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Service Rating Prediction by Exploring Social Mobile Users' Geographical Locations

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Abstract—Recently, advances in intelligent mobile device and positioning techniques have fundamentally enhanced social networks, which allows users to share their experiences, reviews, ratings, photos, check-ins, etc. The geographical information located by smart phone bridges the gap between physical and digital worlds. Location data functions as the connection between user's physical behaviors and virtual social networks structured by the smart phone or web services. We refer to these social networks involving geographical information as location-based social networks (LBSNs). Such information brings opportunities and challenges for recommender systems to solve the cold start, sparsity problem of datasets and rating prediction. In this paper, we make full use of the mobile users' location sensitive characteristics to carry out rating predication. We mine: 1) the relevance between user's ratings and user-item geographical location distances, called as user-item geographical connection, 2) the relevance between users' rating differences and user-user geographical location distances, called as user-user geographical connection. It is discovered that humans' rating behaviors are affected by geographical location significantly. Moreover, three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, are fused into a unified rating prediction model. We conduct a series of experiments on a real social rating network dataset Yelp. Experimental results demonstrate that the proposed approach outperforms existing models.

Index Terms—Geographical location, rating prediction, recommender system, location-based social networks

1 INTRODUCTION

RECENTLY , with the rapid development of mobile devices and ubiquitous Internet access, social network services, such as Facebook, Twitter, Yelp, Foursquare, Epinions, become prevalent. According to statistics, smart phone users have produced data volume ten times of a standard cellphone. In 2015, there were 1.9 billion smart phone users in the world, and half of them had accessed to social network services. Through mobile device or online location based social networks (LBSNs), we can share our geographical position information or check-ins. This service has attracted millions of users. It also allows users to share their experiences, such as reviews, ratings, photos, check-ins and moods in LBSNs with their friends. Such information brings opportunities and challenges for recommender systems. Especially, the geographical location information bridges the gap between the real world and online social network services. For example, when we search a restaurant considering convenience, we will never choose a faraway one. Moreover, if the geographical location information and social networks can be combined, it is not difficult to find that our mobility may be influenced by our social relationships as users may prefer to visit the places or consume the items their friends visited or consumed before.

In our opinion, when users take a long journey, they may keep a good emotion and try their best to have a nice trip. Most of the services they consume are the local featured things. They will give high ratings more easily than the local. This can help us to constrain rating prediction. In addition, when users take a long distance travelling a far away new city as strangers. They may depend more on their local friends. Therefore, users' and their local friends' ratings may be similar. It helps us to constrain rating prediction. Furthermore, if the geographical location factor is ignored, when we search the Internet for a travel, recommender systems may recommend us a new scenic spot without considering whether there are local friends to help us to plan the trip or not. But if recommender systems consider geographical location factor, the recommendations may be more humanized and thoughtful. These are the motivations why we utilize geographical location information to make rating prediction.

With the above motivations, the goals of this paper are: 1) to mine the relevance between user's ratings and user-item geographical location distances, called as user-item geographical connection, 2) to mine the relevance between users' rating differences and user-user geographical location distances, called as user-user geographical connection, and 3) to find the people whose interest is similar to users. In this paper, three factors are taken into consideration for rating prediction: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity. These factors are fused into a location based rating prediction model. The novelties of this paper are user-item and user-user geographical connections, i.e. we explore users' rating behaviors through their geographical location distances. The main contributions of this paper are summarized as follows:

- We mine the relevance between ratings and user-item geographical location distances. It is discov-

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ered that users usually give high scores to the items (or services) which are very far away from their activity centers. It can help us to understand users' rating behaviors for recommendation.

- We mine the relevance between users' rating differences and user-user geographical distances. It is discovered that users and their geographically far away friends usually give the similar scores to the same item. It can help us to understand users' rating behaviors for recommendation.
- We integrate three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity, into a Location Based Rating Prediction (LBRP) model. The proposed model is evaluated by extensive experiments based on Yelp dataset. Experimental results show significant improvement compared with existing approaches.

The remainder of this paper is organized as follows. In Section 2, the problem we focus on in this paper is defined. Meanwhile, a brief introduction of some related works and compared algorithms is given. In Section 3, we introduce the dataset in detail. In Section 4, the proposed personalized location based rating prediction model is introduced. Experiments and discussions are given in Section 5 and conclusions are drawn in Section 6.

2 Preliminary

In this section, we first introduce some related works, and define the notations utilized in this paper. Then some major approaches in this domain are reviewed. These approaches are all based on matrix factorization, and their performances are systematically compared in our experiments.

2.1 Related Work

The first generation of recommender systems [1] with traditional collaborative filtering algorithms [3]-[9] is facing great challenges of cold start for users (new users in the recommender system with little historical records) and the sparsity of datasets. Fortunately, with the popularity and rapid development of social networks, more and more users enjoy sharing their experiences, reviews, ratings, photos, and moods with their friends. Many social-based models [10]-[16], [62] have been proposed to improve the performance of recommender system. Yang *et al*. [17] propose to use the concept of 'inferred trust circle' based on the domain-obvious of circles of friends on social networks to recommend users favorite items. Jiang *et al*. [18] prove that individual preference is also an important factor in social networks. In their Context Model, user latent features should be similar to his/her friends' according to preference similarity. Hu *et al*. [61] and Lei *et al*. [59] utilize the power of semantic knowledge bases to handle textual messages and recommendations. Our previous works [57], [58] focus on objective evaluation in order to recommend the high-quality services by exploring social users' contextual information.

Except for ratings prediction, there are some systems [19]-[32], [37]-[43], [45]-[54], [63], [64] focusing on location recommendation. Many researchers mine user's interests from the user's location history to make recommendations. Zheng *et al*. [25] propose a hierarchical-graph-based similarity measurement with consideration of the human mobility features. The location based recommender system using the user similarity outperforms those using the Cosine similarity. Bao *et al*. [19] combine user's location and preference to provide effective location recommendations. Jiang *et al*. [56] propose a user topic based collaborative filtering approach for personalized travel recommendation. Gao *et al*. [31] introduce a location recommendation framework with temporal effects based on observed temporal properties. They explore the number of check-ins made by a user at a location to recommend a new location user may prefer. Cheng *et al*. [32] fuse matrix factorization (MF) with geographical and social influence for POI (Point-of-Interest) recommendations on LBSNs, and propose a Multi-center Gaussian Model to model the geographical influence of users' check-in behaviors. Zhang *et al*. propose several location recommendation frameworks by exploiting geographical influence [37], [46], [48], temporal influence [47], categorical correlations [50], spatiotemporal sequential influence [53], [54], user opinions [52], etc. Sang *et al*. [49] conduct an in-depth usage mining on real-world check-in data and present a POI category transition based approach to estimate the visiting probability. For multi-modality datasets, Zheng [60] summarizes existing data fusion methods, classifying them into three major categories to help people to find proper data fusion methods.

There is a paper [43] also focusing on observations on ratings combining with geographical location information. They find that geographical neighborhood has influences on the rating of a business. They perform biases based matrix factorization model with their observations, but there are some differences between us: 1) We focus on the relevance between ratings and user-item geographic distances. They focus on item-item geographic location distances and the impact of items' neighborhoods. 2) We focus more on exploring social users' rating behaviors and social influence, i.e. the relevance between users' rating differences and user-user geographic distances. 3) They perform biases based matrix factorization model, but we perform our model with constraining user and item latent factor vectors. That is to say, formula of our object function is different with theirs.

2.2 Problem Formulation

Symbols and notations utilized in this paper are given in Table 1. In this paper, we focus on predicting the ratings of user u to an unknown item i. We have a set of users $\boldsymbol{U} = \{u_1, \cdots, u_M\}$ and a set of items $\boldsymbol{P} = \{i_1, \cdots, i_N\}$. The ratings expressed by users to items are given in a rating matrix $\boldsymbol{R} = \left[R_{u,i}\right]_{M\times N}$. In this matrix, $R_{u,i}$ denotes the rating of user u on item i. It can be any real number, but ratings are often integers in the range from 1 to 5. In a social network, each user has a set of friends. The interest similarity val-

TABLE 1
NOTATIONS AND THEIR DESCRIPTIONS

Symbol	Description	Symbol	Description
M	the number of users	N	the number of items
F_u	the set of user u's friends	H_u	the set of items rated by user u
r	users' average rating value in the training dataset	k	the dimension of the latent space
$\boldsymbol{R}_{M\times N}$	the rating matrix expressed by users on items	$\widehat{\boldsymbol{R}}_{M\times N}$	the predicted rating matrix based on the latent feature space
$\boldsymbol{P}_{N\times k}$	the item latent feature matrix	$\boldsymbol{U}_{M\times k}$	the user latent feature matrix
$\boldsymbol{W}_{M\times M}$	interpersonal interest similarity matrix	$\boldsymbol{Luu}_{M\times M}$	the user-user geographical connection
$\boldsymbol{Lui}_{M\times N}$	the user-item geographical connection	$\lambda,\beta,\delta,\eta$	the tradeoff parameters in the objective function

ues are represented as matrix $\boldsymbol{W}=\left[W_{u,v}\right]_{M\times M}$. $W_{u,v}\in[0,1]$ denotes the interest similarity of user u to friend v. $Lui_{u,i}\in[0,1]$ denotes the coefficient to adjust the rating user u to item i according to the user-item geographical connection. The coefficient values are represented in matrix $\boldsymbol{Lui}=\left[Lui_{u,i}\right]_{M\times N}$. $Luv_{u,v}\in[0,1]$ denotes ratings similarity between user u and friend v according to the user-user geographical connection. The similarity values are represented as a matrix $\boldsymbol{Luu}=\left[Luu_{u,v}\right]_{M\times M}$.

The task of our LBRP model is: Given a user $u\in \mathrm{U}$ and an item $i\in \mathrm{P}$ for which $R_{u,i}$ is unknown, predicting the rating of user u to item i using $\boldsymbol{R}$, $\boldsymbol{W}$, $\boldsymbol{Lui}$ and $\boldsymbol{Luu}$.

In order to achieve personalized rating prediction, matrix factorization is used to learn the latent features of users and items, and predict the unknown ratings using these latent features. Here we describe related definitions of user and item latent features. Let $\boldsymbol{U}\in \mathrm{R}^{M\times k}$ and $\boldsymbol{P}\in \mathrm{R}^{N\times k}$ be user and item latent feature matrices, with column vectors $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ representing k-dimensional user-specific and item-specific latent feature vectors. 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 characterization of user u and item i. The goal of matrix factorization is to learn these latent feature vectors and exploit them for recommendation.

2.3 Compared Algorithms

Matrix Factorization (MF) is one of the most popular methods for recommender systems [32]. It offers much flexibility for modeling various real-life situations [34], such as allowing incorporation of additional geographical and social information. Therefore, in this paper, the popular matrix factorization is utilized to learn the latent features of users and items. Some major approaches based on probabilistic matrix factorization are introduced as follows.

2.3.1 Basic Matrix Factorization

Recently, many systems [10], [17], [18], [33], [34] employ matrix factorization techniques to learn the latent features of users and items, and predict the unknown ratings. We first introduce the basic probabilistic matrix factorization (BaseMF) approach [33]. They learn the latent features by minimizing the objective function based on the observed rating data $\boldsymbol{R}$:

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

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

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

where r is an offset value, which is empirically set as users' average rating value. $R_{u,i}$ is the real rating values of item i from user u. $\boldsymbol{U}$ and $\boldsymbol{P}$ are the user and item latent feature matrices which need to be learned. $\|\boldsymbol{X}\|_F$ is the Frobenius norm of matrix $\boldsymbol{X}$, and $\|\boldsymbol{X}\|_F=\left(\sum_{i,j}x_{i,j}^2\right)^{1/2}$. The second term is used to avoid over-fitting [33]. This objective function can be minimized efficiently by using gradient descent method. 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.

2.3.2 CircleCon Model

This approach [17] 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 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 a weight $S_{u,v}^{c*}$ in category c. Once the model is trained in c, the rating value in c can be predicted according to (2).

2.3.3 ContextMF

Besides the factor of interpersonal influence, Jiang *et al.* [18] propose another important factor: individual preference. Their results demonstrate the significance of social contextual factors (including individual preference and interpersonal influence). The factor of interpersonal influence is similar to the trust values in the CircleCon model [17]. Another factor of 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' with the weight of their preference similarity in social networks.

2.3.4 PRM

In our previous work [13], we consider more 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 $W_{u,v}^*$ in social networks. The factor of personal interest denotes user's interest vector has a certain similarity to the item's topic vector a user interests in. It focuses on mining the degree of user interest to an item.

2.3.5 NCPD

Hu *et al.* [43] focuses on observations on ratings combining with geographical location information. They find that geographical neighborhood has influences on the rating of a business. They incorporate geographical neighborhood, business category, review content, business popularity, and geographical distance with performing bias based matrix factorization model.

3 Dataset Introduction

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 shopping experience, etc. It combines local reviews and social networking functionality to create a local online community. Moreover, it is proved by the data of Yelp that users are more willing to visit places or to consume items that his/her friends have visited or consumed before. As shown in Table 3, a statistic of rating intersections is given. For each rating of a user, if the item has been rated by his/her friends, we call it rating intersections. It is obvious that the more rating intersections are, the users are more influenced by their friends. In Table 3, it can be discovered that there are many rating intersections between users and their friends. Therefore, it can be concluded that users' mobility and consuming behaviors may be easily influenced by their social relationships.

We have crawled nearly 80 thousand users' social circles and their rated items. Table 2 is the statistic of our dataset which consists of ten categories, 80,050 users, 155,965 items and 1,543,315 ratings. Note that we have items' information including their GPS positions. For a user, the average geographical location of items rated by this user is set as his/her activity center. In other words, for a user u, we represent his/her activity center position as $\left(\frac{\sum_{i\in H_u} lat_i}{|H_u|}, \frac{\sum_{i\in H_u} lon_i}{|H_u|}\right)$, where i denotes the item. H_u denotes the set of items rated by user u. $|H_u|$ denotes the number of items rated by user u. lat_i and lon_i are the latitude and longitude of item i.

4 The Approach

The proposed personalized location based rating prediction model (LBRP) has three main steps: 1) obtain three geo-social factors, interpersonal interest similarity, user-user geographical connection, and user-item geographical connection, through smart phone with the Wi-Fi technology and Global Positioning System (GPS); 2) build up personalized rating prediction model combining with the three factors in the cloud; 3) train the model in the cloud to learn user and item latent feature matrices for rating prediction to recommend suitable items of user's interest. In this paper, we focus on the algorithm part: step 2 and step 3. When the geo-social data through smart phone is given by step 1, as shown in Fig. 1, the model is built up combining geo-social factors to learn user and item latent features. User and item latent feature matrices can be calculated by machine learning methods for rating prediction. Once the ratings are predicted, the items can be ranked by the ratings and provided as TopN recommendation lists as shown in Fig. 1. Hereinafter we turn to the details of our approach.

TABLE 2
Statistic of Our Yelp Datasets

Dataset	Number of users	Number of items	Number of ratings	Sparsity
Active Life	6152	6390	48803	1.24E-03
Arts & Entertainment	11182	5221	108861	1.86E-03
Automotive	1351	2523	6213	1.82E-03
Beauty & Spas	5529	7323	36845	9.10E-04
Event Planning & Services	11447	6028	98491	1.43E-03
Food	9770	21370	341573	1.64E-03
Hotels & Travel	4897	2146	31833	3.03E-03
Restaurants	10,449	67,857	321,551	4.54E-04
Nightlife	11,152	21,647	436,301	1.81E-03
Shopping	8,121	15,460	112,844	8.99E-04

TABLE 3
Statistic of Rating Intersections

Category	Ratings count	Intersections count	Proportion
Restaurants	321,551	98,402	30.6%
Nightlife	436,301	306,294	70.2%
Shopping	112,844	63,821	56.6%

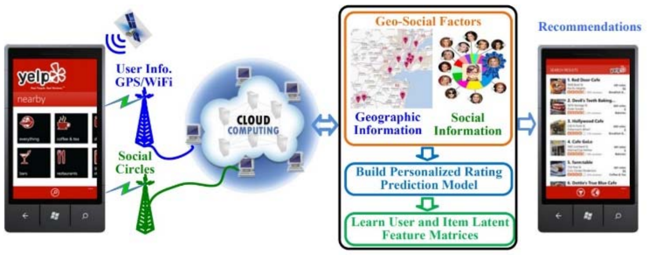

Fig. 1. System overview of our personalized recommendation via geographical social networking, including smart phone user of mobile social network services, cloud computing, rating prediction, and the recommendation lists.

4.1 Geographical Social Factors

Geographical social factors include interpersonal interest similarity, user-item geographical connection and user-user geographical connection. The user-item and user-user geographical connections are measured by ratings through diverse geographical distances. Interpersonal interest similarity is measured by the similarity between user's interest vector and friend's interest vector [13]. Note that, the geographical distance between two latitude/longitude coordinates is calculated by using the Haversine geodesic distance equation proposed in [55].

4.1.1 User-Item Geographical Connection

As mentioned before, mobile social network services have pervasive influence on users' daily life. Based on the analysis of data of Foursquare, users tend to activities in nearby areas. The researchers find that the activity radius of 45% users is no more than 10 miles, and the activity radius of 75% users is no more than 50 miles. Moreover, the same conclusion is drawn in [23]. The relevance of users' rating number and the distances of user-item is shown in Fig. 2. It can be seen that about 45% of the items

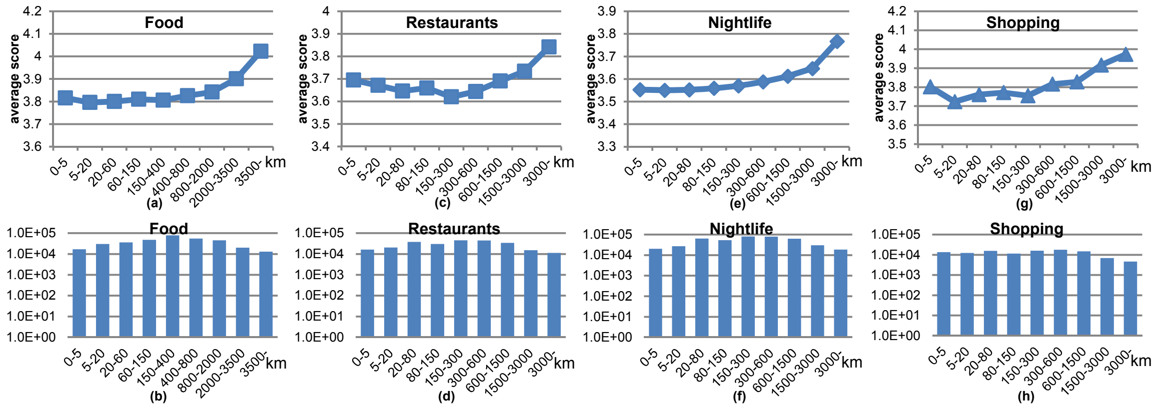

Fig. 3. The distributions of the average scores with different user-item geographical distances (km) based on Yelp Food, Yelp Restaurants, Yelp Nightlife, and Yelp Shopping datasets shown in (a), (c), (e), and (g). Fig. (b), (d), (f), and (h) show the corresponding count of ratings in each group. In (a), (c), (e), and (g), the value of x-axis denotes the geographical distance between user and item, and the value of y-axis denotes the corresponding average ratings. Note 1.0E+0X in (b), (d), (f), and (h) denote 10^x.

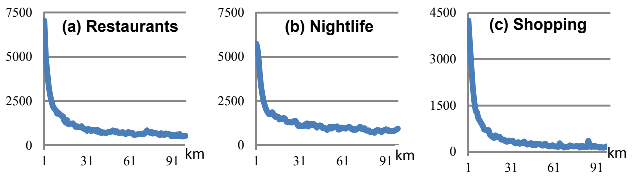

Fig. 2. The distributions of the number of ratings in different distances (km).

users have rated are in the radius of 20 km. It is reasonable that people's activity centers are close to their residences or companies. It can be used to solve the cold start problem, especially when users travel to a new city.

We analyze the relevance between user ratings and user-item location distances. The distributions are shown in Fig. 3 based on *Yelp Food*, *Yelp Restaurants*, *Yelp Nightlife*, and *Yelp Shopping* datasets. Intuitively, the number of items that are very far away is small. Therefore, in Fig. 3, the distances are classified into nine groups with different ranges to make sure that the density of ratings in each region is balanced. In addition, the corresponding rating count in each group is shown to demonstrate the fairness of our grouping in Fig. 3 (b), (d), (f), and (h). The corresponding average rating scores are given on y-axis in Fig. 3 (a), (c), (e), and (g). It is interesting to find that users usually give high scores to the items very far away from their activity centers. The reasons may be: 1) When users take a long distance travel (travelling to a new city/province/state, visiting friends, or taking a business trip), they may keep a good mood. Therefore, they give high ratings more easily. 2) This phenomenon may be caused by the fact that the items/services are local specialties and users prefer to purchase. Whatever the reasons are, user-item geographical connection can be regarded as a kind of biases.

In order to predict ratings more accurately, we integrate user-item geographical connection into our model to learn user and item feature matrices. The basic idea is that the rating of a user to item should match user-item geographical connection which we mined. In other words, user-item geographical connection can be expressed by curve fitting, and then user's ratings can be constrained according to user-item geographical connection by considering diverse user-item distances.

In this paper, we conduct curve fitting by ordinary least squares techniques based on Gaussian model as follows:

$$y = \sum_i a_i \times exp(-((x - b_i)/c_i)^2) \qquad (3)$$

where y denotes the average rating, i.e. the ordinate value in Fig. 3. x denotes the abscissa value in Fig. 3. a_i, b_i and c_i are the coefficients need to be learned by curve fitting. The impact of different curve fitting approaches on performance is discussed in Section 5.3.

Once the coefficients are learned, the proposed user-item geographical connection is expressed as follows:

$$Lui_{u,i} = \sum_i a_i \times exp\left(-\left(\left(d_{u,i} - b_i\right)/c_i\right)^2\right) \qquad (4)$$

where $d_{u,i}$ denote the geographical location distance between user u and item i. a_i, b_i, and c_i are the coefficients learned by curve fitting. Then user's ratings can be constrained according to user-item geographical connection with considering diverse user-item distances.

4.1.2 User-user Geographical Connection

As mentioned before, user-item geographical connection is mined. Therefore, the user-user geographical connection can be learned in the same way.

In this section, we analyze the relevance between users' rating differences and user-user geographical distances. For each user, the difference between his/her rating and his/her friends' to the same item is calculated. Meanwhile, we compute the geographical distance between them. In Fig. 5 (a), (c), (e), and (g), the value of y-axis could be expressed by:

$$y = \left|R_{u,i} - R_{f,i}\right| \qquad (5)$$

where $R_{u,i}$ denotes the rating user u to item i, and $R_{f,i}$ denotes the rating user's friend f to item i. The corresponding value on x-axis could be expressed by:

$$x = Distance(u, f) \qquad (6)$$

where $Distance(u, f)$ denotes the geographical distance between user u and his/her friend f.

In Fig. 5, the distances are classified into nine groups with different ranges, to make sure that the density of ratings in each region is balanced. Moreover, the corre-

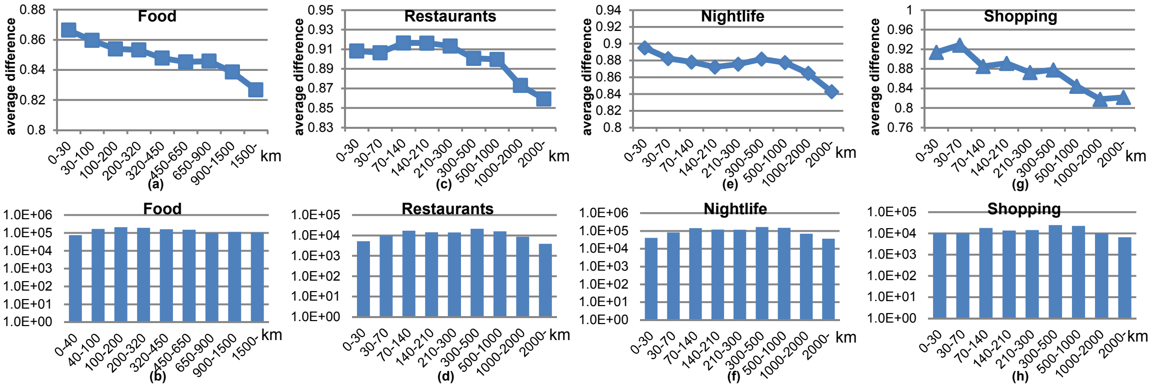

Fig. 5. The distributions of the average differences of users' ratings with different user-user geographical distances (km) based on Yelp Food, Yelp Restaurants, Yelp Nightlife, and Yelp Shopping datasets shown in (a), (c), (e), and (g). Fig. (b), (d), (f), and (h) show the corresponding count of ratings in each group. In (a), (c), (e), and (g), the value of x-axis denotes the geographical distance between user and his/her friends, and the value of y-axis denotes the corresponding average difference between users' ratings and friends' ratings to same items. Note 1.0E+0X in (b), (d), (f), and (h), denote 10^x.

sponding rating count in each group is shown to demonstrate the fairness of our grouping in Fig. 5 (b), (d), (f), and (h).

From Fig. 5 (a), (c), (e), and (g), it can be discovered that users usually give the similar scores with their geographically far away friends. The probable reason can be explained by Fig. 4. In Fig. 4, it can be seen that there are three users, A, B, and C. User A and B's activity center is New York, while user C's activity center is Philadelphia. We can presume A and B are all New York City natives, while C is a visitor. We assume that A and B are friends, B and C are friends. Users A, B, and C all have ratings to the item *Pizza* in New York. When users take a long distance travelling to a new city, which is far away from their familiar hometown, for instance user C travel to New York. Users may rely more on their local friends. User C is likely to be influenced by his friend B and accepts the recommendation from his friend B. Therefore, to the item *Pizza*, user C's rating maybe similar to his friend B's. User A and B are friends, and they are natives. To local items, their ratings may be different, because they depend more on their own experience and preference compared with user C. It can be concluded that: to an item, with the increasing distances between users and their familiar places, users may rely more on their friends. Users' and their friends' ratings will become more similar. Whatever the reasons are, user-user geographical connection can be regarded as a kind of biases.

In order to predict more accurate ratings, user-user geographical connection is integrated into our model to learn user feature matrices. The basic idea is that the ratings users to items should match user-user geographical connection we mined. As for user-item geographical connection, we first express user-user geographical connection by curve fitting, and then adjust users' ratings according to user-user geographical connection with consideration of diverse user-user distances.

We conduct curve fitting by ordinary least squares with Fig. 5 based on Gaussian model. Then the proposed user-user geographical connection is expressed as follows:

$$Luu_{u,v} = \sum_i a'_i \times exp\left(-\left(\left(d_{u,v} - b'_i\right)/c'_i\right)^2\right) \tag{7}$$

Fig. 4. An illustration that could help us to understand the relevance between users' rating differences and user-user geographical distances.

where $d_{u,v}$ denotes the geographical location distance between user u and his/her friend v. a'_i, b'_i, and c'_i are the coefficients learned by curve fitting.

4.1.3 Interpersonal Interest Similarity

User interest is a representative and prevalent factor in recommender system. It is necessary to represent user interest vector. In this paper, we replace topic distribution with category distribution as in previous works [13], [15] to represent user's interest vector. Category distribution vector is utilized to denote the topic of item as follows:

$$D_i = \left[I_{c_1}, I_{c_2}, \cdots, I_{c_n}\right] \tag{8}$$

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. n is the number of categories in the datasets.

Based on the category distribution vector of the item, a user's interest vector can be represented by summarizing the topic vectors of his/her rated items as follows:

$$D_u = \frac{1}{|H_u|} \sum_{i \in H_u} D_i \tag{9}$$

where H_u is the set of items rated by user u. $|H_u|$ is the corresponding item number.

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. The interest similarity value between u and v is represented by $W_{u,v}$.

$$W_{u,v} = \frac{D_u \cdot D_v}{|D_u| \times |D_v|} \tag{10}$$

where D_u and D_v are the topic vectors of user u and v respectively.

4.2 Proposed Rating Prediction Model

The proposed LBRP model contains the following three factors: 1) user-item geographical connection $Lui_{u,i}$ which denotes the relevance between rating and user-item geographical distance, 2) user-user geographical connection $Luu_{u,v}$ which denotes the relevance between user-user rating difference and user-user geographical distance, 3) interpersonal interest similarity $W_{u,v}$ which means whose interest is similar to yours. We combine these three factors with the rating matrix $\boldsymbol{R}$ to decrease the rating prediction errors. As in [13], [17], [18], and [33], the objective function is given by:

$$\begin{aligned}
&\Psi(\boldsymbol{R},\boldsymbol{U},\boldsymbol{P})\\
&=\tfrac{1}{2}\textstyle\sum_u\sum_{i\in H_u}\left(R_{u,i}-\hat{R}_{u,i}\right)^2+\tfrac{\lambda_1}{2}\|\boldsymbol{U}\|_F^2+\tfrac{\lambda_2}{2}\|\boldsymbol{P}\|_F^2\\
&+\tfrac{\beta}{2}\textstyle\sum_u\left(\left(U_u-\sum_{v\in F_u}W^*_{u,v}U_v\right)^T\left(U_u-\sum_{v\in F_u}W^*_{u,v}U_v\right)\right)\\
&+\tfrac{\delta}{2}\textstyle\sum_u\left(\left(U_u-\sum_{v\in F_u}Luu^*_{u,v}U_v\right)^T\left(U_u-\sum_{v\in F_u}Luu^*_{u,v}U_v\right)\right)\\
&+\tfrac{\eta}{2}\textstyle\sum_u\sum_{i\in H_u}\left(Lui^*_{u,i}-U_u^TP_i\right)^2 \qquad (11)
\end{aligned}$$

where $\hat{R}_{u,i}$ is the predicted rating value according to (2). The interpersonal interest similarity weight is enforced by the second term, which means that user latent feature $\boldsymbol{U}_u$ should be similar to the average of his/her friends' latent feature with the weight $W^*_{u,v}$. $W^*_{u,v}$ is the normalization value based on the number of his/her friends, resulting $\sum_{v\in F_u}W^*_{u,v}=1$. The factor of user-user geographical connection is enforced by the third term, which means that user latent feature $\boldsymbol{U}_u$ should be similar to the average of his/her friends' latent feature with the weight $Luu^*_{u,v}$. The factor of user-item geographical connection is enforced by the last term, which means that the predicted ratings are constrained according to the user-item geographical connection $Lui^*_{u,i}$. The set of items user has rated is H_u. Furthermore, the value $Luu^*_{u,v}$ and $Lui^*_{u,i}$ are calculated by $Luu_{u,v}$ and $Lui_{u,i}$ respectively through two steps of data normalization. The first step is rescaling the range of values in [0, 1]. Note that when $Luu_{u,v}$ becomes larger, the similarity between u and v gets smaller, i.e., the weight of U_v in (11) should be smaller. Therefore, the function $f(x)=\frac{max-x}{max-min}$ is utilized to rescale the range of $Luu_{u,v}$. The value of $Lui_{u,i}$ becomes larger, the predicted rating is higher, i.e., the value of $U_u^TP_i$ is larger. Therefore, the function $f(x)=\frac{x-min}{max-min}$ is utilized to rescale the range of $Lui_{u,i}$. The second step is normalizing these values into unity $\sum_{v\in F_u}Luu^*_{u,v}=1$ and $\sum_{i\in|H_u|}Lui^*_{u,i}=1$ respectively.

This objective function is inferred by posterior distribution over the user and item latent features. More detailed derivations of probabilistic matrix factorization are given in [33]. When we get the objective function (11), in order to get the minimum error of rating prediction, our task is to get a local minimum of the objective function. We perform gradient descent in $\boldsymbol{U}$ and $\boldsymbol{P}$ to achieve our goal, which is shown in the next section.

TABLE 4
ALGORITHM OF PROPOSED LBRP

Algorithm of location based rating prediction model LBRP
1) initialization: $\Psi(t)=\Psi(\boldsymbol{U}(t),\boldsymbol{P}(t)), t=0$.
2) set parameters: $k,l,n,\lambda_1,\lambda_2,\beta,\delta,\eta$
3) iteration:
while ($t<n$)
calculate $\frac{\partial\Psi}{\partial U_u}$ and $\frac{\partial\Psi}{\partial P_i}$
$\boldsymbol{U}(t)=\boldsymbol{U}(t)-l\frac{\partial\Psi}{\partial U_u}$ $\boldsymbol{P}(t)=\boldsymbol{P}(t)-l\frac{\partial\Psi}{\partial P_i}$
t++
4) return: $\boldsymbol{U},\boldsymbol{P}\longleftarrow\boldsymbol{U}(n),\boldsymbol{P}(n)$
5) prediction: $\hat{\boldsymbol{R}}=r+\boldsymbol{U}^T\boldsymbol{P}$
6) errors: *RMSE, MAE*

4.3 Model Training

The objective function (11) is utilized to obtain user latent profile $\boldsymbol{U}$ and item latent profile $\boldsymbol{P}$. The objective function can be minimized by the gradient decent approach as in [10], [33]. The gradients of the objective function with respect to the variables $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ are respectively shown as (12) and (13):

$$\begin{aligned}
\frac{\partial\Psi}{\partial U_u}&=\textstyle\sum_{i\in H_u}\left(\hat{R}_{u,i}-R_{u,i}\right)P_i+\lambda_1U_u\\
&+\beta\left(U_u-\textstyle\sum_{v\in F_u}W^*_{u,v}U_v\right)\\
&-\beta\textstyle\sum_{v:u\in F_v}W^*_{v,u}\left(U_v-\sum_{w\in F_v}W^*_{v,w}U_w\right)\\
&+\delta\left(U_u-\textstyle\sum_{v\in F_u}Luu^*_{u,v}U_v\right)\\
&-\delta\textstyle\sum_{v:u\in F_v}Luu^*_{v,u}\left(U_v-\sum_{w\in F_v}Luu^*_{v,w}U_w\right)\\
&+\eta\textstyle\sum_{i\in H_u}\left(U_u^TP_i-Lui^*_{u,i}\right)P_i \qquad (12)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial\Psi}{\partial P_i}&=\textstyle\sum_u I_{u,i}\left(\hat{R}_{u,i}-R_{u,i}\right)U_u+\lambda_2P_i\\
&+\eta\textstyle\sum_u I_{u,i}\left(U_u^TP_i-Lui^*_{u,i}\right)U_u \qquad (13)
\end{aligned}$$

where H_u is the set of items rated by user u, $\hat{R}_{u,i}$is the predicted rating value user u to item i. $I_{u,i}$ is the indicator that is equal to 1 if user u has rated item i, and equal to 0 otherwise. The initial values of $\boldsymbol{U}$ and $\boldsymbol{P}$ are sampled from the normal distribution with zero mean. $\boldsymbol{U}$ and $\boldsymbol{P}$ are set to the same initial values in different models, even it empirically has little effect on the latent feature matrix learning. The user and item latent feature vectors $\boldsymbol{U}_u$ and $\boldsymbol{P}_i$ are updated based on the previous values and gradients to insure the fastest decreases of the objective function at each iteration.

Note that the step size is a considerable issue. However, it is always fair to set the step as an appropriate invariant for performance comparison. The step is adjusted to insure the decrease of the objective function in training. The smaller the step is, a more accurate result we will get, and meanwhile the more iterations will be needed. In this paper, in order to reach a converged result with an acceptable time cost, the maximum iteration number is set to 200 and the step size is set to 2×10^{-4}. Under the same condition, the results empirically represent the performance of each model.

TABLE 5
PERFORMANCE COMPARISON RESULTS ON YELP DATASETS

Method	Measure	Active Life	Arts & Enter-tainment	Automo-tive	Beauty & Spas	Event Planning & Services	Food	Hotels & Travel	Restau-rants	Nightlife	Shopping	Mean
LBRP	RMSE	**1.036**	1.153	**1.370**	**1.214**	**1.124**	**0.996**	**1.232**	**1.053**	1.126	1.306	**1.161**
	MAE	**0.791**	0.891	**1.150**	**0.917**	**0.882**	**0.769**	**0.961**	**0.851**	0.897	1.023	**0.913**
NCPD	RMSE	1.244	**1.100**	1.482	1.457	1.212	1.060	1.256	1.151	**1.098**	**1.303**	1.236
	MAE	0.966	**0.851**	1.186	1.148	0.944	0.822	0.979	0.900	**0.857**	**1.016**	0.967
PRM	RMSE	1.315	1.222	1.406	1.351	1.229	**0.996**	1.342	1.067	1.183	1.409	1.252
	MAE	0.995	0.931	1.165	1.049	0.949	0.771	1.030	0.858	0.935	1.098	0.978
ContextMF	RMSE	1.512	1.377	1.410	1.409	1.369	1.098	1.473	1.075	1.198	1.445	1.337
	MAE	1.167	1.064	1.173	1.113	1.065	0.800	1.140	0.862	0.946	1.128	1.046
CircleCon	RMSE	1.759	1.471	1.714	1.843	1.505	1.178	1.576	1.109	1.279	1.585	1.502
	MAE	1.340	1.125	1.382	1.436	1.157	0.923	1.208	0.884	1.00	1.226	1.168
BaseMF	RMSE	1.967	1.553	2.367	2.183	1.622	1.291	1.671	1.199	1.372	1.752	1.698
	MAE	1.485	1.178	1.866	1.689	1.235	0.999	1.270	0.944	1.06	1.342	1.307

The proposed algorithm LBRP is shown in Table 4, where l is the step size, and t is the number of iterations. Firstly, we set the initial values of $\boldsymbol{U}$ and $\boldsymbol{P}$, which are sampled from the normal distribution with zero mean. Secondly, the parameters are set. The descriptions of parameters are detailed introduced in Section 5.2. Thirdly, start the training of our model. In every 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 t, the updated $\boldsymbol{U}$ and $\boldsymbol{P}$ are returned as the learned user latent feature matrix and item latent feature matrix in the fourth step. Fifthly, the learned $\boldsymbol{U}$ and $\boldsymbol{P}$ are utilized to predict the ratings in the test set. At last, according to the predicted ratings, the RMSE and MAE as (14), (15) are calculated to measure the performance.

5 EXPERIMENTS

In this section, we conduct a series of experiments to evaluate the performance of our LBRP model, and compare with the existing approaches on our Yelp datasets. The compared approaches include BaseMF [33], CircleCon [17], ContextMF [18], and PRM [13], and NCPD [43].

5.1 Performance Measures

The data is split into 5 groups in order to perform 5-fold cross-validation as our evaluation methodology. The evaluation metrics we use in our experiments are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). They are the most popular accuracy measures in the literature of recommender systems [10], [13], [15], [16], [17], [18], [33], [43]. RMSE and MAE are defined as:

$$RMSE = \sqrt{\sum_{(u,i)\in\Re_{test}}\left(R_{u,i} - \hat{R}_{u,i}\right)^2 / |\Re_{test}|} \qquad (14)$$

$$MAE = \sum_{(u,i)\in\Re_{test}}\left|R_{u,i} - \hat{R}_{u,i}\right| / |\Re_{test}| \qquad (15)$$

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

5.2 Evaluation

5.2.1 Parameter Settings

Here we focus on parameter settings. First, the meaning of each parameter is explained as follows.

- $\boldsymbol{k}$: The dimension of the latent vector. If k is too small, it is difficult for the model to make a distinction among users or items. If k is too large, the complexity will considerably increase. Previous works [10], [33], [62] have investigated the changes of performance with different k. But whatever the k is, it is fair for all compared algorithms when we set it as an invariant. Here we set k = 10 as in [13], [15] and [17].
- λ_1 and λ_2: The parameters of trading-off over-fitting factor in (11).
- β: The weight of the inferred interest similarity in (11).
- δ: The weight of user-user geographical connection in the third term of (11).
- η: The weight of the user-item geographical connection in the last term of (11).

These parameters play the roles of balancing factors. As in [18], to balance the components in each algorithm, these parameters are proportional as follows:

$$\lambda_1 : \lambda_2 : \beta : \delta : \eta = \frac{1}{\|\boldsymbol{U}\|_F^2} : \frac{1}{\|\boldsymbol{P}\|_F^2} : \frac{1}{\left\|\boldsymbol{U} - \sum_v \boldsymbol{W}^{*T}\boldsymbol{U}\right\|_F^2} : \frac{2}{\left\|\boldsymbol{U} - \sum_v \boldsymbol{Luu}^{*T}\boldsymbol{U}\right\|_F^2} : \frac{2}{\left\|\boldsymbol{Lui}^{*} - \boldsymbol{U}^T\boldsymbol{P}\right\|_F^2} \qquad (16)$$

where $\boldsymbol{U}$ and $\boldsymbol{P}$ are set the initial values which are sampled from the normal distribution with zero mean, the matrices $\boldsymbol{W}^*$, $\boldsymbol{Luu}^*$, and $\boldsymbol{Lui}^*$ have been calculated in Section 4.1. The ratios among the coefficients can be calculated directly. Note that, we focus more on geographical social factors, thus the weights of $\boldsymbol{Luu}^*$ and $\boldsymbol{Lui}^*$ are doubled.

In the performance comparison of different algorithms, we set the same parameter to make sure of fairness. For example, both CircleCon and ContextMF consider user influence. The parameters are set to the same value.

5.2.2 Performance Comparison

In this section, we compare the performance of LBRP algorithm with the existing models, including BaseMF [33], CircleCon [17], Context MF [18], PRM [13], [15], and NCPD [43] on our Yelp datasets. In a series of experi-

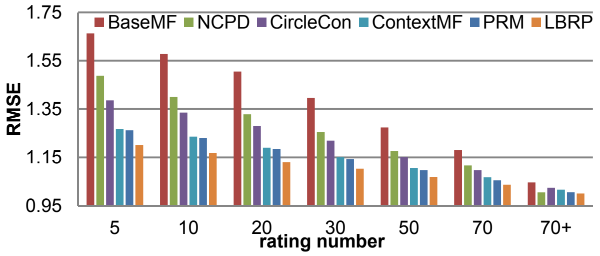

Fig. 6. The RMSE histogram of the impact of rating number.

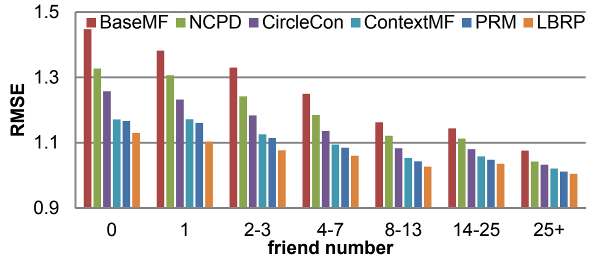

Fig. 7. The RMSE histogram of the impact of friend number.

TABLE 6
THE NUMBER OF USERS IN EACH GROUP ACCORDING TO THE NUMBER OF RATINGS

Rate_num	0-5	6-10	11-20	21-30	31-50	51-70	70+
User count	3188	1440	1609	980	1183	751	1298

TABLE 7
THE NUMBER OF USERS IN EACH GROUP ACCORDING TO THE NUMBER OF USER'S FRIENDS

Friend_num	0	1	2-3	4-7	8-13	14-25	25+
User count	2155	1681	1996	1716	1142	858	901

ments, the effectiveness and reliability of the proposed model are demonstrated according to the experimental results in Table 5. We implement performance comparison with performing 5-fold cross-validation. It can be seen that LBRP is better than other existing approaches on most of Yelp datasets.

5.3 Discussion

Five aspects are discussed in our experiments: the impact of the amount of user information, the impact of the three factors, the impact of geographical location distances, the impact of different curve fitting methods, and the impact of predicted integer ratings on performance.

5.3.1 Impact of User Information

In this part, we discuss the impact of the amount of user information (including the number of ratings and the number of friends) on the accuracy of the proposed model and compared models. Their performance based on *Yelp Restaurants* dataset is shown in Fig. 6 and Fig. 7 respectively.

In order to show the impact of the number of rated items, we divide the test dataset into seven groups according to the number of ratings as Table 6. The RMSE is shown in Fig. 6, where "0-5" in the x-axis means the number of ratings is less than 5, and "70+" means the number of ratings is more than 70. In Fig. 6, it can be seen that when the data are sparse, our approach is much better than other algorithms.

In order to show the impact of friends number, we divide the test dataset into seven groups according to the number of friends. The number of users in each group is shown in Table 7. The RMSE is shown in Fig. 7, where "0" in x-axis means the number of user's friends is zero, and "25+" means the number of user's friends is more than 25. The same conclusion is drawn: when data are sparse, our approach is much better than other algorithms.

5.3.2 Impact of the Three Factors

We compare the performance of the three independent factors in the proposed LBRP based on *Yelp Restaurants* dataset. Fig. 8 shows the corresponding RMSE of every approach. **NoN** denotes the approach that none of the three factors is taken into consideration. **Lui** denotes the approach using the user-item geographical connection. **Luu** denotes the approach using the user-user geographical connection. **IS** denotes the approach using interpersonal interest similarity. **Lui+IS** denotes the approach integrating user-item geographical connection and interest similarity. **Luu+IS** denotes the approach integrating user-user geographical connection and interest similarity. **Lui+Luu** denotes the approach integrating user-item and user-user geographical connections. **LBRP** denotes our approach that the three factors are all taken into account. It can be seen that all of the three factors have an effect on improving the accuracy of rating prediction model.

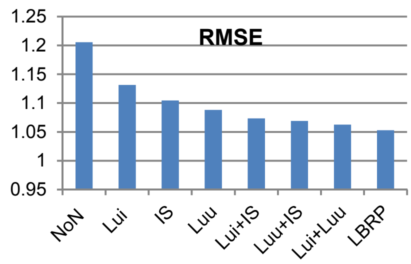

Fig. 8. Discussion on the three factors of LBRP.

5.3.3 Impact of Geographical Distances

In this part, the effect of our algorithm on different user-item distances is discussed based on *Yelp Restaurants* dataset. We classify the test set into nine groups: 0-5km, 5-20km, 20-80km, 80-150km, 150-300km, 300-600km, 600-1500km, 1500-3000km, and 3000km-. In Fig. 9, it can be seen that our LBRP have the best performance. Moreover, the performance fluctuations of LBRP maintain in a smaller range than other algorithms. It can be concluded that our algorithm has effects on different user-item distances, and it has better robustness.

5.3.4 Impact of the Different Curve Fitting Methods

In this part, the impact of different fitting curves on performance is discussed. A series of experimental results are shown in Fig. 10 according to different fitting curves based on *Yelp Restaurants* dataset. Note that, Gauss2 denotes curve fitting based on 2nd degree Gaussian model.

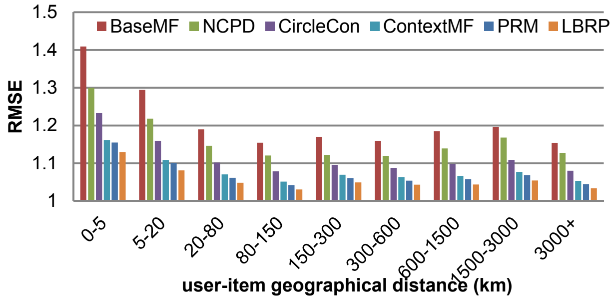

Fig. 9. The RMSE histogram in different distances based on Yelp Restaurants dataset.

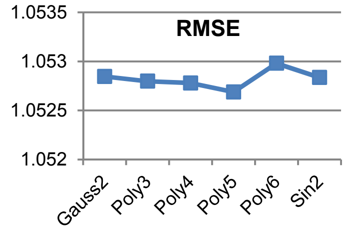

Fig. 10. Discussion on the impact of different curve fitting methods based on Yelp Restaurants dataset.

Poly3, Poly4, Poly5, and Poly6 denote curve fitting based on 3rd, 4th, 5th, and 6th linear polynomial model respectively. Sin2 denotes curve fitting based on 2nd degree sinusoidal model. It can be seen that there is little impact with different fitting curves on the performance. It demonstrates the good robustness of our model.

5.3.5 Impact of the Predicted Integer Ratings

At last, the impact of predicted integer ratings on performance is discussed. The ratings user rated are all discrete values ranging from 1 to 5. But the predicted ratings of matrix factorization model are all decimal. It is necessary to discuss the impact of discrete predicted ratings. Therefore, decimal ratings we predicted are rounded to discrete integers. The result is shown in Table 8. We conduct experiments with 5-fold cross validation based on *Yelp Restaurants*, *Nightlife*, and *Shopping* datasets. It can be seen that when the predicted ratings are integer, RMSE of model increases, but MAE declines. We deeply explore the evaluation methodology RMSE and MAE. MAE gives equal weights to all errors, while RMSE gives extra weights to large errors. Shani *et al*. [44] also claim that: compared to MAE, RMSE disproportionately penalizes large errors. Whatever the value we predict is, it offers us the degree of preference to help us to recommend the more suitable items to users.

TABLE 8
DISCUSSION ON IMPACT OF THE PREDICTED INTEGER RATINGS

Model		LBRP	
Results		Integer	Decimal
RMSE	Restaurants	1.10886	**1.05294**
	Nightlife	1.17512	**1.12568**
	Shopping	1.33418	**1.30558**
MAE	Restaurants	**0.7931**	0.85068
	Nightlife	**0.86174**	0.89738
	Shopping	**0.98792**	1.02294

6 CONCLUSION AND FUTURE WORK

In this paper, we mine: 1) the relevance between users' ratings and user-item geographical location distances, 2) the relevance between users' rating differences and user-user geographical location distances. It is discovered that humans' rating behaviors are affected by geographical location significantly. A personalized Location Based Rating Prediction (LBRP) model is proposed by combining three factors: user-item geographical connection, user-user geographical connection, and interpersonal interest similarity. In particular, the geographical location denotes user's real-time mobility, especially when users travel to new cities, and these factors are fused together to improve the accuracy and applicability of recommender systems. In our future work, check-in behaviors of users will be deeply explored by considering the factor of their multi-activity centers and the attribute of POIs.

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