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Improving Item Ranking by Leveraging Dual Roles Influence

KE XU, YANGJUN XU, HUAQING MIN, AND YI CAI, (Member, IEEE)
Key Laboratory of Robotics and Intelligent Software, South China University of Technology, Guangzhou 510006, China
Corresponding authors: Huaqing Min (hqmin@scut.edu.cn) and Yi Cai (ycai@scut.edu.cn)

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ABSTRACT Ranking items to users is a typical recommendation task, which evaluates users' preferences for certain items over others. Easy access to social networks has motivated researchers to incorporating trust information for recommendation. In this paper, aiming at offering fundamental support to the trust-based research for item recommendation, we conduct an in-depth analysis on Epinions, Ciao, and FilmTrust data sets. We find that a user's selection of an item is influenced not only by her trustees but also by her trusters. We leverage this "dual roles influence" to derive two more accurate matrix factorization (MF)-based ranking models, namely, *BPRDR* and *FSDR*, respectively. In more detail, the first *BPRDR* model performs three pairwise preferences comparisons under the Bayesian personal ranking framework, considering the dual roles influence in its ranking assumptions. The second *FSDR* is an improved factored similarity model as it incorporates dual roles influence to contribute its ranking scores. Extensive experiments on three data sets show that it is essential to consider the dual roles influence when generating top-K item recommendation.

INDEX TERMS Bayesian personalized ranking, factored similarity model, item ranking, matrix factorization, trust relationships.

I. INTRODUCTION

With the booming of online social networks, the trust-based approaches have increasingly gained popularity to improving recommender systems. Although these approaches incorporate trust relationships in rating prediction problem, a few attempts have been provided a ranked list for a target user, also known as Top-K recommendation problem. In fact, item ranking is a more prevalent task and also what we concerned with in this paper.

In a typical social network implementing trust mechanism, like Epinions,[1] a user may pro-actively specify whom to trust and may also be trusted by a number of users. That is, the social influence on one's selection of items may flow in both directions. On the one hand, a user's trustees may affect her opinions on an item. Fig. 1a gives a graphical illustration. Particularly, user u trusts user v, and user v has selected item i. Then, user u may consider her trustee v's choice to decide whether to select i or not. On the other hand, a user's trusters may also affect her opinions on an item. As illustrated in Fig. 1b, user w trusts user u and has selected item i, this may further affect u's choice of the same item i. For clarity, we give this phenomenon a unified name called "dual roles influence" in this paper. Note that we also conduct an empirical analysis to support the idea of dual roles influence in Sec. III.

Therefore, when recommending items for a user, it is more sensible to take into account both trusters and trustees influence simultaneously. Although existing item ranking literatures [1]–[8] have proved that trusted users will influence items' ranking, they neglect the influence of trusters as well as its contribution to ranking generation process. Based on this fact, in this work, we take the view of "dual roles influence" to explain the decision making of item selection by individual users and leverage it to enhance the existing trust-based ranking models.

Matrix Factorization (MF) is one of the most welcomed recommendation algorithms. Among various MF-based models exist, the Bayesian Personalized Ranking (BPR) models (typically *BPR* [9], *SBPR* [4]) and Factored Similarity (FS-) models (typically *FISM* [10], *FST* [8]) have

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

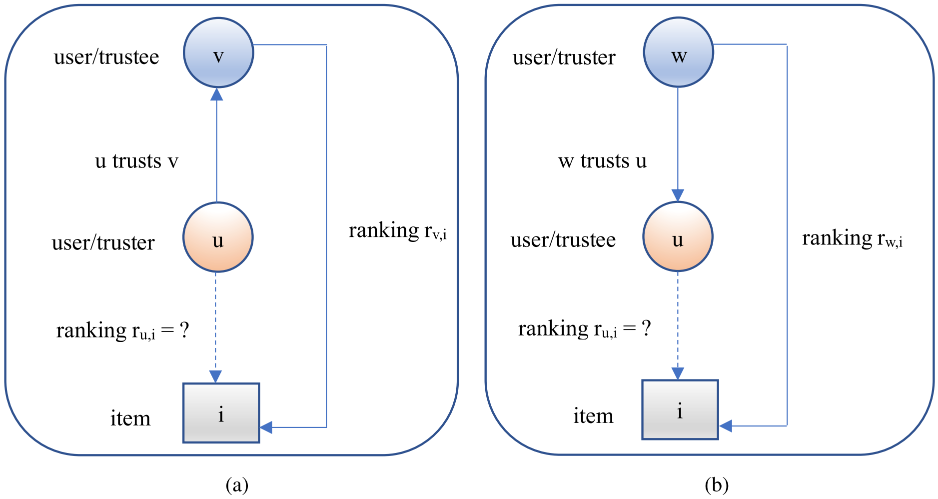


FIGURE 1. The dual roles influence on user *u*'s ranking opinions for the target item *i*. (a) The influence of *u*'s trustees. (b) The influences of *u*'s trusters.

been shown to offer strong results in item ranking tasks. We argue that it is more reasonable to inject the dual roles influence into these sophisticated methods for better results. The key contributions of this work are summarized below:

- The developed trust-based approaches base on the phenomenon that a user is frequently influenced by their trusters as well as trustees when selecting items. To investigate this dual roles influence, we set up an empirical trust analysis on three well-known publicly available datasets. As far as we know, this is the first attempt to simultaneously consider truster- and trustee-specific influence in item ranking task with implicit user-item information and user-user trust relationships.
- We build a BPR-model of users' ranked preferences, namely *BPRDR* for item ranking. In particular, *BPRDR* adopts three pairwise preferences assumptions: the rank of items a user has rated is higher than the items her trustees prefer, the rank of items a user has rated is also higher than the items her trusters prefer, and the rank of items a user's trustee prefer is higher than other items that is not rated by herself, her trusters and her trustees. Specifically, dual roles influence is depicted in these pairwise comparisons for *BPRDR*. Our evaluation shows that *BPRDR* outperforms compared BPR-model.
- We present an improved FS-model with dual roles influence, namely *FSDR* for item ranking. It takes the advantage of representing a user's preferences on an item (through a ranking score) related to four factors: the user-user similarity, the item-item similarity, ant the influence of her trustees/trusters who rated the same item. Specifically, dual roles influence becomes an important part to organize ranking scores in *FSDR*. Our evaluation shows that *FSDR* outperforms compared state-of-the-art FS-models.
- We conduct extensive experiments on Epinions, Ciao, and FilmTrust datasets to evaluate the performance of *FSDR* and *BPRDR*. The experimental results demonstrates that dual roles influence has a positive impact on users' items selection, and thus promotes the performance of Top-K recommendation.

The rest of this paper is organized as follows. Related works are reviewed in Sec. II. We give the motivation of our work in Sec.III. Sec.IV provides notations and problem definition. In Sec. V, the proposed methods are presented in detail. Evaluations are depicted in Sec. VI. We describe and discuss the experimental results in Sec. VII. A conclusion of this paper is given in Sec. VIII.

II. RELATED WORK

Researchers have proposed various proposal to improve recommendation results via the use of user-user trust relationships. In this section, we review related works, including a) rating prediction with trust which has drawn lot of attention previously, and b) item ranking with trust which we study in this work.

A. RATING PREDICTION WITH TRUST

Collaborative filtering (CF) is the most commonly used method to building recommender systems and has been successfully applied in lots of scenarios. In the field of CF, memory- and model- based methods have been widely studied.There are several representative memory-based approaches leveraging trust information for rating tasks. Golbeck presents *TidalTrust* [11], which aggregates the ratings of trusted neighbours and computes trust in a breadth-first manner. Similarly, Massa and Avesani propose a Trust-aware Recommender Systems (*TaRS* or *MoleTrust*) [12]. It gauges trustable users through analyzing trust propagation among the social network and recommend items prefered by these trustable users to the target user. Compared to *TidalTrust*, *TaRS* supports backward exploration, and considers all paths of length up to maximum-depth instead of paths with the shortest distance. In [13], Jamali and Ester propose a random walk method, *TrustWalker*, which incorporates trust- and item- based approach into rating prediction tasks on single items. *FTRA* [14] fuses sparse ratings/trust relationships among the same users for recommendation via using a novel similarity metric and the Katz measure. Guo *et al.* [15] propose *Merge* for recommendation. It incorporates explicitly trusted neighbors to enhance the results as well as alleviate the cold start and data sparsity problems. Hu *et al.* [16] present a method called *SRCF* which employs a new similarity reinforcement mechanism without requiring any additional data source. In particular, it merges user similarity with item similarity reinforcement in a coherent model, at the same time, allows them strengthening each other.

Model-based approaches have been demonstrated their superiority to memory-based approaches [17]. MF approach is an important realization of model-based methods for recommender systems. It predicts unknown ratings based on the factorization of the original user-item rating matrix into two low dimension user- and item- specific matrices [18]. The pioneer algorithm of MF is Probabilistic Matrix Factorization (*PMF*) [19] which is designed for rating prediction tasks. *SVD++* [20] incorporates user/item biases and the influence of rated items for rating prediction. However, all of the above MF approaches, which purely mine the user-item feedback, ignore the social feedback among users. This is inconsistent with reality. Moreover, data sparsity is their most serious limitations. Thanks to the development of online social work, researchers have started to take trust information into consideration for mitigating data sparsity and low accuracy problems. Specifically, Ma *et al.* chronologically developed *SoRec* [21], *RSTE* [22], and *SoReg* [23], by incorporate different trust regularization terms into the *PMF* model. *SoRec* [21] combines user-item matrix with social trust networks via extracting a common shared latent user-feature factor. Due to the lack of interpretability of the SoRec, a more realistic approach *RSTE* is proposed. It linearly combines a basic MF model and a trusted friends model together. Thus, a user's rating is reflected as a balance between her own and her trusted users. Experiments show that *RSTE* outperform *SoRec* in terms of RMSE value. Unlike *RSTE*, *SoReg* [23] treats friends with dissimilar taste differently. Basically, it devises two regularization terms, average- and individual- based, to constraint the MF framework. Within both of the terms, the similarity function is imposed to describe the different appetite of each users' friends. Based on *SoRec*, *SocialMF* [24] is proposed to redesign the contributions of trusted users to target user's user-specific vector while employ trust propagation. The empirical evaluation shows its superiority to *RSTE*. More recently, Tang *et al.* [25] suggest that *SoRec*, *SoReg* and *SocialMF* approaches focus purely on exploiting local social context, while ignore users' reputation. Therefore, they propose *LOCABAL* recommender model taking advantage of local and global social context. Reference [26] investigates to promote recommender results by leveraging different implicit social feedback. Wang *et al.* [27] focuses on the issue of user preferences imbalance in recommender system side and in social trust networks side. Authors in [28] incorporates user-item ratings, explicit social relations and common neighbors data into *PMF* for recommendation. Under ratings-only scenario whenever explicit trust is not available, Taheri *et al.* [29] build a novel recommendation model *Hell-TrustSVD* on *TrustSVD* where both the explicit user-item ratings and implicit social relation involved to boost the rating predictive accuracy. Specifically, Hellinger distance is introduced to extract the set of truster-trustee relationships. Fazeli *et al.* [30] evaluate several Trust Metrics (*TMs*) to obtain the best predict trust scores and then incorporate these trust scores into *socialMF* for recommendation.

From another angle, the aforementioned methods consider users associated with a single role (typically as trusters), neglecting the different roles assigned to users. Therefore, a few works incorporate dual roles factors into their recommendation method. Yang *et al.* [31] suggest that the observed ratings are highly related to the propagation of both truster and trustee influence among users. Therefore, they design a truster model as well as a trustee model to map users into the same latent feature spaces. Then, the two models are naturally synthesized to one fusing model simultaneously fitting available ratings and trust ties, namely *TrustMF*. Similarly, Yao *et al.* [32] propose *RoRec* to learn dual roles (truster/trustee) preferences for recommendation via using both explicit and implicit interactions. Compare to *TrustMF* which learn dual roles preferences independently to estimate ratings, *RoRec* considers both dual roles preferences in learning process because ratings are generated from both roles. Trust in *Fang's* model [33] is connected with multi-aspects trust, including Benevolence, Competence, Predictability and Integrity. Technically, it fuse four trust aspects together into a MF model to predicting ratings. *Fang's* also utilizes a user's influence as truster/trustee to update the user latent feature vectors. Guo *et al.* extend *SVD++* with trust feedback [34], [35]. The proposed *TrustSVD* leverages explicit/implicit influence of ratings and of trust for rating prediction. The rationale behind *TrustSVD* is that the popular ones should be less penalized, whereas, the niche ones should be more regularized.

In summary, all these works have shown that models with dual roles surpass the same model with single role. In this regard, dual roles is helpful to promote the predictive accuracy. However, our work is essentially different from the existing dual roles approaches since it is designed for item ranking rather than rating prediction. More precisely, the argument of this paper is that the feedback from a user's trusters and trustees both influence her item ranking preferences.

B. ITEM RANKING WITH TRUST

We first introduce some representative ranking baselines. *IF-MF* [36] and *BPR-MF* [9] are two state-of-the-art MF methods tailored to implicit scenarios. *IF-MF* adopt a confidence-weighting proposal to decide whether to select the item or not. *BPR-MF* employs a Bayesian probabilistic optimization among relevant and irrelevant items to rank items. *FISM* [10] learns item-item similarity matrix to depict relations between items.

Then, we survey some representative trust-enhanced item ranking approaches. Jamali and Ester extend *TrustWalker* to perform Top-K recommendation namely *Trust-CF* [1]. Different from *TrustWalker*, *Trust-CF* weights trusted users by their correlation with the source user instead of equally treating for all trusted users. In [2], *BPR* is extended to the multi-relational case. In [3], authors propose a probabilistic generative model, namely *SIS*, to capture social information from real datasets via statistical inference for recommendation. *SBPR* [4] takes social relationships into account at learning process. It assumes that users are more likely to rank items that their friends favor. *SPF* [5] is a Poisson probabilistic model, which matches users' preferences with their friends. Authors in [37] propose to use the top one probability and cross entropy with social information when generating the Top-K items. Reference [6] rank items at the top of the candidate list via simultanously minimizes the Social Height and the Social Reverse Height. *UIContexRank* [7] leverages trust relationships and common rated items to rank preferences of users between item pairs. Inspired by *FISM*, the authors in [8] define a user's preferences over an item with social ranking scores.

However, the previous works only either utilize user-item feedback or explore users' single role in making item recommendation. Hence, the user-user relationships are not well studied and exploited. Reference [38] regards users as trusters and trustees, at the same time, considers the structure of the network. However, it only models influence of users' trusted users. In this paper, we systematically analyze the dual roles influence built on MF framework. We also state the detailed differences among the proposed *BPRDR* and (*BPR-MF*, *SBPR*) in Sec. V-A.4, as well as, the detailed differences among the proposed *FSDR* and (*FISM*, *FST*) in Sec.V-B.4.

III. MOTIVATION

In this work, we try to analyze how users' selection of items are affected by their trusters and trustees. Specifically, we focus on dual roles influence of users for item ranking tasks.

A. DATASETS DESCRIPTION

For the purpose of this study, we analyze dual roles influence for item ranking based on three real-world datasets: Epinions,[2] Ciao,[3] and FilmTrust.[4] They are widely used in previous trust-based recommender systems and also adopted in our experiments.

The three publicly available datasets contain both user-item rating information and user-user trust information.

TABLE 1. Statistics of Epinions, Ciao, and FilmTrust datasets.

Statistic	Epinions	Ciao	FilmTrust
user-item information:			
# users	40,163	7,375	1,508
# items	139,738	105,114	2,071
# ratings	664,824	284,086	35,497
rating density	0.0118%	0.0366%	1.14%
user-user information:			
# trusters	33,960	6,792	609
# trustees	49,288	7,297	732
# trusts	487,183	111,781	1,853
average # trusters per user	14	16	3
average # trustees per user	10	15	2
trust density	0.030%	0.23%	0.42%

Since this work focus on solving Top-K recommendation problem, we binaries the data setting all ratings to 1. In particular, Epinions and Ciao are online product (including electronics, sports, etc.) review sites where users can specify whom to trust. FilmTrust is a movie sharing website that provides a movie review function. It describes the concept of trust with original values from 1 to 10. The statistics of the three datasets are illustrated in Table 1. Moreover, to make our basis more clear, we give the comparison results of item coverage probabilities in Fig. 2.

B. OBSERVATIONS

We organize three observations summarizing from the three datasets, which motivate our proposed trust-based models.

Observation 1: Both user-item information and user-user information are very sparse.

From Table 1, we observe that both rating density and trust density are extremely low on three datasets. This phenomenon motivates the intuition that separately leveraging user-item ratings or user-user trust matrix may not generate realistic performance. Therefore, recent works consider fusing these two resources together for better recommendation. Further to this, the sparsity of user-user trust feedback implies the significance of digging out richer information among users and involving them for recommendation.

Observation 2: Users tend to choose items selected by their trusters/trustees.

Fig. 2a gives the probabilities that an item selected by a user is also selected by their trustees, trusters, and randomly sampled users, respectively. Some observations can be obtained from the results: a) in all cases, it is clear that random user selection is lower than trustee selection and truster selection cases, especially obvious in Epinions and Ciao datasets. This means users tend to be affected by their trusters'/trustees' opinions rather than arbitrary ones' opinions when selecting items; and b) in Ciao and FilmTrust datasets, the probability of the same items selected by users' trusters is higher than by their trustees, whereas, the situation is reversed in Epinions dataset. It indicates that the influence of trusters (in item ranking) may be comparable with that of trustees, and hence may also offer valuable clues to boosting the recommendation results.

[2] http://alchemy.cs.washington.edu/data/epinions/
[3] http://www.jiliang.xyz/trust.html
[4] http://www.cs.ubc.ca/ jamalim/datasets/

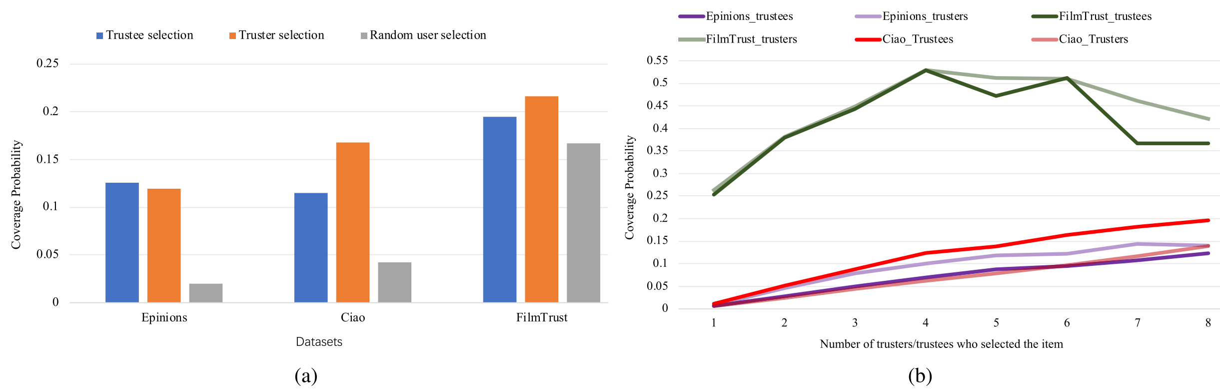


FIGURE 2. Coverage probability analysis. (a) Coverage probability of trustees/trusters/random users. (b) Influence of trusters/trustees on selection probability.

Observation 3: Users tend to select items that more of their trusters/trustees have selected.

Fig. 2b presents monotonous increases in probabilities, which reflect the selection of items is positively related to the number of trusters/trustees who have selected the same item on Epinions and Ciao datasets. However, on FimTrust dataset, the similar trend is disturbed as the X-axis's value is larger than 4. This may attribute to the fact that the average number of trusters/trustees per user is particularly scarce (around 2-3 in FilmTrust) described in Table 1. The observation indicates the more her trusters/trustees choose the item, the higher probability that she selects the item.

In general, for a target user, her trusters' and trustees' opinions both play important roles in her item selection. Therefore, these observations motivate us to take dual roles influence into account when making item recommendation. Note that we also have calculated the probability that items selected by a user's trusters and trustees but not by this user, they are around 0.858, 0.901. 0.921 in Epinions, Ciao and FimTrust datasets, respectively. These results reflects the sparsity of the datasets, and thus requires truster and trustee relationships to be explored and used more efficiently.

IV. NOTATIONS AND PROBLEM DEFINITION

We introduce some notations for the easy of following discussion. All vectors are represented by bold lower case letters (e.g., $\mathbf{p}, \mathbf{q}, \mathbf{x}, \mathbf{y}, \mathbf{b}$) and all matrices are represented by bold upper case letters (e.g., $\mathbf{P}, \mathbf{Q}, \mathbf{X}, \mathbf{Y}$). We also use calligraphic letters to denote set (e.g., $\mathcal{U}, \mathcal{I}$). A value with a hat $\hat{}$ indicate its estimated form, such as $\hat{r}$.

We denote $\mathcal{U}$ and $\mathcal{I}$ as the set of user and items, respectively, where $|\mathcal{U}| = n$, $|\mathcal{I}| = m$. $\mathbf{R}$ represents $n \times m$ user-item feedback matrix. Symbols (u, v, w) and (i, j, k, s) separately indicates individual users and items. An entry (u, i) in $\mathbf{R}$ denoted by $r_{u,i}$ is 1 if user u has provided feedback on item i (observed item) and 0 otherwise (unobserved item). $\mathbf{T}$ represents $n \times n$ user-user trust feedback matrix. An entry (u, v) in $\mathbf{T}$ denoted by $t_{u,i}$ is 1 if user u has specified user v to trust and 0 otherwise. Specifically, we use $\mathcal{T}_u$ ($\mathcal{G}_u$) to define the set of all user u's trustees (trusters), and $\mathcal{I}_u^+$ ($\mathcal{I}_u^-$) to define the set of observed (unobserved) items that user u have (have not) selected. Sets $\mathcal{T}_u, \mathcal{G}_u, \mathcal{I}_u^+$ and $\mathcal{I}_u^-$ are formulated as follows:

$$\mathcal{T}_u = \{v|u, v \in \mathcal{U} \wedge t_{u,v} = 1\}, \tag{1}$$
$$\mathcal{G}_u = \{w|w, u \in \mathcal{U} \wedge t_{w,u} = 1\}, \tag{2}$$
$$\mathcal{I}_u^+ = \{i|i \in \mathcal{I} \wedge r_{u,i} = 1\}, \tag{3}$$
$$\mathcal{I}_u^- = \{j|j \in \mathcal{I} \wedge r_{u,j} = 0\}. \tag{4}$$

The problem discussed in this paper is how to incorporate users' dual role influence to improve recommender systems. More precisely, given user-item matrices $\mathbf{R}$ and user-user matrices $\mathbf{T}$, for each user, we aim to output a ranked list including K items by considering both the influence of her trustees and the influence of her trusters.

V. PROPOSED METHODS

Based on the studies among three real-world datasets presented in Sec. III, leveraging dual roles influences to better predict users' preferences on items is the task we concern in this paper. In this regard, we propose two different types of models in this work, namely *BPRDR* (See Section. V-A) and *FSDR* (See Section V-B), which build upon dual roles influences for Top-K item recommendation. The former *BPRDR* is purely a Bayesian Personal Ranking (BPR-) model, which assumes that users are likely to assign higher ranks to items that their trustees/trusters prefer; The latter *FSDR* is a Factored Similarity (FS-) model which takes the assumption that a users' ranking score over an item is reflected as the balance among users/items similarities and the influence of trusters/trustees.

A. BPRDR: A BPR-MODEL WITH DUAL ROLES INFLUENCE

1) MODEL FORMULATION

We first define the four sets that will be used for our proposed *BPRDR*, including positive user-item set, trustee user-item set, truster user-item set, and negative user-item set.

- *Positive user-item set*. Positive user-item set $\mathcal{PO}_u$ contains user-item pairs of user u and u's observed items.

We formulate $\mathcal{PO}_u$ as follow:

$$\mathcal{PO}_u = \{(u,i)|u \in \mathcal{U} \land i \in \mathcal{I} \land r_{u,i} = 1\}. \tag{5}$$

- *Trustee user-item set*. Trustee user-item set $\mathcal{EP}_u$ contains user-item pairs of user u and items that at least one of her trustees selected. We formulate $\mathcal{EP}_u$ as follow:

$$\mathcal{EP}_u = \{(u,k)|u, v \in \mathcal{U} \land k \in \mathcal{I} \land v \in \mathcal{T}_u \land r_{v,k} = 1 \land r_{u,k} = 0\}. \tag{6}$$

- *Truster user-item set*. Truster user-item set $\mathcal{RP}_u$ contains user-item pairs of user u and items that at least one of her trusters selected. We formulate $\mathcal{RP}_u$ as follow:

$$\mathcal{RP}_u = \{(u,s)|u, w \in \mathcal{U} \land s \in \mathcal{I} \land w \in \mathcal{G}_u \land r_{w,s} = 1 \land r_{u,s} = 0\}. \tag{7}$$

- *Negative user-item set*: Negative user-item set $\mathcal{NE}_u$ contains user-item pairs of user u and items that neither herself nor any of her trusters and trustees selected. We formulate $\mathcal{NE}_u$ as follow:

$$\mathcal{NE}_u = \{(u,j)|u, v, w \in \mathcal{U} \land j \in \mathcal{I} \land v \in \mathcal{T}_u \land w \in \mathcal{G}_u \land r_{u,j} = 0 \land r_{v,j} = 0 \land r_{w,j} = 0\}. \tag{8}$$

Note that $\mathcal{PO}_u \cup \mathcal{EP}_u \cup \mathcal{RP}_u \cup \mathcal{NE}_u$ covers all of the user-item pairs, $\mathcal{PO}_u \cap \mathcal{EP}_u = \varnothing$, $\mathcal{PO}_u \cap \mathcal{RP} = \varnothing$, and $\mathcal{PO}_u \cap \mathcal{EP} \cap \mathcal{RP}_u \cap \mathcal{NE}_u = \varnothing$.

We then focus on the underlying hypotheses of *BPRDR* with three comparisons:

$$X_{(u,i)} \succeq X_{(u,k)}, X_{(u,i)} \succeq X_{(u,s)}, X_{(u,k)} \succeq X_{(u,j)}, \tag{9}$$

where $(u,i) \in \mathcal{PO}_u$, $(u,k) \in \mathcal{EP}_u$, $(u,s) \in \mathcal{RP}_u$, and $(u,j) \in \mathcal{NE}_u$. It's worth noticing that the dual roles influence in *BPRDR* is depicted via the pairwise comparisons presented in (9). More precisely, for a typical user u, we take the assumption that a) u prefers her observed item i to any of her trustee's observed item k, denoted by the relationship $X_{(u,i)} \succeq X_{(u,k)}$; b) u prefers her observed item i to any of her truster's observed item s, denoted by $X_{(u,i)} \succeq X_{(u,s)}$; and c) u prefers her trustee's observed item k over item j that neither herself nor her trusters/trustees observed, denoted by $X_{(u,k)} \succeq X_{(u,j)}$.

For each user, we build an optimization criterion on top of (9). Technically, the maximization of AUC can be employed to estimate the three comparisons, which is described in (10).

$$\prod_{\substack{(u,i),(u,k)\in\\(\mathcal{PO}_u\cup\mathcal{EP}_u)}} Pr(X_{ui} \succeq X_{uk})^{\delta(u,i,k)}[1-Pr(X_{ui} \succeq X_{uk})]^{1-\delta(u,i,k)}$$
$$\prod_{\substack{(u,i),(u,s)\in\\(\mathcal{PO}_u\cup\mathcal{RP}_u)}} Pr(X_{ui} \succeq X_{us})^{\epsilon(u,i,s)}[1-Pr(X_{ui} \succeq X_{us})]^{1-\epsilon(u,i,s)}$$
$$\prod_{\substack{(u,k),(u,j)\in\\(\mathcal{EP}_u\cup\mathcal{NE}_u)}} Pr(X_{uk} \succeq X_{uj})^{\varrho(u,k,j)}[1-Pr(X_{uk} \succeq X_{uj})]^{1-\varrho(u,k,j)}, \tag{10}$$

where $\delta(\cdot)$, $\epsilon(\cdot)$, and $\varrho(\cdot)$ are binary random variables. They are denoted as follows:

$$\delta(u,i,k) = \begin{cases} 1 & \text{if } ((u,i) \in \mathcal{PO}_u) and\ ((u,k) \in \mathcal{EP}_u) \\ 0 & \text{if } otherwise \end{cases},$$
$$\epsilon(u,i,s) = \begin{cases} 1 & \text{if } ((u,i) \in \mathcal{PO}_u)\ and\ ((u,s) \in \mathcal{RP}_u) \\ 0 & \text{if } otherwise \end{cases},$$
$$\varrho(u,k,j) = \begin{cases} 1 & \text{if } ((u,k) \in \mathcal{EP}_u)\ and\ ((u,j) \in \mathcal{NE}_u). \\ 0 & \text{if } otherwise \end{cases} \tag{11}$$

The above formula can be rewritten as follow:

$$\frac{\sum_{(u,i)\in\mathcal{PO}_u,(u,k)\in\mathcal{EP}_u} Pr(X_{ui} \succeq X_{uk})}{|\mathcal{PO}_u||\mathcal{EP}_u|} + \frac{\sum_{(u,i)\in\mathcal{PO}_u,(u,s)\in\mathcal{RP}_u} Pr(X_{ui} \succeq X_{us})}{|\mathcal{PO}_u||\mathcal{RP}_u|} + \frac{\sum_{(u,k)\in\mathcal{EP}_u,(u,j)\in\mathcal{NE}_u} Pr(X_{uk} \succeq X_{uj})}{|\mathcal{EP}_u||\mathcal{NE}_u|}. \tag{12}$$

To address the issue, we adopt a sigmoid function to approximate the function $Pr(\cdot)$, so that our goal can be achieved by maximizing the following objective function:

$$\mathbb{O} = \sum_u \Bigg[\sum_{(u,i)\in\mathcal{PO}_u} \sum_{(u,k)\in\mathcal{EP}_u} In(\sigma(\frac{X_{ui}-X_{uk}}{1+co_{uk}}) + \sum_{(u,i)\in\mathcal{PO}_u} \sum_{(u,s)\in\mathcal{RP}_u} In(\sigma(\frac{X_{ui}-X_{us}}{1+co_{us}}) + \sum_{(u,k)\in\mathcal{EP}_u} \sum_{(u,j)\in\mathcal{NE}_u} In(\sigma(X_{uk}-X_{uj}))\Bigg] \tag{13}$$
$$-Reg, \quad where$$
$$X_{ui} = \mathbf{c}_u^\top \mathbf{d}_i + b_i, \quad X_{uk} = \mathbf{c}_u^\top \mathbf{d}_k + b_k,$$
$$X_{us} = \mathbf{c}_u^\top \mathbf{d}_s + b_s, \quad X_{uj} = \mathbf{c}_u^\top \mathbf{d}_j + b_j,$$
$$co_{uk} = \sum_{v\in\mathcal{T}_u} r_{v,k}, \quad co_{us} = \sum_{w\in\mathcal{G}_u} r_{w,s}.$$

In the above (13), Reg is a regularization term. The preferences functions $(X_{ui}, X_{uk}, X_{us}, X_{uj})$ are all modeled by matrix factorization, where $\mathbf{C} \in \mathbb{R}^{d\times N}$, $\mathbf{D} \in \mathbb{R}^{d\times M}$, $\mathbf{b} \in \mathbb{R}^M$ and d is the latent factor numbers. We adopt l_2-norm regularization for $\mathbf{C}, \mathbf{D}, \mathbf{b}$. Particularly, we adopt coefficients co_{uk} and co_{us} to express a measurement of the importance of each sampled training pair to $\mathbb{O}$. In more detail, co_{uk} counts the number of times that user u's trustees select item k but u does not. Similarly, co_{us} calculates the number of times that user u's trusters select item s but u does not.

2) PARAMETERS LEARNING

Stochastic gradient descent (SGD) is employed to optimize $\mathbb{O}$ described in (13). It randomly selects (positive, truster), (positive, trustee) and (truster, negative) pairs, calculates the derivative and iteratively updates $\mathbf{C}, \mathbf{D}, \mathbf{b}$ in each training epoch. Detailed learning algorithm of *BPRDR* model is given in Algorithm 1.

Algorithm 1 The Learning Algorithm of *BPRDR* Model

input: $\mathbf{R}$, $\mathbf{T}$, λ_{bpr}, η_{bpr}
output: $\mathbf{C}$, $\mathbf{D}$, $\mathbf{b}$.
Initialize $\mathbf{C}$, $\mathbf{D}$, $\mathbf{b}$ with random gaussian $\sim$ (0,1);
while $\mathbb{O}$ not converged **do**
  for each # training sample **do**
    sample a user u from $\mathcal{U}$
    sample a user-item pair (u, i) from $\mathcal{PO}_u$, a user-item pair (u, k) from $\mathcal{EP}_u$, a user-item pair (u, s) from $\mathcal{RP}_u$, and a user-item pair (u, j) from $\mathcal{NE}_u$,
    calculate co_{uk} and co_{us} by (13)
    $a_{uik} \leftarrow \sigma(-\frac{(X_{ui}-X_{uk})}{1+co_{uk}})$
    $a_{uis} \leftarrow \sigma(-\frac{(X_{ui}-X_{us})}{1+co_{us}})$
    $a_{ukj} \leftarrow \sigma(-(X_{uk} - X_{uj}))$
    $b_i \leftarrow b_i + \eta_{bpr}(\frac{a_{uik}}{1+co_{uk}} + \frac{a_{uis}}{1+co_{us}} - \lambda_{bpr} b_i)$
    $b_k \leftarrow b_k + \eta_{bpr}(\frac{a_{uik}}{1+co_{uk}} + a_{ukj} - \lambda_{bpr} b_k)$
    $b_s \leftarrow b_s + \eta_{bpr}(\frac{a_{uis}}{1+co_{us}} - \lambda_{bpr} b_s)$
    $b_j \leftarrow b_j + \eta_{bpr}(-a_{u,k,j} - \lambda_{bpr} b_j)$
    $\mathbf{c}'_u \leftarrow a_{uik} \frac{(\mathbf{d}_i-\mathbf{d}_k)}{1+co_{uk}} + a_{uis} \frac{(\mathbf{d}_i-\mathbf{d}_s)}{1+co_{us}}$
    $\mathbf{d}'_k \leftarrow a_{uik}(\frac{-\mathbf{c}_u}{1+co_{uk}}) + a_{ukj}\mathbf{c}_u$
    $\mathbf{d}'_s \leftarrow a_{uis}(\frac{-\mathbf{c}_u}{1+co_{us}})$
    $\mathbf{c}_u \leftarrow \mathbf{c}_u + \eta_{bpr}(\mathbf{c}'_u - \lambda_{bpr}\mathbf{c}_u)$
    $\mathbf{d}_i \leftarrow \mathbf{d}_i + \eta_{bpr}(a_{uik} \frac{\mathbf{c}_u}{1+co_{uk}} + a_{uis} \frac{\mathbf{c}_u}{1+co_{us}} - \lambda_{bpr}\mathbf{d}_i)$
    $\mathbf{d}_k \leftarrow \mathbf{d}_k + \eta_{bpr}(\mathbf{d}'_k - \lambda_{bpr}\mathbf{d}_k)$
    $\mathbf{d}_s \leftarrow \mathbf{d}_s + \eta_{bpr}(\mathbf{d}'_s - \lambda_{bpr}\mathbf{d}_s)$
    $\mathbf{d}_j \leftarrow \mathbf{d}_j + \eta_{bpr}(a_{ukj}(-\mathbf{c}_u) - \lambda_{bpr}\mathbf{d}_j)$
  end for
end while
return $\mathbf{C}$, $\mathbf{D}$, $\mathbf{b}$

3) ITEM RECOMMENDATION

Finally, we predict the preferences of user u on item j according to $X_{u,j} = \mathbf{c}_u^\top \mathbf{d}_j + b_j$, and then sort Top-$K$ items to form the candidate list for u.

4) RELATION TO EXISTING BPR MODELS

In this section, we will review the two of *BPR-* models, including *BPR-MF* [9] and *SBPR* [4].

- *BPR-MF.* *BPR-MF* is the pioneer work of Bayesian Personal Ranking method presented by Rendle *et al.* It focuses on utilizing user-item implicit feedback for Top-K recommendation, and its basic assumption can be represented as follow:
$$X_{ui} \succeq X_{uj}, \tag{14}$$
where $i \in \mathcal{I}_u^+, j \in \mathcal{I}_u^-$. *BPR-MF* is easy to understand and widely used. However, it dose not consider any additional information, such as user-user trust relations.
- *SBPR.* *SBPR* is a state-of-the-art trust-based model proposed by Zhao *et al.* It incorporates user-user trust information into *BPR-MF* and takes the preferences assumption as follow:
$$X_{ui} \succeq X_{uk}, X_{uk} \succeq X_{uj}, \tag{15}$$
where $(u, i) \in \mathcal{PO}_u$, $(u, k) \in \mathcal{EP}_u$, $j \in \mathcal{I}_u^- \cap \mathcal{I}_k^-$. Apparently, the main difference between our *BPRDR* and *SBPR* is a new term ($X_{ui} \succeq X_{us}$) added in (15), which brings richer interactions among users by the consideration of trusters' influence on a user's item selection, and as a consequence provide more valuable information for recommendation.

We can find that when users have no trusters, our proposed *BPRDR*'s truster feedback will evaporate and the preferences assumption will discard the influence of trusters on item selection. Furthermore, when users have no trustees either, *BPRDR* is reduced to *BPR-MF*, which dose not consider trust information for item ranking. Generally, comparing to *SBPR* and *BPR-MF*, *BPRDR* adopts a fine-grained preferences order assumption as it considers the dual roles influence for item recommendation.

B. FSDR: A FS-BASED MODEL WITH DUAL ROLES INFLUENCE

1) MODEL FORMULATION

In *FSDR*, we define an item ranking score (indicated by $\hat{r}_{u,i}$) for an active user by incorporating the four factors: item similarities, user similarities, the influence of trusters and the influence of trustees, given by:

$$\begin{aligned}\hat{r}_{u,i} &= b_i + o\,|\mathcal{U}_{i-u}|^{-\beta} \sum_{v\in\mathcal{I}_{u-i}} \mathbf{p}_v^\top \mathbf{q}_u + (1-o)\,|\mathcal{U}_{u-i}|^{-\alpha} \sum_{j\in\mathcal{I}_{u-i}} \mathbf{x}_j^\top \mathbf{y}_i \\ &\quad + h\,|\mathcal{T}_u|^{-\gamma} \sum_{v\in\mathcal{T}_u} \mathbf{p}_v^\top \mathbf{y}_i + (1-h)\,|\mathcal{G}_u|^{-\varsigma} \sum_{w\in\mathcal{G}_u} \mathbf{p}_w^\top \mathbf{y}_i,\end{aligned} \tag{16}$$

where $\alpha, \beta, \gamma, \varsigma \geqslant 0$ respectively denotes the number of rated items, similar users, trustees, and trusters. $o, h \in [0, 1]$ are trade-off parameters. o controls the relative importance of user similarity and item similarity. The dual roles influence is depicted by the last two terms in (16), while h balances between the influence of trusters and trustees. For each trustee $v \in \mathcal{T}_u$, dot product $\mathbf{p}_v^\top \mathbf{y}_i$ describes the quantity of influence made by trustee v on item i. For each truster $w \in \mathcal{G}_u$, dot product $\mathbf{p}_w^\top \mathbf{y}_i$ describes the strength of influence made by truster w on item i. $\mathcal{I}_{u-i}$ is the set contains items rated by user u except for item i. $\mathcal{U}_{i-u}$ is the set including users who have rated item i excluding user u herself if she has rated.

In general, (16) reflects the basic idea of item ranking of *FSDR*, as it learns a) the item-item similarity matrix as a product of $\mathbf{X}$ and $\mathbf{Y}$; b) the user-user similarity matrix as a product of $\mathbf{P}$ and $\mathbf{Q}$; c) the influence of users' trustees for item selection as a product of $\mathbf{P}$ and $\mathbf{Y}$; and d) the influence of users' trusters for item selection as a product of $\mathbf{P}$ and $\mathbf{Y}$.

2) PARAMETERS LEARNING

Suggested by [8], we learn parameters $\mathbf{P}$, $\mathbf{Q}$, $\mathbf{X}$, $\mathbf{Y}$, and $\mathbf{b}$ of *FSDR* via (17).

$$\mathbb{J} = \frac{1}{2} \sum_{u\in\mathcal{U}} \sum_{i\in\mathcal{I}_u^+, j\in\mathcal{I}_u^-} \left\| \left(r_{u,i} - r_{u,j}\right) - \left(\hat{r}_{u,i} - \hat{r}_{u,j}\right) \right\|_F^2$$

$$+\frac{\lambda_{fs}}{2}\left(\|\mathbf{P}\|_F^2+\|\mathbf{Q}\|_F^2+\|\mathbf{X}\|_F^2+\|\mathbf{Y}\|_F^2+\|\mathbf{b}\|_F^2\right), \tag{17}$$

where the estimates $\hat{r}_{u,i}$ and $\hat{r}_{u,j}$ are computed using (16). To reduce complexity, we assign the same λ_{fs} for the regularization of $\mathbf{P}$, $\mathbf{Q}$, $\mathbf{X}$, $\mathbf{Y}$ and $\mathbf{b}$. $\|\cdot\|$ is the Frobenius norm. We also adopt SGD algorithm to achieve an optimal solution to (17). The learning algorithm of *FSDR* model is showed in Algorithm 2.

3) ITEM RECOMMENDATION

Finally, we generate a candidate list for the target user u. It contains K items possessing the highest raking scores $\hat{r}_{u,i}$.

4) RELATION TO EXISTING FS MODELS

We will review the two of *FS*- models, including *FISM* [10] and *FST* [8].

- *FISM: Factored Item Similarity Model. FISM* is the pioneer work of Factored Similarity (FS-) method proposed by Kabbur *et al.* [10]. The ranking score is calculated as follow:

$$\hat{r}_{u,i}=b_i+|\mathcal{U}_{i-u}|^{-\alpha}\sum_{j\in\mathcal{U}_{i-u}}\mathbf{x}_j\mathbf{y}_i^\top, \tag{18}$$

  where the terms mean the same as in (16). The advantage of *FISM* is to consider the neighborhood factors of items into a MF model. The disadvantage of *FISM* is the ignorance of user similarities and trust relationships among social network.

- *FST: FISM with social trust.* *FST* is a state-of-the-art trust-enhanced item ranking work proposed by Guo *et.al* [8]. Technically, it adds trusted users' influence and items similarity to *FISM*, given by:

$$\begin{aligned}\hat{r}_{u,i}&\\ =b_i&+o\,|\mathcal{U}_{i-u}|^{-\beta}\sum_{v\in\mathcal{U}_{i-u}}\mathbf{p}_v^\top\mathbf{q}_u\\ &+(1-o)\,|\mathcal{I}_{u-i}|^{-\alpha}\sum_{j\in\mathcal{I}_{u-i}}\mathbf{x}_j^\top\mathbf{y}_i+|\mathcal{T}_u|^{-\gamma}\sum_{v\in\mathcal{T}_u}\mathbf{p}_v^\top\mathbf{y}_i,\end{aligned} \tag{19}$$

  where the terms mean the same as in (16). Obviously, the main difference between our *FSDR* and *SBPR* is a new term ($|\mathcal{G}_u|^{-\varsigma}\sum_{w\in\mathcal{G}_u}\mathbf{p}_w^\top\mathbf{y}_i$) added in (16), which introduces richer interactions among users via the consideration of trusters' influence on a user's item selection, and thus extracting plentiful information for recommendation. In addition, a variable h is embedded to control the influence between a user's followers and followees in *FSDR*. Furthermore, *FSDR* has a merit that *SBPR* dose not possess. That is, *FSDR* promotes mutual-trusting users assign higher ranking scores for their selected items.

We can find that when the variable $h=1$, the last term in (16) will vanish and our proposed *FSDR* will reduce to *FST*, which dose not consider the influence of trusters on users' personalized item ranking. Furthermore, when the last three term in (16) is deleted while the variable o is set to 1, *BPRDR* is reduced to *FISM*, which dose not consider trust

Algorithm 2 The Learning Algorithm of *FSDR* Model

input: α, β, γ, ς and ρ, λ_{fs}, η_{fs}
output: $\mathbf{b}$, $\mathbf{P}$, $\mathbf{Q}$, $\mathbf{X}$ and $\mathbf{Y}$.

Initialize $\mathbf{b}$, $\mathbf{P}$, $\mathbf{Q}$, $\mathbf{X}$, $\mathbf{Y}$ with random values in (0, 0.01);
while $\mathbb{J}$ not converged **do**
  for each $u\in U$ **do**
    for each $i\in\mathcal{I}_u^+$ **do**
      $\mathcal{Z}\leftarrow sample(\rho,\mathcal{I}_u^-)$
      $m_{ki}\leftarrow\sum_{k\in\mathcal{I}_{u-i}}\mathbf{x}_k$, $w_{ki}\leftarrow|\mathcal{I}_{u-i}|^{-\alpha}$
      $m_{vi}\leftarrow\sum_{v\in\mathcal{U}_{i-u}}\mathbf{p}_v$, $w_{vi}\leftarrow|\mathcal{U}_{i-u}|^{-\beta}$
      $m_{t^+}\leftarrow\sum_{ee\in\mathcal{T}_u}\mathbf{p}_{ee}$, $w_t^+\leftarrow|\mathcal{T}_u|^{-\gamma}$
      $m_{t^-}\leftarrow\sum_{er\in\mathcal{G}_u}\mathbf{p}_{er}$, $w_t^-\leftarrow|\mathcal{G}_u|^{-\varsigma}$
      $g\leftarrow 0, h\leftarrow 0, l_1\leftarrow 0, l_2\leftarrow 0$
      for each $j\in\mathcal{Z}$ **do**
        $m_{kj}\leftarrow\sum_{k\in\mathcal{I}_{u-j}}\mathbf{x}_k$, $w_{kj}\leftarrow|\mathcal{I}_{u-j}|^{-\alpha}$
        $m_{vj}\leftarrow\sum_{v\in\mathcal{U}_{j-u}}\mathbf{p}_v$, $w_{vj}\leftarrow|\mathcal{U}_{j-u}|^{-\beta}$
        compute $\hat{r}_{u,i}$, $\hat{r}_{u,j}$ by (16)
        $r_{u,j}\leftarrow 0$
        $e\leftarrow(r_{u,i}-r_{u,j})-(\hat{r}_{u,i}-\hat{r}_{u,j})$
        $b_i\leftarrow b_i+\eta_{fs}(e-\lambda_{fs}b_i)$
        $b_j\leftarrow b_j-\eta_{fs}(e-\lambda_{fs}b_j)$
        $\mathbf{q}_u\leftarrow\mathbf{q}_u-\eta_{fs}(e(w_{vj}m_{vj}-w_{vi}m_{vi})-\lambda_{fs}\mathbf{q}_u)$
        $\mathbf{y}_i\leftarrow\mathbf{y}_i+\eta_{fs}(e(w_{ki}m_{ki}+w_{t^+}m_{t^+}+w_{t^-}m_{t^-})-\lambda_{fs}\mathbf{y}_i)$
        $\mathbf{y}_j\leftarrow\mathbf{y}_j-\eta_{fs}(e(w_{vj}m_{vj}+w_{vi}m_{vi}+w_{t^-}m_{t^-})-\lambda_{fs}\mathbf{y}_j)$
        $g\leftarrow g-ew_{ki}\mathbf{q}_u$
        $h\leftarrow h+e(w_{kj}\mathbf{y}_j-w_{ki}\mathbf{y}_i)$
        $l_1\leftarrow l_1+ew_{t^+}(\mathbf{y}_j-\mathbf{y}_i)$
        $l_2\leftarrow l_2+ew_{t^-}(\mathbf{y}_j-\mathbf{y}_i)$
        for each $v\in U_{j-u}$ **do**
          $\mathbf{p}_v\leftarrow\mathbf{p}_v-\eta_{fs}(ew_{vj}\mathbf{q}_u-\lambda_{fs}\mathbf{p}_v)$
        end for
      end for
      for each $v\in\mathcal{U}_{i-u}$ **do**
        $\mathbf{p}_v\leftarrow\mathbf{p}_v-\eta_{fs}(g/\rho+\lambda_{fs}\mathbf{p}_v)$
      end for
      for each $k\in\mathcal{I}_{u-i}$ **do**
        $\mathbf{x}_k\leftarrow\mathbf{x}_k-\eta_{fs}(h/\rho+\lambda_{fs}\mathbf{x}_k)$
      end for
      for each $ee\in\mathcal{T}_u^+$ **do**
        $\mathbf{p}_{ee}\leftarrow p_{ee}-\eta_{fs}(l_1/\rho+\lambda_{fs}\mathbf{p}_{ee})$
      end for
      for each $er\in\mathcal{T}_u^-$ **do**
        $\mathbf{p}_{er}\leftarrow p_{er}-\eta_{fs}(l_2/\rho+\lambda_{fs}\mathbf{p}_{er})$
      end for
    end for
  end for
end while
return $\mathbf{b}$, $\mathbf{P}$, $\mathbf{Q}$, $\mathbf{X}$ and $\mathbf{Y}$

TABLE 2. ***BPRDR*** **performance results on Epinions dataset for varying α, β, γ, and ς.**

Epinions Dataset		$\alpha = 0.5$			$\alpha = 1$			$\alpha = 2$		
(γ, ς)	P@K	$\beta = 0.5$	$\beta = 1$	$\beta = 2$	$\beta = 0.5$	$\beta = 1$	$\beta = 2$	$\beta = 0.5$	$\beta = 1$	$\beta = 2$
$(0.5, 0.5)$	P@5	*0.01159*	*0.01202*	*0.01199*	*0.01134*	*0.01207*	*0.01162*	*0.01014*	*0.01177*	*0.01040*
$(\times 10^{-1})$	P@10	0.09205	0.09045	**0.09466**	0.09308	0.09272	0.08797	0.08944	0.09135	0.08989
$(1, 0.5)$	P@5	*0.01160*	*0.01194*	*0.01123*	*0.01062*	*0.01011*	*0.01017*	***0.01218***	*0.01173*	*0.01105*
$(\times 10^{-1})$	P@10	0.09178	0.09351	0.0898	0.08809	0.08862	0.09087	0.09012	0.09095	0.09169
$(1, 1)$	P@5	*0.01116*	*0.01133*	*0.01128*	*0.01193*	*0.01198*	*0.01055*	*0.01067*	*0.01038*	*0.01179*
$(\times 10^{-1})$	P@10	0.08948	0.09016	0.09066	0.08926	0.09093	0.09027	0.09125	0.09023	0.09019
$(0.5, 1)$	P@5	*0.01107*	*0.01130*	*0.01184*	*0.01137*	*0.01176*	*0.01130*	*0.01055*	*0.01195*	*0.01104*
$(\times 10^{-1})$	P@10	0.0893	0.09186	0.09127	0.08819	0.08982	0.09064	0.09068	0.09239	0.08796

information and user similarities for item ranking. Generally, comparing to *FST* and *FISM*, *FSDR* exhibits as a more comprehensive ranking model which incorporates the four factors, especially the dual roles influence.

VI. EVALUATIONS

We present a) datasets and metrics, b) comparative methods, and c) parameter settings in the section.

A. DATASETS AND METRICS

We conduct experiments on Epinions, FilmTrust, and Ciao datasets. The statistics of the three datasets are shown in Table 1. We use fivefold cross validation for learning and testing. Recall, Precision and F1 Score metrics are employed to evaluate our proposed methods. Note that $@K$ means the top K ranked items are taken into consideration.

B. COMPARATIVE METHODS

To demonstrate the effectiveness of the proposed *FSDR* and *BPRDR*, we compare our models with the five following methods focusing on item recommendation.

1) ***FST*** [8]. *FST* is a state-of-the-art FS model. Considering that *FSDR* shares a close relationship with *FST*, we choose *FST* as the main baseline to compare against.
2) ***SBPR*** [4]. *SBPR* is a state-of-the-art BPR model that considers social relationships in the learning process. Since *BPRDR* extends *SBPR* with dual roles influence, we mainly compare *BPRDR* with *SBPR* in our experiments.
3) ***FISM*** [10]. *FISM* is the pioneer FS model for item ranking. It generate recommendations merely based on user-item implicit feedback.
4) ***FSRand***. *FSRand* is a variation of *FSDR*, which replaces the last two terms of followers influence and followees influence in Eq. 16 by random users' influence, respectively. It is leveraged to verify the effect of dual roles influence coming from followers and followees compared with random users.
5) ***PopRec***. *PopRec* recommends the most popular items for all the users.

C. PARAMETERS SETTING

For *FSDR* model, we search the values of parameters $\alpha, \beta, \gamma, \varsigma$ in the range of $\{0.5, 1, 2\}$, and fix the sampling factor ρ to 10 as suggested by [8] and [10].We use the LibRec library [39] for all competing methods. For each of these, we use the optimal parameter settings publishing on LibRec website.[5] We also fix the number of latent factors $d = 10$ for all the MF methods as suggested in works [4] and [8]. We adopt grid search in $\{0.0001, 0.001, 0.01, 0.1\}$ to obtain optimal values of regularization parameters, eg. λ_{fs} and λ_{bpr}. We output the estimating results of $N = 5, 10$ as most of the related works do for the rest of experiments.

VII. EXPERIMENTS AND RESULTS

We conduct experiments to evaluate the advantage of proposed *BPRDR* and *FSDR*. All of the methods run on an Intel Core i7 with 2.2 GHz, 64GB RAM, 64 bit system.

A. PARAMETERS SENSITIVITY EXPERIMENTS

α, β, γ, ς, o and h affect the performance of *FSDR*. Their tuning experiments are described in the next two subsections. Note that for the proposed *BPRDR* model, there are no extra parameters to adjust.

1) EFFECT OF PARAMETERS α, β, γ, AND ς

We explore the recommendation accuracy evaluated with Precision@K (short for P@K) via varying α, β, γ, and ς. More precisely, we vary α and β, whereby they are separately set to 0.5, 1, 2 on three datasets. Given each fixed pair of α and β, we change the number of γ, ς while fixing the values of parameter o and h to be 0.5. To save the pages, we respectively illustrate results using P@5/P@10 that γ, ς is tuned from 0.5 to 1 on three datasets (See Tables 2, 3 and 4). The results states that optimal parameters settings on Precision@5/@10 are ($\alpha = 2$, $\beta = 0.5$, $\gamma = 1$, $\varsigma = 0.5$)/($\alpha = 0.5$, $\beta = 2$, $\gamma = 0.5$, $\varsigma = 0.5$) for Epinions dataset, ($\alpha = 0.5$, $\beta = 2$, $\gamma = 1$, $\varsigma = 0.5$)/($\alpha = 0.5$, $\beta = 2$, $\gamma = 0.5$, $\varsigma = 1$) for Ciao dataset, and ($\alpha = 1$, $\beta = 2$, $\gamma = 1$, $\varsigma = 0.5$)/($\alpha = 0.5$, $\beta = 0.5$, $\gamma = 0.5$, $\varsigma = 0.5$) for FilmTrust dataset.

2) EFFECT OF PARAMETER h

$o, h \in [0, 1]$ are trade-off parameters in (16). o controls the relative importance of user similarity and item similarity, while h controls the contribution to the ranking score from the dual roles influence. To simplify the tuning process,

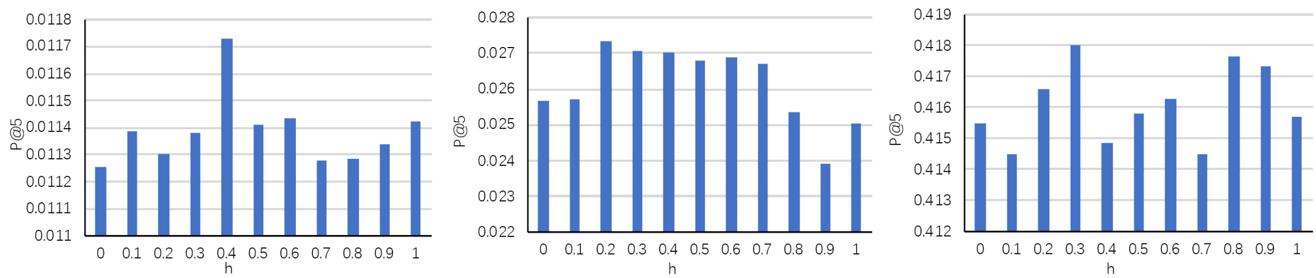
[5] https://www.librec.net

TABLE 3. ***BPRDR*** **performance results on Ciao dataset for varying α, β, γ, and ς.**

Ciao Dataset		$\alpha = 0.5$			$\alpha = 1$			$\alpha = 2$		
(γ, ς)	P@K	$\beta = 0.5$	$\beta = 1$	$\beta = 2$	$\beta = 0.5$	$\beta = 1$	$\beta = 2$	$\beta = 0.5$	$\beta = 1$	$\beta = 2$
$(0.5, 0.5)$	P@5	*0.02547*	*0.02649*	*0.02537*	*0.02545*	*0.0256*	*0.02681*	*0.02533*	*0.02565*	*0.02610*
	P@10	0.02045	0.02161	0.02118	0.02091	0.02116	0.02139	0.02096	0.02070	0.02066
$(1, 0.5)$	P@5	*0.02575*	*0.02673*	*0.02702*	*0.02520*	*0.02643*	*0.02665*	*0.02599*	*0.02646*	*0.02637*
	P@10	0.02047	0.02143	**0.02164**	0.02065	0.02125	0.02138	0.02044	0.02104	0.02103
$(1, 1)$	P@5	*0.02537*	*0.02664*	*0.02675*	*0.02537*	*0.02604*	*0.02653*	*0.02512*	*0.02609*	*0.02654*
	P@10	0.02086	0.02139	0.02126	0.02103	0.02144	0.02140	0.02109	0.0213	0.02064
$(0.5, 1)$	P@5	*0.02597*	*0.02668*	***0.02713***	*0.02535*	*0.02553*	*0.02666*	*0.02549*	*0.02682*	*0.0256*
	P@10	0.02087	0.02137	0.02157	0.02064	0.02134	0.02138	0.02062	0.02140	0.02138

TABLE 4. ***BPRDR*** **performance results on FilmTrust dataset for varying α, β, γ, and ς.**

FilmTrust Dataset		$\alpha = 0.5$			$\alpha = 1$			$\alpha = 2$		
(γ, ς)	P@K	$\beta = 0.5$	$\beta = 1$	$\beta = 2$	$\beta = 0.5$	$\beta = 1$	$\beta = 2$	$\beta = 0.5$	$\beta = 1$	$\beta = 2$
$(0.5, 0.5)$	P@5	*0.41799*	*0.41428*	*0.41703*	*0.41657*	*0.41861*	*0.41727*	*0.41824*	*0.41767*	*0.41520*
	P@10	**0.35187**	0.34814	0.34948	0.34797	0.35070	0.35149	0.35152	0.3496	0.34960
$(1, 0.5)$	P@5	*0.41608*	*0.41535*	*0.41643*	*0.41806*	*0.41756*	***0.41851***	*0.41654*	*0.41565*	*0.41606*
	P@10	0.34971	0.34761	0.35045	0.350478	0.34977	0.35004	0.35043	0.35089	0.34982
$(1, 1)$	P@5	*0.41610*	*0.41690*	*0.41390*	*0.41468*	*0.41587*	*0.41624*	*0.41718*	*0.41521*	*0.41595*
	P@10	0.34912	0.35090	0.34689	0.350091	0.34849	0.34904	0.35034	0.34868	0.35070
$(0.5, 1)$	P@5	*0.41797*	*0.41667*	*0.41770*	*0.41685*	*0.41412*	*0.41741*	*0.41440*	*0.41606*	*0.41715*
	P@10	0.35087	0.34918	0.35087	0.350373	0.34824	0.34954	0.34851	0.3495	0.35001



(a) (b) (c)

FIGURE 3. **The effect of parameter *h* on FSDR in terms of Precision@5 on three datasets. (a) Epinions. (b) Ciao. (c) FilmTrust.**

we directly use the the best o values for Epinions (=0.3), Ciao (=0.1), and FilmTrust (=0.8) as suggested by Reference [8]. That is, we just explore the effect of h for the accuracy of *FSDR* using Precision@K. In more detail, we use the best values of parameters α, β, γ, and ς as reported previously, and then vary the values of parameter h from 0 to 1 with step 0.1. The tuning performance results with P@5 on three datasets is illustrated in Fig. 3, from which we obtain the best h values for Epinions is 0.4, for Ciao is 0.4, and for FilmTrust is 0.3. These results indicate that properly combining of trusters' influence and trustees' influence improves item recommendation over leveraging either of the two separately.

B. METHOD COMPARISONS

We compare the effectiveness of six item recommendation methods at $N = 5, 10$. Tables 5 and 6 separately gives the results for Precision and F1 Score across the three datasets. Note that the best two approaches are highlighted in bold.

First, *FSDR* achieves top performance on the three datasets. Notice the strong performance of ranking by popularity (*PopRec*). This reflects that users prefer chasing hot items to some extent. It is only *FSDR* that consistently outperforms this baseline. This also highlights the importance of simultaneously considering user similarities, item similarities, and the dual roles influence for recommendation.

Second, *FSDR* always beats *FST*. This leads to the conclusion that incorporating dual roles influence to ranking scores is beneficial and can improve accuracy by introducing more valuable social influence information. *BPRDR* improves *SBPR* on all evaluation metrics on all three datasets. This demonstrates the advantage of injecting dual roles influence into item ranking via assumed pairwise preferences. We can thus see that the assumption that combines both trusters and trustees influence is indeed more effective than that of single role influence assumed in *SBPR*.

Third, FS-models (*FSDR*, *FISM*, *FST*, and *FSRand*) generally perform better than BPR-models (*SBPR* and *BPRDR*), proving their effectiveness for item recommendation. In particular, the BPR-models (*SBPR* and *BPRDR*) that combine both user-item and user-user trust information are not able to perform better than *FISM* that just utilizes user-item information. We attribute it to the fact that FS- strategy is more

TABLE 5. The performance comparison results on three datasets using Precision.

Datasets	P@N	PopRec	SBPR	BPRDR	FISM	FST	FSRand	FSDR
Epinions	P@5	**0.11677**	0.026	0.02734	0.11237	0.11404	0.1095	**0.12052**
$(\times 10^{-1})$	P@10	0.09178	0.02459	0.02409	0.08908	**0.09202**	0.0871	**0.09512**
Ciao	P@5	**0.26677**	0.10839	0.11122	0.25711	0.25984	0.233	**0.27021**
$(\times 10^{-1})$	P@10	**0.21468**	0.08971	0.0902	0.21026	0.21306	0.2106	**0.21636**
FilmTrust	P@5	**0.4163**	0.4034	0.4088	0.4156	**0.4163**	0.4128	**0.4185**
	P@10	**0.3502**	0.3441	0.3452	0.3486	0.3500	0.3463	**0.3518**

TABLE 6. The performance comparison results on three data sets using F1 score.

Datasets	F1@N	PopRec	SBPR	BPRDR	FISM	FST	FSRand	FSDR
Epinions	F1@5	0.12949	0.02696	0.03381	0.12744	**0.12964**	0.12246	**0.13510**
$(\times 10^{-1})$	F1@10	0.13058	0.03381	0.03567	0.12757	**0.13262**	0.12542	**0.13564**
Ciao	F1@5	**0.24268**	0.08072	0.07890	0.23462	0.24040	0.21753	**0.24581**
$(\times 10^{-1})$	F1@10	**0.26735**	0.09633	0.09584	0.26174	0.26659	0.25417	**0.26997**
FilmTrust	F1@5	**0.40773**	0.39482	0.39881	0.40687	0.40621	0.40102	**0.40977**
	F1@10	**0.45105**	0.44211	0.44314	0.44927	0.45076	0.44541	**0.45215**

sophisticated and beneficial than simply assumed pairwise comparisons.

Fourth, *FSRand* performs worst amongst all other FS-models. It indicates that involving the influence of random users instead of followers and followees pulls the recommendation performance down. This also verifies our idea of incorporating dual role influence into *FST*.

Overall, dual roles influence is noted to impose benefits on item recommendation. Although the relative improvements are small, it may account to the fact that parameters are not thoroughly adjusted and thus leave space for further improvements.

VIII. CONCLUSION AND FUTURE WORK

We exploit dual roles influence to boosting the quality of Top-K recommendation in this work. To be concrete, we first study three real-word datasets and find that a user tends to select items by their trusters/trustees than by randomly users. Moreover, the more her trusters/trustees selected the item, the higher probability that the active user would choose the same item. Particularly, we also find that the influence of trusters (in item of ranking) may be comparable with that of trustees, which is totally neglected by existing item ranking researches. Based on the observations, we then develop two different types of MF models, namely *BPRDR* and *FSDR*, for item ranking. The two methods adopt different ranking methods and loss functions. *BPRDR* incorporates dual roles influence into BPR framework where the influence is depicted by assumed ranking comparisons. *FSDR* enhances existing FS-models with dual roles influence where the influence is regarded as the contribution terms to computing ranking scores. Compared to *BPRDR*, *FSDR* is a more sophisticated model since it considers user/item similarities factors either. More importantly, *FSDR* qualifies the ranking process with ranking scores instead of fuzz comparison, and thus may generate higher recommendation accuracy.

We evaluate the proposed *FSDR* and *BPRDR* models by comparing them with five representative methods includes conventional ones such as *PopRec*, *FISM*, and new ones proposed very recently enhanced by user-user trust information, such as *FST*, *SBPR*. Experimental results suggest that the *FSDR* outperforms all other competitors in terms of Precision and F1 Score. Although *BPRDR* purely performs better than *SBPR*, we can also observe the effectiveness of dual roles influence compared to single role influence. In general, our experiments augment the fact that integrating dual roles influences dose improve the quality of MF item recommendation. We also believe that the performance could be further improved by means of its integrating schemes.

We still have plenty of tasks to perform in the future. In this paper, we only evaluate users between directly connected trusters and trustees. We can also further analyze the influence between users who are implicitly connected. In addition, we would like to exploit other relationships among users, such as distrust, to incorporate these distinct characteristics for better recommendation.

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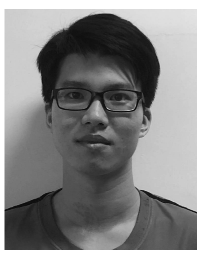
KE XU was born in Changning, Hunan, China in 1982. She received the B.S. degree in computer science and technology from Hunan Normal University, Changsha, China, in 2004, and the M.S. degree in communication engineering and information system from Central South University, Changsha, in 2007. She is currently pursuing the Ph.D. degree in computer application with the South China University of Technology, Guangzhou, China.

In 2011, she was a Visiting Scholar with the IBM China Development Laboratory, Beijing, China. She is currently a Lecturer with the IBM Mainframe System and Education Center, South China University of Technology. Her research interest includes information retrieval, recommendation systems, and mainframe systems. She is the author of two books and over 10 papers, such as the KBS, WI, and DASFAA Workshops.

Ms. Xu's awards include the CSC-IBM Chinese Excellent Teacher Award, the Best Mentor Award of the IBM Blockchain on Linux One Chinese University Student Hackathon, and the Best Mentor Award of the IBM Mainframe Technology and Application Chinese University Student Competition.



YANGJUN XU was born in Maoming, Guangdong, China, in 1996. He is currently pursuing the B.S. degree in computer application with the South China University of Technology, Guangzhou, China. His research interest includes information retrieval and recommendation systems.

Dr. Xu's awards include the Third Place (Second Prize) of the 2017 CCF Big Data and Computational Intelligence Contest (joint captain), the First prize for the second Intellectual Chinese Cup Artificial Intelligence-Based Molecular Screening in 2018 (1/1057), the Second Prize of the 6th Teddy Cup Data Mining Challenge in the 2018 Teddy Cup, the NLP algorithm contest on the df platform in 2018, the Cloud Shift Cup, and the 33rd place in the competition with 1186 teams from across the country.

HUAQING MIN was born in Nanxian, Hunan, China, in 1955. He received the Ph.D. degree in computer software and theory from the Huazhong University of Science and Technology, Wuhan, China, in 1998. He is currently a Professor with the School of Software Engineering, South China University of Technology, Guangzhou, China. His current research interests are focuses on robotics, intelligent software, and automated systems. He also serves as a committee member of the RoboCup in the China Chapter, and makes active contributions to the robot soccer community.

YI CAI (M'15) was born in Beihai, Guangxi, China, in 1980. He received the B.S. degree in polymer materials from Sichuan University, Chengdu, China, in 2003, and the M.S. and Ph.D. degrees in computer science from The Chinese University of Hong Kong, Hong Kong, in 2005 and 2009, respectively.

He was a Visiting Scholar with the KEG of Tsinghua University, Nanyang Technological University. From 2009 to 2011, he held a post-doctoral position with the City University of Hong Kong, Hong Kong. He is currently a Professor with the School of Software Engineering, South China University of Technology, Guangzhou, China. His research interests are recommendation system, personalized search, semantic Web, and data mining.

He published 90 papers, including CIKM, ER, WI, WISE, ICTAI, and JCST, and rw books. He reviewed papers from conferences and journals related to information retrieval, semantic web, recommender system, data mining and database, including TKDE, TOIT, WWWJ, JCST, CIKM and ER. He is a program committee member of conferences, including ICWE, WAIM, ICEBE, and NDBC.