

**HLBPR: A Hybrid Local Bayesian Personal Ranking Method**

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**ABSTRACT**

Bayesian Personal Ranking (BPR) method is a well-known model due to its high performance in the task of item recommendation. However, this method fails to distinguish user preference among the non-interacted items. In this paper, to enhance traditional BPR’s performance, we introduce and analyse a hybrid method, namely Hybrid Local Bayesian Personal Ranking (HLBPR for short). Our main idea is to construct additional item preference pairs among the products which have not been purchased, and then utilize the extended pairs to optimize the ranking object. Experiments on two real-world transaction datasets demonstrated the effectiveness of our approach as compared with the state-of-the-art methods.

**Keywords**

Hybrid Method, Local Similarity, Item Preference Pairs

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**1. INTRODUCTION**

Emerging popularity of e-commerce has highlighted the importance of excavating consumers’ potential interest, with many methods have been investigated. Among these methods, Bayesian Personal Ranking (BPR)\(^2\) is a well-known approach which directly optimizes the ranking objective. However, it doesn’t generate any item preference pairs among the products which haven’t been purchased before. This is impractical because a non-interacted item doesn’t necessarily be a disliked one, people may just haven’t seen it before. Existing methods(such as S-BPR\(^4\), etc.) usually leverage additional information(social information, etc.) to address this problem, but such information is rarely, or even non-existent in many applications. In this paper, we propose a hybrid model, namely Hybrid Local Bayesian Personal Ranking (HLBPR for short) to make traditional BPR method more accurate. Comparing with the existing methods, the key features of our approach are: 1) we construct extra item preference pairs among the non-interacted products to obtain more accurate ranking-based models. 2) we design two patterns: general pattern and sequential pattern to capture users’ potential interests. 3) By using a hybrid pattern, we can achieve better performance in the task of item recommendation. 4) Throughout our modeling process, only user-item interaction records are necessary. Experimental results on two real-world transaction datasets demonstrated the effectiveness of our approach as compared with the state-of-the-art models.

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**2. PROPOSED MODEL: HLBPR**

To make our exposition more clear and consistent. Let \( U \) be a set of users and \( I \) a set of items. We are given a matrix with training data \( R \in \{0, 1\}^{|U| \times |I|} \). \( R_{ui} = 1 \) indicates that there is a known interaction between user \( u \in U \) and item \( i \in I \). \( R_{ui} = 0 \) indicates that there is no such information. Our goal is to build more item preference pairs among the non-interacted items.

**NSP-BPR.** We first consider user’s non-sequential behavior (general patterns). Preference pairs are constructed based on the user-item likeness-scores. To derive a user’s likeness to an item, we first represent the user as a vector based on his/her transaction history is \( R_u = \{a, b, \{a, d\}, \{c\}\} \), his/her vector could be represented as \( R_u = \{a : 2, b : 1, c : 1, d : 1\} \) (Figure 1). Then the likeness-score of user \( u \) to item \( i \) could be calculated by: \( \text{nsp-score}(u, i) = \sum_{v \in T(i)} \text{nsp-simi}(u, v) \), where \( T(i) \) denotes the set of users who have interacted with item \( i \), \( \text{nsp-simi}(u, v) \) is the similarity between \( u \) and \( v \), which could be derived from several methods, here we simply select cosine similarity.

For a specific user \( u \), many ways have been attempted to build the set of preference relations \( D_{\text{nsp}}^u \), and finally we determine the method as follows:

\[
D_{\text{nsp}} = \{(u, k, j) | \text{nsp-score}(u, k) > t_{\text{upper}} \}, \\
\text{nsp-score}(u, j) <= t_{\text{lower}}, k, j \in I^{-} \} \quad (1)
\]
where $I_u^−$ denotes the set of items user $u$ hasn’t interacted, $th_{lower}$ and $th_{upper}$ are threshold values.

SP-BPR. It has been demonstrated that users’ interest could be captured from the sequential perspective[3]. An intuitive example is that a user who purchased a cell phone recently may be more likely to buy a battery than the users who haven’t interacted with cell phones. Motivated by this phenomenon, we design sequential patterns to obtain users’ potential favorite items in this section.

To capture sequential features, we represent a user as a vector based on the pairwise sequences in his/her purchase history. For the user mentioned above, his/her vector could be represented as $S_u = \{ a \rightarrow a : 1, a \rightarrow d : 1, b \rightarrow a : 1, b \rightarrow d : 1, a \rightarrow c : 1, d \rightarrow c : 1 \}$ (Figure 1).

Unlike general patterns, users’ successive interests based on his last transaction should be valued more in sequential patterns, thus we design the following method to model users’ preferences: 

\[ sp\_score(u, i) = \sum_{v \in S(last_u)} sp\_sim(u, v), \]

where $last_u$ denotes the set of items in user $u$’s last transaction, $S(last_u, i)$ is $\{ v | v \text{ contains sequence pair } (k, i), k \in last_u \} (k, i)$ appears more than support times in all the users’ transaction records$, sp\_sim(u, v)$ is the similarity between user $u$ and $v$.

**Hybrid Model.** It is not straightforward to integrate NSP-BPR and SP-BPR directly, because they may derive completely opposite conclusions for a user’s preference on two specific products. To address this challenge, we designed a simple method to drop the ambiguous pairs. Specifically, suppose $(u, i, j) \in D_{nsp}$ and $(u, j, i) \in D_{sp}$, as $d_{nsp}(u, i, j) = nsps\_score(u, i) - nsps\_score(u, j) \in D_{nsp}$ and $(u, i, j)$ or $d_{sp}(u, i, j) = sp\_score(u, i) - sp\_score(u, j)) \in D_{sp}$, then we see $S(last_u, i) = S(last_u, j)$ over $j$, little $d_{sp}(u, i, j)$ $d_{sp}(u, j, i)$ means more unertainty when deciding user’s preference in hybrid model, so we remain $(u, i, j)$ or $(u, j, i)$ in $D_{nsp}$ only when $d_{nsp}(u, i, j)$ or $d_{sp}(u, j, i)$ is significantly higher($\geq th$) than $d_{sp}(u, i, j)$ or $d_{nsp}(u, j, i))$ which would make our inference more reliable. For the pairs which exhibit the same conclusions in both NSP-BPR and SP-BPR and the pairs only appear in $D_{nsp}^*$ or $D_{sp}^*$, we collect them in $D_{nsp}$ without further process.

3. EXPERIMENTS

We evaluate different recommenders based on two real-world transaction datasets, i.e. Ta-Feng and BBG. Ta-Feng is a common dataset released by Recsys conference. BBG is sampled from the log data of Yunhou1. The statistics of these datasets could be seen in table 1.

<table>
<thead>
<tr>
<th></th>
<th>Users</th>
<th>Items</th>
<th>Records</th>
<th>Sparsity</th>
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<td>7913</td>
<td>288253</td>
<td>0.004</td>
</tr>
<tr>
<td>BBG</td>
<td>3855</td>
<td>3023</td>
<td>108949</td>
<td>0.009</td>
</tr>
</tbody>
</table>

Table 1: Statistics of the datasets

3. EXPERIMENTS

- Ta-Feng and BBG, Ta-Feng is a common dataset released by Recsys conference. BBG is sampled from the log data of Yunhou1. The statistics of these datasets could be seen in table 1.
- To demonstrate the effectiveness of our models, we select BPR++[12], which is a state-of-art method to enhance the performance of BPR utilizing only user-item interaction information, and three traditional recommendation methods: TOP-POP, NMF3, BPR4 as our baseline methods. When implementing our models, we empirically evaluate different values for $\alpha$, support, $th_{lower}$ and $th_{upper}$ and finally determined a set of fixed values: $th_{lower} = th_{upper} = 0.001$ in $D_{nsp}$, $th_{lower} = th_{upper} = 0.003$, support $= 5$ in $D_{nsp}^*$, $th = 0.001$, $th_{lower} = th_{upper} = 0.002$, support $= 5$ in $D_{sp}^*$. In our experiments, F1-score@5, Hit-Ratio@5 and NDCG@5 are selected to help evaluate different models.

4. RESULTS

- From the results shown in Figure 2, we could find that all of our models including NSP-BPR, SP-BPR, HLBPR could make significant improvements against the best baseline method BPR++(T) on 0.01 and 0.005 level respectively, it is as expected because BPR++(T) only constructs additional pairs among the purchased items and fail to capture users’ potential interests for the products which haven’t been interacted. NSP-BPR performs better than SP-BPR which indicates that comparing with sequential characters(SP-BPR), general taste characters(NSP-BPR) are more relevant in both datasets. Since taking both sequential and non-sequential information into consideration, HLBPR could perform better than NSP-BPR and SP-BPR.

5. CONCLUSIONS

- In this paper, we surprisingly discovered that we can extract informative preference pairs from non-purchased items to boost the performance of BPR. In the future, we will attempt to investigate other ranking-based methods and the theoretical basis for personalized recommendation.

6. REFERENCES