Social Bayesian Personal Ranking for Missing Data in Implicit Feedback Recommendation

Yijia Zhang[1,2], Wanli Zuo[1,2], Zhenkun Shi[1,2(✉)], Lin Yue[3], and Shining Liang[1,2]

[1] College of Computer Science and Technology, Jilin University, Jilin 130000, China
shizkl4@mails.jlu.edu.cn
[2] Key Laboratory of Symbol Computation and Knowledge Engineering of Ministry of Education, Changchun 130012, China
[3] School of Computer Science and Information Technology, Northeast Normal University, Changchun 130117, China

Abstract. Recommendation systems estimate user's preference to suggest items that might be interesting for them. Recently, implicit feedback recommendation has been steadily receiving more attention because it can be collected on a larger scale with a much lower cost than explicit feedback. The typical methods for recommendation are not well-designed for implicit feedback recommendation. Some effective methods have been proposed to improve implicit feedback recommendation, but most of them suffer from the problems of data sparsity and usually ignore the missing data in implicit feedback. Recent studies illustrate that social information can help resolve these issues. Towards this end, we propose a joint factorization model under the BPR framework utilizing social information. Remarkable, the experimental results show that our method performs much better than the state-of-the-art approaches and is capable of solving implicit problems, which indicates the importance of incorporating social information in the recommendation process to address the poor prediction accuracy.

Keywords: Implicit feedback recommendation · BPR · Social information

1 Introduction

Recommendation system plays a vital role in daily lives. With the explosion of data, people are faced with an increasingly severe "Information Overload". Recommendation Systems are information filtering systems mitigating the information overload problem by filtering vital information according to user's preferences, interests, and observed behavior about items [1]. Recommender systems help to capture users' individualized preferences using a variety of information gathering techniques [2]. User information such as reviews, ratings, and relevant feedback provided by individuals on their initiative which directly reflect user's preference is called explicit feedback. While the information that can't directly express user's preference for things such as purchase history, search mode, and click method is called implicit feedback. Implicit feedback recommendations have received considerable attention in recent years owing to implicit feedback information makes the recommendation method based on it more adaptively.

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However, the implicit feedback is lack of negative feedback, where only positive feedback is available. Apart from the positive feedback, the remaining data is a mixture of real negative feedback and missing values. Therefore, it is hard to reliably infer which item a user did not like from implicit feedback, which makes it a big challenge for the recommendation. To deal with the problem of missing negative samples, several approaches have been proposed which can be roughly classified into two categories: sample-based learning and whole data-based learning. The previous samples negative feedback from the missing data, while the later treats all the missing data as negative. Therefore, sample-based approaches are more effective while whole-data based approaches provide higher coverage [3]. With the advent of online social networks, incorporating social relations into recommender systems has demonstrated potential to improve recommendation performance, and to help mitigate some public issues, such as data sparsity and cold start [4].

In this paper, we focus on implicit feedback. Moreover, we build our recommendation systems under the BPR framework utilizing social information to deal with missing data. To investigate this phenomenon, we conduct our experiment based on two well-known publicly available datasets (FilmTrust and Last.fm).

Our contributions are summarized as follows:

1. We present a novel model incorporating social relations information. In our model, we show that user relations can be considered as a specialization of implicit feedback issues and we construct the extended matrix to deal with missing data issues for implicit feedback recommendation.
2. We build our model by factorizing the interactions of user-item, user-extended item, and user-user jointly; we utilize social information as auxiliary knowledge to learn personalized ranking effectively.
3. We evaluate the proposed method on two real-world datasets, and empirical results show that the proposed model can improve recommendation performance compared to state-of-the-art methods.

The rest of this paper is organized as follows: Some related work is discussed in Sect. 2. The problem definition is presented in Sect. 3. We introduce our proposed model in Sect. 4. Our experiments are reported in Sect. 5. Finally, we conclude the paper and present some directions for future work.

2 Related Work

Social recommender systems have been widely studied, considered that a social recommender system improves the accuracy of the traditional recommendation system by taking social relations as additional inputs [5]. Koren et al. [6] proposed a model SVD++ which latent factor models and neighborhood models are merged smoothly. Ma et al. [7] design the SoRec approach by fusing the user-item rating matrix with user-user trust matrix. However, this model suffers from the problem of low interpretability. To model trust information more realistically, they further proposed RSTE, which interprets user's rating decision as the balance between user's taste and her trusted neighbors' favors [8]. Jamali et al. [9] proposed a random walk method (TrustWalker) which combines trust-based and item-based recommendation. Wang et al. [10] proposed a contextual social network model that takes into account both participants' personal characteristics and mutual relations. Yang et al. [11] proposed a hybrid method TrustMF that combines both a truster model and a trustee model from the perspectives of trusters and trustees, both the users who trust the active user and those who are trusted by the user will influence the user's ratings on unknown items. Yang et al. [12] proposed model FIP (Friendship-Interest Propaga). In the model, a probability model is established for the relationship between user-item and user-user respectively. The author assumes that the relationship between the user and the item is depended on the distribution of visual and potential features simultaneously. Pan et al. [13] proposed a new and improved assumption called group Bayesian personalized ranking (GBPR) and designed an efficient algorithm correspondingly. Ester et al. [14] proposed model to approximate tie strength and extended the popular Bayesian Personalized Ranking (BPR) model to incorporate the distinction between strong and weak ties.

It should be noted that Zhao et al. [15] proposed a model SBPR to improve personalized ranking for collaborative filtering, our work differs from it in three ways. Firstly, our model constructs an extended matrix to deal with the missing data for implicit feedback utilizing social information, instead of paying attention to the ranking of single user's preference. Second, except for the user-item interaction, we consider user-user interaction simultaneously. Third, we build a joint model to learn the personalized ranking more effectively.

3 Preliminares

In this section, we first introduce the implicit feedback recommendation, then formalize Bayesian-based ranking (BPR), which is designed for optimizing users' preferences over pair-wise samples.

3.1 Implicit Feedback

Let $U = [u_1, \cdots, u_M] \in \mathbb{R}^{D \times M}$ denotes the user latent vectors and $V = [v_1, \cdots, v_N] \in \mathbb{R}^{D \times N}$ denotes the item latent vectors, where D is the latent feature dimension, M is the number of users, N is the number of items. We define user-item interaction matrix $Y \in \mathbb{R}_{M \times N}$ as,

$$y_{ui} = \begin{cases} 1, & \text{if interaction (user u, item i) is observed;} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Here a value of 1 for y_{ui} indicates that there is an interaction between user u and item i; however, it does not mean u actually likes i. Similarly, a value of 0 does not necessarily mean u does not like i, it can be that the user is not aware of the item.

3.2 Bayesian Personalized Ranking (BPR)

Bayesian personalized ranking (BPR) model is widely known as the state-of-the-art method to tackle the recommendation with implicit feedback [16]. The main idea of it is to learn a personalized pairwise ranking function $p(>_u|\Theta)$ which generates a partial order [17]. The optimization objective for BPR is based on the maximum posterior estimator, and the ranking function is represented as,

$$\begin{aligned} p\,(v_i >_u v_j|\Theta) &= \sigma(r_{uij}) \\ &= \sigma(u^T v_i - u^T v_j) \end{aligned} \tag{2}$$

Where $\sigma = 1/(1 + e^{-x})$ is the logistic sigmoid function; Θ denotes all parameters (K-dimensional latent factors of users and items). $v_i >_u v_j$ indicates user prefers item i than item j. r is the estimate preference. In order to estimate the parameters, we minimize the following negative log-likelihood function as,

$$L_{bpr} = -\sum_{(u,v_i,v_j \in D)} \ln p\,(v_i >_u v_j|\Theta) + \lambda\|\Theta\|_F^2 \tag{3}$$

Where the subset D consists of training triples, λ is regularization parameter.

4 Our Proposed Approaches

In this section, we present our model for recommending with social relations information. Our first assumption is constructing the extended matrix utilizing social information. We then consider that user relations can be expressed as special implicit feedback issues. Lastly, we propose a novel joint model to learn user and item latent features effectively.

4.1 Social Information for Missing Data

Social information has been proved to have a good effect on implicit feedback issues. Due to stable and long-lasting social bindings, people tend to trust recommendations from their friends more than those from strangers [18]. Therefore, it is realistic to fill the missing data accounts for the preferences of user's friends.

In this paper, we first construct the extended user-item interaction matrix. We assume that if user's friends have interacted with the particular item that is not observed by the user, the user may prefer the item on a significant probability. Figure 1 illustrates how we construct the extended matrix using an original user-item matrix with social information to fill the missing data. As for missing data, we consider it as a weak positive instance if user's friends have observed it. We can see the extended matrix is less sparse than the original matrix and it can solve the cold start problems. The extended matrix $M \in \mathbb{R}_{M \times N}$ is define

$$m_{ui} = \begin{cases} 1, & \text{if interaction (user u, item i) is observed directly or indirectly;} \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

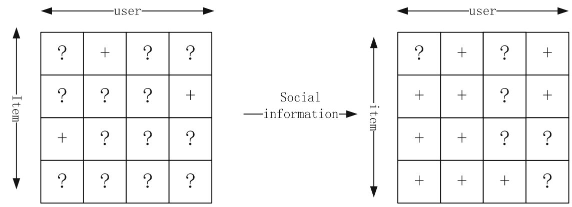

Fig. 1. The process for constructing extended matrix. On the left, the origin user-item matrix is shown, it is extended with social relation to the right matrix.

4.2 Implicit User Interactions

User-user interaction acts as an important role in implicit feedback recommendation systems. The interactions between users reflect the trust between users, and users with interactive relationships have greater similarity than others. We think user show preference for their friends, which is consistent with the user's preference for items that he or she interacts with. We define user-user interaction matrix $S \in \mathbb{R}_{M \times M}$ as,

$$S_{ui} = \begin{cases} 1, & \text{if interaction (user u, item i) is observed directly or indirectly;} \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Where a value of 1 for s_{uv} shows user u and v are known to each other, and they are friends. A value of 0 shows user u and user v have no interaction in the social network [19]. We represent user-user interaction as an inherent feedback problem by constructing the user-user interaction matrix. Moreover, our goal is to estimate the preference that user have for other users.

4.3 Joint Factorization with BPR

So far, we have developed two instantiations of our model. Figure 3 shows the main idea of the model. To make them together, we build our model to fuse the two instantiations under the BPR framework, so that they can mutually reinforce each other to learn the user latent features and item latent features. The objective function is devised as,

$$\begin{aligned} L = -\alpha \sum_{(u,i,j) \in D_y} \ln \sigma\left(\widehat{y}_{uij}\right) - (1-\alpha) \sum_{(u,i,j) \in D_m} \ln \sigma\left(\widehat{m}_{uij}\right) \\ -(1-\alpha) \sum_{(u,i,j) \in D_s} \ln \sigma\left(\widehat{s}_{uij}\right) + \lambda\left(\|U\|^2 + \|V\|^2\right) \end{aligned} \tag{6}$$

Where D_y, D_m and D_S are the training sets for the user-item entries in the matrix $Y \in \mathbb{R}_{M \times N}$, $M \in \mathbb{R}_{M \times N}$ and user-user entry in the matrix $S \in \mathbb{R}_{M \times M}$, λ is the regularization parameter, U and V are the matrices of user and item latent features, α is the parameter to balance the performance of the three parts of the function.

It is obvious that the objective function learns a personalized ranking for recommendation jointly, and our function aims to optimize the latent features with relations as (7), where $\widehat{r}_{ui}$, $\widehat{r}_{uj}$ and $\widehat{r}_{uk}$ indicates the estimate scores of the user to the positive item, weak positive item and negative item.

$$\begin{cases} \widehat{r}_{ui} > \widehat{r}_{uj} \\ \widehat{r}_{ui} > \widehat{r}_{uk} \end{cases} \begin{cases} \widehat{r}_{ui} > \widehat{r}_{uk} \\ \widehat{r}_{uj} > \widehat{r}_{uk} \end{cases} \tag{7}$$

In sum, the first term accounts for typical user-item interaction, the second item is based on extended matrix, and the third term pays attention to user-user interaction. Since we are dealing with a ranking problem, it makes sense to use a loss function that is optimized for ranking. It has been proved that BPR is suitable for the task of ranking in social networks because it is tailored to data where only positive feedback is available [20]. And [21, 22] provided empirical evidence that factorizing the relations jointly is at least as good as the sequential approach (Fig. 2).

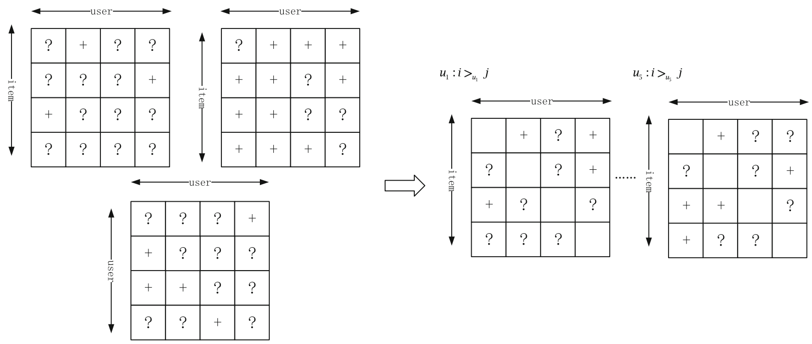

Fig. 2. The architecture of S-BPR. On the left side, there are three kinds of interactions which are user-item, user-extended item, user-user, our approach creates user-specific pairwise preferences $i >_u j$ between a pair of items. On the right side, plus (+) indicates that a user prefers item i over the item j; minus (–) indicates that he prefers j over i

4.4 Solutions

In our method, we inherit the SGD strategy to realize our designed framework. Specifically, the optimization procedure is conducted with respect to D_y, D_m and D_s. A training instance is randomly sampled at each iteration, and a gradient descent step for all related parameters regarding the loss of the training instance is performed. Algorithm 1 details the procedure of optimization. The derivative of the loss function presented in Eq. (6) is as:

$$\frac{\partial L_{S-BPR}\left(\hat{y}_{uij}\right)}{\partial \Theta} = \alpha \cdot \frac{-e^{-\hat{y}_{uij}}}{1 + e^{-\hat{y}_{uij}}} \cdot \frac{\partial \hat{y}_{uij}}{\partial \Theta} - \lambda_\Theta \cdot \Theta \tag{8}$$

$$\frac{\partial L_{S-BPR}\left(\hat{m}_{uij}\right)}{\partial \Theta} = (1-\alpha) \cdot \frac{-e^{-\hat{m}_{uij}}}{1+e^{-\hat{m}_{uij}}} \cdot \frac{\partial \hat{m}_{uij}}{\partial \Theta} - \lambda_{\Theta} \cdot \Theta \tag{9}$$

$$\frac{\partial L_{S-BPR}\left(\hat{s}_{uij}\right)}{\partial \Theta} = (1-\alpha) \cdot \frac{-e^{-\hat{s}_{uij}}}{1+e^{-\hat{s}_{uij}}} \cdot \frac{\partial \hat{s}_{uij}}{\partial \Theta} - \lambda_{\Theta} \cdot \Theta \tag{10}$$

The partial derivatives are:

$$\frac{\partial \hat{y}_{uij}}{\partial \Theta} = \begin{cases} v_{if} - v_{jf} & if\ \theta = u_f \\ u_f & if\ \theta = v_{if} \\ -u_f & if\ \theta = v_{jf} \\ 0 & else \end{cases} \tag{11}$$

$$\frac{\partial \hat{m}_{uij}}{\partial \Theta} = \begin{cases} v_{if} - v_{jf} & if\ \theta = u_f \\ u_f & if\ \theta = v_{if} \\ -u_f & if\ \theta = v_{jf} \\ 0 & else \end{cases} \tag{12}$$

$$\frac{\partial \hat{s}_{uij}}{\partial \Theta} = \begin{cases} u_{if} - u_{jf} & if\ \theta = u_f \\ u_f & if\ \theta = u_{if} \\ -u_f & if\ \theta = u_{jf} \\ 0 & else \end{cases} \tag{13}$$

Where f denotes the f_{th} latent features of the entry instance.

Algorithm 1 The optimization for S-BPR

1 Random initialize Θ;
2 Repeat
3 Repeat
4 Draw (u, v_i, v_j) from D_y :
5 $\Theta \leftarrow \Theta + \mu\left(\alpha \cdot \frac{e^{-\hat{y}_{uij}}}{1+e^{-\hat{y}_{uij}}} \cdot \frac{\partial \hat{y}_{uij}}{\partial \Theta} + \lambda_{\Theta}\Theta\right)$;
6 Until convergence
7 Repeat
6 Draw (u, v_i, v_j) from D_m :
7 $\Theta \leftarrow \Theta + \mu\left((1-\alpha) \cdot \frac{e^{-\hat{m}_{uij}}}{1+e^{-\hat{m}_{uij}}} \cdot \frac{\partial \hat{m}_{uij}}{\partial \Theta} + \lambda_{\Theta}\Theta\right)$;
8 Until convergence
9 Repeat
10 Draw (u, u_i, u_j) from D_s :
11 $\Theta \leftarrow \Theta + \mu\left((1-\alpha) \cdot \frac{e^{-\hat{s}_{uij}}}{1+e^{-\hat{s}_{uij}}} \cdot \frac{\partial \hat{s}_{uij}}{\partial \Theta} + \lambda_{\Theta}\Theta\right)$;
12 Until convergence
13 Until convergence or max-iteration has been reached;

5 Experiments

In this section, we conduct experiments on the two real-world datasets to demonstrate the effectiveness of the proposed method. We provide analysis of the experimental results. We also do some extensive experiments to compare the performance with different settings.

5.1 Datasets

We use two social network datasets to evaluate our models: FilmTrust and Last.fm. They are publicly accessible on the websites and used widely in the evaluation of previous trust-aware recommender systems. The statistics of four datasets are given in Table 1.

FilmTrust. This is a dataset crawled from the entire FilmTrust website in June 2011.

Last.fm.[1] This dataset contains social networking, tagging, and music artist listening information from a set of 2K users from Last.fm online music system.

Table 1. Statistics of the four statistics

Statistics	FilmTrust	Last.fm
# of users	1508	1892
# of items	2071	17632
# of ratings	35497	92834
Density	1.14%	0.27%
# of trusters	609	1892
# of trustees	732	1892
# of trusts	1853	25434
Density	0.42%	0.71%

5.2 Baselines

BPR. This is a sampling-based algorithm that optimizes the pair-wise ranking between observed instances and sampled negative instances.

MF. This a traditional method for recommendation.

STE. This a matrix factorization approach for the social network-based recommendation. Their method is a linear combination of basic matrix factorization approach and a social network-based approach.

[1] http://ir.ii.uam.es/hetrec2011.

MR-BPR. This method combines multi-relational matrix factorization models and BPR models based on the users' feedback on items and social relations simultaneously.

SBPR. This method improves personalized ranking for collaborative filtering using social connections based on BPR.

5.3 Performance Comparison and Analysis

In this paper, we choose three popular metrics for implicit feedback recommendation to evaluate the performance of different models: Precision@K, NDCG@K and AUC. For all the datasets, we randomly choose 80% of each user's ratings for training, leaving 20% of the dataset left for testing.

The optimal experimental settings for each method are determined either by our experiments or suggested by previous works. For our model, we randomly initialized model parameters with a Gaussian distribution (with a mean of 0 and standard deviation of 0.01), and we use stochastic gradient (SGD) to optimize the model. The latent feature dimension in our experiment is set as 4, the learning rate of 0.1, the regularization parameter of 0.01, the balance parameter is 0.5, the number of iteration is 30, and in order to increase the speed of optimizing, we use batch technologies where the batch size is set as 256, we conduct 256 instances at each time, the epoch number is calculated by the sum of the instances and batch size. We conduct top-10 recommendation on the FilmTrust and Last.fm dataset. As for each test instance, we choose 100 negative items randomly as negative samples.

The experimental results for top-10 recommendation are summarized in Table 2. From the result, we can see that: (1) Among the baseline methods our model performs best on both of datasets which is as expected because we use social information to fill the missing data so that we can learn the personalized ranking more effectively. (2) By utilizing social information, MR-BPR and SBPR perform better than BPR, STE performs better than MF, which shows the importance of social information for the recommendation. (3) The accuracy improvements on the two datasets are significant, especially in terms of AUC, our method performs much better than other methods. Although in terms of other metrics, our model improves less significant than SBPR, it still outperforms all the baselines in the top-10 recommendation. Thus, we can say it is effective for a recommendation in most cases.

Table 2. Performance comparison

		BPR	MF	STE	MR-BPR	SBPR	Our model
FilmTrust	AUC	0.8295	0.8220	0.8229	0.8251	0.8356	**0.8467**
	NDCG@10	0.3245	0.2786	0.3684	0.4204	0.4902	**0.5184**
	Precision@10	0.1548	0.1288	0.2682	0.2606	0.3492	**0.3897**
Last.fm	AUC	0.8778	0.8136	0.8090	0.8285	0.8792	**0.8832**
	NDCG@10	0.0291	0.0017	0.0227	0.0368	0.0387	**0.0558**
	Precision@10	0.0220	0.0030	0.0144	0.0334	0.0431	**0.0455**

To investigate the performance of our model on the different values of N, we compare these methods on three metrics where N = [10, 20, 50, 100], Figs. 3, 4, 5, 6, 7 and 8 illustrates the results by varying N values on the two datasets. In is easy to notice that the recommendation accuracy on the FilmTrust dataset is decreasing as N get lager, whereas it is increasing on the Last.fm dataset. Apparently, the impact of N on the Last. fm dataset is more significant than that on the FilmTrust dataset. Figures 3 and 4 illustrates our model performs better among all baselines in terms of AUC, which means our model has a good effect on personalized ranking, and it shows the values of AUC are stable with the increase of N on both of the datasets. We also observe that BPR, MR-BPR and SBPR perform better than MF and STE, this is possibly due to the fact that the BPR framework can improve the personalized ranking of recommendation. From Figs. 5, 6, 7 and 8 we can see that the performance of our model is less significant than SBPR when the value of N is 10 and 20, but still better than it and other baselines, and our model performs much better than all the baselines with the rise of N values.

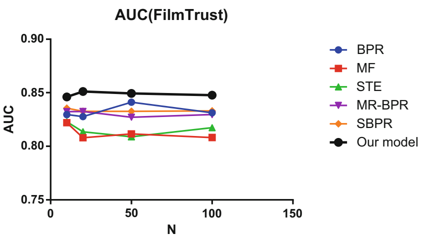

Fig. 3. AUC (FilmTrust)

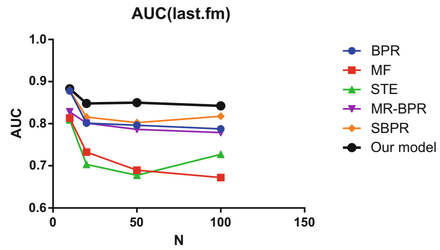

Fig. 4. AUC (last.fm)

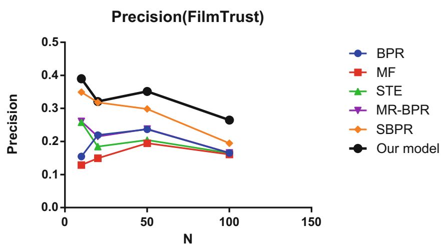

Fig. 5. Precision (FilmTrust)

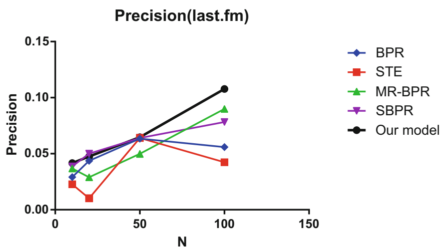

Fig. 6. Precision (last.fm)

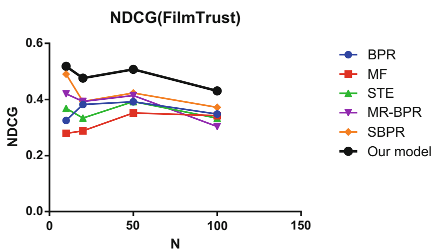

Fig. 7. NDCG (FilmTrust)

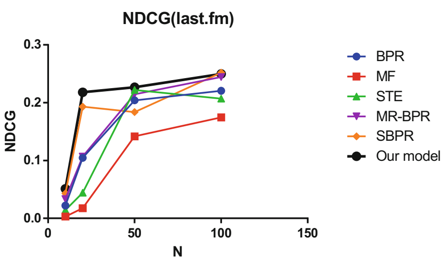

Fig. 8. NDCG (last.fm)

6 Conclusion and Future Work

In this paper, we propose a novel joint factorization model incorporating with social information. We aim at missing data issues in implicit feedback utilizing social information. Moreover, we consider user-user interaction as implicit feedback issue so that we can learn interactions between users under the framework of BPR. The experimental results show the proposed model performs better on the two real-world datasets comparing with other recommendation methods, which indicates the importance of social information for the implicit feedback recommendation. In future, we aim to find a more effective method to fill the missing data utilizing social information. We will focus on indirect relations between users considering context data of users rather than their ratings only to improve recommendation accuracy further.

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