A Recommendation Technique Based on the Social Networks and Sequential Behaviors

Bin PAN¹,a, Jun-Yi WANG¹,b,*

¹College of Computer Science, Inner Mongolia University
Hohhot, Inner Mongolia, China
ªpb1010a@163.com, bwjyi@imu.edu.cn
*Corresponding author

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Abstract. Collaborative filtering is one of the most successful method for recommendation. But it also has disadvantages such as cold-start problems and data sparseness which influence the result of recommendation. The probability Matrix Factorization Technique is one of the method of model based CF and it always ignore the relationship of users. Sequential behaviors is often one of the most important factor which is easy to be ignored. In this paper, in order to solving the problems of collaborative filtering, we not only consider the effect on the user rating matrix but also take the social networks and time factor into account. Putting these important factors in the PMF model is an effective way for making recommendation.

Introduction

With the dramatic development of Internet, there is lots of information we can get through the internet. But it becomes difficult for users to find the information which they really need because of the explosion of information. Although there are many ways to make recommendation such as collaborative filtering and memory based method, it doesn’t perform well when recommend items which can cover the interest of user. So we need to take account of other information in our daily life. Recommender systems are broadly classified into three categories: Collaborative Filtering (CF) based, Content based and hybrid. Contend based method often focus on the content of user and users’ attributions. Collaborative filtering is one of the most successful methods to make recommendation. It can be classified into two categories: memory based and model based. Although CF has improved the efficiency to recommend items to users and bring great profit to companies, it still has disadvantages such as cold-start and sparse rating.

The social network based approach to recommendation has emerged. This approach assumes a social network among users and makes recommendation for a user based on the ratings of the users that have direct or indirect social relations with the given user. The method based on the social relationships can solve the cold-start of collaborative filtering. For example, a new user logs in the system first time. And he doesn’t have rating of items or has just a few ratings. If the system wants to recommend something to him, it is a good way to use his social network. We can recommend things for him based on the ratings of his friends. One of the most popular approaches to collaborative filtering is based on low-dimensional factor models.

Nowadays, user’s social network can be employed to enhance the traditional recommender system, many methods have been proposed. The most successful methods are proposed by Hao Ma and Yehuda Korean [1-2]. Ma proposed a matrix factorization framework with social regularization with two social recommendation systems, one is a social friend network and the other contains a social trust network. Yehuda Korean proposed a methods called SVD++ which is not only contain the social network, but also have the information of time the similarity between users and so on.

In this paper, we propose a matrix factorization which is probability matrix factorization. We predict the rating based on the probability, and the users will choose the items which he is interested
in by a set of probability. We consider the relationship between friendship which is called explicit relationship, and we explore the implicit network through rating matrix combined with the attributions of trust. The sequence information is also an important factor will affect the result of the recommendation. We hope to propose a model which can solve the cold-start of new users and make the rating be less sparse.

The rest of this paper is organized as follows: The Preliminaries and The related work by using Probabilistic Matrix Factorization (PMF) are presented in section 2. We introduce our proposed model in section 3. Finally, we conclude the paper and present some directions for future work.

**Preliminaries**

**Probabilistic Matrix Factorization**

Probabilistic Matrix Factorization (PMF) is proposed by Ruslan Salakhutdinov and Andriy Mnih in 2008 [3]. PMF is a kind of Matrix Factorization and it assumes that the characteristic vector matrix of the user and the product is consistent with Gauss distribution. We first review the basic matrix factorization approach for recommendation using only user-item rating matrix. The conditional probability of the observed rating is defined as:

\[
p(R | U, V, \sigma^2) = \prod_{i=1}^{N} \prod_{j=1}^{M} \left[ N(R_{i,j} | g(U_i^T V_j), \sigma^2) \right]^{I_{ij}}
\]

(1)

Where \(N(x|\mu,\sigma^2)\) is the probability density function of the Gaussian distribution with mean \(\mu\) and variance \(\sigma^2\) and \(I_{ij}\) is the indicator function that is equal to 1 if user \(i\) rated item \(j\) and equal to 0 otherwise. We also place zero-mean spherical Gaussian priors on user and item feature vectors:

\[
p(V | \sigma^2_u) = \prod_{j=1}^{M} N(V_j | 0, \sigma^2_u I), \quad p(V | \sigma^2_v) = \prod_{j=1}^{M} N(V_j | 0, \sigma^2_v I)
\]

(2)

The graphical model of PMF is present in figure 1.

![Figure 1. The original probability matrix model.](image)

**Related Work**

Probability Matrix factorization has been widely used in the model based recommendation. And some models consider not only the user-item matrix but also take the social network into account. TidalTrust [4] performs a modified breadth first search in the trust network to compute a prediction.
And MoleTrust [5] is similar with the TidalTrust. In 2010, Mohs en Jamili [6] proposed a model which incorporates trust propagation into a matrix factorization model for recommendation in social networks. In his paper, the behaviors of user $u$ is affected by his direct neighbors. He formulates the influence as follows:

$$
\hat{U}_u = \sum_{v \in N_u} T_{u,v} U_v
$$

(3)

Where $\hat{U}_u$ is the estimated latent feature vector of $u$ given the feature vectors of his direct neighbors. Since the social networks we are working with are all binary social networks, all none-zero values of $T_{u,v}$ are 1. We normalize each row of the trust matrix so that $\sum_{v=1}^{N} T_{u,v} = 1$.

The equation for the posterior probability of latent feature vector given the rating and social trust matrices is presented like:

$$
p(U,V | R,T,\delta^u_i,\delta^v_j) \propto p(R | U,V,\delta^u_i)p(U | T,\delta^u_i,\delta^v_j)p(V | \delta^v_j)
$$

$$
= \prod_{u=1}^{N} \prod_{i=1}^{M} [N(R_{u,i} | g(U^T V), \delta^u_i)] 
\times \prod_{u=1}^{N} [N(U^T | \sum_{v \in N_u} T_{u,v}, \delta^v_j I)] 
\times \prod_{u=1}^{N} [N(U^T | 0, \delta^v_j I)] \times \prod_{i=1}^{M} [N(V_i | 0, \delta^v_j I)]
$$

(4)

The graphical model of SMF is present in Figure 2.

![Figure 2. The SMF model considers user-matrix and social network.](image)

A model which is called SequentialMF is proposed by GuangFu Sun [7]. But he only considered the sequential in his paper and didn’t uses the social network, so it can’t solve the problems of cold-start.

We propose our method based on the model Probability matrix factorization(PMF). Mohsen Jamali had offered a model based on PMF and social network, but it just rely on the direct trust of friends. Now based on the method of Jamali and Sun, we combine more information in social network to solve the problems of cold-start and improve the predictions of recommender system.
Our Proposed Model

The Similarity Based on the User’s Relationship of Friends

Although the dataset like the Epinions has given the trust relationship, but it only uses 0 to represent there is no trust relation between users and use 1 to represent there has the trust between two users. When considering the similarity in the social relationship, we often take the friendship into consideration because we trust friends in daily life. The decision of friends often affects our choice. For the information of the relationship of friends, it can be described as a relational graph.

![Figure 3. The graph of user trust relation.](image)

We define the graph in Figure 3 as an undirected graph because we consider the trust relationship of friends is equal. Where the nodes represent the users. The lines represent the similarity between the users. We define two kinds of friends [8].

**First Class Friends.** In the user trust social network, two users who are connected with each other directly, we call them first class friends. The similarity of them is calculated like this:

\[
S_{i \rightarrow j} = w_{ij} 
\]

\[
w_{ij} = \frac{|\text{friend}(u_i) \cap \text{friend}(u_j)|}{|\text{friend}(u_i) \cup \text{friend}(u_j)|} 
\]

(5)

(6)

Where friend(u_i) represents the friends set of user u_i, and friend(u_j) represents the friends set of user u_j.

**Second Class Friends.** In this paper, we propose the second class friends to represent the relationship of users who have the same first class friends. The similar between u_i and his second friend u_z can be calculated by their first class friends.

\[
S_{i \rightarrow z} = \max_{u_j \in V(u_i) \cap V(u_z)} \{w_{ij} \times w_{ij}\} 
\]

(7)

Where V(u_i) represents the first class friends of u_i and V(u_z) represents the first class friends of u_z, u_i is the friends of both u_i and u_z. The second class friends can fill the trust matrix between users.

We can see in Figure 3 {B, D, E} are first class friends of A, and {C, G, F} are second class friends of A. Then we can use the formula (6) and (7) to calculate the weight between users.

The Influence of Sequential Factor

Traditional collaborative filtering has ignored the time of users who evaluate the items, we can make use of the sequential factor to dig the relation between users and items. For example, user A has watched a movie before user B a short time ago. If this kind of condition often appears, there may be some connection between users A and B. The user consume network and item consume work are presented in Figure 4 and Figure 5.
In the user consume network $G = \{U, E\}$, $U$ is the set of users and $E$ is the set of lines. $W$ represents the weight on each line. “()” represents the number of items which are evaluated by user. If we suppose $U_i$ and $U_j$ evaluate a same item one after another in a period of time (like one day), the $W_{i \rightarrow j}$ increases 1. We find all items like this in the consume network, then we can calculate the influence like:

$$T_{i \rightarrow j} = \frac{W_{i \rightarrow j}}{f(U_i, U_j)}$$

(8)

Where $f(U_i, U_j)$ is the set of items which are evaluated by $U_i$ and $U_j$ at the same period. $T_{i \rightarrow j}$ is the influence of $U_i$ on $U_j$.

We can set the influence between different items in the same way like above.

$$P_{i \rightarrow j} = \frac{W_{i \rightarrow j}}{f(V_i, V_j)}$$

(9)

**SATMF Model**

Considering the trust relationship and sequential factor, we introduce $\alpha$ to mix these two important factors together like:

$$F_{i \rightarrow j} = \alpha S_{i \rightarrow j} + (1 - \alpha) T_{i \rightarrow j}$$

(10)

When $\alpha=0$, the similarity between two users is decided by the trust relationship of them. When $\alpha=1$, the similarity between two users is decided by the sequential factor.

Our proposed model SATMF which uses the social network and sequential factor is presented in Figure 6.
The Nu and Ni in Figure represent the nearest neighbors of U_u and V_i, they are decided by the similarity which is presented in formula (8). We choose Top K neighbors.

The final equation for the posterior probability of latent feature vector given the rating, social trust matrices and sequential factor is presented as follow:

\[
p(U,V|R,F,P,\sigma_R^2,\sigma_F^2) \propto p(R|U,V,\sigma_R^2)p(U|F,\sigma_U^2,\sigma_F^2)p(V|P,\sigma_P^2,\sigma_F^2)
\]

\[
= \prod_{u=1}^{N} \prod_{i=1}^{M} \prod_{j=1}^{I} N(R_{uij}|g(U_u^T V_i, \sigma_R^2))^{p_{uij}} \times \prod_{u=1}^{N} \prod_{v \in N_u} F_{uv} U_v \sigma_U^2 I \times \prod_{u=1}^{N} N(U_u^T|0, \sigma_U^2 I) \times \prod_{i=1}^{M} N(V_i^T|0, \sigma_V^2 I) \times \prod_{j=1}^{I} \sum_{v \in N_j} P_{vj} V_j \sigma_V^2 I
\]  

(11)

Summary

In this paper, we propose a novel PMF model not only consider the social relation of users, but also treat sequence behavior as an important factor when recommend. PMF model is a basic model in collaborative. If we just use the user-item matrix, the recommender system will ignore the addition factors in real life and results in cold-star and sparse problems. In the future, we will conduct the experiments with Data Sets and take more factors such as user interest profile, user behaviors into account.

References


