set of negative feedback used to complement the target feedback, where $r_{ui} = 1$ if $(u, i) \in \mathcal{R}^P$ and $r_{ui} = 0$ otherwise.
Gradients (1/2)

To learn the parameters $\Theta^{(\ell)}$, we use the stochastic gradient decent (SGD) algorithm and have the gradients of the model parameters for a randomly sampled pair $(u, i) \in \mathcal{R}^P \cup \mathcal{R}^A$,

\[
\nabla U_u. = -e_{ui} \frac{1}{\sqrt{|U_i^P \setminus \{u\}|}} \sum_{u' \in U_i^P \setminus \{u\}} P_{u'} - e_{ui} \frac{1}{\sqrt{|U_i^{\mathcal{E}(\ell)}|}} \sum_{w \in U_i^{\mathcal{E}(\ell)}} E_w + \lambda_u U_u.,
\]

\[(6)\]

\[
\nabla V_i. = -e_{ui} \frac{1}{\sqrt{|I_i^P \setminus \{i\}|}} \sum_{i' \in I_i^P \setminus \{i\}} \tilde{P}_{i'} - e_{ui} \frac{1}{\sqrt{|I_i^{\mathcal{E}(\ell)}|}} \sum_{j \in I_i^{\mathcal{E}(\ell)}} \tilde{E}_j + \alpha_V V_i.,
\]

\[(7)\]

\[
\nabla P_{u'}. = -e_{ui} \frac{1}{\sqrt{|U_i^P \setminus \{u\}|}} U_u. + \lambda_p P_{u'}, u' \in U_i^P \setminus \{u\},
\]

\[(8)\]
Gradients (2/2)

\[ \nabla E_w. = - e_{ui} \frac{1}{\sqrt{|U^E_i|}} U_u. + \lambda_e E_w., \quad w \in U^E_i, \quad (9) \]

\[ \nabla \tilde{P}_{i'} = - e_{ui} \frac{1}{\sqrt{|I^P_u \setminus \{i\}|}} V_i. + \alpha_p \tilde{P}_{i'}, \quad i' \in I^P_u \setminus \{i\}, \quad (10) \]

\[ \nabla \tilde{E}_j = - e_{ui} \frac{1}{\sqrt{|I^E_u|}} V_i. + \alpha_e \tilde{E}_j, \quad j \in I^E_u, \quad (11) \]

\[ \nabla b_u = - e_{ui} + \beta_u b_u, \quad \nabla b_i = - e_{ui} + \beta_v b_i, \quad (12) \]

where \( e_{ui} = r_{ui} - \hat{r}_{ui} \) is the difference between the true preference and the predicted preference.
Update Rules

We have the update rules,

$$\theta^{(\ell)} \leftarrow \theta^{(\ell)} - \gamma \nabla \theta^{(\ell)},$$

(13)

where $\gamma$ is the learning rate, and $\theta^{(\ell)} \in \Theta^{(\ell)}$ is a model parameter to be learned.
Identification of $\mathcal{I}_{u}^{E(\ell)}$ and $\mathcal{U}_{i}^{E(\ell)}$

Note that we identify $\mathcal{U}_{i}^{E(\ell)}$ and $\mathcal{I}_{u}^{E(\ell)}$ by the following way,

- For each user $u \in \mathcal{U}_{i}^{E}$, we estimate the preference for the target item $i$, i.e., $\hat{r}_{ui}^{(\ell)}$, and take $\tau |\mathcal{U}_{i}^{E}| (\tau \in (0, 1])$ users with the highest scores as the potential users that are likely to purchase the target item $i$.

- For each $j \in \mathcal{I}_{u}^{E}$, similarly, we estimate the preference $\hat{r}_{uj}^{(\ell)}$, and take $\tau |\mathcal{I}_{u}^{E}|$ items with the highest scores as the candidate items.

Finally, we save the model and data of the last $L_0$ epochs. The estimated preference is the average value of $\hat{r}_{ui}^{(\ell)}$, where $\ell$ ranges from $L - L_0 + 1$ to $L$. 
Algorithm of DSLM

1: **Input:** $\mathcal{R}^P$, $\mathcal{R}^E$, $T$, $L$, $L_0$, $\rho$, $\gamma$, $\lambda_*$, $\alpha_*$, $\beta_*$.  
2: **Output:** $\mathcal{U}^E(\ell)$, $\mathcal{I}^E(\ell)$ and $\Theta(\ell)$, $\ell = L - L_0 + 1, \ldots, L$.  
3: Let $\mathcal{U}^E(1) = \mathcal{U}^E$, $\mathcal{I}^E(1) = \mathcal{I}^E$, $\tau = 1$  
4: **for** $\ell = 1, \ldots, L$ **do**  
5: Initialize the model $\Theta(\ell)$  
6: **for** $t = 1, \ldots, T$ **do**  
7: Randomly sample $\mathcal{R}^A \subset \mathcal{R} \setminus \mathcal{R}^P$ with $|\mathcal{R}^A| = \rho |\mathcal{R}^P|$  
8: **for** $t_2 = 1, \ldots, |\mathcal{R}^P \cup \mathcal{R}^A|$ **do**  
9: Randomly pick up $(u, i) \in \mathcal{R}^P \cup \mathcal{R}^A$  
10: Calculate $\hat{r}^{(\ell)}_{ui}$ via (4)  
11: Calculate $\nabla \theta$, $\theta \in \Theta(\ell)$ via (6)−(12)  
12: Update $\theta$, $\theta \in \Theta(\ell)$ via (13)  
13: **end for**  
14: **end for**  
15: **if** $\ell > L - L_0$ **then**  
16: Save the current model and data ($\Theta(\ell)$, $\mathcal{U}^E(\ell)$, $\mathcal{I}^E(\ell)$)  
17: **end if**  
18: **if** $L > 1$ and $L > \ell$ **then**  
19: $\tau \leftarrow \tau \times 0.9$  
20: Select $\mathcal{I}^E(\ell+1)$ with $|\mathcal{I}^E(\ell+1)| = \tau |\mathcal{I}^E|$ for each $u$  
21: Select $\mathcal{U}^E(\ell+1)$ with $|\mathcal{U}^E(\ell+1)| = \tau |\mathcal{U}^E|$ for each $i$  
22: **end if**  
23: **end for**
Datasets and Evaluation Metrics

For direct comparison, we use the same datasets as TJSL, including ML100K, ML1M and Alibaba2015.

| Dataset       | |U| | |I| | |R^P| | |R^E| | |R^P^te| |
|---------------|---------|---------|----------|---------|---------|---------|---------|
| ML100K        | 943     | 1682    | 9438     | 45285   | 2153    |
| ML1M          | 6040    | 3952    | 90848    | 400083  | 45075   |
| Alibaba2015   | 7475    | 5257    | 9290     | 62659   | 2322    |

For performance evaluation, we adopt two commonly used ranking-oriented metrics, i.e., Precision@5 and NDCG@5.

The data and code are available at
http://csse.szu.edu.cn/staff/panwk/publications/DSLM/
For comparative studies, we include the competitive methods as follows:

- BPR (Bayesian personalized ranking)
- FISM (Factored item similarity model)
- TJSL (Transfer via joint similarity learning)
- RBPR (Role-based Bayesian personalized ranking)

For parameter configurations, we fix the number of latent dimension $d = 20$, the learning rate $\gamma = 0.01$ and sampling parameter $\rho = 3$, and search the tradeoff parameters from $\{0.001, 0.01, 0.1\}$ and the best iteration number $T$ from $\{100, 500, 1000\}$ via NDCG@5 performance.
# Main Results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>BPR</th>
<th>FISM</th>
<th>TJSL</th>
<th>RBPR</th>
<th>DSLM</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML100K</td>
<td>0.0552± 0.0006</td>
<td>0.0628± 0.0015</td>
<td><strong>0.0697± 0.0016</strong></td>
<td>0.0654± 0.0013</td>
<td>0.0694± 0.0014</td>
</tr>
<tr>
<td>NDCG@5</td>
<td>0.0874± 0.0020</td>
<td>0.1029± 0.0017</td>
<td><strong>0.1133± 0.0047</strong></td>
<td>0.1058± 0.0047</td>
<td><strong>0.1140± 0.0022</strong></td>
</tr>
<tr>
<td>ML1M</td>
<td>0.0928± 0.0008</td>
<td>0.0971± 0.0013</td>
<td><strong>0.1012± 0.0011</strong></td>
<td>0.1086± 0.0009</td>
<td><strong>0.1107± 0.0015</strong></td>
</tr>
<tr>
<td>NDCG@5</td>
<td>0.1121± 0.0010</td>
<td>0.1189± 0.0008</td>
<td><strong>0.1248± 0.0010</strong></td>
<td>0.1327± 0.0016</td>
<td><strong>0.1353± 0.0012</strong></td>
</tr>
<tr>
<td>Alibaba2015</td>
<td>0.0050± 0.0006</td>
<td>0.0046± 0.0003</td>
<td><strong>0.0071± 0.0004</strong></td>
<td>0.0076± 0.0005</td>
<td><strong>0.0087± 0.0006</strong></td>
</tr>
<tr>
<td>NDCG@5</td>
<td>0.0138± 0.0017</td>
<td>0.0126± 0.0009</td>
<td><strong>0.0200± 0.0008</strong></td>
<td>0.0220± 0.0013</td>
<td><strong>0.0269± 0.0017</strong></td>
</tr>
</tbody>
</table>

**Observations:**

- In all cases, TJSL, RBPR and DSLM perform significantly better than BPR and FISM, which shows the effectiveness of introducing the auxiliary feedback to assist the task of learning users’ preferences; and

- DSLM performs better than TJSL and RBPR in most cases, e.g., it is the best on ML1M and Alibaba2015, and is comparable with TJSL on ML100K, which clearly shows the usefulness of the dual similarity in capturing the correlations between users and items.
We propose a novel solution, i.e., dual similarity learning model (DSLM), for a recent and important recommendation problem called heterogeneous one-class collaborative filtering (HOCCF).

In particular, we jointly learn the dual similarity among both users and items so as to exploit the complementarity well. Extensive empirical studies on three public datasets clearly show the effectiveness of our solution.
Thank you!

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