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: $\alpha = 0.05$, $\lambda_W = 0.002$, $\lambda_{H^+} = \lambda_{H^-} = 0.0001$.

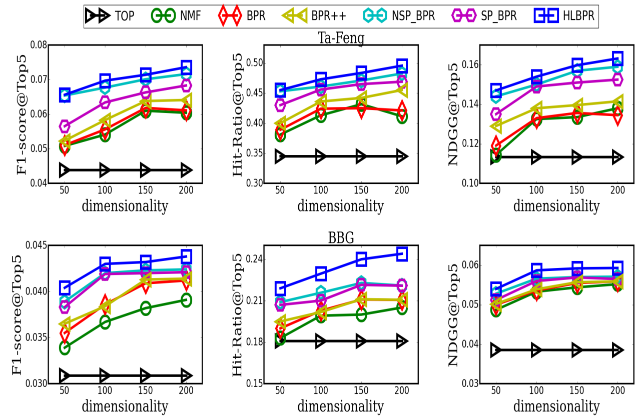

Figure 2: Performance comparison of NSP-BPR, SP-BPR, HLBPR among TOP, NMF, BPR and BPR++ over two datasets. The dimentionality is increase from 50 to 200.

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.

6. REFERENCES

[1] L. Lerche and D. Jannach. Using graded implicit feedback for bayesian personalized ranking. In *Recsys*, 2014.

[2] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme. Bpr: Bayesian personalized ranking from implicit feedback. In *UAI*, 2009.

[3] G.-E. Yap, X.-L. Li, and S. Y. Philip. Effective next-items recommendation via personalized sequential pattern mining. In *Database Systems for Advanced Applications*, 2012.

[4] T. Zhao, J. McAuley, and I. King. Leveraging social connections to improve personalized ranking for collaborative filtering. In *CIKM*, 2014.