Personalized Recommendation Combining User Interest and Social Circle

Xueming Qian, *Member, IEEE*, He Feng, Guoshuai Zhao, and Tao Mei, *Senior Member, IEEE*

Abstract—With the advent and popularity of social network, more and more users like to share their experiences, such as ratings, reviews, and blogs. The new factors of social network like interpersonal influence and interest based on circles of friends bring opportunities and challenges for recommender system (RS) to solve the cold start and sparsity problem of datasets. Some of the social factors have been used in RS, but have not been fully considered. In this paper, three social factors, personal interest, interpersonal interest similarity, and interpersonal influence, fuse into a unified personalized recommendation model based on probabilistic matrix factorization. The factor of personal interest can make the RS recommend items to meet users' individualities, especially for experienced users. Moreover, for cold start users, the interpersonal interest similarity and interpersonal influence can enhance the intrinsic link among features in the latent space. We conduct a series of experiments on three rating datasets: Yelp, MovieLens, and Douban Movie. Experimental results show the proposed approach outperforms the existing RS approaches.

Index Terms—Interpersonal influence, personal interest, recommender system, social networks

1 Introduction

RECOMMENDER system (RS) has been successfully exploited to solve information overload. In E-Commerce, like Amazon, it is important to handling mass scale of information, such as recommending user preferred items and products [64]. A survey shows that at least 20 percent of the sales in Amazon come from the work of the RS. It can be viewed as the first generation of RSes [7] with traditional collaborative filtering algorithms [8]–[12], [22]–[32] to predict user interest. However, with the rapidly increasing number of registered users and various products, the problem of cold start for users (new users into the RS with little historical behavior) and the sparsity of datasets (the proportion of rated user-item pairs in all the user-item pairs of RS) have been increasingly intractable.

Fortunately, the appearance of web2.0 greatly improves user's initiative on the Internet, and then brings volume of social networks such as Facebook, Twitter, Yelp[1], Douban[2], Epinions[3], etc. The interpersonal relationship, especially the circles of friends, of social networks makes it possible to solve the cold start and sparsity problem. The rich of social media give us some valuable clues to recommend user favorite items [48]–[57], [59], [61], such as music [53], video [54], [55], preferred brand/products [56], [57], user's preferred tags when sharing a photo to social media networks [61], and user interested travel places by exploring social community contributed photos [59]–[63].

Many social network based models [3], [13]–[19], [33]–[37] have been proposed to improve the performance of the RS. Recently, Yang *et al*. [1] propose to use the concept of 'inferred trust circle' based on the domain-obvious circles of friends on social networks to recommend user favorite items. Their approach not only refines the interpersonal trust in the complex networks, but also reduces the load of big data. Meanwhile, besides the interpersonal influence, Jiang *et al*. [2] demonstrate that individual preference is also a significant factor in social network. Just like the idea of interpersonal influence, due to the preference similarity, user latent features should be similar to his/her friends' based on the probabilistic matrix factorization model [4], [48]–[52]. However, do all users actually need the relationship on the social networks to recommend items? Does the relationship submerge user's personality, especially for the experienced users? It is still a great challenge to embody user's personality in RS, and it is still an open issue that how to make the social factors be effectively integrated in recommendation model to improve the accuracy of RS.

Phelan *et al*. [42] proposed a news recommendation technique utilizing real-time Twitter data as the basis for ranking and recommending articles from a collection of really simple syndication feeds. And one of the conclusions is that users with more friends tend to benefit more. Chen et al. [43] explored three separate dimensions in designing such a recommender: content sources, topic interest models for users, and social voting. They demonstrated that both topic relevance and the social voting process were helpful in providing recommendations.

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

- *X. Qian, H. Feng, and G. Zhao are with the SMILES LAB of Xi'an Jiaotong University, Xi'an CN710049, China. E-mail: qianxm@mail.xjtu.edu.cn; fenghe7658@sina.com; zhaoguoshuai0011@126.com.*
- *T. Mei is with Microsoft Research, Beijing CN10080, China. E-mail: tmei@microsoft.com.*

Manuscript received 15 Apr. 2013; revised 24 Sep. 2013; accepted 30 Sep. 2013. Date of publication 24 Oct. 2013; date of current version 9 July 2014.
Recommended for acceptance by N. Ramakrishnan.
For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below.
Digital Object Identifier 10.1109/TKDE.2013.168

The quality of recommendations and usability of six online recommender systems was examined in [44]. The results show that the user's friends consistently provided better recommendations. For example 90% of users believe the book recommended is good from friends, 75% of users believe that the recommendation is useful from friends. This research shows that the interpersonal influence is important in social media. Java *et al*. [45] had analyzed a large social network in a new form of social media known as micro-blogging. It has a high degree correlation and reciprocity, indicating close mutual acquaintances among users. They had identified different types of user intentions and studied the community structures. Categorizing friends into groups (e.g. family, co-workers) would greatly benefit the adoption of micro-blogging platforms to analyze user intentions. That is to say user intentions or interests can be reflected by those of its friends.

Rahman and Hailes provide and discuss a model for supporting trust in virtual communities, which is based on experience and reputation [46]. We can see the significance of user's information such as the number of ratings in every category and his/her reputation or reliability.

Yuan *et al*. have explored a kind of social relation, the membership, and its combined effect with friendship [47]. The two types of heterogeneous social relations are fused into the Collaborative Filtering based recommender via a factorization process. And the distinguished effectiveness of social relationships in the sparse data condition was demonstrated.

"Moves as one desires, decides as you like." Just like the logo says, user's choice is always closely related to his/her personal interest. It is very popular for users to share, upload, and comment their favorite content. Thus, users' personal interests can be disclosed by their historical rating records in social rating networks [39]–[41].

In this paper, three social factors, personal interest, interpersonal interest similarity, and interpersonal influence, fuse into a unified personalized recommendation model based on probabilistic matrix factorization. The personality is denoted by user-item relevance of user interest to the topic of item. To embody the effect of user's personality, we mine the topic of item based on the natural item category tags of rating datasets. Thus, each item is denoted by a category distribution or topic distribution vector, which can reflect the characteristic of the rating datasets. Moreover, we get user interest based on his/her rating behavior. We then assign to the effect of user's personality in our personalized recommendation model proportional to their expertise levels. On the other hand, the user-user relationship of social network contains two factors: interpersonal influence and interpersonal interest similarity. We apply the inferred trust circle of Circle-based Recommendation (CircleCon) model [1] to enforce the factor of interpersonal influence. Similarly, for the interpersonal interest similarity, we infer interest circle to enhance the intrinsic link of user latent feature.

The main contributions of this paper are summarized as follows: 1) Propose a personalized recommendation system combining user personal interest, interpersonal interest similarity, and interpersonal influence. The factor of user personal interest makes direct connections between user and item latent feature vectors. And the two other social factors make connections between user and his/her friends' latent feature vectors. 2) Propose a personalized recommendation approach by enforcing user personal interests, which is category related and represented by a multi-level tree structure. Personal unique interest is modeled to get an accurate model for the cold start user and user with very few friends and rated items. The impacts of the three factors to the recommendation performances are systematically compared. 3) Extensive experiments based on three datasets including Yelp, MovieLens, and Douban Movie show the effect of proposed model to solve the user cold start and sparsity problem. 4) We share our datasets for researchers in social recommendation area. The most salient feature of the shared datasets is that objective social recommendation performance evaluation can be carried out.

Compared with our preliminary [52], several enhancements are made which are as follows: 1) More experiments are provided. We carry out experiments on MovieLens, Yelp, and Douban Movie datasets respectively. 2) More detailed steps of the proposed approach are provided. 3) More comparisons and discussions are given.

The remainder of this paper is organized as follows. In Section 2, we define the problem we focus on in this paper. In Section 3, we present the related works on probabilistic matrix factorization model for rating and adoption prediction problem. In Section 4, the proposed personalized recommendation model combining user interest and social circle is introduced in detail. Experiments and discussions are given in Section 5 and conclusions are drawn in Section 6.

2 Problem Formulation

Symbols and notations utilized in this paper are given in Table 1. For personalized RS, the system aims at recommending user interested items based on their historical behavior and interpersonal relationship of social networks. Moreover, we predict the ratings of user u on an unknown item i to measure how much user u interested in item i in social rating networks (like Netflix[4], Yelp, Epinions). In RS, we have a set of users and a set of items $U = \{u_1, \dots, u_M\}$. The ratings expressed by users on items $P = \{i_1, \dots, i_N\}$ are given in a rating matrix $\boldsymbol{R} = [R_{u,i}]_{M\times N}$. In this matrix, $R_{u,i}$ denotes the rating of user u on item i. It can be any real number, but often ratings are integers in the range of 1 to 5. In a social rating network, each user u has a set of friends, and $S_{u,v} \in [0, 1]$ denotes the value of user u trust on user v or the influence of user v to user u. The trust values are given in a matrix $\boldsymbol{S} = [S_{u,v}]_{M\times M}$. Note that S is asymmetric in general, because the influence of user v to user u maybe different from the influence of user u to user v. Meanwhile, $W_{u,v} \in [0, 1]$ denotes the interest similarity of user u to user v. The interest similarity values are given in a matrix $\boldsymbol{W} = [W_{u,v}]_{M\times M}$, which is symmetric in general. And $Q_{u,i} \in [0, 1]$ denotes the relevance of user u's interest to the topic of item i. The relevance values are given in a matrix $\boldsymbol{Q} = [Q_{u,i}]_{M\times N}$, which represents users' personal interests.

Thus the task of our personalized recommender is as follows: Given a user $u \in U$ and an item $i \in P$ for which

4. http://www.netflix.com

TABLE 1
Symbols and Their Descriptions Utilized in this Paper

Symbol	Description	Symbol	Description
U	a set of users	u	a user in the set of users
P	a set of items	i	an item in the set of items
$\boldsymbol{R}_{M\times N}$	the rating matrix expressed by users on items	$\hat{\boldsymbol{R}}_{M\times N}$	the predicted rating matrix based on the latent feature space
M	the number of users in the test social network	N	the number of items in the test social network
c	the category of the items (Table 3)	v	a friend of user u
F_u^c	the set of user u's friends in c	H_u^c	the set of items rated by user u in c
I	the indicator function	D	the topic distribution vector
$\boldsymbol{Q}_{M\times N}$	the relevance matrix of user u's interest to the topic of item i	$\boldsymbol{W}_{M\times M}$	the interest similarity matrix of user u to user v
$\boldsymbol{S}_{M\times M}$	the matrix of user u trust on v	$\boldsymbol{U}_{M\times k}$	the user latent feature matrix
$\boldsymbol{P}_{N\times k}$	the item latent feature matrix	k	the dimension of the latent space
r	users' average rating value in the training dataset	λ, β, γ, η	the tradeoff parameters in the objective function
Ω	zero-mean spherical Gaussian priors	$\mathcal{N}$	Gaussian observation noise
Ψ	the objective function of the recommendation model	$\boldsymbol{X}^c$	the variable corresponding to $\boldsymbol{X}$ in category c
$\boldsymbol{X}^{c*}$	the normalized matrix of $\boldsymbol{X}$ in category c	$\boldsymbol{X}^{\mathrm{T}}$	the transposition of matrix $\boldsymbol{X}$

$R_{u,i}$ is unknown, predict the rating for u on item i using $\boldsymbol{R}$, $\boldsymbol{S}$, $\boldsymbol{W}$ and $\boldsymbol{Q}$.

In this paper, we employ matrix factorization techniques [1]–[5] to learn the latent features of users and items, and predict the unknown ratings using these latent features. Let $\boldsymbol{U} \in R^{M\times k}$ and $\boldsymbol{P} \in R^{N\times k}$ be latent user and item feature matrices, with row vectors $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ representing k-dimensional user-specific and item-specific latent feature vectors of user u and item i, where k is far less than M and N, and it is the rank of the latent matrices $\boldsymbol{U}$ and $\boldsymbol{P}$. Moreover, $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ can be seen as the brief characterization of user u and item i. The goal of matrix factorization is to learn these latent variables and exploit them for recommendation.

3 Related Work

In this paper, we focus on probabilistic matrix factorization with consideration of factors of social network. In the following, we briefly review some relevant works to this paper, including the basic matrix factorization model [4] without any social factors, the CircleCon model [1] with the factor of interpersonal trust values and the Social Contextual (ContextMF) model [2] with interpersonal influence and individual preference.

3.1 Basic Matrix Factorization

To introduce various sophisticated approaches [1]–[3], [5], we first briefly review the basic probabilistic matrix factorization (BaseMF) approach [4], which does not take any social factors into consideration.

The task of RS is to decrease the error of predicted value using $\boldsymbol{R}$ to the real rating value. Thus, the BaseMF model is trained on the observed rating data by minimizing the objective function

$$\Psi(\boldsymbol{R},\boldsymbol{U},\boldsymbol{P}) = \frac{1}{2}\sum_{u,i}\left(R_{u,i}-\hat{R}_{u,i}\right)^2 + \frac{\lambda}{2}\left(\|\boldsymbol{U}\|_F^2+\|\boldsymbol{P}\|_F^2\right), \quad (1)$$

where $\hat{R}_{u,i}$ denotes the ratings predicted by (2), $\hat{\boldsymbol{R}} \in R^{M\times N}$, M is the number of users, N is the number of items, $R_{u,i}$ is the real rating values in the training data for item i from user u, $\boldsymbol{U}$ and $\boldsymbol{P}$ are the user and item latent feature matrices which need to be learn from the training data, $\|X\|_F$ is the Frobenius norm of matrix $\boldsymbol{X}$, and $\|X\|_F = \left(\sum_{i,j} x_{i,j}^2\right)^{1/2}$. The second term is used to avoid over-fitting [3], [6]. This objective function can be minimized efficiently using gradient descent method in [3].

$$\hat{\boldsymbol{R}} = r + \boldsymbol{U}\boldsymbol{P}^{\mathrm{T}}, \quad (2)$$

where r is an offset value [1], which is empirically set as users' average rating value in the training data.

Once the low-rank matrices $\boldsymbol{U}$ and $\boldsymbol{P}$ are learned by the gradient decent approach, which we detail in Section 4. And then, rating values can be predicted according to (2) for any user-item pairs.

3.2 CircleCon Model

The CircleCon model [1] has been found to outperform BaseMF and SocialMF [3] with respect to accuracy of the RS. The approach focuses on the factor of interpersonal trust in social network and infers the trust circle.

The trust value of user-user is represented by the matrix $\boldsymbol{S}$. Furthermore, the whole trust relationship in social network is divided into several sub-networks $\boldsymbol{S}^c$, called inferred circle [1], and each circle is related to a single category c of items. For example, the item *The Dakota Bar* of

New York belongs to the category **Night Life** in Yelp as shown in Table 3. If user u rated the item, then user u is in the circle of category **Night Life**. In category c, the directed and weighted social relationship of user u with user v (the value of u trusts v or the influence of v to u) is represented by a positive value $S^c_{u,v} \in [0,1]$. And we have the normalized interpersonal trust value $S^{c*}_{u,v} = S^c_{u,v} / \sum_{v \in F^c_u} S^c_{u,v}$ (except user u has no friends in the same category). Here F^c_u is the set of user u's friends in c. In this model, the four variants of defining interpersonal trust value $S^c_{u,v}$ are systematically compared: **1) CircleCon1**, $S^c_{u,v} = 1$, which means each user v gets assigned the same trust value to user u in c; **2) CircleCon2a**, $S^c_{u,v} = |H^c_v|$, where H^c_v is the set of items rated by user v in c and $|H^c_v|$ is the total number of items in H^c_v; **3) CircleCon2b**, $S^c_{u,v} = |H^c_v| * B^c$, where B^c is the voting value in c from all followers of user v. The intuition is that if most of v's followers have many ratings in c, it is a good indication that v is an expert in c; **4) CircleCon3**, trust splitting. Assume user $u1$ and user $u2$ both belong to category $c1$ and $c2$, $u1$ is a friend of $u2$, and the number of ratings $u1$ issued in category $c1$ and $c2$ are 7 and 3 respectively. The trust value in original social network is $S_{u2,u1} = 1$. Now after trust splitting, they get $S^{c1}_{u2,u1} = 0.7$ and $S^{c2}_{u2,u1} = 0.3$.

To decrease the predicted error, the CircleCon model combines interpersonal trust value $\boldsymbol{S}$ with the rating matrix $\boldsymbol{R}$, and the objective function is just like SocialMF [3], but the difference is that the CircleCon model is trained in each category. And the basic idea is that a user in social network may be influenced by other users, especially his/her friends in the same category. Thus their objective function is as follows:

$$\begin{aligned}\Psi^c(\boldsymbol{R}^c, \boldsymbol{U}^c, \boldsymbol{P}^c, \boldsymbol{S}^{c*}) &= \frac{1}{2}\sum_{u,i}(R^c_{u,i} - \hat{R}^c_{u,i})^2 + \frac{\lambda}{2}\left(\|\boldsymbol{U}^c\|_F^2 + \|\boldsymbol{P}^c\|_F^2\right) \\ &+ \frac{\beta}{2}\sum_u\left(\left(U^c_u - \sum_{v\in F^c_u} S^{c*}_{u,v}U^c_v\right)\left(U^c_u - \sum_{v\in F^c_u} S^{c*}_{u,v}U^c_v\right)^{\mathrm{T}}\right),\end{aligned} \tag{3}$$

where the estimated ratings for a user is category related which is expressed as follows:

$$\hat{R}^c_{u,i} = r^c + \boldsymbol{U}^c_u \boldsymbol{P}^{c\mathrm{T}}_i, \tag{4}$$

where r^c is empirically set as user's average rating value in category c. In (3), the factor of interpersonal trust is enforced by the last term in the objective function, which says that user latent feature $\boldsymbol{U}_u$ should be similar to the average of his/her friends' latent features with weight $S^{c*}_{u,v}$ of in category c.

Only ratings in category c are used to train user and item latent feature matrices $\boldsymbol{U}$ and $\boldsymbol{P}$ in this model. And once the model is trained in c, the rating value in c can be predicted according to (4).

3.3 ContextMF Model

Jiang *et al*. [2] demonstrate the significance of social contextual factors (including interpersonal influence and individual preference) for item adopting on real Facebook and Twitter style datasets. The task of ContextMF model in [2] is to recommend acceptable items from sender u to receiver v. Here, the factor of interpersonal influence is similar to the trust values in CircleCon model [1]. Moreover, individual preference is mined from receiver's historical adopted items. And the interpersonal preference similarity values are represented by the matrix $\boldsymbol{W}$. Each of the rows is normalized to unity $\sum_v W^*_{u,v} = 1$. The objective function of this model is

$$\begin{aligned}\Psi(\boldsymbol{R}, \boldsymbol{U}, \boldsymbol{P}, \boldsymbol{S}^*, \boldsymbol{W}^*) &= \frac{1}{2}\sum_{u,i}\left(R_{u,i} - \hat{R}_{u,i}\right)^2 + \frac{\lambda}{2}\left(\|U\|_F^2 + \|\boldsymbol{P}\|_F^2\right) \\ &+ \frac{\beta}{2}\sum_u\left(\left(\boldsymbol{U}_u - \sum_v S^*_{u,v}\boldsymbol{U}_v\right)\left(\boldsymbol{U}_u - \sum_v S^*_{u,v}U_v\right)^{\mathrm{T}}\right) \\ &+ \frac{\gamma}{2}\sum_{u,v}\left(W^*_{u,v} - \boldsymbol{U}_u\boldsymbol{U}_v^{\mathrm{T}}\right)^2,\end{aligned} \tag{5}$$

where the factor of individual preference is enforced by the last term in (5), which means that user latent feature $\boldsymbol{U}_u$ should be similar to his/her friends' latent feature with weight of their preference similarity $W^*_{u,v}$ in social network, and the rating values $\hat{R}_{u,i}$ is predicted by (1). Once the model is trained, the rating values can be predicted according to (1) for any user-item pairs.

Besides the interpersonal influence (similar to the trust values in CircleCon model [1]), individual preference is a novel factor in ContextMF model, and is enforced by the last term in (5). Note that we still execute the interpersonal influence as CircleCon model [1] and omit the topic relevance of items, as we also predict ratings of items in Epinions style datasets and use the circle based idea in our experiments. Although individual preference is proposed in this model, user u's latent feature is still connected with his/her friends rather than his/her characteristic. In fact, the factor of individual preference of this model is enforced by interpersonal preference similarity.

Comparing ContextMF model, the proposed personalized recommendation model has three differences: 1) the task of our model is to recommend user, regardless of sender or receiver, interested and unknown items. 2) user personal interest is directly related to his/her rated items rather than connect with his/her friends. 3) the factor of user interest in our model mined from user rated items has more influence than individual preference in ContextMF model, because it easier for the recommended items of our model to be transformed into purchase rate than the adopted items in Facebook style social networks.

4 The Approach

The proposed personalized recommendation approach fuses three social factors: user personal interest, interpersonal interest similarity, and interpersonal influence to recommend user interested items. The illustration of our approach is shown in Fig. 1. Among the three factors, user personal interest and interpersonal interest similarity are the main contributions of the approach and all related to user interest. Thus, we introduce user interest factor firstly. And then, we infer the objective function of the proposed

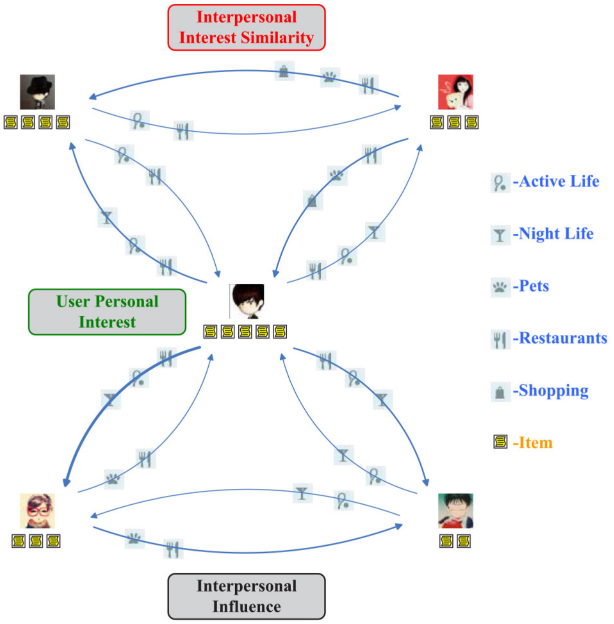


Fig. 1. Three main social factors in our recommendation model, including user personal interest, interpersonal interest similarity, and interpersonal influence. The items under users are historical rating records, which can be used to mine users' personal interest. The category icon on line between two users denotes their interest similarity. And the boldness of the line between users indicates the strength of interpersonal influence.

personalized recommendation model. At last, we give the training approach of the model. Hereinafter we turn to the details of our approach.

4.1 User Interest Factor

Besides the trust values between friends in the same category [1], user interest is another significant factor to affect users' decision-making process, which has been proved by psychology and sociology studies [38]. Moreover, Jiang *et al.* [2] demonstrated the effect of ContextMF model with consideration of both individual preference and interpersonal influence. However, there are two main differences of the user interest factor in our model to individual preference in ContextMF [2]: 1) The independence of user interest. It means we can recommend items based on user interest at a certain extent. In other words, we utilize user's connection with the items to train the latent feature vectors, especially for the experienced users. 2) Interest circle inference. Just like CircleCon model [1], we divide the tested social network into several sub-networks, and each of them correspond to a signal category of items. Considering the cold start users who has a few rating records, we use friends' interest in the same category to link user latent feature vector.

4.1.1 *User Interest Description*

According to the natural item category tags of rating datasets, we can get category distribution of the item, which can be seen as the naïve topic distribution of the item D_i. For example, each item has the tags of its category in Yelp. Just like the item *The Dakota Bar* of New York belongs to the category **Night Life**, then **Night Life** is one of the category tags of the item. From user's historical rating data in category c, we summarize all the rated items to measure user interest D_u^c:

$$D_u^c = \frac{1}{|H_u^c|} \sum_{i \in H_u^c} D_i, \tag{6}$$

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

Note that the method we use to get the topic distribution D_i is also different from ContextMF [2]. We apply the tree structure of categories of items, shown in Fig. 2, to extract the topic distributions of items, just as that we utilized in [56], [57]. The first level of the tree structure is the big category of items. For example, we have 8 big categories: #1**Active Life**, #2**Beauty and Spas**, #3**Home Services**, #4**Hotels & Travel**, #5**Night Life**, #6**Pets**, #7**Restaurants**, and #8**Shopping** according to Yelp data shown as Table 3. The second level is the subcategory of each big category in the first level.

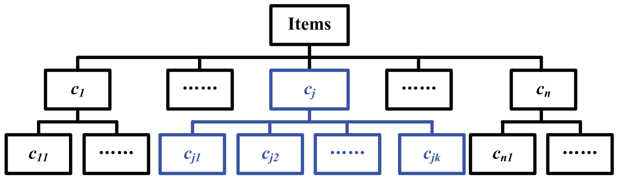


Fig. 2. Tree structure of categories of items.

We get two level topic distributions of each item in the datasets corresponding to the two level of the tree as following:

$$D1_i = [I_{c_1}, I_{c_2}, \ldots, I_{c_n}] \tag{7}$$
$$D2_i = [I_{c_{j1}}, I_{c_{j2}}, \ldots, I_{c_{jl}}], j \in [1, n], \tag{8}$$

where I_{cj} is the indicator that is equal to 1 if the i-th item belongs to the category c_j, and equal to 0 otherwise, and n is the number of category in the datasets, for Yelp $n = 8$, for MovieLens and Douban Movie $n = 1$.

Thus, we measure user interest with $D1_u^c$ and $D2_u^c$, which have different meanings: $D1_u^c$ represents user global point of interest distribution which is an overall description; $D2_u^c$ represents user local point of interest distribution which is a detailed description.

4.1.2 *Personal Interest*

Due to the individuality, especially users with many rating records, users usually choose items all by themselves with little influence by their friends. However, many previous works [1]–[3] took the circles of friends in social networks to solve the cold start problem. It did work for the cold start users with a few records, but ignored the individuality for experienced users. In other words, the relevance of user and item latent feature vector depends on the relevance of user interest D_u and item topic D_i to a certain extent. More formally, we denote the relevance of user u's personal interest to the topic of item i in our recommendation model by $Q_{u,i}$

$$Q_{u,i} = Sim(D_u, D_i). \tag{9}$$

Thus, for the user and item latent feature vectors on the personal interest, we have the conditional distribution according to [4]:

$$p(\boldsymbol{Q} \mid \boldsymbol{U}, \boldsymbol{P}, \Omega) = \prod_u \prod_i \left[N\left(Q_{u,i} \middle| \boldsymbol{U}_u \boldsymbol{P}_i^{\mathrm{T}}, \Omega \right) \right]^{I_{u,i}^R}, \tag{10}$$

where $\mathcal{N}(x \mid \mu, \Omega)$ is the normal distribution with mean μ and variance Ω, and $I_{u,i}^R$ is the indicator function that is equal to 1 if user u has rated item i and equal to 0 otherwise.

Note that the conditional distribution based on personal interest is similar to the conditional probability of the observed ratings [4]:

$$p(\boldsymbol{R} \mid \boldsymbol{U}, \boldsymbol{P}, \Omega) = \prod_u \prod_i \left[N\left(R_{u,i} \middle| \boldsymbol{U}_u \boldsymbol{P}_i^{\mathrm{T}}, \Omega \right) \right]^{I_{u,i}^R}. \tag{11}$$

Actually, the factor of personal interest $Q_{u,i}$ can be viewed as the latent real rating value of user u to item i. Thus it can also enhance the robustness of the recommender system to reduce the attack of malicious rating.

4.1.3 Interest Circle Inference

Similar to the trust circle inference in CircleCon model [1], we propose the interest circle inference. The basic idea is that user latent feature vector should be similar to his/her friends' latent feature vector based on the similarity of their interest. Here we denote the interest similarity value between u and v by $W_{u,v}$, and each of the rows is normalized to unity $\sum_v W_{u,v}^* = 1$.

$$W_{u,v} = Sim(D_u, D_v). \tag{12}$$

According to [3], zero mean Gaussian priors are assumed for user latent feature vectors:

$$p(U \mid \Omega) = \prod_u \mathcal{N}(U_u \mid 0, \Omega). \tag{13}$$

Thus, for the user latent feature vectors based on interest circle inference, we have the conditional distributions given the latent features of his circles of friends:

$$p(\boldsymbol{U}^c \mid \boldsymbol{W}^c, \Omega^c) = \prod_u \mathcal{N}\left(\boldsymbol{U}_u^c \middle| \sum_{v \in F_u^c} W_{u,v}^{c*} \boldsymbol{U}_v^c, \Omega^c \right), \tag{14}$$

where F_u^c is the set of user u's friends in c, $W_{u,v}^{c*}$ is the normalized interpersonal interest similarity matrix in c.

4.2 Personalized Recommendation Model

The personalized recommendation model contains the following three aspects: 1) Interpersonal influence $S_{u,v}^{c*}$ [1], which means whom you would trust. 2) Interest circle inference $W_{u,v}^{c*}$, which means whose interest is similar to yours. 3) User personal interest $Q_{u,i}^{c*}$, which has effect on what items you would interest in.

According to BaseMF model [3], [4], through a Bayesian inference, the posterior probability of the latent variables $\boldsymbol{U}$ and $\boldsymbol{P}$ can be obtained as follows:

$$\begin{aligned} p(U, \boldsymbol{P} \mid \boldsymbol{R}, \Omega) &\propto p(\boldsymbol{R} \mid \boldsymbol{U}, \boldsymbol{P}, \Omega) p(\boldsymbol{U} \mid \Omega) p(\boldsymbol{P} \mid \Omega) \\ &= \prod_u \prod_i [\mathcal{N}(R_{u,i} \mid \boldsymbol{U}_u \boldsymbol{P}_i^{\mathrm{T}}, \Omega)] \times \prod_u \mathcal{N}(\boldsymbol{U}_u \mid 0, \Omega) \\ &\times \prod_i \mathcal{N}(\boldsymbol{P}_i \mid 0, \Omega). \end{aligned} \tag{15}$$

As aforementioned, we combine interpersonal influence $\boldsymbol{S}$, interpersonal interest similarity $\boldsymbol{W}$, and user personal interest $\boldsymbol{Q}$ with the rating matrix $\boldsymbol{R}$ to decrease the predicted error. Thus, for each category c, through Bayesian inference, we define the posterior probability of latent features giving the rating and social context factors as follows:

$$\begin{aligned} &p(\boldsymbol{U}^c, \boldsymbol{P}^c \mid \boldsymbol{R}^c, \boldsymbol{S}^{c*}, \boldsymbol{W}^{c*}, \boldsymbol{Q}^{c*}, \Omega^c) \\ &\quad \propto p(\boldsymbol{R}^c \mid \boldsymbol{U}^c, \boldsymbol{P}^c, \Omega^c) p(\boldsymbol{U}^c \mid \boldsymbol{S}^{c*}, \Omega^c) p(\boldsymbol{U}^c \mid \boldsymbol{W}^{c*}, \Omega^c) \\ &\quad\quad p(\boldsymbol{Q}^{c*} \mid \boldsymbol{U}^c, \boldsymbol{P}^c, \Omega^c) p(\boldsymbol{U}^c \mid \Omega^c) p(\boldsymbol{P}^c \mid \Omega^c) \\ &\quad = \prod_u \prod_i \left[\mathcal{N}\left(R_{u,i}^c \middle| \boldsymbol{U}_u^c \boldsymbol{P}_i^{c\mathrm{T}}, \Omega^c \right) \right]^{I_{u,i}^{cR}} \\ &\quad \times \prod_u \mathcal{N}\left(\boldsymbol{U}_u^c \middle| \sum_{v \in F_u^c} S_{u,v}^{c*} \boldsymbol{U}_v^c, \Omega^c \right) \\ &\quad \times \prod_u \mathcal{N}\left(\boldsymbol{U}_u^c \middle| \sum_{v \in F_u^c} W_{u,v}^{c*} \boldsymbol{U}_v^c, \Omega^c \right) \\ &\quad \times \prod_u \prod_i \left[\mathcal{N}(Q_{u,i}^{c*} \mid \boldsymbol{U}_u^c \boldsymbol{P}_i^{c\mathrm{T}}, \Omega^c) \right]^{I_{u,i}^{cR}} \\ &\quad \times \prod_u \mathcal{N}(U_u^c \mid 0, \Omega^c) \\ &\quad \times \prod_i \mathcal{N}(P_i^c \mid 0, \Omega^c) \end{aligned} \tag{16}$$

Then the logarithm of the posterior probability can be seen as the objective function. Keeping the parameters (observation noise and prior variance) fixed, we can get:

$$\begin{aligned} &\Psi^c(\boldsymbol{R}^c, \boldsymbol{U}^c, \boldsymbol{P}^c, \boldsymbol{S}^{c*}, \boldsymbol{W}^{c*}, \boldsymbol{Q}^{c*}) \\ &\quad = \frac{1}{2} \sum_{u,i} (R_{u,i}^c - \hat{R}_{u,i}^c)^2 + \frac{\lambda}{2} \left(\|\boldsymbol{U}^c\|_F^2 + \|\boldsymbol{P}^c\|_F^2 \right) \\ &\quad + \frac{\beta}{2} \sum_u \left(\left(U_u^c - \sum_v S_{u,v}^{c*} \boldsymbol{U}_v^c \right) \left(\boldsymbol{U}_u^c - \sum_v S_{u,v}^{c*} \boldsymbol{U}_v^c \right)^{\mathrm{T}} \right) \\ &\quad + \frac{\gamma}{2} \sum_u \left(\left(\boldsymbol{U}_u^c - \sum_v W_{u,v}^{c*} \boldsymbol{U}_v^c \right) \left(\boldsymbol{U}_u^c - \sum_v W_{u,v}^{c*} \boldsymbol{U}_v^c \right)^{\mathrm{T}} \right) \\ &\quad + \frac{\eta}{2} \sum_{u,i} \left| H_u^{c*} \right| \left(Q_{u,i}^{c*} - \boldsymbol{U}_u^c \boldsymbol{P}_i^{c\mathrm{T}} \right)^2, \end{aligned} \tag{17}$$

where $\hat{R}_{u,i}^c$ is the predicted rating value in c according to (4). $|H_u^{c*}|$ is the normalized number of items that user u has rated in c, which denotes how much a user depends on his/her individuality to rate an item. The idea of interpersonal influence is enforced by the second term, which says that user latent feature $\boldsymbol{U}_u$ should be similar to the average of his/her friends' latent feature with weight of $S_{u,v}^{c*}$ in c. The factor of interpersonal interest similarity is enforced by the third term, which says that user latent feature $\boldsymbol{U}_u$ should be similar to the average of his/her friends' latent feature with weight of $W_{u,v}^{c*}$ in c. And the factor of user personal interest is enforced by the last term, which says user latent feature $\boldsymbol{U}_u$ should directly connect with item latent feature $\boldsymbol{P}_i$ in c.

Note that the objective function of CircleCon model [1] is the first two terms in (17), and the ContextMF model is similar to the first three terms. Here the third term has a little difference from (5), because we still use the concept of inferred circle in [1], which has shown the superiority.

4.3 Model Training

For each category c, we get the corresponding matrix factorization model as (17) to obtain a separate user latent profile $\boldsymbol{U}^c$ and item latent profile $\boldsymbol{P}^c$. 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 (18) and (19) respectively:

$$\begin{aligned}\frac{\partial \Psi^c}{\partial \boldsymbol{U}_u^c} = &\sum_{i \in H_u^c} I_{u,i}^{R^c}\left(\hat{R}_{u,i}^c - R_{u,i}^c\right)\boldsymbol{P}_i^c + \lambda \boldsymbol{U}_u^c \\ &+ \beta\left(\boldsymbol{U}_u^c - \sum_{v \in F_u^c} S_{u,v}^{c*}\boldsymbol{U}_v^c\right) \\ &- \beta \sum_{v: u \in F_v^c} S_{v,u}^{c*}\left(\boldsymbol{U}_v^c - \sum_{w \in F_v^c} S_{v,w}^{c*}\boldsymbol{U}_w^c\right) \\ &+ \gamma\left(\boldsymbol{U}_u^c - \sum_{v \in F_u^c} W_{u,v}^{c*}\boldsymbol{U}_v^c\right) \\ &- \gamma \sum_{v: u \in F_v^c} W_{v,u}^{c*}\left(\boldsymbol{U}_v^c - \sum_{w \in F_v^c} W_{v,w}^{c*}\boldsymbol{U}_w^c\right) \\ &+ \eta \sum_{i \in H_u^c} I_{u,i}^{R^c}\left|H_u^{c*}\right|\left(U_u^c P_i^{c\mathrm{T}} - Q_{u,i}^{c*}\right)\boldsymbol{P}_i^c \end{aligned} \tag{18}$$

$$\begin{aligned}\frac{\partial \Psi^c}{\partial \boldsymbol{P}_i^c} = &\sum_{u} I_{u,i}^{R^c}\left(\hat{R}_{u,i}^c - R_{u,i}^c\right)\boldsymbol{U}_u^c + \lambda \boldsymbol{P}_i^c \\ &+ \eta \sum_{u} I_{u,i}^{R^c}\left|H_u^{c*}\right|\left(\boldsymbol{U}_u^c \boldsymbol{P}_i^{c\mathrm{T}} - Q_{u,i}^{c*}\right)\boldsymbol{U}_u^c, \end{aligned} \tag{19}$$

where $I_{u,i}^{R^c}$ is the indicator function that 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 in c according to (4). $|H_u^{c*}|$ is the normalized number of items that user u has rated in c, which is the factor of a user depends on his/her personal interest to rate an item. The initial values of $\boldsymbol{U}^c$ and $\boldsymbol{P}^c$ are sampled from the normal distribution with zero mean. It empirically has little effect on the latent feature matrix learning. 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 in each iteration. Note that the step size is a considerable issue. We adjust it to insure the decreases of the objective function in training. The algorithm is shown as Table 2, where l is the step size, and t is the iteration times.

5 Experiments

In this section, we conduct series of experiments to evaluate the performance of proposed personalized recommendation combining user interest and social circle and compare with the existing approaches on three datasets: Yelp[5], MovieLens, and Douban Movie[6]. Among them, we choose Yelp as the main test dataset because it own many local directory service and user's review with attribute of social networks. The compared approaches include BaseMF [3], [4], CircleCon [1], and ContextMF [2].

TABLE 2
Algorithm of Personalized Recommendation

Algorithm of Personalized Recommendation Model (PRM)
Initialization: $\Psi^c(0) = \Psi^c(\boldsymbol{U}^c(0), \boldsymbol{P}^c(0))$.
Require: $0<l<1$, $t=0$.
while($t<1000$)
calculate $\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}$, $\frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
search optimal l
$\boldsymbol{U}^c(t)=\boldsymbol{U}^c(t)-l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}$, $\boldsymbol{P}^c(t)=\boldsymbol{P}^c(t)-l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
If ($\Psi^c(t) < \varepsilon$)
break;
t++;
end

5.1 Datasets

5.1.1 Yelp Dataset

Yelp is a local directory service with social networking 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 networking functionality to create a local online community. Yelp allows real people to contribute their own reviews. This body of social reviews creates a participatory culture where anyone can share their insight and suggestions and add to a body of "collective intelligence" on local businesses, here we call items, by using their personal knowledge and skill sets to post, revise, and assign them numeric ratings in the range of 1 to 5. Essentially, this form of intelligence allows people to actively participate and share their knowledge with other users, especially their friends. Different form the Epinion datasets [21], the friendships between users are bidirectional: if user A is in user B's friend list, then user B is also in user A's friend list. However, the influence between users with friendship is unidirectional: if user A's trust value towards B is 0.5, then user B's trust value towards A may be 0.3.

We have crawled nearly 60 thousand users' circles of friends and their rated items from November 2012 to January 2013. We first collect some active users in New York as origin, and then crawl these users' friends to build the sub-networks of Yelp. Except the user without any rated history (at least one rated item), the dataset consists of ratings from 10,555 users who rated a total of 1,783,922 items from 22 big categories (**actually, Yelp has 26 big categories, the other four categories are with a few user and items**). The average number of user ratings is about 169. The distribution of the ratings cross all categories is

5. http://www.yelp.com

6. http://movie.douban.com

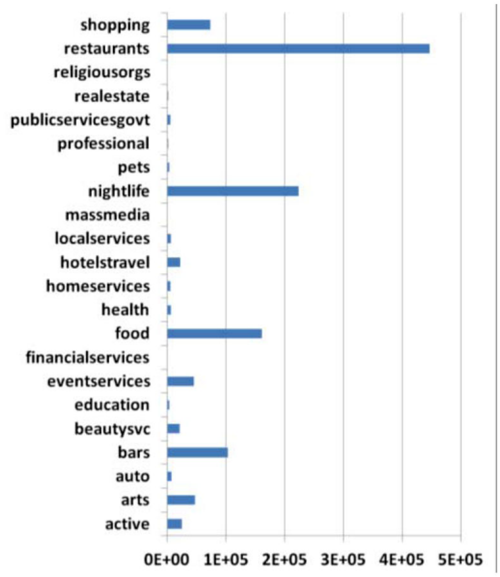


Fig. 3. Distribution of the ratings in the 22 categories of Yelp dataset.

TABLE 3
Yelp Data: Statistic of the Test Categories

Category	User Count	Item Count	Rating Count	Sparsity	r^c
Active Life	5327	7495	24395	6.110e-4	4.021
Beauty and Spas	5466	8495	21345	4.597e-4	3.937
Home Services	2500	3213	5180	6.449e-4	3.707
Hotels & Travel	4712	5883	21658	7.813e-4	3.824
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-3	3.677
Shopping	3000	16154	33352	6.882e-4	3.819

plotted in Fig. 3. We can see that the top three popular categories are **Restaurants**, **Night Life**, and **Shopping**. Note that we merge the similar categories like **Restaurants** and **Food**, **Night Life** and **Bars**. To test the applicability of the proposed model, we choose eight categories based on the popularity distribution of the 22 categories. There are three most popular categories, three common categories (**Active Life**, **Beauty and Spas**, **Hotels and Travel**) and two less rating but interesting categories (**Home Services** and **Pets**). **Finally, the eight categories are selected as our dataset. More detail of this dataset can be found from website of SMILES LAB[7]. Note that we try our best to remove personal information manually before sharing this dataset.** Table 3 is a statistic of users and items in the eight categories, where is users' average rating value in c.

7. http://smiles.xjtu.edu.cn

TABLE 4
Statistics of MovieLens and Douban Movie Datasets

Dataset	User Count	Item Count	Rating Count	Sparsity	r^c
MovieLens	6040	3706	1000209	0.0447	3.571
Douban Movie	2965	39695	911041	0.0077	3.762

5.1.2 MovieLens Dataset

MovieLens dataset is shared by GroupLens[8] research group. **This dataset is with a single layer with 18 categories in total. Note that this dataset only has the ratings of each user to the rated movies. Users in this dataset are independent and do not have social relationships**. It only has user's rating to movies, but interpersonal relationship. The dataset contains 1,000,209 anonymous ratings of 3,706 movies made by 6,040 MovieLens users who joined MovieLens in 2000.

5.1.3 Douban Movie Datasets

Douban is one of the most popular social networks in China. It includes several parts: Douban Movie, Douban Read and Douban Music, etc. Douban Movie provides the latest movie info, and users can record the movies they wish to watch and rate what they watched. Moreover, they can share the reviews to their friends. **We crawl the ratings of the Douban Movie according to the naïve 36 categories. This dataset is also with a single layer. Users in this dataset have social relationships.** We have crawled nearly 50 thousand users' circles of friends and their rated movies from December 2012 to March 2013. We first collect some active users in Douban as origin, and then further crawl these users' friends to build the sub-networks of Douban. Except the user without any rated history (at least one rated item) and any friends (at least one friend), the dataset consists of ratings from 2,965 users who rated a total of 911,041 movies. This dataset is also available in our website. The average number of user ratings is about 307. Table 4 is a statistic of users and items in the MovieLens and Douban Movie datasets, where r^c is users' average rating value in c. Note that Yelp dataset is sparser than MovieLens and Douban Movie datasets. Actually, MovieLens and Douban Movie can be seen as another two independent categories of Yelp.

5.2 Performance Measures

In each category of Yelp, MovieLens, and Douban Movie dataset, we use 80% of data as the training set and the remaining 20% as the test set. More formally, we use 80% of each user's rating data as the training set to insure all users' latent features are learnt in the training set. The evaluation metrics we use in our experiments are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), as these are the most popular accuracy measures in the

8. www.grouplens.org

literature of recommender systems [1]–[4]. RMSE and MAE are defined as

$$RMSE = \sqrt{\frac{\sum_{(u,i)\in\Re_{test}}\left(R_{u,i} - \hat{R}_{u,i}\right)^2}{|\Re_{test}|}} \tag{20}$$

$$MAE = \frac{\sum_{(u,i)\in\Re_{test}}\left|R_{u,i} - \hat{R}_{u,i}\right|}{|\Re_{test}|}, \tag{21}$$

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 (4), and $\Re_{test}$ is the set of all user-item pairs in the test set.

5.3 Evaluation

5.3.1 Comparative Algorithms

We conducted series of experiments to compare our personalized recommendation model (PRM) with the following existing models.

- **BaseMF**: This model is the basic matrix factorization approach proposed in [4] without consideration of any social factors.
- **CircleCon**: This method is proposed in [1], including four variants: CircleCon1, CircleCon2a, CircleCon2b, and CircleCon3. It improves the accuracy of BaseMF and SocialMF [3] by introducing the inferred trust circle of social network. And Yang *et al*. have demonstrated CircleCon2a, CircleCon2b, and CircleCon3 have much better performance. Thus, we just omit CircleCon1.
- **ContextMF**: This method [2] improves the accuracy of traditional item-based collaborative filtering model in [9], influence-based model in [16], and SoRec in [17] by taking both interpersonal influence and individual preference into consideration. As stated in Section 3, we train the model as (5).
- **PRM1**: The factor of user personal interest in Section 4 is represented by $Q_{u,i}$ derived from (7), in which the item topic distribution vector is calculated from the first level of the category tree. And the similarity in (9) is measured by cosine similarity as

$$Sim(D_u, D_i) = \frac{D_u \bullet D_i}{|D_u| \times |D_i|}. \tag{22}$$

- **PRM2**: Analogous, $Q_{u,i}$ is derived from (8), in which the item topic distribution vector is calculated from the second level of the category tree. And also the similarity is measured by cosine similarity.

5.3.2 Parameter Settings

Here we focus on the meanings and settings of all parameters, and implement algorithms of our model and all compared method with these parameters.

- ***k***: The dimension of the latent space. If k is too small, it is difficult for the model to make a distinction among users or items. If k is too large, users and items will be too unique for the system to calculate their similarities and the complexity will considerably increase. Previous works [2], [3] have investigated the change of performance with different k. But, whatever the k is, it is fair for all compared algorithms. Here we set $k = 10$ as [1].
- λ: The normalized parameter in (17). Here we also set $\lambda = 0.1$ as [1].
- β: The weight of the inferred trust circle enforced in the second term of the objective function (17). Here we set $\beta = 30$.
- γ: The weight of the inferred interest circle enforced in the third term of (17). Here we also set $\gamma = 30$ to balance with the factor of interpersonal influence.
- η: The weight of the personal interest factor in the last term of (17). Here we set $\eta = 30$. Note that user experience level $|H_u^{c*}|$ is also used to adjust the weight.

Among these parameters, β, γ, and η are tradeoff parameters in our model. And they play the role of adjusting the strengths of different terms in the objective function.

5.3.3 Performance Comparison

In this section, we compare the performance of our PRM algorithm with the existing models including BaseMF [3], [4], CircleCon [1], and ContextMF [2] on the three datasets: Yelp, MovieLens, and Douban Movie.

In Tables 5 and 6, we show the performance based on the Yelp dataset. Note that we enforce the interpersonal influence in other methods as CircleCon2b and CircleCon3 in Tables 5 and 6 respectively. Comparing Tables 3 and 5 (also Tables 3 and 6), we can see that the more rating information a category has, the higher accuracy the RS achieves. From Table 5, we can see that the accuracy of our personalized recommendation model is much better than the BaseMF for the social factors. For the social recommendation models, we decrease the prediction error by 34% and 6% on MAE, by 45% and 12% on RMSE over CircleCon2b and ContextMF. The same conclusion holds in Table 6. The results demonstrate the significant of users' individuality in RS. Comparing Tables 5 and 6, the average performance of CircleCon3 is higher than CircleCon2b, which is consistent with the conclusion of Jiang [1] in Epionions datasets.

As stated above, the MovieLens and Douban Movie datasets are two independent categories. Moreover, there are no users' circles of friends in MovieLens Dataset. Thus, we can only perform the proposed PRM2 model which mines user's detailed interest based on the subcategory of movie, like **Adventure**, **Comedy** and so on. And we compare it with BaseMF and ContextMF without CircleCon model because it needs the information of circles of friends in the dataset. Note that we also remove the second term in (5) and (15) corresponding to the ContextMF and PRM2 model respectively. In Table 7, we show the performance of BaseMF, ContextMF, and the proposed PRM2 based on the MovieLens dataset. From Table 7, we can see that the performance of PRM2 is close to ContextMF and much better than the BaseMF.

For Douban Movie dataset, we compare the proposed PRM2 model with BaseMF, CircleCon2a, and ContextMF model. And the performance is shown as Table 8. Form Table 8, we can see that the performance of PRM2 is the optimal and decrease the prediction error by 25% and 14%

TABLE 5
Performance Comparison Based on CircleCon2b of Training on Each Category of Yelp

Category	BaseMF		CircleCon2b		ContextMF		PRM1		PRM2	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Active Life	2.846	2.182	1.779	1.380	1.360	1.026	**1.278**	**1.007**	1.289	1.011
Beauty and Spas	3.176	2.481	1.950	1.533	1.567	1.203	1.436	1.135	**1.432**	**1.131**
Home Services	3.259	2.570	2.136	1.676	1.723	1.340	1.654	1.331	**1.638**	**1.311**
Hotels & Travel	2.857	2.208	1.862	1.459	1.409	1.085	**1.310**	**1.037**	1.328	1.049
Night Life	2.197	1.647	1.497	1.159	1.320	1.023	**1.147**	**0.914**	1.152	0.920
Pets	3.532	2.778	2.190	1.724	1.715	1.289	**1.551**	**1.219**	1.581	1.254
Restaurants	1.884	1.385	1.340	1.035	1.280	0.995	1.088	0.869	**1.083**	**0.867**
Shopping	2.516	1.900	1.727	1.337	1.413	1.087	1.340	1.046	**1.318**	**1.029**
Average	2.783	2.144	1.810	1.413	1.473	1.131	**1.351**	**1.070**	1.353	1.072

TABLE 6
Performance Comparison Based on CircleCon3 of Training on Each Category of Yelp

Category	BaseMF		CircleCon3		ContextMF		PRM1		PRM2	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Active Life	2.846	2.182	1.808	1.409	1.379	1.036	**1.298**	**1.018**	1.325	1.034
Beauty and Spas	3.176	2.481	1.946	1.530	1.572	1.202	1.438	1.125	**1.430**	**1.129**
Home Services	3.259	2.570	2.065	1.642	1.707	1.340	1.700	1.348	**1.646**	**1.317**
Hotels & Travel	2.857	2.208	1.847	1.441	1.444	1.103	**1.345**	**1.057**	1.347	1.061
Night Life	2.197	1.647	1.485	1.155	1.318	1.025	**1.147**	**0.914**	1.149	0.915
Pets	3.532	2.778	2.127	1.694	1.731	1.317	1.619	1.266	**1.489**	**1.170**
Restaurants	1.884	1.385	1.364	1.056	1.272	0.991	1.010	0.876	**1.091**	**0.869**
Shopping	2.516	1.900	1.694	1.318	1.421	1.085	**1.319**	**1.028**	1.328	1.043
Average	2.783	2.144	1.792	1.406	1.481	1.137	1.360	1.079	**1.351**	**1.067**

on MAE, by 24% and 18% on RMSE over CircleCon2a and ContextMF.

From Tables 5 to 8, we can see that the circles of friends in social networks have a big impact to the accuracy of RS. Furthermore, the proposed PRM model is suitable for the sparse dataset, and can achieve higher performance. Through experiments on these three available rating datasets, we demonstrate that the proposed personalized recommendation model can better integrate the factors of user personality and the social factors. It can achieve higher accuracy than basic matrix factorization approach, the CircleCon model [1] with inferred trust circle only, and also ContextMF [2] combining interpersonal influence and user preference.

TABLE 7
Performance Comparison Based on the MovieLens

Dataset	BaseMF		ContextMF		PRM2	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Mov-ieLens	2.214	1.683	1.124	0.941	**1.123**	**0.940**

5.4 Discussion

Comparing the performance of the proposed PRM and the existing BaseMF, CircleCon, and ContextMF model in Tables 5, 6, 7, and 8, we discuss four aspects in our experiments: adjustment of the trade-off parameters in the objective function, different similarity measurements of topic distribution vectors in (22), the impact of the amount of user information (the number of user rated items in a category and the number of friends in the same category), and the impact of the three independent factors.

5.4.1 Trade-off Parameters

To be fair with the compared models, we conducted series of experiments using CircleCon2b, ContextMF, and PRM1

TABLE 8
Performance Comparison Based on CircleCon2a of Training on the Douban Movie Dataset

Dataset	BaseMF		CircleCon2a		ContextMF		PRM2	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Douban Movie	1.807	1.338	1.712	1.277	1.553	1.161	**1.377**	**1.022**

TABLE 9
Discussion β in CircleCon2b of Training on Restaurants of Yelp

Performance	β=10	β=20	β=30	β=40	β=50	β=60	β=70	β=80	β=90	β=100	β=150
RMSE	1.608	1.456	1.340	1.257	1.198	1.175	1.133	1.108	1.092	1.085	**1.057**
MAE	1.207	1.113	1.035	0.986	0.945	0.927	0.899	0.881	0.874	0.868	**0.852**

TABLE 10
Discussion γ in ContextMF of Training on Restaurants of Yelp

Performance	γ=10	γ=20	γ=30	γ=40	γ=50	γ=60	γ=70	γ=80	γ=90	γ=100	γ=150
RMSE	1.051	1.047	**1.045**	1.046	1.045	1.048	1.045	1.051	1.048	1.050	1.055
MAE	0.846	0.844	**0.841**	0.842	0.842	0.844	0.842	0.845	0.843	0.846	0.851

TABLE 11
Discussion η in PRM1 Based on CircleCon2b of Training on Restaurants of Yelp

Performance	η=10	η=20	η=30	η=40	η=50	η=60	η=70	η=80	η=90	η=100	η=150
RMSE	1.034	**1.031**	1.033	1.033	1.033	1.033	1.034	1.033	1.033	1.033	1.036
MAE	0.838	**0.836**	0.837	0.837	0.837	0.837	0.837	0.836	0.835	0.837	0.837

TABLE 12
Performance Comparison of Different Similarity Measurement in PRM1 and PRM2 Based on CircleCon2b of Training on Restaurants of Yelp

Performance	CS		ED		MD	
	PRM1	PRM2	PRM1	PRM2	PRM1	PRM2
RMSE	1.088	1.083	1.083	1.083	1.083	1.086
MAE	0.869	0.867	0.869	0.867	0.869	0.871

in **Restaurants** of Yelp. In CircleCon2b, we let β range from 10 to 150. The performance is shown as Table 9. From Table 9, we can see that the performance is close to the optimal value with increase of the weight of interpersonal influence. In ContextMF, we set $\beta = 150$, and let γ range from 10 to 150. The performance is shown as Table 10. From Table 10, we can see that the performance gets the optimal value when $\gamma = 30$. And the optimal performance outperforms over 1% than the best of Table 9 on both RMSE and MAE. To test the importance of user personal interest in the RS, we set $\beta = 150$ and $\gamma = 30$ as constant, and let η range from 0 to 150. The performance is shown as Table 11. From Table 11, we can see that the performance is optimal when $\eta = 20$, and offers over 1% performance increase again, which means the proposed factor user personal interest is indispensible for RS to achieve higher accuracy in Yelp dataset.

5.4.2 Similarity Measurements

In Section 4, we measure user personal interest by the similarity between the topic distribution vector of user interest and item as in (9). There are various methods to measure the similarity including Cosine Similarity (CS), Euclidean Distance (ED), and Manhattan Distance (MD). Here we conduct series of experiments to compare these methods using PRM1 and PRM2 model based on CircleCon2b in **Restaurants** of Yelp. The performance is shown as Table 12. From Table 12, we can see that the error of these three

TABLE 13
Number of Users in Each Group According to the Number of User Rated Items in Restaurants of Yelp

Item_num	0-9	10-19	20-29	30-39	40-	Total
User_num	570	287	220	139	784	2000

TABLE 14
Number of Users in Each Group According to the Number of User's Friends in Restaurants of Yelp

Friend_num	0	1-4	5-9	10-14	15-	Total
User_num	255	792	333	185	435	2000

measurements is no more than 0.005 on RMSE and 0.004 on MAE, which shows the reliability of the proposed personalized recommendation model.

5.4.3 Impact of User Information

In this section, through statistic, we have found the impact of the amount of user information (user's number of rated items and number of friends) to the accuracy of the proposed model and compared models in **Restaurants** of Yelp. For one thing, we divide the test dataset into five groups according to the number of user rated items. The number of users of each group is shown as Table 13. The RMSE and MAE histograms are shown as Fig. 4, where "0–9" in the horizontal axis means the number of user's rated items is less than 9, and "40-" means the number of user rated items is more than 40. And the group of "40-" can be seen as the experienced users. From Fig. 4, we can see that the proposed approaches PRM1 and PRM2 are superior to the other compared models (BaseMF, CircleCon, and ContextMF) for each group in **Restaurants** of Yelp. It is because the proposed model is not only consider the cold start users with factors of interpersonal influence and interest similarity but also the experienced users with the factor of user personal interest. For another, we also divide the test dataset into five groups according to the number of user's friends. The number of users of each group is shown as Table 14. The RMSE and MAE histograms are shown as Fig. 5, where "0" in the horizontal axis means the number of user's friends is zero, and "15-" means the number of user's friends is more than 15. The same conclusion holds in Fig. 5, which demonstrates the social factors are effectively integrated into the proposed personalized recommendation model.

5.4.4 Impact of The Three Social Factors

Here, we compare the performances of the three independent factors with PRM in Restaurants of Yelp respectively. In this test, we set $\beta = 30$ and $\gamma = \eta = 0$ for the factor of interpersonal influence; we set $\gamma = 30$ and $\beta = \eta = 0$ for the factor of interpersonal interest similarity; we set $\eta = 30$ and $\beta = \gamma = 0$ for the factor of user personal interest. The performance comparison is shown as Fig. 6(a) and (b).

The approach using none, one, two, and three of the three factors are systematically compared and the corresponding RMSE and MAE of our approach under PRM1 and PRM2 are shown in Fig. 6(a) and (b) respectively. In the Fig. 6, **NON** denotes the approach where none of the three factors is taken into consideration (corresponds to BaseMF [4]). **II** denotes the approach only using interpersonal influence, **IS** denotes the approach using only interpersonal Interest Similarity, **UI** denotes the approach using only user personal interest, **II+IS** denotes the approach integrating two factors: interpersonal influence and interest similarity, **IS+UI** denotes the approach integrating two factors: interest similarity and user personal interest, **UI+II** denotes the approach integrating two factors: user personal interest and interpersonal influence, **ALL** denotes our approach when all the three factors are all taken into account.

We can see that all of the three factors have effect on improving the accuracy of RS. From Table 5 and Fig. 6, we

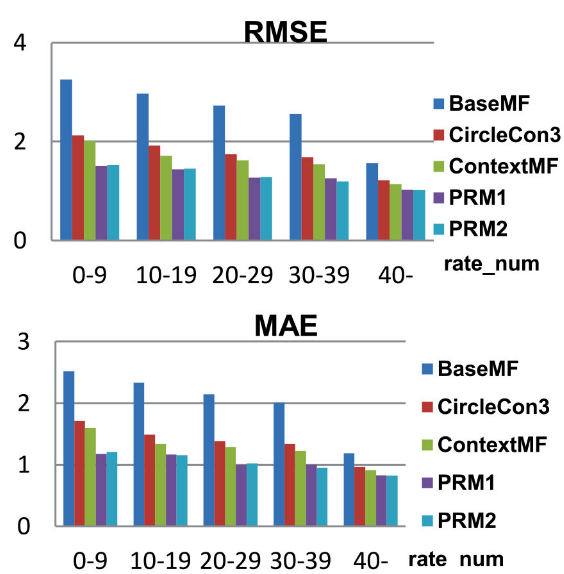


Fig. 4. RMSE and MAE histograms of impact of user's rated number in Restaurants of Yelp.

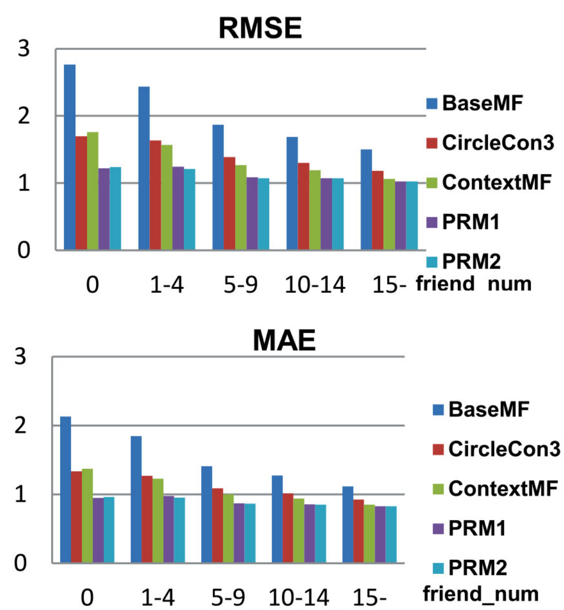
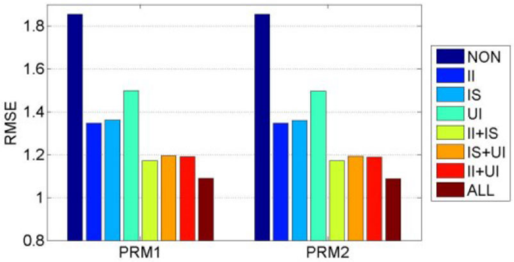
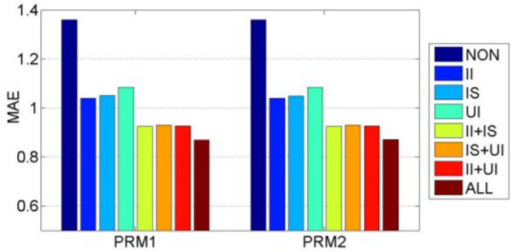


Fig. 5. RMSE and MAE histograms of impact of user's friend number in Restaurants of Yelp.



(a)



(b)

Fig. 6. Dicussions on the impacts the three factors to recommendation performances of our approach under PRM1 and PRM2 on Restaurants of Yelp: (a) RMSE of the three factors (b) MAE of the three factors.

can see that the proposed PRM effectively fuse the three factors into a unified personalized recommendation model.

6 Conclusion

In this paper, a personalized recommendation approach was proposed by combining social network factors: personal interest, interpersonal interest similarity, and interpersonal influence. In particular, the personal interest denotes user's individuality of rating items, especially for the experienced users, and these factors were fused together to improve the accuracy and applicability of recommender system. We conducted extensive experiments on three large real-world social rating datasets, and showed significant improvements over existing approaches that use mixed social network information. At present, the personalized recommendation model only takes user historical rating records and interpersonal relationship of social network into consideration. In our future works, we will take user location information to recommend more personalized and real-time items.

Acknowledgments

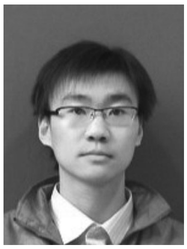
This paper was supported in part by NSFC 60903121, 61173109, 61332018 and in part by Microsoft Research Asia.

References

[1] X.-W. Yang, H. Steck, and Y. Liu, "Circle-based recommendation in online social networks," in *Proc. 18th ACM SIGKDD Int. Conf. KDD*, New York, NY, USA, Aug. 2012, pp. 1267–1275.
[2] M. Jiang *et al.*, "Social contextual recommendation," in *Proc. 21st ACM Int. CIKM*, New York, NY, USA, 2012, pp. 45–54.
[3] M. Jamali and M. Ester, "A matrix factorization technique with trust propagation for recommendation in social networks," in *Proc. ACM Conf. RecSys*, Barcelona, Spain, 2010, pp. 135–142.
[4] R. Salakhutdinov and A. Mnih, "Probabilistic matrix factorization," in *Proc. NIPS*, 2008.
[5] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 42, no. 8, pp. 30–37, Aug. 2009.
[6] M. E. Tipping and C. M. Bishop, "Probabilistic principal component analysis," *J. Roy. Statist. Soc.*, Ser. B, vol. 61, no. 3, pp. 611–622, 1999.
[7] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, Jun. 2005.
[8] R. Bell, Y. Koren, and C. Volinsky, "Modeling relationships at multiple scales to improve accuracy of larg e recommender systems," in *Proc. 13th ACM SIGKDD Int. Conf. KDD*, San Jose, CA, USA 2007, pp. 95–104.
[9] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl, "Item-based collaborative filtering recommendation algorithms," in *Proc. 10th Int. Conf. WWW*, Hong Kong, China, 2001, pp. 285–295.
[10] M. Jahrer, A. Toscher, and R. Legenstein, "Combining predictions for accurate recommender systems," in *Proc. 16th ACM SIGKDD Int. Conf. KDD*, Washington, DC, USA, 2010, pp. 693–702.
[11] Y. Zhang, B. Cao, and D. Y. Yeung, "Multi-domain collaborative filtering," in *Proc. 26th Conf. UAI*, 2010.
[12] G.-R. Xue *et al.*, "Scalable collaborative filtering using cluster-based smoothing," in *Proc. 28th Annu. Int. ACM SIGIR Conf. Research Development Information Retrieval*, Salvador, Brazil, 2005, pp. 114–121.
[13] H. Ma, I. King, and M. R. Lyu, "Learning to recommend with social trust ensemble," in *Proc. 32nd Int. ACM SIGIR Conf. Research Development Information Retrieval*, Boston, MA, USA, 2009, pp. 203–210.
[14] M. Jamali and M. Ester, "Trustwalker: A random walk model for combining trust-based and item-based recommendation," in *Proc. 15th ACM SIGKDD Int. Conf. Knowledge Discovery Data Mining*, Paris, France, pp. 397–406, 2009.
[15] X. Yang, Y. Guo, and Y. Liu, "Bayesian-inference based recommendation in online social networks," in *Proc. 30th Annu. IEEE INFOCOM*, Shanghai, China, 2011, pp. 551–555.
[16] J. Huang, X. Cheng, J. Guo, H. Shen, and K. Yang, "Social recommendation with interpersonal influence," in *Proc. 19th ECAI*, Amsterdam, Netherlands, pp. 601–606, 2010.
[17] H. Ma, H. Yang, M. R. Lyu, and I. King, "SoRec: Social recommendation using probabilistic matrix factorization," in *Proc. 17th ACM CIKM*, Napa Valley, CA, USA, 2008, pp. 931–940.
[18] H. Ma, D. Zhou, C. Liu, M. R. Lyu, and I. King, "Recommender systems with social regularization," in *Proc. ACM Int. Conf. WSDM*, Hong Kong, China, 2011, pp. 287–296.
[19] F. Liu and H. Lee, "Use of social network information to enhance collaborative filtering performance," *Expert Syst. Appl.*, vol. 37, no. 7, pp. 4772–4778, Jul. 2010.
[20] P. Massa and P. Avesani, "Trust-aware recommender systems," in *Proc. 2007 ACM Conf. Recommender Systems*, Minneapolis, MN, USA, pp. 17–24.
[21] M. Richardson and P. Domingos, "Mining knowledge-sharing sites for viral marketing," in *Proc. 8th ACM SIGKDD Int. Conf. KDD*, Edmonton, AB, Canada, 2002.
[22] R. Keshavan, A. Montanari, and S. Oh, "Matrix completion from noisy entries," *J. Mach. Learn. Res.*, vol. 11, pp. 2057–2078, Jul. 2010.
[23] Y. Koren, "Factorization meets the neighborhood: A multifaceted collaborative filtering model," in *Proc. 14th ACM SIGKDD Int. Conf. KDD*, Las Vegas, NV, USA, 2008, pp. 426–434.
[24] Y. Koren, "Collaborative filtering with temporal dynamics," in *Proc. 14th ACM SIGKDD Int. Conf. KDD*, Paris, France, 2009, pp. 447–456.
[25] A. Paterek, "Improving regularized singular value decomposition for collaborative filtering," in *Proc. KDDCup*, San Jose, CA, USA, 2007.
[26] M. Balabanovic and Y. Shoham, "Fab: Content-based, collaborative recommendation," *Commun. ACM*, vol. 40, no. 3, pp. 66–72, Mar. 1997.
[27] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl, "Evaluating collaborative filtering recommender systems," *ACM Trans. Inform. Syst.*, vol. 22, no. 1. pp. 5–53, Jan. 2004.
[28] J. Wang, A. P. de Vries, and M. J. T. Reinders, "Unifying user-based and item-based collaborative filtering approaches by similarity fusion," in *Proc. 29th Annu. Int. ACM SIGIR Conf. Research Development Information Retrieval*, Seattle, WA, USA, 2006.

[29] N. N. Liu, M. Zhao, and Q. Yang, "Probabilistic latent preference analysis for collaborative filtering," in *Proc. 18th ACM CIKM*, Hong Kong, China, 2009, pp. 759–766.
[30] Q. Liu, E. Chen, H. Xiong, C. Ding, and J. Chen, "Enhancing collaborative filtering by user interest expansion via personalized ranking," *IEEE Trans. Syst., Man, Cybern. B*, vol. 42, no. 1, pp. 218–233, Feb. 2012.
[31] Y. Chen and J. Canny, "Recommending ephemeral items at web scale," in *Proc. 34th Int. ACM SIGIR Conf. Research Development Information Retrieval*, New York, NY, USA, 2011, pp. 1013–1022.
[32] M. Harvey, M. J. Carman, I. Ruthven, and F. Crestani, "Bayesian latent variable models for collaborative item rating prediction," in *Proc. 20th ACM Int. CIKM*, 2011, Glasgow, U.K. pp. 699–708.
[33] L. Yu, R. Pan, and Z. Li, "Adaptive social similarities for recommender systems," in *Proc. 5th ACM Conf. RecSys*, New York, NY, USA, 2011.
[34] P. Bedi, H. Kaur, and S. Marwaha, "Trust based recommender system for semantic web," in *Proc. 20th IJCAI*, 2007, pp. 2677–2682.
[35] J. O'Donovan and B. Smyth, "Trust in recommender systems," in *Proc. 10th Int. Conf. IUI*, San Diego, CA, USA, 2005, pp. 167–174.
[36] J. Leskovec, A. Singh, and J. Kleinberg, "Patterns of influence in a recommendation network," in *Lecture Notes in Computer Science.*, Berlin, Germany: Springer, 2006, pp. 380–389.
[37] P. Cui *et al.*, "Who should share what? Item-level social influence prediction for users and posts ranking," in *Proc. 34th Int. ACM SIGIR Conf. Research Development Information Retrieval*, Beijing, China, 2011, pp. 185–194.
[38] R. Bond and P. B. Smith, "Culture and conformity: A meta-analysis of studies using Asch's (1952b, 1956) line judgment task," *Psychol. Bull.*, vol. 119, no. 1, pp. 111–137, Jan. 1996.
[39] H. R. Kim and P. K. Chan, "Learning implicit user interest hierarchy for context in personalization," in *Proc. Int. Conf. Intelligent User Interface*, New York, NY, USA, 2003.
[40] M. Grcar, D. Mladenic, and M. Grobelnik, "User profiling for interest-focused browsing history," in *Proc. UserSWeb*, 2005.
[41] X. Zhou *et al.*, "Utilizing search intent in topic ontology-based user profile for web mining," in *Proc. IEEE Int. Conf. Web Intelligence*, Hong Kong, China, 2006.
[42] O. Phelan, K. McCarthy, and B. Smyth, "Using twitter to recommend realtime topical news," in *Proc. 3rd ACM Conf. Recommender Systems*, Hong Kong, China, 2009, pp. 385–388.
[43] J. Chen, R. Nairn, L. Nelson, M. Bernstein, and E. Chi, "Short and tweet: Experiments on recommending content from information streams," in *Proc. 28th Int. Conf. Human Factors Computing Systems*, Atlanta, GA, USA, 2010, pp. 1185–1194.
[44] R. Sinha and K. Swearingen, "Comparing recommendations made by online systems and friends," in *Proc. DELOS Workshop Personalisation Recommender Systems Digital Libraries*, Dublin, Ireland, 2001.
[45] A. Java, X. Song, T. Finin, and B. Tseng, "Why we twitter: Understanding microblogging usage and communities," in *Proc. 9th WebKDD, 1st SNA-KDD*, San Jose, CA, USA, 2007, pp. 56–65.
[46] A. Rahman and S. Hailes, "Supporting trust in virtual communities," in *Proc. 33rd Int. Conf. System Sciences*, Maui, HW, USA, 2000.
[47] Q. Yuan, L. Chen, and S. Zhao, "Factorization vs. regularization: Fusing heterogeneous social relationships in top-N recommendation," in *Proc. 5th ACM Conf. Recommender Systems*, Chicago, IL, USA, 2011.
[48] M. Ou *et al.*, "Comparing apples to oranges: A scalable solution with heterogeneous hashing," in *Proc. 19th ACM SIGKDD*, Chicago, IL, USA, 2013.
[49] P. Cui, F. Wang, S. Liu, M. Ou, and S. Yang, "Who should share what? Item-level social influence prediction for users and posts ranking," in *Proc. Int. ACM SIGIR Conf.*, Beijing, China, 2011.
[50] P. Cui, F. Wang, and S. Yang, "Item-level social influence prediction with probabilistic hybrid factor matrix factorization," in *Proc. 25th AAAI Conf. Artificial Intelligence*, 2011.
[51] M. Jiang *et al.*, "Social recommendation across multiple relational domains," in *Proc. 21st ACM Int. CIKM*, Maui, HI, USA, 2012.
[52] H. Feng and X. Qian, "Recommendation via user's personality and social contextual," in *Proc. 22nd ACM CIKM*, New York, NY, USA, 2013.
[53] J. Shen, H. Pang, M. Wang, and S. Yan, "Modeling concept dynamics for large scale music search," in *Proc. 35th Int. ACM SIGIR Conf. Research Development Information Retrieval*, New York, NY, USA, 2012, pp. 455–464.
[54] J. Shen and Z. Cheng, "Personalized video similarity measure," *Multimedia Syst.*, vol. 17, no. 5, pp. 421–433, 2011.
[55] J. Shen, D. Tao, and X. Li, "Modality mixture projections for semantic video event detection," *IEEE Trans. Circuits. Syst. Video Technol.*, vol. 18, no. 11, pp. 1587–1596, Nov. 2008.
[56] H. Feng and X. Qian, "Mining user-contributed photos for personalized product recommendation," *Neurocomputing*, vol. 129, pp. 409–420, 2014.
[57] H. Feng and X. Qian, "Recommend social network users favorite brands," in *Proc. 14th Pacific-Rim Conf. Multimedia*, Nanjing, China, 2013.
[58] S. Jiang, X. Qian, T. Mei, K. Lan, and L. Zhang, "Mobile multimedia travelogue generation by exploring geo-locations and image tags," in *Proc. ISCAS*, Beijing, China, 2013, pp. 881–884.
[59] S. Jiang, X. Qian, Y. Xue, F. Li, and X. Hou, "Generating representative images for landmark by discovering high frequency shooting locations from community-contributed photos," in *Proc. IEEE ICME*, San Jose, CA, USA, 2013.
[60] J. Shen, W. Meng, S. Yan, H. Pang, and X. Hua, "Effective music tagging through advanced statistical modeling," in *Proc. 33rd Int. ACM SIGIR*, Geneva, Switzerland 2010, 635–642.
[61] X. Qian, X. Liu, C. Zheng, Y. Du, and X. Hou, "Tagging photos using users' vocabularies," *Neurocomputing*, vol. 111, pp. 144–153, Jul. 2013.
[62] J. Li, X. Qian, Y. Tang, L. Yang, and C. Liu, "GPS estimation from users' photos," in *Proc. MMM*, Huangshan, China, 2013, pp. 118–129.
[63] J. Li, X. Qian, Y. Tang, L. Yang, and T. Mei, "GPS estimation for places of interest from social users' uploaded photos," *IEEE Trans. Multimedia*, vol. 15, no. 8, pp. 2058–2071, Dec. 2014.
[64] P. Cremonesi, Y. Koren, and R. Turrin, "Performance of recommender algorithms on top-n recommendation tasks," in *Proc. 4th ACM Conf. Recommender Systems*, New York, NY, USA, 39–46.

Xueming Qian (M'10) received the B.S. and M.S. degrees from Xi'an University of Technology, Xi'an, China, in 1999 and 2004, respectively, and the Ph.D. degree from the School of Electronics and Information Engineering, Xi'an Jiaotong University, Xi'an, China, in 2008. He was awarded the Microsoft Fellowship in 2006. From 1999 to 2001, he was an Assistant Engineer at Shannxi Daily. Since 2008, he has been an Associate Professor in the School of Electronics and Information Engineering, Xi'an Jiaotong University. Now, he is an Associate Professor in the School of Electronics and Information Engineering, Xi'an Jiaotong University. He is the Director of SMILES LAB. He was a Visiting Scholar at Microsoft Research Asia from August 2010 to March 2011. His research interests include social media big data mining and search. His research is supported by NSFC, Microsoft Research, and MOST. He is a member of the IEEE, ACM, and Senior Member of CCF.



He Feng was a member of SMILES LAB of Xi'an Jiaotong Univerisity, Xi'an, China, September 2011 to July 2013. He received the M.S. degree from the School of Electronics and Information Engineering, Xi'an Jiaotong University in 2013. His current research interests include social recommendation.

Guoshuai Zhao is a member of SMILES LAB of Xi'an Jiaotong Univerisity, Xi'an, China, from September 2012. His current research interests include social recommendation.

Tao Mei (M'07-SM'11) is a Lead Researcher with Microsoft Research, Beijing, China. He received the B.E. degree in automation and the Ph.D. degree in pattern recognition and intelligent systems from the University of Science and Technology of China, Hefei, China, in 2001 and 2006, respectively. His current research interests include multimedia information retrieval and computer vision. He has authored or co-authored over 100 papers in journals and conferences, 10 book chapters, and edited three books. He holds 11 U.S. granted patents and more than 20 in pending. Dr. Mei was the recipient of several paper awards from prestigious multimedia journals and conferences, including the IEEE Circuits and Systems Society Circuits and Systems for Video Technology Best Paper Award in 2014, the IEEE Trans. on Multimedia Prize Paper Award in 2013, the Best Student Paper Award at the IEEE VCIP in 2012, and the Best Paper Awards at ACM Multimedia in 2009 and 2007, etc. He received Microsoft Gold Star Award in 2010, and Microsoft Technology Transfer Awards in 2010 and 2012. He is an Associate Editor of *IEEE Transactions on Multimedia, Multimedia Systems, and Neurocomputing*, a Guest Editor of six international journals. He is the General Co-chair of ICIMCS 2013, the Program Co-chair of IEEE MMSP 2015 and MMM 2013, and the Workshop Co-chair of ICME 2012 and 2014. He is a Senior Member of the IEEE and the ACM.