User-Service Rating Prediction by Exploring Social Users' Rating Behaviors

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***Abstract*—With the boom of social media, it is a very popular trend for people to share what they are doing with friends across various social networking platforms. Nowadays, we have a vast amount of descriptions, comments, and ratings for local services. The information is valuable for new users to judge whether the services meet their requirements before partaking. In this paper, we propose a user-service rating prediction approach by exploring social users' rating behaviors. In order to predict user-service ratings, we focus on users' rating behaviors. In our opinion, the rating behavior in recommender system could be embodied in these aspects: 1) when user rated the item, 2) what the rating is, 3) what the item is, 4) what the user interest that we could dig from his/her rating records is, and 5) how the user's rating behavior diffuses among his/her social friends. Therefore, we propose a concept of the rating schedule to represent users' daily rating behaviors. In addition, we propose the factor of interpersonal rating behavior diffusion to deep understand users' rating behaviors. In the proposed user-service rating prediction approach, we fuse four factors—user personal interest (related to user and the item's topics), interpersonal interest similarity (related to user interest), interpersonal rating behavior similarity (related to users' rating behavior habits), and interpersonal rating behavior diffusion (related to users' behavior diffusions)—into a unified matrix-factorized framework. We conduct a series of experiments in the Yelp dataset and Douban Movie dataset. Experimental results show the effectiveness of our approach.**

***Index Terms*—Data mining, recommender system, social networks, social user behavior.**

I. Introduction

RECENTLY people have been receiving more and more digitized information from Internet, and the volume of information is larger than any other point in time, reaching a point of information overload. To solve this problem, the recommender system has been created in response to the need to disseminate so much information. It does not only filter the noise, but also help to select attractive and useful information. Recommender system has achieved initial success based on a survey that shows at least 20 percent of sales on Amazon's website come from the recommender system.

Social networks gather volumes of information contributed by users around the world. This information is versatile. It always contains item/services descriptions (including textual descriptions, logos and pictures), users' comments, moods and users' social circles, prices, and locations. It is very popular for recommending users' favorite services from crowd-source contributed information.

In 1994, the GroupLens system [1] utilized a CF (collaborative filtering) algorithm based on common users' preferences, known as user-based CF. The authors note that users will favor items recommended by users with similar interests. Sarwar *et al.* [2] proposed an item-based CF in 2001. The authors found that users favor items similar to those in which the user was previously interested. These are the most famous recommender system algorithms. The basic idea of CF is grouping users or items according to similarity. Most recent work has followed the two aforementioned directions (i.e., user-based and item-based). For example, Herlocker *et al.* [3] propose the similarity between users or items according to the number of common ratings. Deshpande and Karypis [4] apply an item-based CF combined with a condition-based probability similarity and Cosine Similarity. Collaborative filtering-based recommendation approaches [5]–[18], [59] can be viewed as the first generation of recommender system [19].

However, with the rapid increase in number of registered Internet users and more and more new products available for purchase online, the issue of cold start for users and sparsity of datasets has become increasingly intractable. Fortunately, with the popularity and rapid development of social networks, more and more users enjoy sharing their experiences, such as reviews, ratings, photos and moods. The interpersonal relationships have become transparent and opened up as more and more users share this information on social media websites such as Facebook, Twitter, Yelp, Douban, Epinions [20], etc. The circles of friends also bring opportunities and challenges for a recommender system to solve the issues of cold start and sparsity.

Many models based on social networks [21]–[51] have been proposed to improve recommender system performance. The concept of 'inferred trust circle' based on circles of friends was proposed by Yang *et al.* [21] to recommend favorite and useful items to users. Their approach, called the CircleCon Model, not only reduces the load of big data and computation complexity, but also defines the interpersonal trust in the complex social networks. Besides interpersonal influence, Jiang *et al.* [22]

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prove that individual preference is also an important factor in social networks. The above algorithms are based on the probabilistic matrix factorization model [52]. Symeonidis *et al.* [41] propose Social-Union, a method which combines similarity matrices derived from heterogeneous (unipartite and bipartite) explicit or implicit social rating networks, and generalize their model for combining multiple social networks. Lee *et al.* [43] propose a recommender system that uses the concepts of experts to find both novel and relevant recommendations. Wang *et al.* [44] design a joint social-content recommendation framework to suggest users for videos that users are likely to import or re-share in the online social network. Meanwhile, there are some interesting works to infer social contexts. For example, Servia-Rodriguez *et al.* [45] propose a model to infer social contexts by several Natural Language Processing and data mining techniques over users' interaction data on Facebook. Fang *et al.* [49] propose a relational latent SVM model to combine user features, attribute inference, and attribute relations. Mao *et al.* [6] propose to model user's vocal competence for personalized song recommendation.

Except for ratings prediction and products recommendations, location-based social networks (LBSNs) are attracting more and more users' attention [60]. Cho *et al.* [53] have developed a model of human mobility that combines periodic short range movements with travel based on the social network structure. Cheng *et al.* [34] fuse matrix factorization (MF) with geographical and social influence for POI (Point-of-interest) recommendations on LBSNs, and propose a novel Multi-center Gaussian Model to model the geographical influence of users' check-in behaviors. Jiang *et al.* [46] propose a user topic based collaborative filtering approach for personalized travel recommendation. Zahálka *et al.* [51] propose an interactive and multimodal content-based venue explorer based on location-based social networks. Chen *et al.* [61] propose to conduct personalized travel recommendation by taking user attributes and social information. Furthermore, there are some previous works [54], [55] focusing on objective evaluation in order to recommend the high-quality services by exploring social users' spatial-temporal information.

In this paper, we propose a user-service rating prediction model based on probabilistic matrix factorization by exploring rating behaviors. Usually, users are likely to participate in services in which they are interested and enjoy sharing experiences with their friends by description and rating. Like the saying "birds of a feather flock together," social users with similar interests tend to have similar behaviors. It is the basis for the collaborative filtering based recommendation model. Social users' rating behaviors could be mined from the following four factors: personal interest, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior diffusion. Why do we consider these four factors? In our opinion, the rating behavior in recommender system could be embodied in these aspects: when user rated the item, what the rating is, what the item is, what the user interest we could dig from his/her rating records is, and how user's rating behavior diffuse among his/her social friends. In this paper, we propose a user-service rating prediction approach by exploring social users' rating behaviors in a unified matrix factorization framework.

The main contributions of this paper are shown as follows.

1) We propose a concept of the rating schedule to represent user daily rating behavior. We leverage the similarity between user rating schedules to represent interpersonal rating behavior similarity.
2) We propose the factor of interpersonal rating behavior diffusion to deep understand users' rating behaviors. We explore the user's social circle, and split the social network into three components, direct friends, mutual friends, and the indirect friends, to deep understand social users' rating behavior diffusions.
3) We fuse four factors, personal interest, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior diffusion, into matrix factorization with fully exploring user rating behaviors to predict user-service ratings. We propose to directly fuse interpersonal factors together to constrain user's latent features, which can reduce the time complexity of our model.

The rest of this paper is organized as follows: In Section II, we define the problem we focus on in this paper, and briefly introduce comparable algorithms. In Section III, the proposed user-service rating prediction approach combining with personal interest, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior diffusion is introduced in detail. The experimental results and some discussions are given in Section IV. The main conclusions are drawn in Section V.

II. Preliminary

In this paper, we focus on probabilistic matrix factorization. Thus, in this section, we first define the notations which are utilized in this paper, and then review the compared approaches in this domain.

A. Problem Formulation

In Table I, we define the notations which are utilized in this paper. The proposed model aims to predict unknown ratings in social rating networks (like Yelp,[1] Epinions[2]). We utilize latent feature vectors to predict user ratings.

We extract a set of users $\mathrm{U} = \{u_1, \ldots, u_M\}$ and a set of items $\mathrm{P} = \{i_1, \ldots, i_N\}$ from our dataset, which we collect from Yelp and Douban Movie[3] website. We set a rating matrix $\boldsymbol{R} = [R_{u,i}]_{M\times N}$ which represents ratings matrix, where $R_{u,i}$ denotes the rating of user u to item i. The ratings may be any real number in different rating networks, but in the Yelp dataset they are integers ranging from 1 to 5.

There are four significant parameters which represent the factors we consider. The interest similarity values are given

[1] [Online]. Available: http://www.yelp.com
[2] [Online]. Available: http://www.epinions.com
[3] [Online]. Available: http://movie.douban.com

TABLE I
NOTATIONS AND THEIR DESCRIPTIONS

Notations	Description	Notations	Description
$\boldsymbol{R}_{M\times N}$	the rating matrix expressed by users on items	$\hat{\boldsymbol{R}}_{M\times N}$	the predicted rating matrix
M	the number of users	N	the number of items
c	the category of the item	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	k	the dimension of the latent space
$\boldsymbol{Q}_{M\times N}$	the relevance matrix of user interest to the topic of item	$\boldsymbol{W}_{M\times M}$	interpersonal interest similarity matrix
$\boldsymbol{E}_{M\times M}$	interpersonal rating behavior similarity matrix	$\boldsymbol{D}_{M\times M}$	interpersonal rating behavior diffusion matrix
$\boldsymbol{P}_{N\times k}$	the item latent feature matrix	$\boldsymbol{U}_{M\times k}$	the user latent feature matrix
r	users' average rating value in the training dataset	λ, β, η	the tradeoff parameters in the objective function

in matrix $\boldsymbol{W} = [W_{u,v}]_{M\times M}$, where $W_{u,v} \in [0, 1]$ denotes the interest similarity between user u and user v. The rating behavior similarity values are given in matrix $\boldsymbol{E} = [E_{u,v}]_{M\times M}$, where $E_{u,v} \in [0, 1]$ denotes the rating behavior similarity between user u and user v. The smooth degree of interpersonal rating behavior diffusions between users is represented by matrix $\boldsymbol{D} = [D_{u,v}]_{M\times M}$. The last factor of users' personal interest is represented by matrix $\boldsymbol{Q} = [Q_{u,i}]_{M\times N}$, where $Q_{u,i} \in [0, 1]$ denotes the relevance between user u's interest and the topic of item i.

The task of the proposed algorithm is as follows: Given a user $u \in \mathrm{U}$ and an item $i \in \mathrm{P}$, whose rating $R_{u,i}$ is unknown, we predict the rating of u to i using $\boldsymbol{R}, \boldsymbol{W}, \boldsymbol{E}, \boldsymbol{D}$ and $\boldsymbol{Q}$ based on the probabilistic matrix factorization model.

We train the latent features of users and items with matrix factorization techniques [21]–[23], [52], [56] in this paper, and predict the unknown ratings using these latent features. We set $\boldsymbol{U} \in \mathbb{r}^{M\times k}$ and $\boldsymbol{P} \in \mathbb{r}^{N\times k}$ as user and item latent features matrices, in which row vectors $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ represent k-dimensional user and item latent feature vectors. Certainly k is much less than M and N. 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 features and exploit them to predict user-service ratings.

B. Compared Algorithms

In this subsection, we will review some major approaches about social factors in this domain, and all of them focus on probabilistic matrix factorization. The basic matrix factorization model [52] without any social factors, the CircleCon model [21] with the factor of interpersonal trust values, the Social Contextual (Context MF) model [22] with interpersonal influence and individual preference, and the PRM model [37], [39] with more factors will be outlined.

1) Basic Matrix Factorization: As a basic model, the basic probabilistic matrix factorization (BaseMF) approach [52] will be reviewed first, without any social factors taken into consideration. They learn the latent features by minimizing the objective function on the observed rating data $\boldsymbol{R}$

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

where $\hat{R}_{u,i}$ denotes the ratings predicted by

$$\hat{R} = r + \boldsymbol{U}\boldsymbol{P}^T \tag{2}$$

where r is an offset value, which is empirically set as users' average rating value in the training data. $R_{u,i}$ 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 learned from the training data. $\|\boldsymbol{X}\|_F$ is the Frobenius norm of matrix $\boldsymbol{X}$, and $\|\boldsymbol{X}\|_F = (\sum_{i,j} x_{i,j}^2)^{1/2}$. It is used to avoid over-fitting [23]. This objective function can be minimized efficiently using the gradient descent method as in [23]. Once the low-rank matrices $\boldsymbol{U}$ and $\boldsymbol{P}$ are learned, rating values can be predicted according to (2) for any user-item pairs.

2) CircleCon Model: This approach [21] focuses on the factor of interpersonal trust in social network and infers the trust circle. The trust value of user-user is represented by matrix $\boldsymbol{S}$. Furthermore, the whole trust relationship in social network is divided into several sub-networks $\boldsymbol{S}^c$, called inferred circle, and each circle is related to a single category c of items. The basic idea is that user latent feature $\boldsymbol{U}_u$ should be similar to the average of his/her friends' latent features with weight of $S_{u,v}^{c*}$ in category c. Once the model is trained in c, the rating value in c can be predicted according to (2).

3) Context MF: Besides the factor of interpersonal influence, Jiang *et al.* [22] propose another important factor: the individual preference. Interpersonal preference similarity is mined from the topic of items adopted from the receiver's history. The basic idea is that user latent feature $\boldsymbol{U}_u$ should be similar to his/her friends' latent feature with the weight of their preference similarity in social networks.

4) PRM: In our previous work [37], [39], we consider three social factors to constrain user and item latent features, involving interpersonal influence, interpersonal interest similarity, and personal interest. The basic idea of interpersonal interest similarity is that user latent feature $\boldsymbol{U}_u$ should be similar to his/her friends' latent feature with the weight of interpersonal interest similarity $W_{u,v}^*$. The factor of personal interest $Q_{u,i}^*$ focuses on mining the degree of user interest to an item.

5) Differences: In this paper, we consider four factors, personal interest $Q_{u,i}^*$ (related to user and the item's topics), interpersonal interest similarity $W_{u,v}^*$ (related to user interest), interpersonal rating behavior similarity $E_{u,v}^*$ (related to users' rating behavior habits), and interpersonal rating behavior diffusion $D_{u,v}^*$ (related to users' behavior diffusions), to explore users' rating behaviors.

The differences between our work and previous works are as follows.

Rating \ Day	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1				1			
2	3		2		1		
3		7		1	6	4	2
4		2	4		3	5	2
5	9		2				1

Fig. 1. Example of the rating schedule. The schedule shows the statistic of the rating behavior given by user's rating historical records.

1) We focus on exploring user rating behaviors. A concept of the rating schedule is proposed to represent user daily rating behavior. The factor of interpersonal rating behavior diffusion is proposed to deep understand users' rating behaviors. We consider these two factors to explore users' rating behaviors.
2) We fuse three factors, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior diffusion, together to directly constrain users' latent features, which can reduce the time complexity.

III. The Approach

In this paper, in order to predict user-service ratings, we focus on users' rating behaviors. We fuse four factors, personal interest, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior diffusion, into matrix factorization. Among these factors, interpersonal rating behavior similarity and interpersonal rating behavior diffusion are the main contributions of our approach. Hereinafter we turn to the details of our approach.

A. *User Rating Behavior Exploration*

The factors of interpersonal interest similarity $W^*_{u,v}$ and personal interest $Q^*_{u,i}$ proposed in [37], [39] have been proved effective. Thus, in this subsection, we turn to the details of our proposed interpersonal rating behavior similarity and interpersonal rating behavior diffusion.

1) Interpersonal Rating Behavior Similarity: The behavior habit is essential. It could not be separated from temporal information. Thus, we define rating behavior in this paper as what the user has done and when it happened. This kind of behavior presentation arouses us to the curriculum schedule. The schedule arranges which course would we take and when we should go to class. From the schedule it can be sensed that the student's daily study behavior. Therefore, we put forward a concept of the rating schedule shown in Fig. 1.

We leverage a rating schedule for the statistic of the rating behavior given by user's rating historical records. For example, the user has rated an item 1 star and another 3 stars on Thursday. It can be seen that the user has little possibility to take rating behavior on Thursday. We leverage this kind of rating schedule to represent users' rating behaviors. The behavior similarity could embody user latent features similarity to some extent. For example, a student's curriculum schedule could represent his/her study behavior to a certain degree. If the student's curriculum schedule is similar with another student, we could infer that they have similar study behaviors, and furthermore, they may be classmates. Thus, we could extend it to the rating schedule to calculate interpersonal rating behavior similarity.

We set a rating behavior matrix $B^u = [B^u_{r,d}]_{X \times Y}$, which represents user u's rating behavior, where $B^u_{r,d}$ denotes the behavior count that user u has rated r stars in day d. In this paper, we set the rating schedule in the type of the week from Monday to Sunday, and the rating is integer in the range of 1 to 5. That is to say, X and Y are set as 5 and 7 respectively in this paper. Interpersonal rating behavior similarity is given by

$$E_{u,v} = \sqrt{\sum_{r=1}^{X}\sum_{d=1}^{Y}\left(B^u_{r,d} - B^v_{r,d}\right)^2} \tag{3}$$

where $E_{u,v}$ denotes the rating behavior similarity between user u and his/her friend v. The basic idea of interpersonal rating behavior similarity is that user u's rating schedule should be similar to his/her friend v to some extent. In order to be fair in measuring the similarity degree, each row of $\boldsymbol{E}$ is normalized to unity $\sum_v E^{c*}_{u,v} = 1$.

2) Interpersonal Rating Behavior Diffusion: In this paper, we consider the factor of social users' rating behavior diffusions. We explore the diffusion of user rating behavior by combining the scope of user's social network and the temporal information of rating behaviors. For a user, we split his/her social network into three components, direct friends, mutual friends, and the indirect friends shown in Fig. 2.

a) Firstly, in our opinion, if a friend has many mutual friends with the user, such as A, B, and C shown in Fig. 2, we regard them as close friends of the user. On the contrary, we regard D as a distant friend of the user. In other words, the more mutual friends they have, the closer they are. Thus, we leverage the weight $|Friends_{u \cap v}|/|Circle_u|$ as a coefficient of interpersonal rating behavior diffusions, where $|Friends_{u \cap v}|$ denotes the number of mutual friends between u and v, $|Circle_u|$ denotes the total number of user u's direct friends and indirect friends.
b) Secondly, we deem that the more items user and his/her friends both have rated, the smoother the diffusion of interpersonal rating behaviors is. In addition, we regard temporal rating actions as an important information to distinguish whether the diffusions are smooth. Thus we design this coefficient as $\sum_{\forall i \in \{R_u \cap R_v\}} \exp(-|R_{u,i} - R_{v,i}| \times |Day_{u,i} - Day_{v,i}|)$, where $|Day_{u,i} - Day_{v,i}|$ denotes the date difference between the day user u rated item i and the day user v rated item i. $|R_{u,i} - R_{v,i}|$ denotes the rating difference in order to distinguish whether the diffusion is positive. It means that the diffusion is smooth if both the date difference and the rating difference are small.
c) At last, we utilize rating count to measure expertise level of users as in [21] because of the concept that rating behaviors may be more easily diffused from expert users. The intuition is that if most of v's followers have lots of

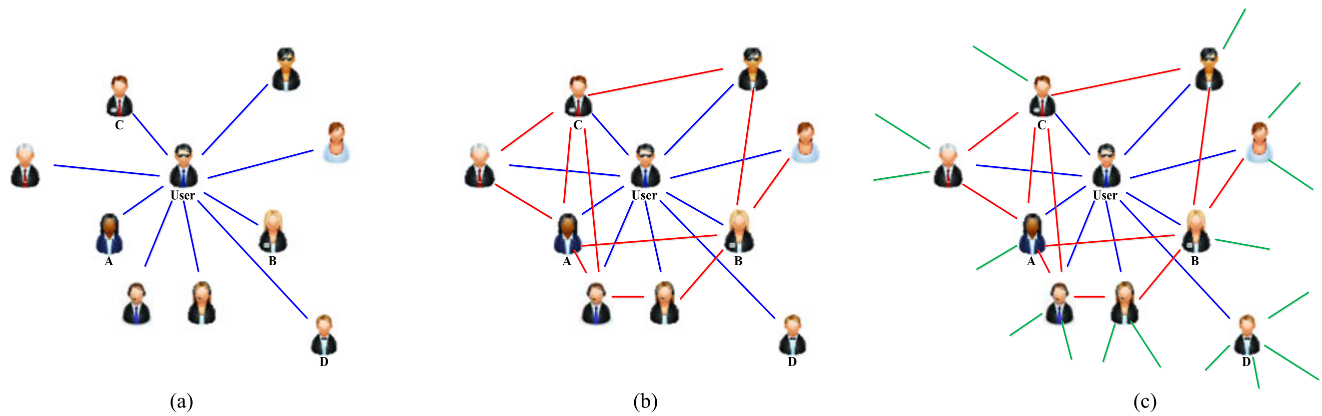

Fig. 2. Example of a user's social network. We split the user's social network into three components: direct friends (blue lines), mutual friends (red lines), and the indirect friends (green lines). Generally, if a friend has many mutual friends with the user, such as A, B, and C, we regard them as close friends of the user. On the contrary, we regard D as a distant friend.

ratings in category c, and they all trust v, it is a good indication that v is an expert in category c. This coefficient is represented as $N_v^c \times \sum_{w\in F_v^c} \frac{N_w^c}{N_w}$, where N_v^c denotes the number of v's ratings in category c, $w \in F_v^c$ denotes w is a friend of v in category c, N_w denotes the total number of w's ratings.

Thus, the smooth degree of interpersonal rating behavior diffusion from friend v to user u is given by

$$D_{u,v}^c = N_v^c \times \sum_{w\in F_v^c} \frac{N_w^c}{N_w} \times \frac{|Friends_{u\cap v}^c| + 1}{|Circle_u^c| + 1} \times \left(1 + \sum_{\forall i \in \{R_u^c \cap R_v^c\}} \exp\left(-|R_{u,i} - R_{v,i}| \times \left|Day_{u,i} - Day_{v,i}\right|\right)\right). \tag{4}$$

In order to be fair in measuring the smooth degree, each row of $\boldsymbol{D}$ is normalized to unity $\sum_v D_{u,v}^{c*} = 1$. We leverage $D_{u,v}^{c*}$ to constrain user u and v's latent features. The basic idea is that the easier interpersonal rating behavior diffusions are, the more similar interpersonal latent features are.

B. Proposed Model

We fuse user personal interest, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior diffusion, into matrix factorization. The proposed model contains these following aspects:

1) the Frobenius norm of matrix $\boldsymbol{U}$ and $\boldsymbol{P}$, which are used to avoid over-fitting [23];
2) user interpersonal rating behavior similarity $E_{u,v}^{c*}$, which means the rating behavior similarity degree according to rating records;
3) the factor of interpersonal rating behavior diffusion $D_{u,v}^{c*}$, which means the smooth degree of interpersonal rating behavior diffusions between user u and friend v; and
4) interpersonal interest similarity $W_{u,v}^{c*}$, and user personal interest $Q_{u,i}^c$ proposed in previous work [37], [39].

The objective function of our model is given by

$$\begin{aligned}
&\Psi\left(\boldsymbol{R}^c, \boldsymbol{U}^c, \boldsymbol{P}^c\right) \\
&= \frac{1}{2}\sum_u\sum_i I_{u,i}^{R^c}\left(R_{u,i}^c - \hat{R}_{u,i}^c\right)^2 + \frac{\lambda_1}{2}\|\boldsymbol{U}^c\|_F^2 + \frac{\lambda_2}{2}\|\boldsymbol{P}^c\|_F^2 \\
&\quad + \frac{3\beta}{2}\sum_u\left(\left(U_u^c - \sum_{v\in F_u^c}\frac{1}{3}\left(D_{u,v}^{c*} + E_{u,v}^{c*} + W_{u,v}^{c*}\right)U_v^c\right)\right. \\
&\qquad\left.\left(U_u^c - \sum_{v\in F_u^c}\frac{1}{3}\left(D_{u,v}^{c*} + E_{u,v}^{c*} + W_{u,v}^{c*}\right)U_v^c\right)^T\right) \\
&\quad + \frac{\eta}{2}\sum_u\sum_i |H_u^{c*}|\left(Q_{u,i}^{c*} - U_u^c P_i^{cT}\right)^2
\end{aligned} \tag{5}$$

where $I_{u,i}^c$ 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 in category c for user u to item i according to (2). $|H_u^{c*}|$ is the normalized number of items that user u has rated in c, which denotes how much of a user depends on his/her individuality to rate an item. Namely, it could measure the user experience in c. We directly fuse interpersonal factors together to constrain users' latent features by the second term, which could reduce the time complexity compared with previous work. It would be discussed in the section of experiments. The idea of interpersonal factors enforced by the second term means that user latent feature $\boldsymbol{U}_u$ should be similar to the average of his/her friends' latent features with the weight of $\frac{1}{3}\left(D_{u,v}^{c*} + E_{u,v}^{c*} + W_{u,v}^{c*}\right)$ in c.

C. Model Training

We need to find a local minimum of this objective function by performing the gradient descent method on $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ for all users and items. For each category c, we get the corresponding matrix factorization model as (5) to obtain user latent profile $\boldsymbol{U}^c$ and item latent profile $\boldsymbol{P}^c$.

The proposed algorithm EURB (Exploring Users' Rating Behaviors) for rating prediction is performed as follows. Firstly, we set the initial values of $\boldsymbol{U}$ and $\boldsymbol{P}$, which are sampled from the normal distribution with zero mean. Secondly, we set the parameters, and the descriptions of parameters are detailed introduced in Part C of Section IV. Thirdly, we start training our model. In each iteration, we calculate gradients of the objective function with respect to the variables $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$, and then update $\boldsymbol{U}$ and $\boldsymbol{P}$. Once the number of iterations reaches to the predefined t, we return the updated $\boldsymbol{U}$ and $\boldsymbol{P}$ as the learned user latent feature vector and item latent feature vector in the fourth step. Fifthly, we utilize the learned $\boldsymbol{U}$ and $\boldsymbol{P}$ to predict the ratings in test dataset. At last, according to the predicted ratings, we calculate the RMSE and MAE as (6) and (7) to measure the performance.

IV. Experiments

We implement a series of experiments on Yelp dataset and Douban Movie dataset to estimate the performance of the proposed approach. Compared approaches include BaseMF [52], CircleCon [21], Context MF [22] and PRM [37], [39]. In this section, we will show the introduction of our datasets, the performance measures, the evaluation of our model, and some discussions.

A. Datasets

1) Yelp Dataset: Yelp is a local directory service with social networks and user reviews. It is the largest review site in America. Users rate the businesses, submit comments, communicate experience, etc. It combines local reviews and social networking functionality to create a local online community. Yelp dataset[4] contains eight categories, including *Active Life*, *Beauty & Spas*, *Home Services*, *Hotels & Travel*, *Night Life*, *Pets*, *Restaurants*, and *Shopping*. More details are shown in our previous work [37]. We experiment with 80% of each user's rating data randomly as the training set and the rest 20% of each user's rating data as the test set in each category, to ensure all users' latent features are learned.

2) Douban Movie Dataset: Additionally, we use a second dataset Douban Movie[5] to enrich our experiments. 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 information. Users record the movies they wish to watch and share the reviews and ratings with their friends. We have crawled 3,468,485 ratings from 11,668 users who rated a total of 59,704 movies. The average number of user ratings is about 297. Table II is a statistic of users and items in Douban Movie dataset.

B. Performance Measures

We split each dataset into 5 groups in order to perform 5-fold cross-validation as our evaluation methodology. 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. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are the most popular accuracy measurements [21]–[23], [37], [39], [40], [52], which are defined as follows:

$$RMSE = \sqrt{\sum_{(u,i)\in\Re_{\text{test}}} \left(R_{u,i} - \hat{R}_{u,i}\right)^2 / \left|\Re_{\text{test}}\right|} \tag{6}$$

$$MAE = \sum_{(u,i)\in\Re_{\text{test}}} \left|R_{u,i} - \hat{R}_{u,i}\right| / \left|\Re_{\text{test}}\right| \tag{7}$$

where $R_{u,i}$ is the real rating value of user u to item i, $\hat{R}_{u,i}$ is the corresponding predicted rating value according to (2). $\Re_{\text{test}}$is the set of all user-item pairs in the test set. $|\Re_{\text{test}}|$denotes the number of user-item pairs in the test set.

TABLE II
Statistic of Douban Movie Dataset

Dataset	User Count	Item Count	Rating Count	Sparsity	r^c
Douban Movie	11,668	59,704	3,468,485	4.979e-03	3.790

C. Evaluation

1) Compared Algorithms: We performed a series of experiments to compare our model with existing models:

a) *BaseMF:* This model is the basic matrix factorization approach proposed in [52] without consideration of any social factors.

b) *CircleCon:* This method is proposed in [21], including four variants: CircleCon1, CircleCon2a, CircleCon2b, and CircleCon3.

c) *Context MF:* This method [22] exceeds traditional item-based collaborative filtering model in [2], influence-based model in [57], and Sorec in [27] by taking interpersonal influence and individual preference into consideration.

d) *PRM:* This is our previous work [37]. This method considers user interpersonal interest similarity, user influence and personal interest.

e) *EURB:* The proposed model in this paper by exploring social users' rating behaviors.

2) Parameter Settings:

a) k: The dimension of the latent vector. If k is too large, the time cost will be larger and it will be difficult to calculate the similarity between users. But if k is too small, it will be difficult to embody user and item features. Whatever the k is, it is fair for all compared algorithms if we set them the same value. Here in performance comparison, we set $k = 10$ as in [21].

b) λ_1 and λ_2: The parameters of trading-off over-fitting factor in (5).

c) β: The weight of the interpersonal factors enforced in the second term of the objective function (5).

d) η: The weight of the personal interest factor in the last term of (5).

These parameters in all algorithms play the role of balancing each factor. As in [22], to balance the components in each

[4][Online]. Available: http://smiles.xjtu.edu.cn/Download/Download_yelp.html

[5][Online]. Available: http://smiles.xjtu.edu.cn/Download/Download_Douban.html

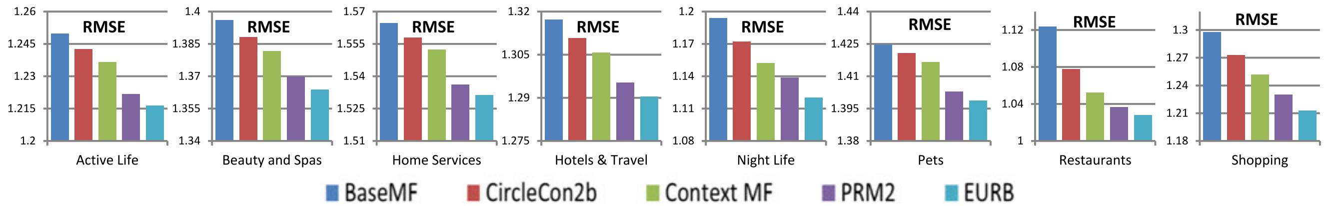

Fig. 3. Performance comparison of training in each category of Yelp based on RMSE.

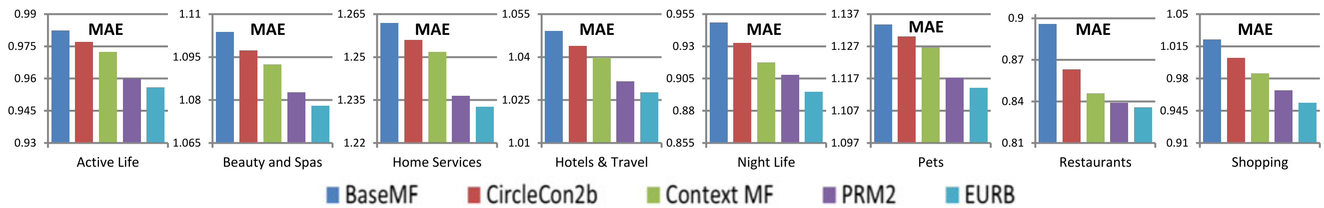

Fig. 4. Performance comparison of training in each category of Yelp based on MAE.

algorithm, these parameters are proportional as follows:

$$\lambda_1 : \lambda_2 : \beta : \eta = \frac{1}{\|\boldsymbol{U}\|_F^2} : \frac{1}{\|\boldsymbol{P}\|_F^2} : \frac{1}{\left\|\boldsymbol{U} - \sum_v \frac{1}{3}\left(\boldsymbol{D} + E + W\right)\boldsymbol{U}^T\right\|_F^2} : \frac{1}{\left\|\boldsymbol{Q} - UP^T\right\|_F^2} \tag{8}$$

where $\boldsymbol{U}$ and $\boldsymbol{P}$ are set the initial values which are sampled from the normal distribution with zero mean, the matrices $\boldsymbol{D}$, $\boldsymbol{E}$, $\boldsymbol{W}$, and $\boldsymbol{Q}$ have been calculated in Section III. We could calculate the ratios among the coefficients directly.

Note that we set the same initialization and gradually reduced learning rate for all compared algorithms considering with fairness. After each iteration, we decrease the learning rate by a factor 0.9 as [10], [58]. We obtain approximate optimal result with 50 iterations for each algorithm, which will be discussed in Part D of Section IV. We set the same parameters and operating environment for each compared algorithm for fair comparison.

3) Performance Comparison: In this subsection, we compare the performance of our EURB algorithm with the existing models including BaseMF [52], CircleCon [21], Context MF [22] and PRM [37] in Yelp and Douban Movie datasets.

We show the performance comparison in Yelp dataset in Figs. 3 and 4. The performance comparison in Douban Movie dataset is shown in Table III. It can be seen that our model EURB is better than other compared algorithms on performance.

TABLE III
PERFORMANCE COMPARISON IN DOUBAN MOVIE DATASET

Model	BaseMF	CircleCon2a	ContextMF	PRM	EURB
RMSE	1.00823	1.00154	0.99489	0.99699	0.99128
MAE	0.79933	0.79430	0.78926	0.79100	0.78673

D. Discussions

Besides the performance comparison of the proposed EURB with the existing BaseMF, CircleCon, ContextMF and PRM model, here, we discuss six aspects in our experiments: the impact of iteration count, the impact of the dimension of the latent vector, the impact of predicted integer ratings, the impact of different factors, and the impact of the variants of the rating schedule on performance. At last, we conduct time complexity comparison.

1) The Impact of Iteration Count: The iteration count plays an important role in matrix factorization. Here we show the relevance between performance and iteration count based on three datasets, *Nightlife*, *Shopping*, and *Hotels & Travel* datasets in Fig. 5.

From above figures, it can be seen that the performance rises up slower and slower after 20 iterative computations. Thus, setting iteration count as 50 is reasonable, where all algorithms have achieved stable optimal results.

2) The Impact of the Dimension of the Latent Vector: We conduct some experiments to discuss the impact of the dimension of the latent vector on performance. Some related works [22], [23], [10], [11] have conducted this discussion, but most of them just increase the dimension without considering fairness of comparison. $\|U^c\|_F^2$ is increasing with the dimension of the user latent vector. Meanwhile, the equation of rating prediction given by (2) is related to the dimension of the latent vector. That is to say, they just increase the dimension to conduct performance comparison with different initializations.

Thus, we should decrease the value of initialization while increasing the dimension in order to maintain fairness of comparison. We set the initialization of 10-dimensional user latent feature matrix as the matrix X. We can get

$$\|U_{10}^c\|_F^2 = \sum_i^M \sum_j^{10} X_{i,j}^2 \tag{9}$$

where M is the number of users.

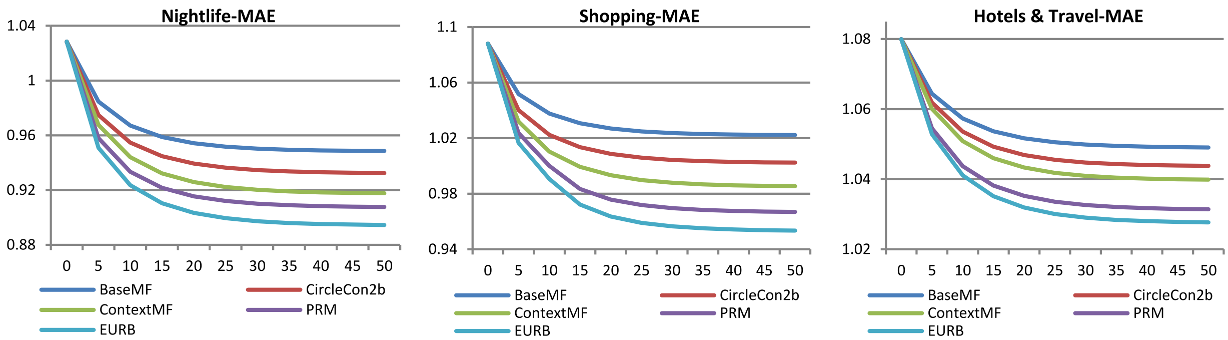

Fig. 5. Discussions on the impact of iteration count in Nightlife, Shopping, and Hotels & Travel datasets.

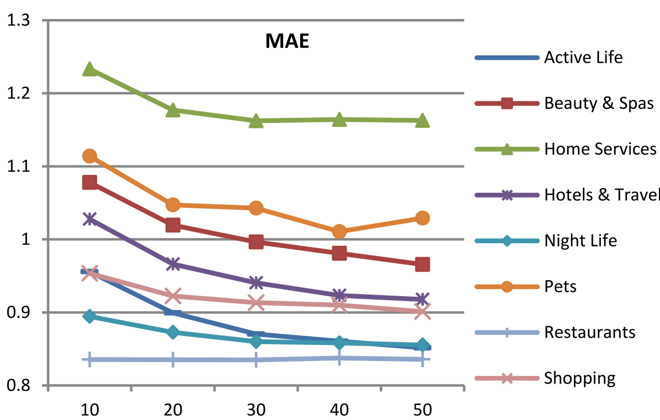

Fig. 6. Discussion on the impact of the dimension of the latent vector on performance.

We add a factor a to the initialization to represent the $\|U_d^c\|_F^2$ as

$$\|U_d^c\|_F^2 \approx \frac{d}{10} \times a^2 \times \sum_i^M \sum_j^{10} X_{i,j}^2 \tag{10}$$

where d denotes the dimension. In order to maintain fairness of comparison, we keep the equality between (9) and (10). Thus, we get the factor a

$$a = \sqrt{\frac{10}{d}}. \tag{11}$$

As the expressions above, we conduct some experiments to discuss the impact of the dimension of the latent vector on performance shown in Fig. 6.

It can be seen that performance is not absolutely increasing with the deeper dimension. But for most of the datasets, besides *Pets* and *Restaurants* datasets, with the dimension increasing, MAE reduces gradually, and it obviously shows that when $d > 20$, MAE decreases very slowly.

3) The Impact of Predicted Integer Ratings: Because the predicted ratings are decimal, we discuss the impact of predicted integer ratings on performance. The ratings user rated are all discrete values ranging from 1 to 5. But the predicted results of matrix factorization model are all decimals. Thus, it is necessary to discuss the impact of integer predicted ratings. We round decimal ratings we predicted into discrete integers. The performance comparison is shown in Table IV. It can be seen that when we predict integer ratings, RMSE of the model will increase, but MAE will decline, whatever the dataset is. We deep explore the evaluation methodology RMSE and MAE, and find that RMSE squares errors. That is to say, MAE gives equal weight to all errors, while RMSE gives extra weight to large errors. Thus, when we round predicted ratings, RMSE of the model will increase. But whatever the value we predict is, it just offers us the degree of user preference to help us recommend the right items to users.

4) The Impact of Different Factors: In this subsection, we discuss the impact of different factors on performance in Yelp *Nightlife* and *Shopping* datasets. Meanwhile, we add the performance of compared algorithms to analyze what is the factor that yielded better results. We show the performance of different factors and compared algorithms in Figs. 7 and 8. Note the following:

1) B-MF represents BaseMF approach. Namely, it is the approach without considering any factor.
2) PI denotes the approach with considering personal interest.
3) IS denotes the approach with considering interpersonal interest similarity.
4) RBS denotes the approach with considering interpersonal rating behavior similarity.
5) RBD denotes the approach with considering interpersonal rating behavior diffusion.
6) "+" denotes we take another factor into consideration. For example, PI + IS denotes the approach with considering the factors of personal interest and interpersonal interest similarity.

In Figs. 7 and 8, it can be seen that all factors have an effect on improving performance. Deeply, it can be seen that the factor of PI (personal interest) has a better effect than other factors in Yelp *Shopping* dataset. On the contrary, it has a worse effect than other factors in Yelp *Nightlife* dataset. Thus, these factors have different effectiveness in different datasets. But if we consider more thoughtful factors, we will get more accurate results. For instance, taking any three factors into consideration will get better performance than any two factors. Additionally, we think it is convergent because the improvements are diminishing.

5) The Impact of Variants of the Rating Schedule: In this subsection, we discuss the impact of the variants of the rating schedule on performance. As mentioned before, we put forward

TABLE IV
DISCUSSION ON THE IMPACT OF PREDICTED INTEGER RATINGS

		Active Life	Beauty & Spas	Home Services	Hotels & Travel	Night Life	Pets	Restaurants	Shopping
RMSE	Integer	1.24373	1.39491	1.55448	1.32158	1.17036	1.45593	1.07762	1.23929
	Decimal	**1.21632**	**1.36369**	**1.53189**	**1.29044**	**1.12028**	**1.39889**	**1.02765**	**1.21324**
MAE	Integer	**0.92220**	**1.05570**	**1.20621**	**0.99813**	**0.86861**	**1.11020**	**0.76259**	**0.91569**
	Decimal	0.95591	1.07804	1.23322	1.02769	0.89449	1.11407	0.83560	0.95360

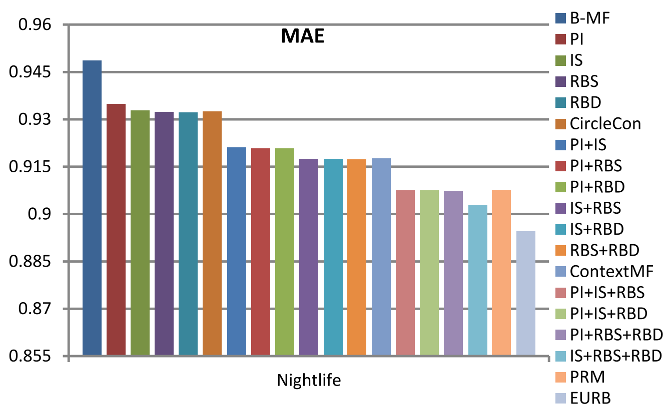

Fig. 7. Discussion on the impact of different factors on performance in the Yelp Nightlife dataset.

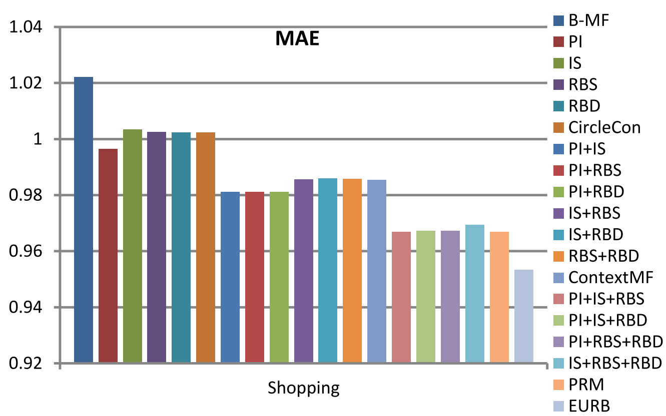

Fig. 8. Discussion on the impact of different factors on performance in the Yelp Shopping dataset.

a concept of the rating schedule, which is similar to the curriculum schedule. But actually the curriculum schedule is weekly. Our rating schedule could be normalized in different periods, such as one week, one month, and one year. For instance, we leverage the weekly rating schedule as in Fig. 1. But when we try to leverage the monthly rating schedule, the size of rating behavior matrix should be set as 5×31 (31 days per month). When we try to leverage the yearly rating schedule, the size of rating behavior matrix should be set as 5×12 (12 months per year). Here, the impact of the variants of the rating schedule normalized in different periods on performance is discussed. The discussions is shown in Table V.

It can be seen that there is not much impact of the variants of the rating schedule on performance. But the overall performance of our model with the weekly rating schedule is better than others. We deem that it is due to the sparsity of our datasets. The size of the weekly rating schedule is 5×7, while the size of the monthly rating schedule is 5×31, and the size of the yearly rating schedule is 5×12. The larger the size of the rating schedule is, the sparser the rating behavior matrix is. But for the Restaurants category, user's average rating count is nearly 46 [37]. It seems that it is more suitable with the yearly rating schedule.

6) Time Complexity Comparison: In this paper, we propose to directly fuse interpersonal factors together to constrain users' latent features, which can reduce the time complexity. In previous work [37], we leverage each factor directly to constrain latent feature vectors. If we utilize that model again, our Original EURB model will be constructed as

$$
\begin{aligned}
&\Psi\left(\boldsymbol{R}^c, \boldsymbol{U}^c, \boldsymbol{P}^c\right) \\
&= \frac{1}{2}\sum_u \sum_i I_{u,i}^{R^c}\left(R_{u,i}^c - \hat{R}_{u,i}^c\right)^2 + \frac{\lambda_1}{2}\left\|\boldsymbol{U}^c\right\|_F^2 + \frac{\lambda_2}{2}\left\|\boldsymbol{P}^c\right\|_F^2 \\
&\quad + \frac{\beta}{2}\sum_u\left(\left(U_u^c - \sum_{v\in F_u^c} D_{u,v}^{c*}U_v^c\right)\left(U_u^c - \sum_{v\in F_u^c} D_{u,v}^{c*}U_v^c\right)^T\right) \\
&\quad + \frac{\gamma}{2}\sum_u\left(\left(U_u^c - \sum_{v\in F_u^c} E_{u,v}^{c*}U_v^c\right)\left(U_u^c - \sum_{v\in F_u^c} E_{u,v}^{c*}U_v^c\right)^T\right) \\
&\quad + \frac{\delta}{2}\sum_u\left(\left(U_u^c - \sum_{v\in F_u^c} W_{u,v}^{c*}U_v^c\right)\left(U_u^c - \sum_{v\in F_u^c} W_{u,v}^{c*}U_v^c\right)^T\right) \\
&\quad + \frac{\eta}{2}\sum_u \sum_i \left|H_u^{c*}\right|\left(Q_{u,i}^{c*} - U_u^c P_i^{cT}\right)^2 \qquad (12)
\end{aligned}
$$

where $I_{u,i}^c$ 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 in category c for user u to item i according to (2). $|H_u^{c*}|$ is the normalized number of items that user u has rated in c, which denotes how much of a user depends on his/her individuality to rate an item. $D_{u,v}^*$ denotes the smooth degree of interpersonal rating behavior diffusions from friend v to user u. $E_{u,v}^*$ denotes the interpersonal ratings similarity between user u and friend v. $W_{u,v}^*$ denotes the interpersonal interest similarity between user u and friend v.

We perform Original EURB model shown as (12) and improved EURB model shown as (5) based on the same operating environment. Their time complexities are shown in Table VI, where the COST is the average needed running time of each iteration. It can be seen that the method of directly fusing interpersonal factors to constrain user latent feature

TABLE V
DISCUSSIONS ON THE IMPACT OF VARIANTS OF THE RATING SCHEDULE

Dataset		Active Life	Beauty & Spas	Home Services	Hotels & Travel	Night Life	Pets	Restaurants	Shopping
Weekly	MAE	**0.95591**	**1.07804**	**1.23322**	**1.02769**	**0.89449**	**1.11407**	0.83560	**0.95360**
Monthly	MAE	0.95596	1.07806	1.23328	1.02777	0.89450	1.11408	0.83569	0.95361
Yearly	MAE	0.95593	1.07805	1.23325	1.02773	0.89452	1.11412	**0.83544**	**0.95360**

TABLE VI
TIME COMPLEXITY COMPARISON

Category	Measurement	PRM	Original EURB	EURB
Active Life	MAE	0.96009	0.95562	0.95592
	COST (min)	**0.2643**	**0.3725**	**0.1563**
Beauty & Spas	MAE	1.08268	1.07793	1.07804
	COST (min)	**0.2304**	**0.3218**	**0.1385**
Home Services	MAE	1.23642	1.23261	1.23322
	COST (min)	**0.0525**	**0.0789**	**0.0303**
Hotels & Travel	MAE	1.03142	1.02731	1.02769
	COST (min)	**0.2134**	**0.3202**	**0.1275**
Night Life	MAE	0.90762	0.89486	0.89449
	COST (min)	**0.2836**	**0.3024**	**0.2578**
Pets	MAE	1.11714	1.11425	1.11407
	COST (min)	**0.0146**	**0.0217**	**0.0084**
Restaurants	MAE	0.83910	0.83549	0.83560
	COST (min)	**0.3128**	**0.3203**	**0.2874**
Shopping	MAE	0.96689	0.95327	0.95360
	COST (min)	**0.1096**	**0.1293**	**0.0895**
Average	MAE	1.01783	1.01153	1.01170
	COST (min)	**0.1852**	**0.2334**	**0.1369**

vectors reduces the time complexity. Meanwhile, there is not much performance loss.

V. CONCLUSION

In this paper, we propose a user-service rating prediction approach by exploring users' rating behaviors with considering four social network factors: user personal interest (related to user and the item's topics), interpersonal interest similarity (related to user interest), interpersonal rating behavior similarity (related to users' rating habits), and interpersonal rating behavior diffusion (related to users' behavior diffusions). A concept of the rating schedule is proposed to represent user daily rating behavior. The similarity between user rating schedules is utilized to represent interpersonal rating behavior similarity. The factor of interpersonal rating behavior diffusion is proposed to deep understand users' rating behaviors. We explore the user's social circle, and split the social network into three components, direct friends, mutual friends, and the indirect friends, to deep understand social users' rating behavior diffusions. These factors are fused together to improve the accuracy and applicability of predictions. We conduct a series of experiments in Yelp and Douban Movie datasets. The experimental results of our model show significant improvement.

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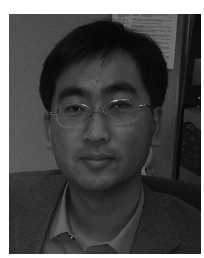

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