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 fail 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 method(HLBPR for short). Our main idea is to construct additional item preference pairs among the products which haven't been purchased, and then utilize the extened 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

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 optimize 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 rarity, 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 patterns, 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.

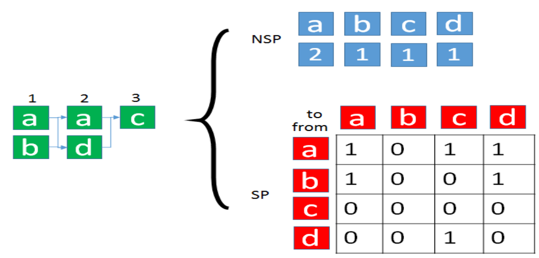

Figure 1: User's NSP and SP representation

2. PROPOSED MODEL:HLBPR

To make our exposition more clear and consistent. Let $\mathcal{U}$ be a set of users and $\mathcal{I}$ a set of items. We are given a matrix with training data $\mathsf{R} \in \{0,1\}^{|\mathcal{U}|\times|\mathcal{I}|}$. $\mathsf{R}_{ui} = 1$ indicates that there is a known interaction between user $u \in \mathcal{U}$ and item $i \in \mathcal{I}$. $\mathsf{R}_{ui} = 0$ 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) purchased items. For instance, suppose a user's transaction history is $\{\{a,b\},\{a,d\},\{c\}\}$, 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: $nsp\_score(u,i) = \sum_{v\in T(i)} nsp\_simi(u,v)$, where $T(i)$ denotes the set of users who have interacted with item i, $nsp\_simi(u,v)$ 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^*_{nsp}, and finally we determine the method as follows:

$$D^*_{nsp} = \{(u,k,j) | nsp\_score(u,\ k) > th_{upper},$$
$$nsp\_score(u,\ j) <= th_{lower}, k, j \in \mathcal{I}^-\} \quad (1)$$

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Table 1: Statistics of the datasets

	Users	Items	Records	Sparsity
Ta-Feng	9238	7973	288251	0.004
BBG	3885	3023	108049	0.009

where $\mathcal{I}^-$ 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 $S_u = \{a \to a : 1, a \to d : 1, b \to a : 1, b \to d : 1, a \to c : 1, d \to c : 1\}$(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:$sp\_score(u,i) = \sum_{v \in S(last_u, i)} sp\_simi(u,v)$, where $last_u$ denotes the set of items in $u's$ last transaction, $S(last_u, i)$ is $\{v|v\ contains\ sequence\ pair\ (k,i), k \in last_u, (k,i)\ appears\ more\ than\ support\ times\ in\ all\ the\ users'\ transaction\ records\}$, $sp\_simi(u,v)$ is the similarity between 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 $d_{nsp}(u,i,j) = nsp\_score(u,i) - nsp\_score(u,j)$(or $d_{sp}(u,i,j) = sp\_score(u,i) - sp\_score(u,j)$) reveal the degree of $u's$ likeness to i over j, little $d_{nsp}(u,i,j) - d_{sp}(u,j,i)$ means more uncertainty when deciding user's preference in hybrid model, so we remain (u,i,j)(or (u,j,i)) in D^*_{hybrid} only when $d_{nsp}(u,i,j)$(or $d_{sp}(u,j,i)$) is significantly higher($> th$) than $d_{sp}(u,j,i)$(or $d_{nsp}(u,i,j)$) 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^*_{sp} or D^*_{nsp}, we collect them in D^*_{hybrid} 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 YunHou[1]. The statistics of these datasets could be seen in table 1.

To demonstrate the effectiveness of our models, we select BPR++[1][2], 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, NMF[3], BPR[4] as our baseline methods. When implementing our models, we empirically evaluate different values for α, $support$, 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^*_{sp}, $th = 0.001$, $th_{lower} = th_{upper} = 0.002$, $support = 5$ in D^*_{hybrid}. In our experiments, F1-score@5, Hit-Ratio@5 and NDCG@5 are selected to help evaluate different models.

[1]http://www.yunhou.com/

[2]we select BPR++(T) as our baseline because it performs best in both of our datasets as compared with other variants.

[3]For implementation we used the publicly available codes from http://cogsys.imm.dtu.dk/toolbox/nmf.

[4]Grid search is conducted to find the optimal parameters, the learning rate α and regularization coefficients are finally set as: $\alpha = 0.05$, $\lambda_W = 0.002$, $\lambda_{H^+} = \lambda_{H^-} = 0.0001$.

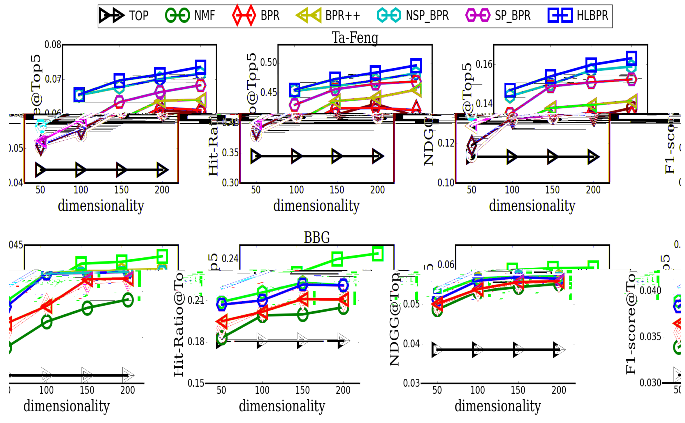

Figure 2: Performance comparison of NSP-BPR, SP-BPR, HLBPR among TOP, NMF, BPR and BPR++ over two datasets. The dimentionality is increase from 50 to 200.

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 construct 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.

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