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How friends affect user behaviors? An exploration of social relation analysis for recommendation

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ABSTRACT

Incorporating the influence of social relationships effectively is fundamental to social recommendation (SR). However, most of the SR algorithms are based on the homophily assumption, where they ignored friends' different influence on users and users' different willingness to be influenced, which may make improper influence information integrated and harm the recommendation results. To address this, we propose a unified framework to properly incorporate the influence of social relationships into recommendation by the guidance of buddy (friends who have strong influence on user) and susceptibility (the willingness to be influenced) mining. Specifically, the Social Influence Propagation (SIP) method is proposed to identify each user's buddies and susceptibility and the Social Influence based Recommendation model is proposed to generate the final recommendation. Experiments on the real-world data demonstrate that the proposed framework can better utilize users' social relationships, resulting in increased recommendation accuracy.

1. Introduction

To deal with the information overload on the internet, recommender systems have emerged by suggesting users the potential enjoyed items. Traditional Collaborative Filtering (CF) methods predict users' interests by mining users' rating history. The increasing popular social networks provide additional information to enhance pure rating-based CF. Recently, based on the homophily assumption [1] that users linked with each other in social networks tend to have similar tastes, some social recommendation (SR) methods have been proposed to improve recommendation accuracy by leveraging the social relationships between users. However, among the large volume of information in social relationships, it has much noise which will disturb the recommendation. To get better results, we should take deep analysis on effectively modeling the influence of social relationships into recommendation.

Studies on social networks show that the social relationships have multiple aspects of influence on users. First, they can affect users' decisions directly, which can be regarded as the short-term influence of social relationships. In [2,3], psychology and sociology studies have proved that users' decisions are affected simultaneously by *individual tastes* and *social influence*. This is also intuitive in online social networks. In a product review sites, such as Epinions,[1] when a user rates an item, she/he usually cares about the item's characteristic to see whether it is interesting, depending on the individual tastes. She/He also cares about the opinions from the trusted friends,[2] which is the social influence. Second, users' individual tastes are also affected by friends with time elapsing, which can be regarded as the long-term influence of social relationships. In [4], the authors studied the interaction between taste similarity and social influence in product review sites. They observed that the average difference of rating behaviors between the users and their friends decreased after their relations established, and it continued decreasing as time going. Therefore, it is necessary to incorporate the influence of social relations properly and comprehensively into recommendation. However, the homophily assumption about social relationships used in traditional SR algorithms is debatable.

On the one hand, not all friends are influential to users in social network. As we know, social networks sometimes serve a more general purpose of allowing users socialise among themselves instead of just reflecting their agreement in item ratings. For

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[1] Epinions: http://www.epinions.com.
[2] In directed networks such as Twitter, the "friends" in our paper represent the persons who link from the user.

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instance, when a user establishes a link to a person she/he knows in the real world, she/he may just want to be informed of the person's activities, and they do not necessarily have similar preferences or influence each others' decisions. This is a common situation in Facebook, Twitter and some other social networks. Therefore, among the hundreds of friends in the social network, there is much noise and only part of them really have effects on users' decisions. It is unnecessary to consider all the friends' influence when predicting the rating behavior. Additionally, in [5], it is indicated that the really influential friends' behaviors play a very important role on diffusion of items. To the best of our knowledge, previous SR works do not pay attention on the effects of these really influential friends, and most of them take account of all the friends' influence uniformly. In our work, we attempt to detect each user's *buddies* who have strong influence on the user, and focus on their rating influence on users. Simultaneously, we treat these buddies differently according to their influence strength.

On the other hand, not all the people are apt to be influenced by others in the social networks. Some users are more susceptible while some are less, which has been revealed in [5] by randomized experimentation on samples of 1.3 million Facebook users. For example, the authors found that younger users are more susceptible to be influenced than older ones, married individuals are the least susceptible to be influenced. Thus, we should also treat the target users differently when considering their friends' influence. For the susceptible users, their rating decisions may depend more on their friends' influence, while for the unsusceptible users, more effects come from their individual tastes. In previous social recommendation works, they confused all the target users together without taking the role of susceptibility into account.

To address all the problems, we propose a novel recommendation framework integrating individual *buddy* and *susceptibility* analysis into *social* influence based *recommendation*, named BSSR for short. To detect each user's buddies and susceptibility, as well as the influence strength of buddies, we develop a *Social Influence Propagation (SIP)* method based on the theory of factor graphs and sum-product algorithm [6]. Specifically, an *Influence Factor Graph* is constructed, which captures users' rating behaviors and social network structure into a unified model to analyze the relationships. Then the accuracy of recommendation can be improved by considering the short-term and long-term social influence guided by the buddy's and susceptibility's effects. The main contributions of this paper are summarized below:

- Proposing a novel social recommendation framework, BSSR, guided by mining users' buddy sets and susceptibility to incorporate social relations more properly than traditional SR methods.
- Developing a Social Influence Propagation (SIP) method based on the unified Influence Factor Graph to mine buddy sets and susceptibility simultaneously.
- Two aspects of social influence, short-term and long-term influence, are considered in the final social influence based recommendation.

The rest of the paper is organized as follows. We first discuss the related work in Section 2. Then, our new recommendation framework, BSSR, is introduced in Section 3. The Social Influence Propagation method for individual buddy and susceptibility mining is described in Section 4, a social influence based recommendation model guided by buddy and susceptibility is presented in Section 5. Then we analyze experimental results on benchmark datasets in Section 6. Finally, we conclude this work in Section 7.

2. Related work

In this section, we review some related works, including traditional recommendation approaches based on collaborative filtering (CF), recommendation techniques enriched by social relationship, and works about social relation analysis.

2.1. Collaborative filtering

Techniques based on collaborative filtering are widely used in recommender systems [7–11]. In general, it is based on the fundamental assumption that similar users have similar behaviors on similar items [12–15]. CF methods are mainly divided into two categories: memory-based and model-based. Memory-based methods [7,8] usually ask for similar users' or items' advice to produce a prediction. They can be further categorized as user-based methods [16,8,17] or item-based methods [7,18,19], depending on whether the recommendation for a user is aggregated from users with similar preference to her/him or from items similar to those she/he already liked. However, memory-based methods are limited in handling highly sparse data since it is difficult to estimate the similarity accurately.

Different from memory-based methods, the model-based methods learn a model based on patterns recognized in the known ratings of users by machine learning and statistical techniques, and then apply the model to do recommendation. Examples include the latent semantic models [20,21], clustering models [22,23], graphical models [24], and Bayesian models [25,26]. Among different model-based methods, low-rank matrix factorization (MF) techniques have attracted much research attention [9–11,27], due to the advantages of scalability and accuracy. Based on the premise that users' tastes can be represented by a small number of factors, MF techniques learn the low-rank latent factors of users and items from the observed ratings in the user-item rating matrix, and then utilize them to predict user's behavior. However, all the CF methods mentioned above rely only on users' history rating behaviors, it may be insufficient in the context of social networks where the users' interactions influence the decision making dramatically.

2.2. Social recommendation

Several social recommendation (SR) algorithms have been proposed to investigate how social relations can be utilized to provide better recommendations [28–35]. In [28], the authors proposed the trust-based model by extending traditional memory-based methods with social network among users. They replace the similarity computation process with the use of a trust metric and make recommendations based on the ratings of users who are trusted. However, the experiments on a large real dataset show that this work can only increase the coverage (number of ratings that are predictable) but fail to improve the prediction accuracy. Jamali and Ester [34] employ the random walk approach [36] to combine the trust-based model and the item-based model. It considers not only ratings of the target item, but also those of similar items. The random walk model helps to measure the confidence of a recommendation. Their experiments show that this method outperform other existing memory based approaches. However, it is not scalable to large datasets, since it needs to calculate pairwise similarities for each prediction.

Recently, some social recommendation methods based on matrix factorization techniques show substantial improvements. One popular way for fusing social relationship into MF model is to factorize the user-item rating matrix and user–user social relation matrix jointly by sharing a common user latent factor matrix.