TBPR: Trinity Preference based Bayesian Personalized Ranking for Multivariate Implicit Feedback

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ABSTRACT

In e-commerce systems, user preference can be inferred from multivariate implicit feedback (i.e., actions). However, most methods merely focus on homogeneous implicit feedback (i.e., *purchase*). In this paper, we adopt another two typical actions, i.e., *view* and *like*, as auxiliaries to enhance *purchase* recommendation, whereby a trinity Bayesian personalized ranking (TBPR) method is proposed. Specifically, we introduce *trinity preference* to investigate the difference of users' preference among three types of items: 1) items with purchase action; 2) items with only auxiliary actions; 3) items without any action. Empirical study on the real-world dataset demonstrates that our method significantly outperforms state-of-the-art algorithms.

Keywords

Recommendation, implicit feedback, trinity preference

1. INTRODUCTION

Personalized recommendation has become an indispensable part of e-commerce service. The study on implicit feedback (i.e., actions) based recommendation methods has received much attention nowadays since explicit feedback (i.e. ratings) may not always available. Implicit feedback is actually multivariate in real-word systems. Taking an online shopping website as an example, users may perform various actions on items such as *view* (browse the details), *like* (click the 'like' button) and *purchase* (buy the item). Although *view* and *like* are not directly related to purchase, they help model user preference as useful side information, called *auxiliary* in our study. However, existing studies [1, 3] mainly focus on homogeneous implicit feedback and merely consider *purchase*, thus to inherently suffer from the *data sparsity* problem. The only work integrating multivariate implicit feedback for item ranking is Adaptive Bayesian Personalized Ranking (ABPR) proposed by Pan et al. [2]. It adopts *view* as *auxiliary* but the assumption of BPR preference for homogeneous implicit feedback [3] is utilized. Moreover, too many parameters are introduced to learn the difference between user preference towards items with *purchase* and those with *view*. Besides, the generality is limited since it cannot handle more than one types of *auxiliary*.

In this paper, we propose a trinity Bayesian personalized ranking (TBPR) method which is the first approach that incorporates multiple types of *auxiliary* (i.e., *view* and *like*) with *purchase* for better recommendation. A fine-grained assumption, *trinity preference*, is utilized to investigate user preference towards three types of items: those with *purchase*, with only *auxiliary*, with no action. Furthermore, our method can automatically learn the importance of user preference difference towards items with different user actions based on the overlap of the *auxiliary* and *purchase* with few parameters. The empirical results show that our method significantly outperforms state-of-the-art algorithms by 22% in terms of AUC and 114% in terms of MAP.

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2. OUR TBPR METHOD

The basic assumption of BPR preference restricts that user u prefers item i to item j if i is with *purchase* while j is not. However, user preference among items without *purchase* can be distinguished when *auxiliary* is considered. Hence, we classify items into three types as mentioned in Section 1 and define an *item trinity* for each user, $T(u) = \{(i,j,k) \mid i \in I_p^u, j \in I_{oa}^u, k \in I_n^u\}$, I_p^u, I_{oa}^u and I_n^u are sets of items with *purchase*, with only *auxiliary* and with no action, respectively. User preference towards items in $T(u)$ should be significantly different. *Purchase*, *auxiliary* and no action indicate strong, weak and no user preference. Thus, we assume that for user u, her preference towards item j is stronger than that towards item k but weaker than that towards item i if $(i,j,k) \in T(u)$, namely *trinity preference*.

Following [3], we maximize the likelihood of preference for all users based on *trinity preference*. $\sigma(x-y) = 1/(1 + e^{-(x-y)})$ is utilized to approximate the probability $P(x > y)$, and log-likelihood is adopted to reduce the computational complexity. The objective function for TBPR model is,

$$\max f(\theta) = \sum_u \left\{ \sum_{i,j} \ln \sigma\left(\frac{\hat{x}_{uij}(\theta)}{\alpha_u}\right) + \sum_{j,k} \ln \sigma\left(\hat{x}_{ujk}(\theta)\right) \right\} - \mathcal{R}(\theta),$$

where θ is a set of model parameters to be learnt; $\mathcal{R}(\theta)$ is the regularization term to avoid overfitting; $\hat{x}_{uij}(\theta) = \hat{r}_{ui}(\theta) - \hat{r}_{uj}(\theta)$ is the estimated preference difference of u for i with *purchase* and j with *auxiliary*; α_u is a parameter which controls the contribution of the estimated preference difference $\hat{x}_{uij}$.

In fact, the smaller the preference difference between i, j, the less contributions $\hat{x}_{uij}$ should make in the objective function $f(\theta)$, which means the larger α_u should be. Smaller preference difference between i and j can be inferred from higher correlation between user u's *purchase* and *auxiliary*. In other words, α_u is positively influenced by the correlation between *purchase* and *auxiliary* of user u. Since a user can perform multiple actions on an item, there is overlap between *purchase* and *auxiliary*. More overlap indicates higher correlation, i.e., the larger α_u. Thus, we adopt the overlap to initialize α_u, based on which, α_u can be finely learnt. Let $\alpha_u^{(0)} = \omega \cdot O^u$, where $\alpha_u^{(0)}$ is the initial value of α_u; $\omega > 0$ is the coefficient controlling the importance of O^u; O^u represents the overlap percentage of *purchase* and *auxiliary* for user u. However, we find that the overlap percentage of *auxiliary* in *purchase* (O^u_{ap}) and that of *purchase* in *auxiliary* (O^u_{pa}) are asymmetric. Thus, O^u named *overlap index* should be influenced by both O^u_{ap} and O^u_{pa}, $O^u = 2 \cdot O^u_{pa} \cdot O^u_{ap}/(O^u_{pa} + O^u_{ap})$. Since we consider two types of *auxiliary*: *view* and *like*, $O^u(view)$ (the *overlap index* for *view* and *purchase*) and $O^u(like)$ (the *overlap index* for *like* and *purchase*) is calculated respectively. Note that due to the complicated motivation for a user to click '*like*', some *like* has nothing to do with *purchase*. For instance, people share something cool on their homepages and their friends would click '*like*' as support. To filter out the noise in *like*, we select items with both *like* and *view* to compose the filtered *like* item set, since most users would view before they purchase. The final $\alpha_u^{(0)}$ is given by: $\alpha_u^{(0)} = \rho \cdot \alpha_u^{(0)}(view) + (1-\rho) \cdot \alpha_u^{(0)}(like)$, where $\rho \in [0,1]$ controls the importance of *view*. Note that if user u only performs *view*/*like*, then $\rho = 1/0$; Based on $\alpha_u^{(0)}$, α_u can be further finely learnt by our model.

3. EXPERIMENTS AND ANALYSIS

A dataset originated from an online fashion app, Sobazaar (4,712 users perform 18,267 *purchase*, 225,651 *view* and 100,067 *like* over 7,015 items), is used in our empirical study.

We apply the 5-fold cross validation and 6 widely used metrics, including precision@5, recall@5, area under the ROC curve (AUC), normalized discounted cumulative gain (NDCG), mean average precision (MAP) and mean reciprocal rank (MRR), to evaluate the performance of each method. Larger values of these metrics indicate better recommendation performance. We compare two baseline methods with different versions of TBPR: (1) **BPR** [3] is the classic Bayesian personalized ranking method; (2) **ABPR** [2] is the adaptive BPR method and the first work to incorporate one type of *auxiliary*, i.e., *view*; (3) **TBPR**$_{cv}$ only considers *view* and sets $\alpha_u^{(0)}$ to a same constant for all users; (4) **TBPR**$_v$ only considers *view*; (5) **TBPR**$_l$ only considers *like*; (6) **TBPR**$_{fl}$ only considers filtered *like*; (7) **TBPR**$_b$ considers both *view* and filtered *like*.

Table 1: Recommendation performance of different methods on Sobazaar dataset.

Methods	*Pre*@5	*Rec*@5	**AUC**	**MAP**	**NDCG**	**MRR**
BPR	0.0100	0.0358	0.7299	0.0257	0.1463	0.0337
ABPR	0.0101*	0.0364*	0.7314*	0.0262*	0.1468*	0.0341*
TBPR$_{cv}$	0.0111	0.0400	0.8481	0.0302	0.1589	0.0388
TBPR$_v$	0.0146	0.0596	0.8868	0.0496	0.1860	0.0574
TBPR$_l$	0.0104	0.0378	0.7816	0.0269	0.1505	0.0348
TBPR$_{fl}$	0.0106	0.0377	0.8052	0.0297	0.1544	0.0367
TBPR$_b$	**0.0172**	**0.0682**	**0.8901**	**0.0561**	**0.1929**	**0.0654**
Improve	55%	70%	22%	114%	31%	92%

Table 1 shows the performance of all comparison methods, where the best performance of our method is highlighted in bold, and the best performance of baseline methods is marked by '*'. The row 'Improve' indicates the improvements of our best performance relative to the '*' results. Some interesting observations can be noted: 1) ABPR performs better than BPR, indicating the importance of auxiliary action for better recommendation; 2) TBPR$_v$ consistently outperforms ABPR across all the metrics, which demonstrates that our fine-grained assumption is able to help model user preference more accurately; 3) The performance of TBPR$_v$ is better than that of TBPR$_{cv}$, verifying that it is more reasonable to treat each user distinctively by learning α_u. 4) TBPR$_{fl}$ outperforms TBPR$_l$ slightly. This implies that *auxiliary* having higher correlation with *purchase* are more effective to enhance recommendation performance; 5) TBPR$_b$ incorporating both *view* and *like* performs best, which suggests that the best performance can be generated by appropriately integrating both types of *auxiliary*.

4. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a *trinity preference* based Bayesian personalized ranking (TBPR) model for multivariate implicit feedback. A fine-grained assumption was presented to distinguish the user preference difference between items with *purchase* and those with *auxiliary* more accurately. Empirical study shows that our method achieves significant better recommendation performance than state-of-the-art algorithms. For future work, we plan to find ways to incorporate other types of *auxiliary*.

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