Modeling User Exposure with Explicit and Implicit Social Relations for Recommendation

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ABSTRACT
Social recommender systems have been well studied in both academia and industry. Social information helps to solve the data sparsity and cold start problems in traditional recommender systems, while most existing works in social recommendation assume that social friends have similar preferences. This assumption is too strict and not accord with real world situations, because of the diversity of social relations. We tend to share item information with our socially connected friends. We don't know whether they will like the items, while we help them be exposed to the items. So we model the social information for exposure rather than preferences. In this paper, we propose a novel social exposure-based recommendation model by integrating social information into the basic ExpoMF model [5]. In order to address the sparse issue in social network, we exploit implicit social relations. To the author's knowledge, the work reported is the first to extend exposure model with explicit and implicit social relations for recommendation. Experimental results on the two public datasets demonstrate that our approach SoEx++ performs the best comparing to other three models.

CCS Concepts
• **Information systems → Collaborative filtering;**

Keywords
Social recommendation; exposure; implicit social relations; explicit social relations

1. INTRODUCTION
Collaborative filtering (CF) algorithm has been most widely adopted in recommender systems. The CF algorithm is facing challenges of data sparseness and cold start. One potential way to solve these problems is to explore social networks. In our real life, we ask our friends for recommendation and influenced by our friends more or less, which implies that the underlying social networks of users might play a fundamental role in helping them filter information.

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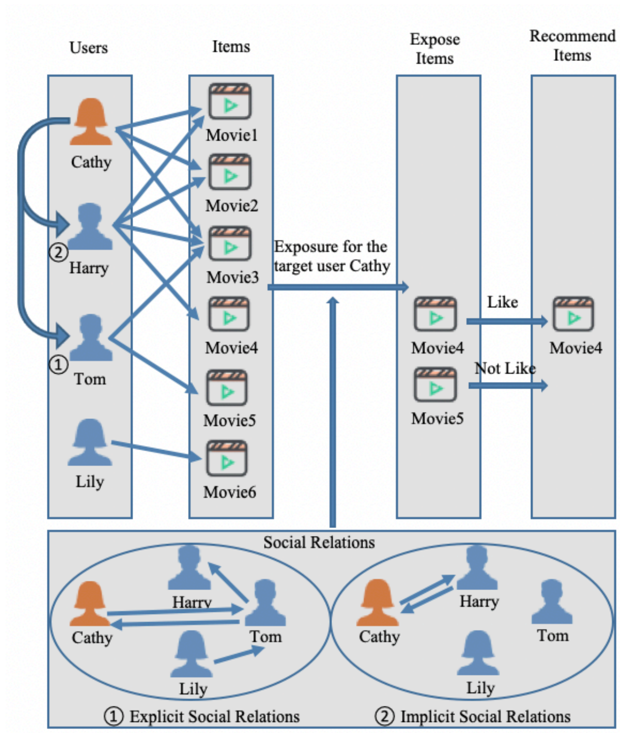


Figure 1. An example of our proposed model SoEx++

How to make use of the social relations is the key of social recommendation methods. Many works have been done to incorporate social information into the MF model. We can classify the social recommendation methods into three categories according to the way they incorporate social information into the MF model [12]: (1) co-factorization methods [6], which assume that the given user should share the same user preference vector in the rating space (rating information) and the social space (social information). The recommender systems in these categories factorize the user-item matrix and the user–user social relation matrix by sharing the same user preference latent factor, (2) ensemble methods [11, 7], which assume that a given user's preference vector is a linear combination of ratings from the user and his social friends, (3) regularization methods [8, 4], which assume that users' latent factor vectors are similar to those of their social friends.

Most of the recent works in social recommendation assume that people share similar preferences with their socially connected friends. But this assumption is too strong to reflect the real world situations. Our social friends may be our relatives, alumni and colleagues. Youngers in our family may like cartoons, while we may have no interests in them. We make social friends not because of sharing similar preferences, but they indeed influence us in our interactions with the items. Our social friends may also be famous people we trust, but we may trust them in specific fields. We may trust a singer in music fields, but we may not trust him in coding. So we model the social information for exposure rather than preferences.

In this paper, we proposed a novel social exposure-based recommendation model by integrating social information into the basic ExpoMF model [5]. The exposure is modeled as a latent variable and it can help us make better use of the unobserved data. We show an example of our proposed model SoEx++ in Figure 1. In the example, our goal is to predict the consumption behaviors of the target user Cathy, if the user have a large probability to watch the movies, we will recommend them to the user. We have two types of social relations in our SoEx++ model, explicit social relations and implicit social relations. Explicit social relations can get from the datasets directly, our explicit social friends may be our relatives, alumni, colleagues and the net friends we trust. The explicit social network data is sparse, so we add implicit social relations. If two users' consumption behaviors are similar, we think they have implicit social relations. Implicit social friends have similar preferences with the target user and can help us learn the scope of the target user. Since people often share information with their socially connected friends, the target user Cathy tend to know movie4 by the influence of her explicit social friends Harry. We assume that similar users have similar scope, so the target user Cathy may know movie5 inferred from her implicit social friends Tom. Movie6 is only watched by Lily, it is not popular. Neither Cathy's explicit social friends nor her implicit social friends have watched movie6, so Cathy tends to not know movie6. Then we find the movies that Cathy is exposed to and hasn't watched, movie4 and movie5. We learned the user's preferences from her historical consumption behaviors, and infer Cathy likes movie4, so we recommend movie4 to Cathy.

To summarize, we make the following contributions:

- We recognize the effects of exposure in social recommender systems, and integrating social information into the basic ExpoMF model [5].
- In order to address the sparse issue in social network, we exploit implicit social relations. The implicit social relations have a new perspective of reflecting the exposure on similar users may be exposed to similar items. To the author's knowledge, the work reported is the first to extend exposure model with explicit and implicit social relations for recommendation.
- Experimental results on the two datasets demonstrate that our approach SoEx++ performs the best comparing to other three models.

2. RELATED WORK

2.1 Social Recommendation

Social recommender systems have been widely studied. We use both social information and rating information to predict the users' preferences. MF techniques have three advantages [12]: (1) many optimization methods such as gradient based methods can be applied to find a well-worked optimal solution, scaled to thousands of users with millions of trust relations, (2) matrix factorization has a nice probabilistic interpretation with Gaussian noise, (3) it is very flexible and allows us to include prior knowledge. Most existing social recommender systems in this category are based on matrix factorization of trust relations. Due to the above reasons, many works have been done to incorporate social information into the MF model.

Ma et al. proposed a social recommender method (SoRec) which factorize the user-item matrix and the user–user social relation matrix by sharing the same user preference latent factor [6].Then the same author proposed a social trust ensemble method (RSTE) which assumes that a given user's preference vector is a linear combination of ratings from the user and her social friends [7]. Jamali and Ester proposed a method called SocialMF, which assumes that the preference of a user is close to the average preference of the user's social friends [4]. Later Ma et al. proposed a method SoReg, which assume that the distance between the two connected users should be small [8]. Yang et al. proposed TrustMF method [14], which build a trustor model and a trustee model and then combine them. In the model, the author map users into two low-dimensional spaces called trustor space and trustee space. The vector of trustor and trustee in two space describe "to trust by reading ratings or reviews" and "to be trusted by generating ratings or reviews". Yang et al. proposed TrustPMF method [15], which discuss the rational of TrustMF from a probabilistic view and contribute a more general framework.

All the work above assume that users' preferences are similar to or influenced by the users whom they are socially connected to. The assumption is too strict and not accord with real world situations. We assume that social relations influence our exposure rather that preferences.

2.2 Recommend with User Exposure

Liang first modeled exposure in recommender systems [5]. It was on top of the Gaussian matrix factorization [10]:

$$\theta_u \sim N\left(0, \lambda_\theta^{-1} I_K\right) \tag{1}$$

$$\beta_i \sim N\left(0, \lambda_\beta^{-1} I_K\right) \tag{2}$$

$$y_{ui} \sim N\left(\theta_u^T \beta_i, \lambda_y^{-1}\right) \tag{3}$$

Where θ_u and β_i represent the latent vector of user u and item i respectively. We use the mean and covariance to parametrize the Gaussian distribution. y_{ui} represents the rating user u gives to item i . λ_θ , λ_β and λ_y are hyper-parameters, denoting the inverse variance. I_K stands for the identity matrix of dimension K .

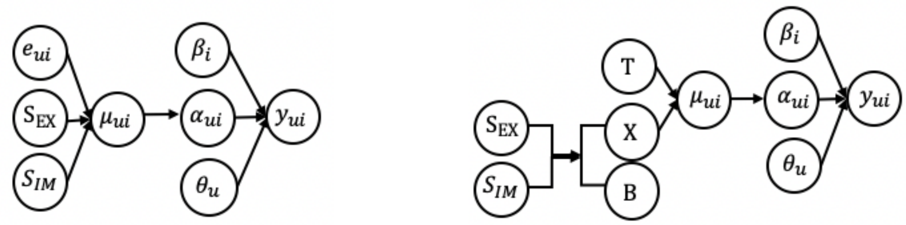
Then we will introduce the exposure model proposed by Liang [5]. Let $U = \{u_1, u_2, \cdots, u_m\}$ and $I = \{i_1, i_2, \cdots, i_n\}$, representing the user set and the item set respectively. μ_{ui} is the prior probability of exposure. a_{ui} indicates whether user u has been exposed to item i . y_{ui} indicates whether user u has clicked item i . δ_0 denotes that $p(y_{ui} = 0 \mid a_{ui} = 0) = 1$.

$$a_{ui} \sim B\left(\mu_{ui}\right) \tag{4}$$

$$y_{ui} \mid a_{ui} = 1 \sim N\left(\theta_u^T \beta_i, \lambda_y^{-1}\right) \tag{5}$$

$$y_{ui} \mid a_{ui} = 0 \sim \delta_0 \tag{6}$$

Whether a user has exposed to an item comes from Bernoulli distribution. When $a_{ui} = 1$, whether user u has clicked item i follows from Gaussian distribution. When $a_{ui} = 0$, user u is not exposed to item i , we assume that user u would not click item i .



(a)Social Boosting SoEx++ (b) Social Regularization SoEx++

Figure 2. Graphical models of SoEx++

3. MODEL DESCRIPTION

In this section, we will discuss the SoEx++ model in detail. The model can be divided into two steps: the Exposure Step and the Rating Step. In the Exposure Step, We use the social trust relations to help calculate the probability we are exposed to the items. The explicit social relations are sparse, so we exploit implicit social relations and incorporate them into explicit social relations. We calculate the implicit social relations based on the similarity between the users. We believe that two similar users tend to have similar preferences, even they don't know each other. Implicit social relations can better reflect our inner preferences. In the Rating Step, we factorize the rating matrix using exposure matrix as a constraint.

In particular, we first show the SoEx++ framework. Then we introduce three key modules of the SoEx++: implicit social relations learning module, prior probability of exposure (μ_{ui}) learning module and using exposure for recommendation module. We proposed two method for learning μ_{ui} , social regularization method and social boosting method.

3.1 SoEx++ Framework

We will first consider the social boosting SoEx++ model in Figure 2(a).

How to learn prior probability of exposure μ_{ui} is vital. Our own scope and awareness can influence the probability of exposure to a specific item. If we have a large stock of information and interest in many fields or the item is very popular, there is a large probability that we have been exposed to it. If our socially connected friends know an item, we may know the item influenced by them. So we model μ_{ui} with the combination of the user scope on the target item (e_{ui}), the influence of explicit social relations (S_{EX}) and implicit social relations (S_{IM}).

We construct the implicit social relations based on the similarity between the users. The implicit social relations have a new perspective of reflecting the exposure on similar users have similar exposure on items. a_{ui} indicates whether user u has been exposed to item i .Whether a user has been exposed to an item comes from Bernoulli distribution, which is shown in Eq.(4). y_{ui} indicates whether user u clicks item i . How to calculate y_{ui} is shown in Eq. (5) and Eq. (6).

Then, we will consider the social regularization SoEx++ model in Figure 1(b). We show another way to learn prior probability of exposure μ_{ui} .

We user MF method to learn trustor-specific latent vector X and trustee-specific latent vector B , so the trustor-specific latent vector X is constrained by social relations. X can also be explained as user exposure latent vector. T represents item exposure latent vector. We use matrix T and X to calculate μ_{ui} . The latter steps of calculating a_{ui} and y_{ui} in social regularization SoEx++ is the same as those in social boosting SoEx++, so we will not explain.

3.2 Learning Implicit Social Trust

The explicit social network data is sparse, it can't model exposure well. One potential solution of this problem is to add implicit social relations.

We assume that similar users are exposed to similar items. We use Pearson Correlation Coefficient (PCC) to calculate the similarity between users in Eq. (7).

$$PCC_{uv} = \frac{\sum_i \left(r_{ui} - \bar{r}_u\right)\left(r_{vi} - \bar{r}_v\right)}{\sqrt{\sum_i \left(r_{ui} - \bar{r}_u\right)^2} \sqrt{\sum_i \left(r_{vi} - \bar{r}_v\right)^2}} \quad (7)$$

$$S_{uv}^{EX} = \begin{cases} PCC_{uv}, PCC_{uv} > \theta \\ 0, PCC_{uv} <= 0 \end{cases} \quad (8)$$

r_{ui} represents the rating user u gives to item i . $\bar{r}_u$ and $\bar{r}_v$ represent user u's average rating and user v's average rating respectively.

The implicit social trust is defined in Eq. (8). Trust matrix has transitivity when θ =0.707 [2].

3.3 Learning Prior Probability of Exposure

3.3.1 Social Regularization

We user the co-factorization method to learn μ_{ui} , inspired by TrustMF [14] and SERec [13]. Let $\mu_{ui} = X_u^T T_i + \eta_i$, X_u is user u' exposure latent vector, T_i is item i' exposure latent vector, η_i is the item i' bias.

$$L_{re} = \sum_{ui} (X_u^T T_i + \eta_i - \mu_{ui})^2 + \lambda_{re} \sum_{uv} (X_u^T B_v - (S_{uv}^{EX} + S_{uv}^{IM}))^2 + \lambda_x \| X_u \|^2 + \lambda_t \| T_i \|^2 + \lambda_b \| B_v \|^2 + \lambda_\eta \| \eta_i \|^2 \quad (9)$$

S_{uv}^{EX} is the explicit social relation between user u and user v , the explicit social relation matrix gets from the dataset directly. S_{uv}^{IM} is the implicit social relation between user u and user v , the implicit social relation matrix learns from the user-item interaction matrix. X_u and B_v represents user u' trustor-specific latent vector and user v' trustee-specific latent vector. In this model, X_u represents how does user u trust others and how does him be exposed to items.

3.3.2 Social Boosting

We model μ_{ui} with the combination of the user scope on the target item (e_{ui}), the influence of explicit social relations (S_{EX}) and implicit social relations (S_{IM}).This model is shown in Eq. (10).

$$\mu_{ui} = e_{ui} + \sum_{f \in EX(u)} c_1 \bullet \mu_{fi} + \sum_{f' \in IM(u)} c_2 \bullet \mu_{f'i} \tag{10}$$

$EX(u)$ and $IM(u)$ represents user u's explicit and implicit socially connected friends, respectively. c_1 and c_2 are the weight of explicit and implicit social influence respectively.

3.4 Using Exposure for Recommendation

In the above sections, we know how to learn prior probability of exposure μ_{ui} . In this section, we use it for recommendation.

The exposure model is defined in Eq. (4), Eq. (5) and Eq. (6). We get the log joint probability of the exposure variance a_{ui} and the user-item interaction variance y_{ui} , which is shown in Eq. (11).

$$\begin{aligned} &\log p(\alpha_{ui}, y_{ui} \mid \mu_{ui}, \theta_u, \beta_i, \lambda_y^{-1}) \\ &= \log B(\alpha_{ui} \mid \mu_{ui}) + \alpha_{ui} \log N(y_{ui} \mid \theta_u^T \beta_i, \lambda_y^{-1}) \\ &+ (1-\alpha_{ui}) \log \mathbb{I}[y_{ui} = 0] \end{aligned} \tag{11}$$

4. EXPERIMENTS AND ANALYSES

4.1 Datasets

In order to sufficiently validate the performance of our proposed methods, we consider two representative public datasets for experiments: *Lastfm* [1] and *Epinions* [9].

4.2 Evaluation Metric

The following metric is used to measure the predict accuracy.

Recall@K (Rec@K). This metric quantifies the fraction of consumed items that are in the top-K ranking list sorted by the estimated rankings. For each user u, we define $Rec(u)$ as the set of recommend items in the top-K list, and $Con(u)$ as the set of all the items consumed by the user in the test set:

$$Recall@K = \frac{Rec(u) \cap Con(u)}{Con(u)} \tag{12}$$

4.3 Methods Compared

In this section, in order to show the effectiveness of our proposed recommendation approach, we compare the recommendation results with the following methods:

1. PMF [10] is a baseline matrix factorization method.
2. RSTE [7] is a trust-aware recommendation method that models one user's ratings as the combination of his own favors and the preferences of his/her trust users.
3. WMF [3] is a classic weighted matrix factorization method for implicit data.

We use the average of our two proposed methods as the final result.

4.4 Experimental Results

We show the experimental results in TABLE Ⅰ and TABLE Ⅱ.

Table 1. Results on Epinions

Model	Rec@10	Rec@50
PMF	0.0006	0.0034
RSTE	0.0008	0.0033
WMF	0.0389	0.1082
SoEx++	0.0476	0.1121

Table 2. Results on Lastfm

Model	Rec@10	Rec@50
PMF	0.0003	0.0011
RSTE	0.0049	0.0207
WMF	0.1211	0.3110
SoEx++	0.1320	0.3126

From TABLE Ⅰ and TABLE Ⅱ, we can see that for all the comparing methods, SoEx++ outperforms the best in both datasets, *Epinions* and *Lastfm*. This implies that modeling user exposure with explicit and implicit social relations can improve the accuracy for recommender systems. Among the four methods, PMF gets the lowest score because it does not consider the social information, that is to say social relations is vital for recommending and can improve the accuracy for recommendation. Comparing to RSTE, our method considers the implicit social relations and has a better recommendation. None of the three methods, PMF, RSTE and WMF, take exposure into account, they may not well model the real world situations.

5. CONCLUSIONS

Social information helps to solve the data sparsity and cold start problems in traditional recommender systems, while most existing works in social recommendation assume that social friends have similar preferences, but this is too strict and not accord with real world situations. Social friends may not have similar preferences. In this paper, we proposed a novel method modeling user exposure in social recommendation. In order to address the sparse issue in social network, we exploit implicit social relations. To the author's knowledge, the work reported is the first to extend exposure model with explicit and implicit social relations for recommendation. The experimental results show that our method is superior to the other three methods, that is to say, the consideration of exposure and the implicit social relations can help improve the recommendation accuracy.

6. ACKNOWLEDGMENTS

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