RBPR: Role-based Bayesian Personalized Ranking for Heterogeneous One-Class Collaborative Filtering

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Problem Definition

Heterogeneous One-Class Collaborative Filtering (HOCCF)

- Input: two different sets of user feedback, e.g., browses $B$ and purchases $P$.
- Goal: find some likely-to-purchase items from unpurchased items, i.e., $I \setminus P_u$, for each user $u$. 

Browses  

Purchases
Challenges

How can we exploit the heterogeneous one-class feedback in an effective and efficient way?
1. We model different feedback of a typical user via different roles such as browser and purchaser.

2. We have two tasks of preference learning, including browser-based preference learning and purchaser-based preference learning.
Advantages of Our Solution

- The two-stage preference learning approach can exploit the heterogeneous feedback well.
- RBPR is a very efficient solution (comparable to that of BPR).
In the first step, we assume that a typical user is first a browser before he/she is converted to a purchaser.

And thus, in our first task, we focus on answering the question of “whether a user will browse an item”.

In order to address this task, we propose to combine the two types of one-class feedback, i.e., browses and purchases, together, and then apply an algorithm for homogeneous one-class feedback such as BPR, i.e., $\text{BPR}(B \cup P)$.
Mathematically, we will solve the following optimization problem,

$$\min_{\Theta_{B \cup P}} \sum_{u \in U} \sum_{i \in (B_u \cup P_u)} \sum_{j \in I \setminus (B_u \cup P_u)} f_{uij},$$  \hspace{1cm} (1)

where $B_u$ and $P_u$ are item sets browsed and purchased by user $u$, respectively, $f_{uij}$ is the tentative objective function for a randomly sampled triple $(u, i, j)$, and $\Theta_{B \cup P}$ denotes the set of model parameters to be learned.

Once we have learned the model parameters, we can generate a candidate list of items that a user is likely to browse.
In the second step, we assume that a user will most likely choose an item from the candidate list that he/she has browsed.

For this reason, in our second task, we mainly answer the question of “whether a user will purchase an item”.

In order to solve this task, we propose to use the purchase data only to refine the candidate list from the first step.
Similarly, we again adopt BPR for model training, but use purchase feedback \( \mathcal{P} \) only. Mathematically, we learn the model parameters as follows,

\[
\min_{\Theta_{\mathcal{P}}} \sum_{u \in U} \sum_{i \in \mathcal{P}_u} \sum_{j \in I \setminus \mathcal{P}_u} f_{uij},
\]  

where \( \Theta_{\mathcal{P}} \) denotes the model parameters to be learned from the purchase data only.

With the learned model parameters \( \Theta_{\mathcal{P}} \), we can predict the preference of each item \( i \) in the candidate list of each user \( u \), and then **re-rank** the items in the list.
Method

Algorithm

**Input:** Users’ browses \( B \) and purchases \( P \).

**Output:** Top-\( K \) recommended items for each user.

Step 1. Conduct browser-based preference learning via \( \text{BPR}(B \cup P) \) as shown in Eq.(1) and obtain \( 3K \) candidate items with highest predicted scores.

Step 2. Conduct purchaser-based preference learning via \( \text{BPR}(P) \) as shown in Eq.(2); predict the scores on the \( 3K \) candidate items and refine the list.

Figure: The algorithm of role-based Bayesian personalized ranking (RBPR).
We use three small datasets (i.e., MovieLens 100K, MovieLens 1M, Alibaba2015) from [Pan et al., IEEE Intelligent Systems 2016], and two additional large datasets (i.e., MovieLens 10M and Netflix).

<table>
<thead>
<tr>
<th>Dataset</th>
<th># user</th>
<th># item</th>
<th># purchase</th>
<th># browse</th>
<th># purchase (validation)</th>
<th># purchase (test)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML100K</td>
<td>943</td>
<td>1682</td>
<td>9438</td>
<td>45285</td>
<td>—</td>
<td>2153</td>
</tr>
<tr>
<td>ML1M</td>
<td>6040</td>
<td>3952</td>
<td>90848</td>
<td>400083</td>
<td>—</td>
<td>45075</td>
</tr>
<tr>
<td>Alibaba2015</td>
<td>7475</td>
<td>5257</td>
<td>9290</td>
<td>60659</td>
<td>—</td>
<td>2322</td>
</tr>
<tr>
<td>ML10M</td>
<td>71567</td>
<td>10681</td>
<td>309317</td>
<td>4000024</td>
<td>308673</td>
<td>308702</td>
</tr>
<tr>
<td>Netflix</td>
<td>480189</td>
<td>17770</td>
<td>4554888</td>
<td>39628846</td>
<td>4556347</td>
<td>4558506</td>
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</table>
We include the state-of-the-art baselines for both OCCF and HOCCF.

- **BPR**: Bayesian personalized ranking. BPR is a seminal work based on pairwise preference assumption and usually produces the best performance for OCCF.

- **TJSL**: Transfer via joint similarity learning. TJSL is one of the most recent work for HOCCF.
For BPR, TJSL and RBPR, we fix the dimension as $d = 20$ and the learning rate as $\gamma = 0.01$. For BPR and TJSL on ML100K, ML1M and Alibaba2015, we directly use the results from [Pan et al., IEEE Intelligent Systems 2016]. For RBPR on all the datasets and BPR on ML10M and Netflix, we search the best tradeoff parameter from $\{0.001, 0.01, 0.1\}$ and iteration number from $\{100, 500, 1000\}$ via NDCG@15.
For one-class feedback in HOCCF, we adopt several commonly used evaluation metrics in ranking-oriented item recommendation or information retrieval scenarios:

- Prec@K
- Rec@K
- F1@K
- NDCG@K
- 1-call@K
Results (1/2)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Method</th>
<th>Prec@5</th>
<th>Rec@5</th>
<th>F1@5</th>
<th>NDCG@5</th>
<th>1-call@5</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML100K</td>
<td>BPR</td>
<td>0.0552±0.0006</td>
<td>0.1032±0.0019</td>
<td>0.0673±0.0007</td>
<td>0.0874±0.0020</td>
<td>0.2425±0.0034</td>
</tr>
<tr>
<td></td>
<td>TJSL</td>
<td>0.0697±0.0016</td>
<td>0.1393±0.0028</td>
<td>0.0864±0.0019</td>
<td>0.1133±0.0047</td>
<td>0.3033±0.0071</td>
</tr>
<tr>
<td></td>
<td>RBPR</td>
<td>0.0654±0.0013</td>
<td>0.1275±0.0048</td>
<td>0.0803±0.0021</td>
<td>0.1058±0.0047</td>
<td>0.2890±0.0047</td>
</tr>
<tr>
<td>ML1M</td>
<td>BPR</td>
<td>0.0928±0.0008</td>
<td>0.0829±0.0002</td>
<td>0.0717±0.0003</td>
<td>0.1121±0.0010</td>
<td>0.3609±0.0018</td>
</tr>
<tr>
<td></td>
<td>TJSL</td>
<td>0.1012±0.0011</td>
<td>0.0968±0.0012</td>
<td>0.0821±0.0009</td>
<td>0.1248±0.0010</td>
<td>0.3961±0.0022</td>
</tr>
<tr>
<td></td>
<td>RBPR</td>
<td>0.1086±0.0009</td>
<td>0.1017±0.0015</td>
<td>0.0858±0.0009</td>
<td>0.1327±0.0016</td>
<td>0.4151±0.0055</td>
</tr>
<tr>
<td>Alibaba2015</td>
<td>BPR</td>
<td>0.0050±0.0006</td>
<td>0.0193±0.0026</td>
<td>0.0077±0.0009</td>
<td>0.0138±0.0017</td>
<td>0.0246±0.0031</td>
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<tr>
<td></td>
<td>TJSL</td>
<td>0.0071±0.0004</td>
<td>0.0283±0.0016</td>
<td>0.0110±0.0006</td>
<td>0.0200±0.0008</td>
<td>0.0347±0.0017</td>
</tr>
<tr>
<td></td>
<td>RBPR</td>
<td>0.0076±0.0005</td>
<td>0.0304±0.0023</td>
<td>0.0118±0.0008</td>
<td>0.0220±0.0013</td>
<td>0.0367±0.0024</td>
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<tr>
<td>ML10M</td>
<td>BPR</td>
<td>0.0629±0.0002</td>
<td>0.0855±0.0006</td>
<td>0.0603±0.0003</td>
<td>0.0861±0.0004</td>
<td>0.2648±0.0017</td>
</tr>
<tr>
<td></td>
<td>TJSL</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>RBPR</td>
<td>0.0719±0.0013</td>
<td>0.0977±0.0017</td>
<td>0.0690±0.0014</td>
<td>0.0994±0.0020</td>
<td>0.2990±0.0050</td>
</tr>
<tr>
<td>Netflix</td>
<td>BPR</td>
<td>0.0716±0.0007</td>
<td>0.0480±0.0005</td>
<td>0.0446±0.0005</td>
<td>0.0818±0.0011</td>
<td>0.2846±0.0022</td>
</tr>
<tr>
<td></td>
<td>TJSL</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>RBPR</td>
<td>0.0797±0.0002</td>
<td>0.0595±0.0004</td>
<td>0.0527±0.0003</td>
<td>0.0939±0.0003</td>
<td>0.3174±0.0011</td>
</tr>
</tbody>
</table>

Observations
- RBPR and TJSL are better than BPR ⇒ browses $B$ are useful
- RBPR and TJSL are comparable on three small datasets
- RBPR is a more practical solution regarding the efficiency
Observations

- The second stage of candidate refinement using the purchase data can significantly improve the performance.
- It verifies our main assumption that there are usually two separate stages for a user’s shopping action, i.e., browse and purchase.
Conclusion

- We study an important recommendation problem called heterogeneous one-class collaborative filtering (HOCCF) from a novel perspective of users’ roles.
- We propose a novel role-based preference learning framework, i.e., role-based Bayesian personalized ranking (RBPR), based on the seminal work BPR.
- RBPR is more accurate than the seminal work for OCCF, i.e., BPR, and a very recent similarity learning algorithm for HOCCF, i.e., TJS. RBPR is also very efficient with the inherited merits of BPR.
Thank you!

We thank the support of National Natural Science Foundation of China (NSFC) No. 61502307, and Natural Science Foundation of Guangdong Province Nos. 2014A030310268 and 2016A030313038.