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Leveraging Distrust Relations to Improve Bayesian Personalized Ranking

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Abstract: Distrust based recommender systems have drawn much more attention and became widely acceptable in recent years. Previous works have investigated using trust information to establish better models for rating prediction, but there is a lack of methods using distrust relations to derive more accurate ranking-based models. In this article, we develop a novel model, named TNDBPR (Trust Neutral Distrust Bayesian Personalized Ranking), which simultaneously leverages trust, distrust, and neutral relations for item ranking. The experimental results on Epinions dataset suggest that TNDBPR by leveraging trust and distrust relations can substantially increase various performance evaluations including $F1$ score, AUC, $Precision$, $Recall$, and $NDCG$.

Keywords: distrust relations; trust relations; Bayesian personalized ranking

1. Introduction

Recommendation tasks have been divided into two types: rating prediction and item ranking. In reality, item ranking is more important since explicit ratings may not always be available [1,2]. “Social relations” is a vital source of information which informs us about users’ preferences. In the Epinions (www.epinions.com) dataset, the users’ social relations include “trust relations” that user pairs with positive ratings, “distrust relations” that user pairs with negative ratings, and “neutral relations” that user pairs without any ratings. That is, social relations not only refer to trust relations as usual but also include distrust relations. In this regard, if we would like to recommend items to a user, we should understand what she prefers as well as what she dislikes.

Many works have been proposed to leverage social relations for rating prediction tasks [3–6], For example, Bharadwaj et al. [7] proposed a collaborative filtering model based on user trust computation. Forsati et al. [8] proposed a matrix factorization-based recommendation model by considering distrust as reversing the deviation of latent features. However, few works have focused on item ranking tasks with trust information. For example, Jamali and Ester [9] proposed the Trust-Walker method, which is possibly the first trust-based ranking method by adapting a nearest neighborhood approach to item recommendation. Zhao et al. [10] distinguished the active users’ preference from the one she trusted, which is termed as SBPR. Unlike existing ranking models, which only consider the user’s trust and neutral relations, we also incorporate distrust relations.

In this work, we try to dig out more the user’s preferences reflected in the user’s social relations for certain items. Specifically, we propose a Bayesian Personalized Ranking model, called TNDBPR (Trust Neutral Distrust Bayesian Personalized Ranking), which takes full consideration about users’ social relations. TNDBPR incorporates users’ trust, neutral, and distrust relations to better predict users’ preference and disgust, thereby boosting the performance of item recommendation. Our main contributions are as follows:

- We propose a TNDBPR method for item recommendation tasks. To the best of our knowledge, it is the first work incorporating distrust relations to evaluate users' item ranking preference.
- We conduct experiments to compare the proposed TNDBPR with its variations and four other representative models on Epinions dataset. The results verify that distrust relations has a significant impact on improving item recommendation results.

Main contents of this article are as follows. Related work is shown in Section 2. Section 3 presents the datasets in our research, defines the problem and presents the result of some observations related to the problem. The proposed models and algorithms are established in Section 4. Section 5 gives the results and verifies the contribution of the TNDBPR algorithm to ranking recommendation problems. Section 6 summarizes the whole work and puts forward the future ideas.

2. Related Work

Many previous works have been performed on ranking recommender systems incorporating social trust relations. Shen et al. [11] proposed the joint model of individual and social potential factors recommended by society. Ye et al. [12] proposed a quantitative generative model to capture social impact of friends and exploit social impact to dig the users' preference. Du et al. [13] improved ranking recommendation performance by putting social normalization terms in the BPR framework. Pan and Chen [14] loosened the hypothesis and proposed a Group Bayesian Personalized Ranking (GBPR) method. In [15], a similar assumption is made for user connection, and multi relational BPR (MR-BPR) is proposed for item recommendation. Guo et al. [16] focused on how to use the geographical features and access frequency to improve POI recommendation, and proposed a neighborhood perception recommendation approach from the point of view of NBPR. De Meo et al. [17] combined skills, interactions, and trust relationships to manage the class formation in e-Learning. Considering that people often trust different subsets of friends according to different domains, Liu et al. [18] proposed a novel TruCom model for this multicategory item recommendation issue. TruCom organizes a domain-specific trust network and incorporates the direct and indirect trust information into a matrix factorization model for better rating prediction. Zhang et al. [19] employed matrix factorization techniques to fuse direct trust, indirect trust, trust propagation, and user similarity in a coherent model, namely CETrust for rating prediction. In the context of a Social Internetworking System (SIS), De Meo et al. [20] introduced a trust-based model to represent and handle trust and reputation. Fotia et al. [21] used two different types of trust measures, namely the reliability and the local reputation, to better form cohesive groups. Albanese et al. [22] introduced a multimedia recommendation model for computing customized recommendations by originally combining the inherent characteristics of multimedia objects, past behavior of individual users, and overall behavior of the entire users' community.

Besides, many studies have been tried to incorporate distrust relations into rating recommendation. Ma et al. [23] firstly suggested that the introduction of distrust of information can help to make recommendations. Victor et al. [24] introduced a distrust-enhanced recommendation algorithm which has its roots in TidalTrust. Note that it is a memory-based method. Forsati et al. [8] proposed a MF based social rating network recommendation model, which is appropriate to trust and distrust. It aims to enhance the recommendation quality, reduce data sparsity and cold start user problems. However, the algorithm ignores the neutral users who have none relation with others. Therefore, Forsati et al. [25] proposed a collaborative social ranking model, dubbed PushTrust to grade the userrs latent features based on the simultaneously leverage of trust, distrust, and neutral relations. Ghaznavi et al. [26] considered positive, zero and negative similarities, as well as trust, distrust and zero trust information on the precision of recommendations. It demonstrates that distrust and negative similarity data boosts rating prediction. Fei et al. [27] combined existing trust/distrust information and inferred trust/distrust information to improve collaborative filtering algorithm. The improved cosine similarity is used for measuring the degree of trust and distrust. Mahtar et al. [28] provided five views of trusted users, including cold start user, heavy user, opinionated user, etc. They conducted experiments on two models [1,7] with different types of view and demonstrates the effectiveness on MAE and rating coverage. Chug et al. [29] proposed trust-distrust enhanced recommendations method based on a novel similarity measurement considering ratings and trust values. For more efficient neighbors, it has filtered out distrusted user from the neighborhood set. It also investigates the use of trust-distrust based propagation in resolving the new user and sparsity problems.

3. Definitions and Data Description

3.1. Definitions

Concepts and definitions we use are introduced in this section. We assume that there is a set of users U and a set of items I, where $|U| = m$ and $|I| = n$. We define a trust network $G = (U, E)$, where $(u, v) \in E$ suggests u and v established trust relations. We define a distrust network $G' = (U, E')$, where $(u, v') \in E'$ suggests u and v' established distrust relations. Some important terminologies are defined as follows:

Observed items / Unobserved items: Observed items $O_u \in I$ are the items that user u provides ratings while unobserved items $\bar{O}_u \in I$ are the remaining items.

Positive feedback: Positive feedback is the set of items that user u have rated, which is denoted as O_u.

$$P_u = \left(\bigcup_{i \in O_u} i \right) \tag{1}$$

Trust feedback: Trust feedback is the set of items, which is denoted as $O_v \bigcap \bar{O}_u$. These items could be those user u did not choose but at least one of her trusted users selected.

$$T_u = \left(\bigcup_{k \in O_v} k \right) - P_u \tag{2}$$

Distrust feedback: Distrust feedback is the set of items that user u and her trusted users did not choose but at least one of her distrusted users selected, which is defined as $O_{v'} \bigcap \bar{O}_u \bigcap \bar{O}_v$.

$$D_u = \left(\bigcup_{z \in O_{v'}} z \right) - P_u - T_u \tag{3}$$

Neutral feedback: Neutral feedback is defined as the set of items, which is denoted by $\bar{O}_u \bigcap \bar{O}_v \bigcap \bar{O}_{v'}$. These items could be those that neither user u nor any of her trusted or distrusted users chose.

$$N_u = \left(\bigcup_{j \in I} j \right) - P_u - T_u - D_u \tag{4}$$

It shows that $P_u \bigcap T_u \bigcap D_u \bigcap N_u = \emptyset$ and $P_u \bigcup T_u \bigcup D_u \bigcup N_u$ contains the total item set.

We then introduce two social coefficients: a trust coefficient t_{uk} for $(u, k) \in T_u$ to estimate the preference range of positive and trust feedback, and a distrust coefficient d_{uz} for $(u, z) \in D_u$ estimates the preference distance of neutral and distrust feedback. In more detail:

Trust coefficient: Trust coefficient t_{uk} represents the attitude from u's trust relations to a particular item k. We define that t_{uk} calculates how many trusted people of user u have selected item k. Larger t_{uk}s indicate that more of u's trusted users like this item, which makes u show more preferences on this item.

Distrust coefficient: Distrust coefficient d_{uz} represents the attitude from u's distrust relations to a particular item z. We define that d_{uz} calculates how many distrust people of user u have selected item

z. A large value of the distrust coefficient suggests that u's distrusted users have strong preferences for item z, so we may assume that user u does not like the item.

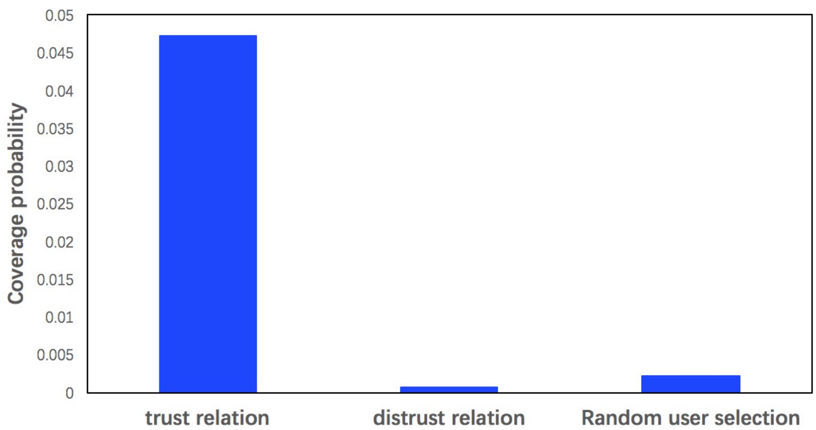
3.2. Data Description

Epinions dataset originates from a popular online consumer reviews website (www.epinions.com). It provides "distrust network" which is not considered in other datasets such as Ciao, Flim Trust, etc. In Epinions dataset, users mark their trust user as "1" and distrust users as "-1". To simplify our work, we collected 103,286 users and 415,877 items from the original dataset. The dataset contains trust and distrust relations. In addition, we removed all negative ratings of less than 4 stars, as suggested by Zhao et al. [10], and eventually obtained 1,255,757 positive feedback and 297,781 trust and distrust relations (See Table 1).

Figure 1a shows the item possibility which preferred by the user and her distrusted users. To make our analysis more convincing, we make a comparisons in three different settings: items preferred by the user and her trusted users, an item preferred by the user and her distrusted users, and items preferred by the user and random users. In all cases, we can clearly see that the second possibility is the lowest. It indicates that a user would prefer items that selected by random users rather than by her distrusted users. Figure 1b indicates the probability of preferring an item increases as the number of trusted users who have prefer it increases, and the probability of a user not preferring an item increases as more and more distrusted users prefer the item.

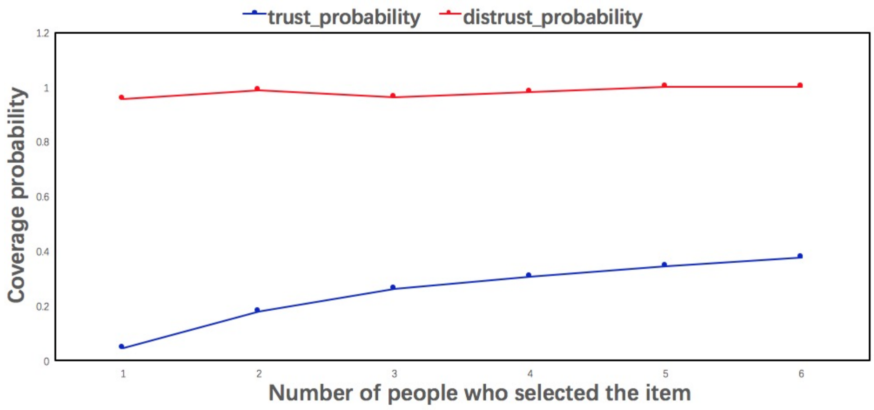
Table 1. Statistics of the Epinions dataset.

Statistics	Quantity
Number of Users	103,286
Number of Item	415,877
Number of Observed feedback	1,255,757
Number of Social relations	297,781
Number of Average Positive feedback	12
Number of Average trust	6
Number of Average distrust	3



(**a**)

Figure 1. *Cont.*



(**b**)

Figure 1. Preference Analysis: (**a**) coverage probability analysis; and (**b**) influence of social relations on selection probability.

4. The Proposed Method

Our model assumptions about positive feedback, trust feedback, distrust feedback, and neutral feedback are investigated in detail in this section, and the proposed TNDBPR model is discussed thoroughly. Unlike existing ranking models, we leverage distrust feedback from users' social networks.

4.1. Model Assumptions

Irwin King et al. [10] described their hypothesis based on the comparison of the users' two pairwise preferences:

$$x_{ui} \succeq x_{uk}, x_{uk} \succeq x_{uj}, i \in P_u, k \in T_u, j \in N_u, \tag{5}$$

where x_{ui}, x_{uk} and x_{uj} represent a user u's preference on positive feedback i, trust feedback k, and neutral feedback j, respectively. $x_{uk} \succeq x_{uj}$ indicates that the user prefers item k to item j.

In our work, we extend the two pairwise preferences presented in [10] resulting in three pairwise preferences assumptions. They are expressed in Assumptions 1 and 2, respectively:

Assumption 1. *A user would prefer positive feedback to trust feedback, prefer trust feedback to neutral feedback, and prefer neutral feedback to distrust feedback.*

$$x_{ui} \succeq x_{uk}, x_{uk} \succeq x_{uj}, x_{uj} \succeq x_{uz}, i \in P_u, k \in T_u, j \in N_u, z \in D_u, \tag{6}$$

where x_{ui}, x_{uk}, x_{uj} and x_{uz} represent the preference on positive feedback i, trust feedback k, neutral feedback j, and distrust feedback z, respectively. The "unobserved" feedback consists of trust feedback, neutral feedback and distrust feedback. Obviously, the assumption we propose is more reasonable and comprehensive than the assumption in Equation (5) since it fully considered the impact of trust, distrust, and positive feedback on user preferences.

Alternatively, considering that users' distrust feedback may not be worse than that of the neutral feedback, we also take the following assumption and verify it in the experiments.

Assumption 2. *A user would prefer positive feedback to trust feedback, prefer trust feedback to neutral feedback, and prefer trust feedback to distrust feedback.*

$$x_{ui} \succeq x_{uk}, x_{uk} \succeq x_{uj}, x_{uk} \succeq x_{uz}, i \in P_u, k \in T_u, j \in N_u, z \in D_u, \tag{7}$$

The main difference between Assumptions 1 and 2 is the preference order of neutral feedback and distrust feedback. However, their model structure and learning method are the same. Note that we focus on discuss formal assumption and will experimentally compare them in Section 5.

4.2. Model Formulation

We take Equation (6) as the task to maximize the value of AUC. Therefore, the optimization criteria for each user u are stated as follow:

$$\begin{aligned}&\prod_{i\in PT_u,k\in PT_u} P(x_{ui}\succeq x_{uk})^{\delta(u,i,k)}[1-P(x_{ui}\succeq x_{uk})]^{1-\delta(u,i,k)}\\&\prod_{k\in TN_u,j\in TN_u} P(x_{uk}\succeq x_{uj})^{\xi(u,k,j)}[1-P(x_{uk}\succeq x_{uj})]^{1-\xi(u,k,j)}\\&\prod_{j\in ND_u,z\in ND_u} P(x_{uj}\succeq x_{uz})^{\omega(u,j,z)}[1-P(x_{uj}\succeq x_{uz})]^{1-\omega(u,j,z)},\end{aligned} \tag{8}$$

where $PT_u = P_u \bigcup T_u$, $TN_u = T_u \bigcup N_u$, $ND_u = N_u \bigcup D_u$. $\delta\,(u,i,k)$, $\xi\,(u,k,j)$ and $\omega\,(u,j,z)$ are indicator functions. They are equal to 1 if $i \in P_u$, $k \in T_u$, $j \in N_u$ and $z \in D_n$, and 0 otherwise. Equation (8) expresses the major hypothesis for specific user that the ranking of preference from large to small is positive feedback, trust feedback, neutral feedback and distrust feedback, successively.

The formula above can be changed to Equation (9) for maximizing AUC value due to the integrity and antisymmetry of a pairwise ordering scheme discussed in [30].

$$\frac{\sum_{i\in Pu,k\in Tu} P\left(x_{ui}\succeq x_{uk}\right)}{|P_u|\,|T_u|}+\frac{\sum_{k\in Tu,j\in Nu} P\left(x_{uk}\succeq x_{uj}\right)}{|T_u|\,|N_u|}+\frac{\sum_{j\in Nu,z\in Du} P\left(x_{uj}\succeq x_{uz}\right)}{|N_u|\,|D_u|} \tag{9}$$

When optimizing AUC, we use a sigmoid function $\sigma\,(x)$ to approximate the function $P\,(\cdot)$. Therefore, we maximize the objective function as follow.

$$\begin{aligned}\sum_u[\sum_{i\in P_u}\sum_{k\in T_u} ln\left(\sigma\left(\frac{x_{ui}-x_{uk}}{1+t_{uk}}\right)\right)+\sum_{k\in T_u}\sum_{j\in N_u} ln\left(\sigma\left(x_{uk}-x_{uj}\right)\right)+\\ \sum_{j\in N_u}\sum_{z\in D_u} ln\left(\sigma((1+d_{uz})(x_{uj}-x_{uz}))\right)]-regularization\end{aligned} \tag{10}$$

In Equation (10), a regularization term is used to prevent overfitting. Matrix factorization is used to build the preference function model, $x_{ui} = P_u^T Q_i + b_i$, $x_{uk} = P_u^T Q_k + b_k$, $x_{uj} = P_u^T Q_j + b_j$, and $x_{uz} = P_u^T Q_z + b_z$. Here, $P \in R^{d\times M}, Q \in R^{d\times N}, b \in R^N$, and d is the number of latent factors. The coefficients t_{uk} and d_{uz} are used to control the achievements of sampling training to the objective function. In more detail, d_{uz} calculates how many distrusted users of user u have selected item z. The more user's distrusted users choose the item, the larger the d_{uz} will be, and thus the more likely that u will not choose this item. t_{uk} calculates how many trusted users of user u have selected item k. The more user's trusted users choose the item, the larger the t_{uk} will be, and thus the more likely that the user will choose this item.

4.3. Model Learning and Complexity

We optimize the objective function Equation (10) with stochastic gradient descent (SGD). Algorithm 1 describes the procedure and gradient descent rules of TNDBPR in detail. Particularly, all the variables are initialized with random small values in (0, 0.1) (Line 1). For each iteration (Lines 3–23), we randomly select (positive, trust), (trust, neutral), and (neutral, distrust) feedback pairs from P_u, T_u, and N_u, D_u to test the model. The variables b, P, and Q are renewed based on SGD rules (Lines 11–22). The process is repeated until the loss value converges reach the maximum number of iterations. Finally, all learning variable quantities return to output state (Line 25). The calculation time of TNDBPR is mainly divided into two stages: (1) Model training for computing gradients and updating rules (Line 5–27, Algorithm 1). The whole complexity in Algorithm 1 is O($f \times l$) where f and l are the number of iterations and training samples, respectively. We set the number of training samples l to $100 \times m$. (2) In model testing process, we calculate ranking scores for candidate items. The complexity is O($m' \times n'$), where m' is the number of testing users and n' is the number of testing items.

Algorithm 1 The learning algorithm of *TNDBPR* model.

input: $\mathbf{U}, \mathbf{I}, \lambda, \eta, d$ and a social network $G = (U, E)$

1: Initialize $\mathbf{P}, \mathbf{Q}, \mathbf{b}$ with random gaussian $\sim$ (0,1);
2: **for** each user do **do**
3: split n items into four parts: $\mathcal{P}_u$, $\mathcal{T}_u$, $\mathcal{N}_u$ and $\mathcal{D}_u$;
4: **end for**
5: **while loss** not converged **do**
6: **for** each # training sample **do**
7: sample a user u from $\mathcal{U}$
8: sample an item i from $\mathcal{P}_u$, an item k from $\mathcal{T}_u$,
9: an item j from $\mathcal{N}_u$, and an item z from $\mathcal{D}_u$,
10: compute t_{uk} and d_{uz}
11: $a_{uik} \leftarrow \sigma(-\frac{(x_{ui} - x_{uk})}{1+t_{uk}})$
12: $a_{ukj} \leftarrow \sigma(-(x_{uk} - x_{uj}))$
13: $a_{ujz} \leftarrow \sigma(-(x_{uj} - x_{uz})(1 + d_{uz}))$
14: $b_i \leftarrow b_i + \eta(\frac{a_{uik}}{1+t_{uk}} - \lambda b_i)$
15: $b_k \leftarrow b_k + \eta(\frac{-a_{uik}}{1+t_{uk}} + a_{ukj} - \lambda b_k)$
16: $b_j \leftarrow b_j + \eta(-a_{ukj} + a_{ujz}(1 + d_{uz}) - \lambda b_j)$
17: $b_z \leftarrow b_z + \eta((-a_{ujz})(1 + d_{uz}) - \lambda b_z)$
18: $\mathbf{p'}_u \leftarrow a_{uik} \frac{(\mathbf{q}_i - \mathbf{q}_k)}{1+t_{uk}} + a_{ukj}(\mathbf{q}_k - \mathbf{q}_j) + a_{ujz}(\mathbf{q}_j - \mathbf{q}_z)(1 + d_{uz})$
19: $\mathbf{q'}_k \leftarrow a_{uik}(\frac{-\mathbf{p}_u}{1+t_{uk}}) + a_{ukj}\mathbf{p}_u$
20: $\mathbf{q'}_j \leftarrow (-a_{ukj})\mathbf{p}_u + a_{ujz}\mathbf{p}_u(1 + d_{uz})$
21: $\mathbf{p}_u \leftarrow \mathbf{p}_u + \eta(\mathbf{p'}_u - \lambda \mathbf{p}_u)$
22: $\mathbf{q}_i \leftarrow \mathbf{q}_i + \eta(a_{uik}(\frac{\mathbf{p}_u}{1+t_{uk}}) - \lambda \mathbf{q}_i)$
23: $\mathbf{q}_k \leftarrow \mathbf{q}_k + \eta(\mathbf{q'}_k - \lambda \mathbf{q}_k)$
24: $\mathbf{q}_j \leftarrow \mathbf{q}_j + \eta(\mathbf{q'}_j - \lambda \mathbf{q}_j)$
25: $\mathbf{q}_z \leftarrow \mathbf{q}_z + \eta(a_{ujz}(-\mathbf{p}_u)(1 + d_{uz}) - \lambda \mathbf{q}_z)$
26: **end for**
27: **end while**
28: return $\mathbf{P}, \mathbf{Q}, \mathbf{b}$

5. Experiments

5.1. Experiment Settings

We conducted a serial of experiments on the Epinions dataset to verify the effectiveness of our proposed method. The five-fold cross validation method was used. That is, the dataset was split into five folds with one randomly used for test sets and others for training sets.

We adopted *F1@N* (F1 Score @N), *AUC*, *Precision@N*, *Recall@N*, and *NDCG@N* to evaluate the recommendation performance. Among these metrics, NDCG is used to evaluate ranked list as it gives higher reward for the top items in a recommended list. *NDCG@N* is defined as:

$$NDCG@N = \frac{DCG@N}{IDCG@N} \tag{11}$$

where $DCG@N = \sum_{i=1}^{N} \frac{2^{y_i}-1}{log_2(i+1)}$, y_i is 1 if recommended item at position i in the ranking is a hit item, and 0 otherwise. IDCG@N is the DCG@N of the sorted optimal ranked list.

We applied grid search to obtain the optimal regularization parameter λ. As can be seen in Figure 2, when the parameters λ was set to 0.1, the model TNDBPR achieves the best performance.

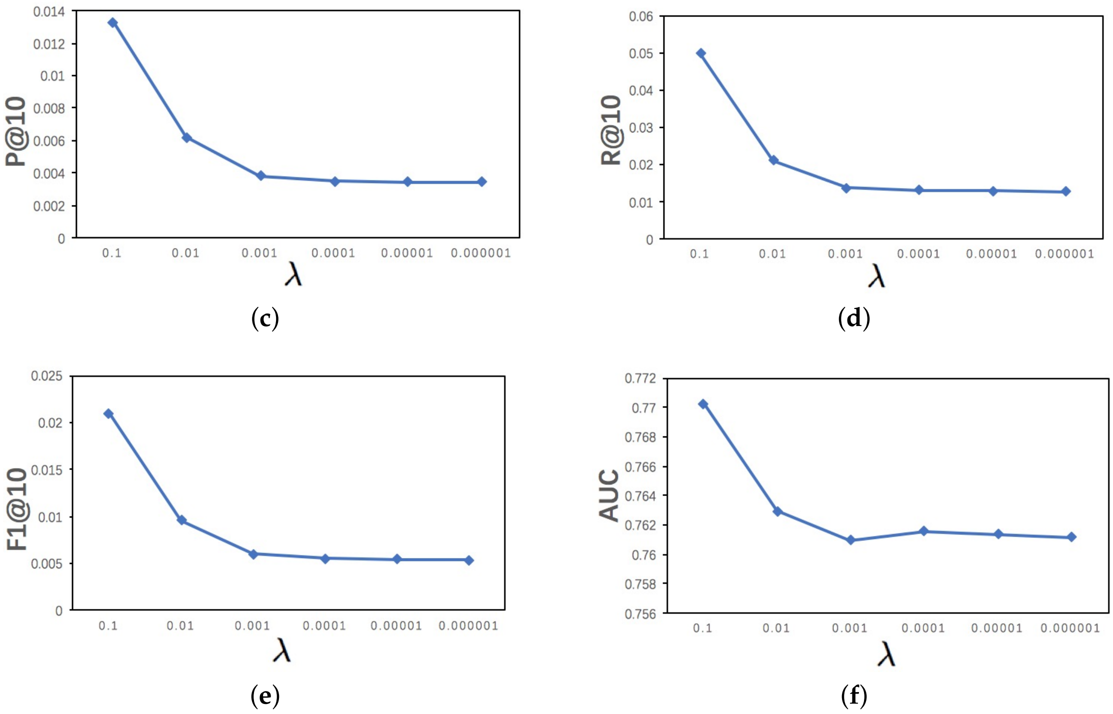


Figure 2. λ Analysis in Epinions DataSet: (**a**) effect on P@10 when varying the λ; (**b**) effect on R@10 when varying the λ; (**c**) effect on F1@10 when varying the λ; and (**d**) effect on *AUC* when varying the λ.

5.2. Comparison Methods

To verify the advantages of our method, we compared TNDBPR with the following recommendation approaches. Note that we only compared with ranking methods, because our target is item ranking not rating prediction.

RankSGD [31]: Based on the matrix decomposition model and the stochastic gradient descent optimizer, a SVD and AFM based on sorting objective function are proposed.

SBPR [10]: The model uses trust relations to effectively estimate users' rankings.

GBPR [14]: This work relaxes the assumption of BPR into a pair of preference hypotheses. The personal positive feedback model is smoothed by aggregating a set of user preferences, and increase the confidence of pairwise classification. Here, we fixed the number of users to 5.

MostPop: This approach provides a list of non-personalized ranked items based on the frequency the items are selected among all users.

TNDBPR-1 and TNDBPR-2 correspond to Assumptions 1 and 2 in Section 4, respectively. TNDBPR-3 corresponds to the case in which distrust coefficient d_{uz} is set to constant 1 in Assumption 1.

5.3. Recommendation Performance

The recommendation performance comparisons on various estimations are shown in Table 2. Specially, the number of latent factors are fixed as 10, and "Improve" represents the improvement of our algorithm TNDBPR-1 over SBPR. Table 2 shows that TNDBPR-1 is the best method in all of approaches including SBPR and GBPR. One possible reason is that SBPR and GBPR cannot simulate how distrust feedback directly affects users' preferences for items, especially when both the users' positive feedback and trust feedback are sparse. In this case, distrust feedback can have a great influence on the recommendation result. The better performance of TNDBPR-1 compared to TNDBPR-3 indicates that the distrust coefficient d_{uz} may have great influence of the model.

Table 2. Comparison results on Epinions dataset.

Method	P@10	R@10	AUC	F1@10	NDCG@10
Improve	14.30%	13.90%	1.10%	14.20%	2.50%
TNDBPR-1	0.01327	0.04978	0.77027	0.02096	0.14364
TNDBPR-2	0.01195	0.04500	0.763187	0.01888	0.141392
TNDBPR-3	0.01302	0.04863	0.76992	0.02054	0.142687
SBPR	0.01138	0.04286	0.76191	0.01798	0.14001
GBPR	0.00100	0.00539	0.74040	0.00169	0.10895
MostPop	0.00180	0.00803	0.70412	0.00294	0.10207
RankSGD	0.00979	0.02120	0.54189	0.01339	0.10583

In fact, the length of the list of recommended items (Top-N) for the user also has a great impact on users' experience. Therefore, we performed experiments on TNDBPR and other algorithms by changing N from 5 to 25. The results are presented in Figure 3. We can observe that the performance of our TNDBPR is always better than other methods as N increases. In addition, the performance gap between TNDBPR-1 and TNDBPR-3 on R@N, P@N and F1@N becomes larger and larger. When N changes from 5 to 25, TNDBPR-1 on R@N rises from 0.033 to 0.077, and SBPR on R@N rises from 0.027 to 0.065. When N changes from 5 to 25, TNDBPR-1 on P@N reduces from 0.017 to 0.009, and SBPR on P@N reduces from 0.014 to 0.007. When N changes from 5 to 25, TNDBPR-1 on F1@N reduces from 0.022 to 0.016, and SBPR on F1@N reduces from 0.019 to 0.012. Compared with the best method SBPR, TNDBPR-1 increases R@25 by 18.4%, P@25 by 28.5%, and F1@25 by 25%. The advantage of TNDBPR-1 is more obvious with the increase of N. It indicates the effectiveness of incorporating both distrust feedback and distrust coefficient d_{uz} in our model.

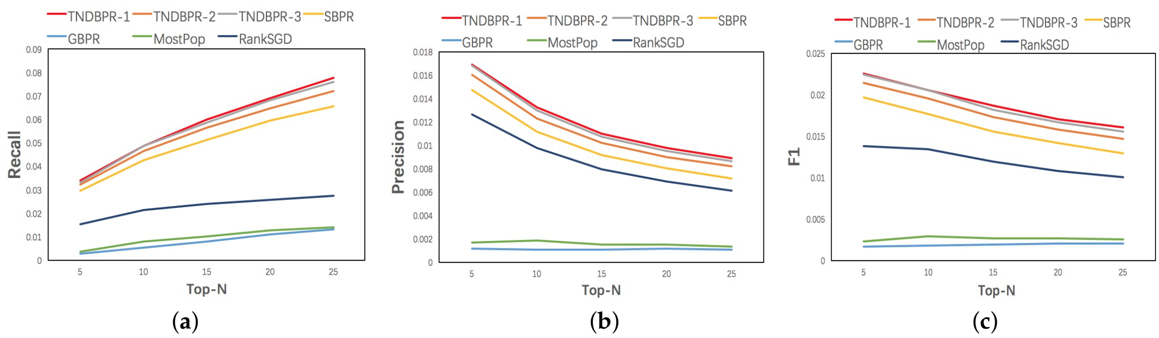


Figure 3. Top-N Analysis. (**a**) Recall; (**b**) Precision; (**c**) F1.

In Section 4, we have proposed two preference sorting assumptions based on neutral and distrust feedback and compare the performance of them. From the experimental results, we find that TNDBPR-1 always outperforms TNDBPR-2, which indicates that users prefer to choose neutral feedback rather than distrust feedback. These results are also consistent with the observational analysis in Section 3.

As suggested in Section 3, we removed all negative ratings which are less than 4 stars to collect positive feedback. However, whether dropping these low ratings will affect the performance of our model is still a question. Therefore, we experimentally explored this issue and present the results in Table 3. Note that every model with right superscript "-" (such as $TNDBPR\text{-}1^{-}$) represents its running in the dataset without dropping low ratings. We can observe that $TNDBPR\text{-}1^{-}$ and $SBPR^{-}$ perform worse than TNDBPR-1 and SBPR in the original dataset, respectively. It indicates that keeping low ratings confuses positive feedback collection, which could have an adverse impact on TNDBPR-1 and SBPR. In addition, the results also show that, without dropping low ratings, our proposed TNDBPR-1 still outputs best results in comparison with all the other methods.

Table 3. Comparison results on Epinions dataset without dropping low ratings.

Method	P@10	R@10	AUC	F1@10	NDCG@10
TNDBPR-1	0.01327	0.04978	0.77027	0.02076	0.14364
$TNDBPR\text{-}1^{-}$	0.01133	0.04178	0.76607	0.01782	0.01374
SBPR	0.01138	0.04286	0.76191	0.01798	0.14001
$SBPR^{-}$	0.00997	0.03442	0.75647	0.01546	0.13270
GBPR	0.00100	0.00539	0.74040	0.00169	0.10895
$GBPR^{-}$	0.00103	0.00566	0.72690	0.00172	0.10120
MostPop	0.00180	0.00803	0.70412	0.00294	0.10207
$MostPop^{-}$	0.00153	0.00741	0.70944	0.00253	0.10124
RankSGD	0.00979	0.02120	0.54189	0.01339	0.10583
$RankSGD^{-}$	0.00981	0.02193	0.50420	0.01355	0.11412

5.4. Feedback Analysis

Different from other ranking models, social feedback based on users' trust and distrust relations is defined in TNDBPR model. We perform some comparison experiments to explore the effect of various feedback, including only positive feedback, positive feedback added with distrust feedback, positive feedback added with trust feedback, and positive feedback added with both trust and distrust feedback. AUC results are presented in Figure 4. The best AUC result is obtained by simultaneously using trust and distrust relations of users to identify social feedback. This demonstrates that combining both trust and distrust feedback can maximize the performance of our proposed model.

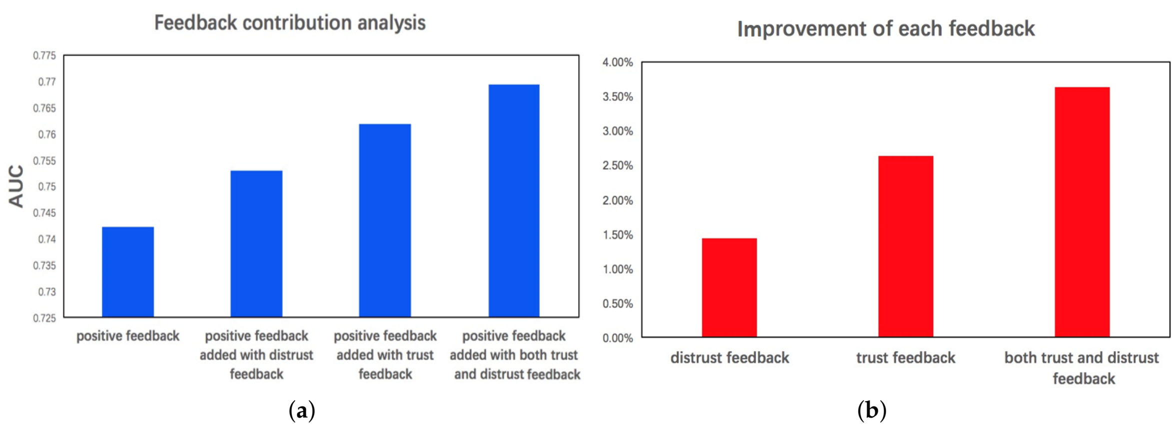


Figure 4. Feedback Analysis. (**a**) Feedback contribution analysis; (**b**) Improvement of each feedback.

5.5. Convergence Analysis

The convergence of the SBPR, TNDBPR-1 and TNDBPR-3 were analyzed to further explore the efficiency of the models. To make them comparable, we set their learning rate to 0.001. Figure 5 shows the results of the comparison. We can find that, at the same number of iterations, our model TNDBPR-1 is always better than SBPR and TNDBPR-3. Figure 5a–c shows the convergence trends based on P@10, R@10 and F1@10, respectively. The convergence trends of three models are basically the same, and there is a great improvement in 40–60 iterations. Figure 5d shows the convergence trend of *AUC*, which is relatively flat. Generally, the four evaluations all converge at 70–80 iterations. Therefore, by comparing convergence trend of TNDBPR-1 with SBPR and TNDBPR-3 respectively, we can conclude that the distrust feedback and distrust coefficient d_{uk} have little effect on convergence performance.

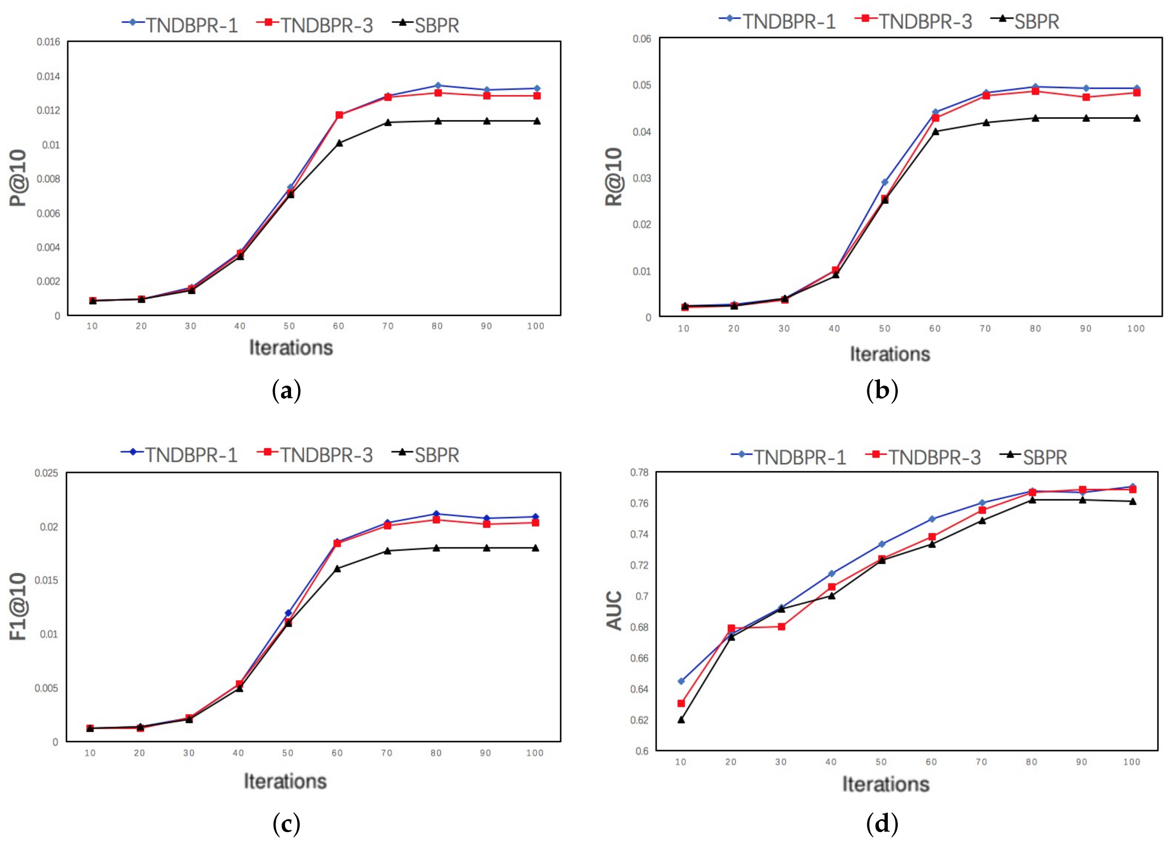


Figure 5. Convergence Analysis in Epinions DataSet: (**a**) effect on P@10 when varying the iteration; (**b**) effect on R@10 when varying the iteration; (**c**) effect on F1@10 when varying the iteration; and (**d**) effect on *AUC* when varying the iteration.

5.6. Run Time Comparisons

We executed all experiments on a server with 32 Genuine Intel(R) CPUs (2.6 GHz), 64 GB memory. The average running time of each model on Epinions dataset is shown in Table 4. We can observe that: (1) RankSGD takes the longest time to execute, whereas MostPop takes the shortest time; and (2) the three Bayesian personalized ranking models (TNDBPR, SBPR, and GBPR) spend almost the same running time cost. Comprehensively, TNDBPR is the optimal model since it achieves the highest recommendation accuracy.

Table 4. Average execution time on Epinions dataset.

	TNDBPR	**SBPR**	**GBPR**	**MostPop**	**RankSGD**
Average time	61 min	59 min	55 min	39 min	574 min

6. Conclusions and Future Work

In this article, we designed a Bayesian personalized ranking model, called TNDBPR. Different from existing methods, TNDBPR leverages both trust relations and distrust relations for Top-*N* item recommendation. It adopts three Bayesian pairwise ordering scheme among trust feedback, neutral feedback, and distrust feedback of users. In addition, a trust coefficient and a distrust coefficient are introduced to enhance our model. We evaluated the performance of the proposed TNDBPR for different numbers of Top-*N* recommendations. In addition, we examined the ranking performance comparing with other methods. Our experiments on Epinions dataset showed that TNDBPR is constantly superior over all the competitive methods in all evaluations and in all settings. These results suggested that simultaneously leveraging users' trust relations and distrust relations boosts item recommendation.

The limitation of this work include: (1) we focused on using users' direct trust and distrust relations, and neglected users' implicit trust and distrust relations for recommendation; (2) Only one dataset (Epinions) was used for the experiments. Therefore, we would like to extend TNDBPR as follows: (1) trying to use implicit trust and distrust relations in the model; and (2) preparing other datasets including both trust and distrust information and conduct extensive experiments to extrapolate our results.

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