Personalized Recommendation by Exploring Social Users' Behaviors

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Abstract. With the popularity and rapid development of social network, more and more people enjoy sharing their experiences, such as reviews, ratings and moods. And there are great opportunities to solve the cold start and sparse data problem with the new factors of social network like interpersonal influence and interest based on circles of friends. Some algorithm models and social factors have been proposed in this domain, but have not been fully considered. In this paper, two social factors: interpersonal rating behaviors similarity and interpersonal interest similarity, are fused into a consolidated personalized recommendation model based on probabilistic matrix factorization. And the two factors can enhance the inner link between features in the latent space. We implement a series of experiments on Yelp dataset. And experimental results show the outperformance of proposed approach.

Keywords: recommender system, entropy, rating behaviors, social networks.

1 Introduction

Recommender system (RS) is an emerging research orientation in recent years, and it has been demonstrated to solve information overload to a certain extent. In E-Commerce, such as Amazon, it also has been utilized to provide attractive and useful products' information for users from mass scales of information. A survey shows that at least 20 percent of the sales in Amazon come from the work of the RS. The traditional collaborative filtering algorithms [7-9] could be deemed to the first generation of recommender systems [6,19,20] to predict user interest. However, with the rapidly increasing number of registered users and more and more new products hit store shelves, the problem of cold start for users (new users into the RS with little historical behavior) and sparsity of datasets (the proportion of rated user-item pairs in all the user-item pairs of RS) have been increasingly intractable. And with the popularity and rapid development of social network, more and more users enjoy sharing their experiences, such as reviews, ratings and moods. So we can mine the information we are interested in from social networks to make the prediction ratings more accurate. In this paper, we propose personalized recommendation approach by exploring social users' behavior.

The main contributions of this paper are as following: 1) Propose a personalized recommendation model based on probabilistic matrix factorization combining two factors: interpersonal rating behaviors similarity, and interpersonal interest similarity.

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And both of them make connections between user's latent feature vectors and his/her friends'. 2) In social circle, we utilize entropy which is based on the same category with rated history in users' circles of friends, to describe interpersonal rating behaviors similarity. 3) Experimental results and discussions show the effectiveness of the proposed approach.

The rest of this paper is organized as following: Related work on personalized recommendation system and probabilistic matrix factorization model for rating and adoption prediction problem is reviewed in section 2. The proposed personalized recommendation model combining interpersonal interest similarity and interpersonal rating behaviors similarity is introduced in detail in section 3. The experiments and results are given in section 4. And at last in section 5 conclusions are drawn.

2 Related Work

The traditional collaborative filtering algorithms [7-9] could be deemed to the first generation of recommender systems [6,19,20,21] to predict user interest. And the model we proposed is based on probabilistic matrix factorization with consideration of factors of social network.

To introduce various complicated approaches and models [1, 2, 3, 5], we firstly review the basic probabilistic matrix factorization (BaseMF) approach [4] briefly, which doesn't take any factors into consideration. It utilizes user latent feature vector and item latent feature to predict the ratings user to item, and then the task of this model is minimizing the objective function which involve the prediction errors and the Frobenius norm of matrix. This objective function can be minimized efficiently using gradient descent method in [3], which is also implemented in this paper.

Nowadays with the popularity of internet, more and more people enjoy the social networks as Facebook, Twitter, Yelp[1], Douban[2], Epinions[3], etc. The interpersonal relationships become transparent and opened, especially the circles of friends, which bring opportunities and challenges for recommender system (RS) to solve cold start and sparsity problem of datasets. Many models based social network [3, 11-14, 17, 18,19,20,21] have been proposed to improve the performance of the RS. Java et al. [11] had analyzed a large social network in a new form of social media known as micro-blog. Such networks were found to have a high degree correlation and reciprocity, indicating close mutual acquaintances among users. And they had identified different types of user intentions and studied the community structures. And we can believe that the ability to categorize friends into groups (e.g. family, co-workers) would greatly benefit the adoption of micro-blog platforms based on author's analysis of user intentions. That is to say user's friends' interest and categories could reflect user intentions and interest. In [21], a personalized product recommendation system is proposed by mining user-contributed photos in existing

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[1] `http://www.yelp.com`
[2] `http://www.douban.com`
[3] `http://www.epinions.com`

social media sharing website such as Flickr[4]. Both visual information and the user generated content are fused to improve recommendation performances. They have shown that the more information we obtained from users' sides, the better performances are achieved. Chen et al. [12] explored three separate dimensions in designing such a recommender: content sources, topic interest models for users, and social voting. They implemented 12 algorithms in the design space they formulated, and demonstrated that both topic relevance and the social voting process were helpful in providing recommendations. Piao et al. [14] proposed an entropy-based recommendation algorithm to solve cold start problem and discover users' hidden interests. A hierarchical user interest mining method is proposed to explore user's potential shopping needs based on user-contributed photos in her/his social media sites [21]. We recommend personalized products according to the mined user interests. Mehta et al. [13] had calculated entropy-based similarity between users to achieve solution for scalability problem. Iwata et al. [15] proposed a model for user behaviors in online stores that provide recommendation services, and estimated the probability of purchasing an item given recommendations for each user based on the maximum entropy principle. In [17], authors proposed a context-aware recommender system, which proceeded contextual information by utilized random decision trees to group the ratings with similar contexts. At the same time Pearson correlation coefficient was proposed to measure user similarity, and then their model could learn user latent factor vectors and item latent factor vectors by matrix factorization.

Recently, Yang et al. [1] proposed using the concept of 'inferred trust circle' based on the circles of friends to recommend user favorite items. Their approach not only refined the interpersonal trust in the complex networks, but also reduced the load of big data. Meanwhile, besides the interpersonal influence, Jiang et al. [2] demonstrated that individual preference is also a significant factor in social network. Just like the idea of interpersonal influence Yang et al. [1] proposed, according to the preference similarity, users latent features should be similar to their friends' based on the probabilistic matrix factorization model [4]. Qian et al. propose to fuse three social factors: personal interest, interpersonal interest similarity, and interpersonal influence, into a unified personalized recommendation model based on probabilistic matrix factorization [19, 20]. They represent personality by user-item relevance of user interest to the topic of item by mining the topic of item based on the natural item category tags of rating datasets. Moreover, each item is denoted by a category/topic distribution vector. The user-user relationship of social network contains two factors: interpersonal influence and interpersonal interest similarity.

3 The Approach

In this paper, two social factors are fused into the proposed personalized recommendation approach: interpersonal interest similarity, and interpersonal rating behaviors similarity. And we will introduce two factors in detail respectively. And

[4] `http://www.flickr.com`

then the objective function of the proposed algorithm based on the probabilistic matrix factorization model is inferred at last.

3.1 Interpersonal Interest Similarity

User interest is a significant factor to affect users' decision-making process, which has been proved by psychology and sociology studies [10]. Moreover, Jiang et al. [2] demonstrated the effect of ContextMF model with consideration of both individual preference and interpersonal influence. However, there is a main difference between user interest factor in our model and individual preference in ContextMF [2]: we utilize friends' interest in same category to link user latent feature vector, that is to say, user latent feature should be similar to his/her friends' latent feature according to the similarity of their interests.

According to natural item category tags of rating datasets, we can get category distribution of the item, which can be seen as the naive topic distribution D_i of item *i*. Just like the item *Steakhouses Argentine* in New York in Yelp dataset belongs to the sub-category **Steakhouses**, meanwhile it certainly belongs to the first-level category **Restaurants**, and in this paper, we just put user into a distinct group according to the first-level, that means, we analyse user interest similarity and the rating behaviors similarity just in single category because the item naive topic distribution is different from other categories, and there are sufficient sub-categories in each category to describe item naive topic distribution, such as the 114 sub-categories in **Restaurants**. According to user's historical rating data, we summarize the number of all the rated items to measure user interest, that is to say, the more rated items are, the more user interest is:

$$D_u^c = \frac{1}{\left|H_u^c\right|} \sum_{i \in H_u^c} D_i \tag{1}$$

where H_u^c is the set of items rated by user *u* in *c*.

And we denote the interest similarity between user *u* and his/her friend *v* by $W_{u,v}$, and each of the rows is normalized to unity $\sum_v W_{u,v}^* = 1$.

$$W_{u,v} = Sim(D_u, D_v) \tag{2}$$

where the similarity function is measured by cosine similarity as:

$$Sim(D_u, D_v) = \frac{D_u \bullet D_v}{|D_u| \times |D_v|} \tag{3}$$

Then the basic idea of this factor is that user latent feature should be similar to his/her friends'.

3.2 Interpersonal Rating behaviors Similarity

Besides the category tags information, user's ratings are more helpful to be utilized to describe user's rating behavior habits and his/her rating standards. As we all know, the higher probability of occurrence of certain information, the easier we predict the user behaviors including ratings. So we can mine user's interest information for predictions by comparing the ratings similarity in same sub-category by entropy algorithm.

There are some existed approaches which describe the similarities and behaviors analysis between users by entropy [13-16], but there are two main differences of our approach: 1) Unlike [13-16], they utilize entropy to calculate the similarity among all users, even there are no connections among some users, while we utilized entropy algorithm in social circle of friends to calculate the similarity of rating behaviors. One of advantages of our approach is with lower computational cost because we confine the calculation by social circle. Another advantage of our approach is that better performances are achieved by filtering out the insignificant information. 2) We extend the scope of entropy to fit the comparability and pervasiveness of ratings between user and his/her friends. Because the ratings of a user and his/her friends to the same item are very few, we replace ratings of the same item with average ratings in same sub-category. Thus we calculate the ratings similarity as follows:

$$E(U_u, U_v) = -\sum_{c'=1}^{n} p(d_{c'}) \log_2 p(d_{c'}) \tag{4}$$

where U_u and U_v denotes user *u* and his/her friend *v*, $p(d_{c'})$ denotes the frequency of the errors $d_{c'}$, which is calculated by the average ratings between user *u* and his/her friend *v* in same sub-category *c'*. To solve sparsity problem of ratings to the same item in social network, we represent $d_{c'}$ as following:

$$d_{c'} = \left|K_{u,v}^{c'}\right| \times \left|R_{u,c'} - R_{v,c'}\right| \tag{5}$$

where $\left|K_{u,v}^{c'}\right|$ is the indicator function, and if both of user *u* and *v* have rated item in sub-category *c'*, $\left|K_{u,v}^{c'}\right|$ is equal to 1, otherwise, it is 0. $R_{u,c'}$ denotes *u*'s average rating in *c'* and $R_{v,c'}$ denotes *v*'s average rating in *c'*.

As we all know, the higher entropy is, the smaller user ratings similarity becomes. So we denote ratings similarity between user *u* and his/her friend *v* by $E_{u,v}$,which is the reciprocal of entropy, and each of the rows is normalized to unity $\sum_{v} E_{u,v}^{*} = 1$.

$$E_{u,v} = \frac{1}{E(U_u, U_v)} \tag{6}$$

Then the basic idea of this factor is that user *u*'s rating behaviors should be similar to its friend *v*'s to some extent.

3.3 Personalized Recommendation Model

The personalized recommendation model contains these following aspects: 1) The Frobenius norm of matrix ***U*** and ***P***, which is used to avoid over-fitting as [3]. 2)

Interest circle influence $W_{u,v}^{c*}$, which means the similarity degree between u and v. 3) User interpersonal ratings similarity $E_{u,v}^{c*}$, which has effects on understanding your rating behaviors and mining the users, whose ratings are similar to yours in circle of your friends.

With similarity to CircleCon Model [1] and Context Model [2], the objective function of our model is as following:

$$\begin{aligned}
&\Psi^c\left(R^c, U^c, P^c, W^{c*}, E^{c*}\right) \\
&= \frac{1}{2}\sum_{u,i}\left(R_{u,i}^c - \hat{R}_{u,i}^c\right)^2 + \frac{\lambda}{2}\left(\left\|U^c\right\|_F^2 + \left\|P^c\right\|_F^2\right) \\
&+ \frac{\beta}{2}\sum_u\left(\left(U_u^c - \sum_v W_{u,v}^{c*} U_v^c\right)\left(U_u^c - \sum_v W_{u,v}^{c*} U_v^c\right)^T\right) \\
&+ \frac{\gamma}{2}\sum_u\left(\left(U_u^c - \sum_v E_{u,v}^{c*} U_v^c\right)\left(U_u^c - \sum_v E_{u,v}^{c*} U_v^c\right)^T\right)
\end{aligned} \tag{7}$$

where $R_{u,i}^c$ is the real rating value and $\hat{R}_{u,i}^c$ is the predicted rating value in c as following:

$$\hat{R}_{u,i}^c = r^c + \boldsymbol{U}_u^c \boldsymbol{P}_i^{c\mathrm{T}} \tag{8}$$

where r^c is empirically set as user's average rating value in category c, $\boldsymbol{U}$ and $\boldsymbol{P}$ is user and item latent feature matrices in this model. And the factor of interpersonal interest similarity is enforced by the second term in the objective function, which denotes that user u's latent feature $\boldsymbol{U}_u$ should be close to the average of his/her friend v's latent feature with weight of $W_{u,v}^{c*}$ in c. The factor of interpersonal ratings similarity is enforced by the last term, which means that user u's latent feature $\boldsymbol{U}_u$ should be close to the average of his/her friend v's latent feature with weight of $E_{u,v}^{c*}$ in c.

3.4 Model Training

In this paper, we aim at the separate user latent feature $\boldsymbol{U}^c$ and item latent feature $\boldsymbol{P}^c$ in category c by the corresponding matrix factorization model as Eq. (7). And the objective function can be minimized by the gradient decent approach as [3]. More formally, the gradients of the objective function with respect to the variables $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ in c are shown as Eq. (9) and Eq. (10) respectively:

$$\begin{aligned}
\frac{\partial \Psi^c}{\partial U_u^c} &= \sum_{i \in H_u^c} I_{u,i}^{R^c}\left(\hat{R}_{u,i}^c - R_{u,i}^c\right)P_i^c + \lambda U_u^c \\
&+ \beta\left(U_u^c - \sum_{v \in F_u^c} W_{u,v}^{c*} U_v^c\right) - \beta \sum_{v: u \in F_v^c} W_{v,u}^{c*}\left(U_v^c - \sum_{w \in F_v^c} W_{v,w}^{c*} U_w^c\right) \\
&+ \gamma\left(U_u^c - \sum_{v \in F_u^c} E_{u,v}^{c*} U_v^c\right) - \gamma \sum_{v: u \in F_v^c} E_{v,u}^{c*}\left(U_v^c - \sum_{w \in F_v^c} E_{v,w}^{c*} U_w^c\right)
\end{aligned} \tag{9}$$

$$\frac{\partial \Psi^c}{\partial P_i^c} = \sum_{i \in H_u^c} I_{u,i}^{R^c} \left(\hat{R}_{u,i}^c - R_{u,i}^c \right) U_u^c + \lambda P_i^c \tag{10}$$

where $I_{u,i}^{R^c}$ is the indicator function which is equal to 1 if user u has rated item i in c, and equal to 0 otherwise. $\hat{R}_{u,i}^c$ is the predicted rating value user u to item i in c according to Eq. (8).

The initial values of $\boldsymbol{U}^c$ and $\boldsymbol{P}^c$ are sampled from the normal distribution with zero mean. We will set $\boldsymbol{U}^c$ and $\boldsymbol{P}^c$ the same initial values when comparing with each factor to insure the fairness, even it empirically has little effect on the latent feature matrix learning. In each iteration, the user and item latent feature vectors $\boldsymbol{U}^c$ and $\boldsymbol{P}^c$ are updated based on the previous values to insure the fastest decreases of the objective function. Note that the step size is a considerable issue. But in this paper, for each appropriate step size, it's always fair to each algorithm if it's set as the invariant, so we just adjust it to insure the decreases of the objective function in training.

Then the algorithm is shown as Table 1, where l is the step size, and t is the iteration time.

Table 1. Personalized recommendation algorithm based on rating behaviors

Algorithm of proposed personalized recommendation model
1) initialization: $\Psi^c(t) = \Psi^c(\boldsymbol{U}^c(t), \boldsymbol{P}^c(t))$, $t=0$.
2) given: parameters $k, l, \lambda, \beta, \gamma$, average rating value r^c.
3) iteration:
while (t<1000)
calculate $\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}, \frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
$\boldsymbol{U}^c(t)=\boldsymbol{U}^c(t)-l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}$, $\boldsymbol{P}^c(t)=\boldsymbol{P}^c(t)-l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
t++
end while
4) return: $\boldsymbol{U}^c, \boldsymbol{P}^c \longleftarrow \boldsymbol{U}^c(1000), \boldsymbol{P}^c(1000)$
5) prediction: $\hat{R}_{u,i}^c = r^c + \boldsymbol{U}_u^c \boldsymbol{P}_i^{c\mathrm{T}}$

4 Experiments

We implement a series of experiments to estimate the performance of proposed approach, and compare the factors by observing the performance and the effectiveness of each factor on Yelp dataset [19,20]. In this section, we will show you the introduction of dataset, the performance measures and results and discussion.

4.1 Yelp Dataset

Yelp is a local directory service with social networks and user reviews. It is one of the most popular consumer review websites and has more than 71 million monthly unique visitors as of January 2012. It combines local reviews and social networks to create a local online community with the slogan: “real people real review”. And most of all, Yelp dataset contains the exact ratings without any subjective factor. It’s the crucial problem to measure the performance of this algorithm with the objective authenticity of test collection. Meanwhile, Yelp dataset is similar to Epinions, which has been used in [1, 2, 3, 5,19,20].

We have crawled nearly 60 thousand users’ circles of friends and their rated items from November 2012 to January 2013. And five categories are utilized to implement experiments and the statistics of them are shown in Table 2. More detail of this dataset can be found from website of SMILES LAB[5].

We experiment with 80% of each user’s rating data as the training set and 20% of each user’s rating data as the test set in each category to ensure all users’ latent features are learned , and certainly sample the data randomly.

Table 2. Yelp Data: Statistics of the test categories

Category	User Count	Item Count	Rating Count	Sparsity	r^c
Home Services	2500	3213	5180	6.449e-4	3.707
Night Life	4000	21337	99878	1.170e-3	3.594
Pets	1624	1672	3093	1.139e-3	3.975
Restaurants	2000	32725	91946	1.405e-03	3.677
Shopping	3000	16154	33352	6.882e-04	3.819

4.2 Performance Measures

When we get user latent feature $\boldsymbol{U^c}$ and item latent feature $\boldsymbol{P^c}$, the performance of our algorithm will be embodied by the errors. From [1-4] we can see Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as the most popular accuracy measures, which are defined as following:

$$RMSE = \sqrt{\frac{\sum_{(u,i)\in\Re_{test}} \left(R_{u,i} - \hat{R}_{u,i}\right)^2}{\left|\Re_{test}\right|}} \tag{11}$$

$$MAE = \frac{\sum_{(u,i)\in\Re_{test}} \left|R_{u,i} - \hat{R}_{u,i}\right|}{\left|\Re_{test}\right|} \tag{12}$$

[5] `http://smiles.xjtu.edu.cn`

Table 3. Performance comparison based on CircleCon2b of training on each category of Yelp

Category	BaseMF		CircleCon2b		ContextMF		URB	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Home Services	3.26	2.57	2.14	1.68	1.72	1.34	**1.58**	**1.26**
Night Life	2.20	1.65	1.50	1.16	1.32	1.02	**1.18**	**0.93**
Pets	3.53	2.78	2.19	1.72	1.72	1.29	**1.46**	**1.16**
Restaurants	1.88	1.39	1.34	1.04	1.28	1.00	**1.15**	**0.91**
Shopping	2.52	1.90	1.73	1.34	1.41	1.09	**1.32**	**1.03**
Average	2.68	2.06	1.78	1.39	1.49	1.15	**1.34**	**1.06**

Table 4. Performance of the two independent factors on Restaurants of Yelp

Factors	**BaseMF (without any factor considered)**	
RMSE	1.854396	
MAE	1.361975	
Factors	**Interpersonal Interest Similarity**	**Ratings similarity**
RMSE	1.35943	1.24698
MAE	1.05077	0.97693
Factors	**Interpersonal Interest Similarity+ Ratings similarity**	
RMSE	1.14942	
MAE	0.91018	

where $R_{u,i}$ is the real rating value of user u on item i, $\hat{R}_{u,i}$ is the corresponding predicted rating value according to Eq. (8), and $\Re_{test}$ is the set of all user-item pairs in the test set.

4.3 Results and Discussion

In this paper, three existing models are compared with our social recommendation algorithm based on users' rating behaviors (URB) on Yelp dataset: BaseMF [3, 4], CircleCon2b [1] and ContextMF [2].

The performance of different algorithms including our algorithm are showed in Table 3 with the parameter λ=0.1 as [1], β=30, and γ=50, which are tradeoffs to adjust the strengths of different terms in the objective function. And the k which denotes the dimensionality of latent feature $\boldsymbol{U}$ and $\boldsymbol{P}$, is set k=10 as [1]. Previous works [2, 3] had investigated the changes of performance with different k, but as an invariable, it is fair for all compared algorithms. And then we demonstrate the effectiveness and reliability of the proposed model according to experimental results shown in Table 3.

Considering the effectiveness of each factor, we compare the performance of the two independent factors in Restaurants of Yelp respectively. And the experimental results are shown in Table 4 from which we can see that both of the factors have effects on improving the accuracy of recommender system.

5 Conclusions

In this paper, a personalized recommendation approach is proposed by combining social network factors: interpersonal interest similarity and interpersonal rating behaviors similarity. In particular, the interpersonal rating behaviors similarity denotes user's rating behavior habits and his/her rating standards. We can mine user's interest information from comparing the ratings similarity in the same sub-category based on entropy algorithm. We conducted a series of experiments in five categories on Yelp dataset to compare existing approaches and the experimental results showed the significant improvements. At the moment, we just exploit user historical rating records and interpersonal relationship of social networks, but this only goes so far. In the future, we will take user location information and interpersonal influence into consideration to improve our algorithm.

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