Knowledge-Based Systems 196 (2020) 105849

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Personalized location recommendation by fusing sentimental and spatial context

Guoshuai Zhao [a], Peiliang Lou [b], Xueming Qian [c,d,*], Xingsong Hou [b]

[a] School of Software Engineering, Xi'an Jiaotong University, Xi'an 710049, China
[b] School of Electronic and Information Engineering, Xi'an Jiaotong University, Xi'an 710049, China
[c] Key Laboratory for Intelligent Networks and Network Security, Ministry of Education, Xi'an 710049, China
[d] SMILES Laboratory, School of Information and Communication Engineering, Xi'an Jiaotong University, Xi'an 710049, China

ARTICLE INFO

Article history:
Received 25 September 2019
Received in revised form 23 March 2020
Accepted 30 March 2020
Available online 3 April 2020

Keywords:
Data mining
Location based social network
POI recommendation
Recommender system
Sentiment analysis

ABSTRACT

Internet users would like to obtain interesting location information for a travel. With the rapid development of social media, many kinds of location recommender systems are proposed in recent years. Existing methods mostly focus on mining user check-in information that could be leveraged to understand their trajectories. However, the characteristics and attributes of geographical locations also play an important role in recommender systems. In this paper, sentimental attributes of locations are explored and we propose a Point of Interest (POI) mining method and a personalized recommendation model by fusing sentimental spatial context. First, a Sentimental–Spatial POI Mining (SPM) method is utilized to mine the POIs by fusing the sentimental and geographical attributes of locations. Second, we recommend the POIs to users by a Sentimental–Spatial POI Recommendation (SPR) model incorporating the factors of sentiment similarity and geographical distance. Last, the advantages and superior performance of our methods are demonstrated by extensive experiments on a real-world dataset.

1. Introduction

In recent years, social networks have a significant development. Through location based social networks (LBSNs) on mobile devices or online, users can share their geographical position information and check-ins. Social network services also encourage them to share their experiences, reviews, ratings, photos, and moods. Such information brings new opportunities for recommender systems. Existing location recommender systems mostly focus on exploring user information [1], which includes users' profiles [2], locations [3], and trajectories [4–6]. Features of locations also attract researchers, such as the frequency of visiting by users and the category attribute of locations [1]. However, in the process of POI mining, the sentimental features of locations are seldom considered. The recommendations may not suit users' sentimental preference. For example, a user living in downtown wants to enjoy a natural and peaceful place to have a rest, but recommender systems mainly focus on the geographical attributes of nearby locations, and it may recommend some POIs full of people and noise. It cannot meet the user's needs. It indicates that POIs have not only geographical attributes but also sentimental attributes, which is an major factor that should be exploited. The POIs with many historical spots are solemn, and the POIs which have business districts and clubs are lively, whereas the POIs with a lot of trees and pools are peaceful and relaxing. The sentimental attributes of POIs can be discovered by analyzing the data on social networks.

Users share their experiences and locations on the websites such as Twitter[1] and Sina Weibo[2] by checking-in. As shown in Fig. 1, *Text* is the user's comment about his/her status or feelings. *Location* shows the GPS position. The information of *Text* is strongly connected with the *Location* in some way. In this study, through sentiment analysis of *Text*, the sentimental attributes of the *Location* could be discovered. After that, POIs with obvious sentimental attributes are mined and will be recommended if they are nearby and matching users' preferences.

First, the Sentimental–Spatial POI Mining (SPM) method is proposed to mine the POIs with obvious sentimental attributes. According to the result of sentiment analysis and GPS positions, the POIs which have a thick density of social media data and

* Corresponding author at: SMILES Laboratory, School of Information and Communication Engineering, Xi'an Jiaotong University, Xi'an 710049, China.
E-mail addresses: guoshuai.zhao@xjtu.edu.cn (G. Zhao), peilianglou@sina.com (P. Lou), qianxm@mail.xjtu.edu.cn (X. Qian), houxs@mail.xjtu.edu.cn (X. Hou).

1 http://www.twitter.com/.
2 http://www.sina.com/.

https://doi.org/10.1016/j.knosys.2020.105849
0950-7051/

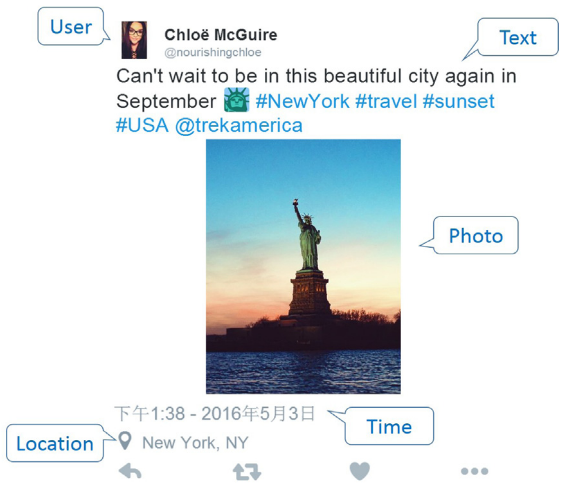

Fig. 1. A user's comment on Twitter.

similar sentimental attributes are discovered. Second, they are recommended to different users by our Sentimental–Spatial POI Recommendation (SPR) model. It incorporates the factors of sentiment similarity and geographical distance. It is based on the widely adopted latent factor model realized by Probabilistic Matrix Factorization (PMF) [7]. A POI with a higher sentiment score should be ranked above a POI with a lower sentiment score. However, users have different preferences for topics [8]. For example, for a restaurant, some users think the price is too high, but others may prefer the unique taste and do not care its price. Thus, the POI with a higher sentiment score does not mean it must be better than a POI with a lower sentiment score for a particular user. Therefore, we prefer to leverage sentiment similarity rather than use absolute sentiment score to optimize the latent features of POIs in our model.

Note that, affect is non-conscious and it is a fundamental and broader concept. Feelings and emotions are the conscious expressions of affect, while the sentiment is a high-level conscious attitude, also is an emotional disposition [9]. In this paper, the topic-based sentiment [10] is a more accurate and straight term than affective attributes to represent user preference and POI attributes.

Our contributions are shown as follows:

- We propose a POI Mining method and a personalized POI Recommendation method by fusing sentimental and spatial context. We explore the rich textual descriptions and users' geographical information and propose new features and factors in our methods. Experiment results demonstrate the superior performance of our methods.
- In our POI Mining method, the sentiment context is proposed as a new attribute of the POI. Additionally, we remove the redundant and noisy microblog posts by a temporal filter to improve the mining performance. Through the POI Mining method, we could discover the POIs with salient sentimental attributes.
- In our POI Recommendation method, we propose two new factors: the factor of sentiment similarity between POIs and the factor of geographical distance between user's multi-activity centers and POIs. We incorporate both of them into Probabilistic Matrix Factorization model for POI recommendation.

The main differences between this paper and our previous work [11] are: (1) we improve SPM method by incorporating spatial and temporal information to remove the redundancy and noise of the data; (2) we improve SPR model by exploring the user's multi-activity centers; (3) we improve the readability of our model by summarizing a whole procedure of our algorithm, and present more details of model training; (4) more datasets, experiments and discussions are implemented.

The rest of this paper is organized as follows. We review the related work on recommender systems and the sentiment analysis in Section 2. The details of our SPM method and SPR model are presented in Section 3 and Section 4. Section 5 gives experiment results and discussions, and Section 6 concludes this paper.

2. Related work

In this section, we first introduce some related work on recommender systems in LBSNs and POI recommendation, and then some methods of sentiment analysis are reviewed. Additionally, we also discuss the main differences between our work with related work.

2.1. The methodologies of recommender systems in LBSNs

The major methodologies used by recommender systems in location-based social networks can be divided into 3 categories, which are content based, link analysis, and collaborative filtering.

Content-based recommendation systems make recommendations by matching users' preferences. Users' preferences are discovered from users' profiles such as gender and age, and features of locations, such as tags and categories. Some works make recommendations by discovering users' locations and activity histories. Xiao et al. [12] modeled a user's GPS trajectories with a semantic location history and then measure the similarity between different users' SLHs to learn users' preferences. Ye et al. [13] extracted features of POIs from (i) explicit patterns of individual places and (ii) implicit relatedness among similar places. In [14], Zhang and Chow exploited the user preference and social information, user preference, social influence, and personalized geographical influence are integrated into a unified geo-social recommendation framework.

Link analysis algorithms can find particular nodes from a complicated structure which is applied for identifying relevant web pages for web searching. By analyzing the LBSN, link analysis algorithms extract locations meeting different needs. Zheng et al. [15] explored interests of locations based on HITS algorithm, and made recommendations by considering the interests of locations and users' travel experiences. Raymond et al. [16] explored users' location histories and spatio-temporal correlations with a popular method in data mining called link propagation to make recommendations. They demonstrated that with the spatio-temporal information is better than those without.

Collaborative filtering is widely utilized in products service [10,17,18], travel recommendation [19,20], music recommendation [21] and service recommendation [22], and emoji recommendation [23]. Lei et al. [10] a sentiment-based rating prediction method (RPS) to improve prediction accuracy in recommender systems. They considered product reputation which can be inferred by the sentimental distributions of a user set that reflect customers' comprehensive evaluation. Sang et al. [19] presented a probabilistic approach, which is highly motivated from a large-scale commercial mobile check-in data analysis, to rank a list of sequential POI categories and POIs. It estimates the transition probability from one POI to another, conditioned on current context and check-in history in a Markov chain. Wei et al. [20] presented a Route Inference framework based on Collective Knowledge to construct the popular routes from uncertain trajectories. They explored the spatial and temporal characteristics of uncertain trajectories and construct a routable graph by collaborative learning among the uncertain trajectories. Zhong et al. [22] developed a Service Co-occurrence LDA to extract latent service co-occurrence topics, including representative services and words, temporal strength, and services' impact on topics. Recommendation systems based on collaborative filtering recommend a location to a user if this location has been visited by a similar user. Zheng and Xie [5] performed two types of travel recommendations by mining multiple users' GPS traces. They incorporated the location correlation into a collaborative filtering (CF)-based model that infers a user's interests in an unvisited location based on her locations histories and that of others.

2.2. POI recommender systems

POI Recommender Systems [2–4,24–31] are utilized to provide recommendations of interesting places based on several factors. Some works recommend POIs according to the geographical influence via collaborative filtering. Geographical influence is one of the major considerations of POI recommendation which indicates that users tend to visit nearby POIs around their homes or offices. Wang et al. [3] made recommendations by exploiting the geographical distances between the users and candidate locations. They assume that the closer locations away from the users should have higher probabilities to be recommended. Moreover, three factors are considered in their model including the geo-influence of POI, the geo-susceptibility of POI, and their physical distance. Liu et al. [32] analyzed geographical characteristics from location perspective using historical check-in data and got instance-level and region-level characteristics to learn latent features of users and locations. Si et al. [24] proposed an adaptive POI recommendation method by combining user activity and spatial features, which can operate adaptively according to user activity. Li et al. [31] studied on how to recommend several good viewpoints for taking photographs of a POI. They considered both aesthetics and diversity to select the high-quality viewpoints.

Additionally, user personalized preference is also an important factor should be considered in POI recommendations. Check-in is very popular in location based social networks, and the check-in data reflect user preference on the locations. Yin et al. [33] built the LCA-LDA Model to mine the users' interest and the local preferences. Users' interest contain the information of what type of venues users may visit and local preferences provide some typical venues for users. Jiang et al. [8] proposed a Geographical-Temporal Influences Aware Graph in order to recommend POIs to a user when he or she wants to visit at a given time. Zhao et al. [34] focused on the time influence on the Successive POI Recommendation performance. Their work hold the view that users would prefer different POIs at different time. Yang et al. [35] extracted check-ins and text-based tips to analyze users' location preference by considering the factor of users' sentiment towards the venues. Yao et al. [4] explored the temporal popularity of POIs and personalize users via learning the latent regularity. Then they modeled the human mobility and measured the degree of temporal matching between POIs and users for POI recommendation.

Several works study geographical influence for POIs by using Matrix Factorization techniques. For example, Cheng et al. [36] considered geographical and social influence and utilized them to constrain user and item latent features in Matrix Factorization. After that, the learned user and item latent features are leveraged to recommend POIs in LBSNs. Our previous works [37,38] explore interpersonal interest and social users' rating behaviors in Matrix Factorization to optimize user and item latent features. Besides, Zhang et al. [39] combined the comments to measure the users' preference or mine topic aspects of POIs. They developed a supervised aspect-dependent approach to detect the polarity of a tip, and fused the calculated polarities with social links and geographical information into a unified POI recommendation framework.

2.3. Sentiment analysis of text

Sentiment analysis of text is a hot topic in the area of Natural Language Processing (NLP). This technique allows recommender systems to understand if customers are talking positively or negatively about their products or services so that the systems could get some key insights and improve the recommendation results.

Generally, the sentences are divided into a set of words, and each work is correlated with a numerical sentiment value by a dictionary to calculate the sentiment polarity, which is called lexicon-based method. It computes the sum of the numerical value of each word as the overall sentiment polarity of texts which is one of the popular methods on sentiment analysis. Benamara et al. [40] leveraged adjectives, adverb and other elements to detect the sentiment polarity of user textual posts. Our previous work [10] proposes a sentiment measurement approach to compute service reputation and fused user sentiment and service reputation into Matrix Factorization for product recommendation. Wang et al. [41] proposed a knowledge-based framework relying on Latent Semantic Analysis and PageRank to address the problem of word sense disambiguation. In [42], they couple sub-symbolic and symbolic AI to automatically discover conceptual primitives from text and link them to commonsense concepts and named entities in a new three-level knowledge representation for sentiment analysis. To deal with the problem that some words can have different senses (positive or negative) depending on the domain, domain-specific lexicons have been introduced. In these works, sentiment classifiers are trained on a large set of labeled examples, which usually requires manual annotation.

The sentiment analysis for microblog posts has raised the attention of researchers in recent years. The works [43–45] explore the use of emoticons which are pictorial symbols expressing diversified emotions. Zhao et al. [43] conducted sentiment analysis for user posts on Sina Weibo by the proposed MoodLens system. It leverages an emoticon-based method for sentiment classification. In addition, the context is considered in their method including the user profile, social circles and the geographical locations, Hu et al. [44] focused on the social relationship between users. Toshitaka et al. [46] proposed a word-embeddings based sentiment analysis by considering the word importance. You et al. [45] analyzed the online sentiment changes of online users through studying the textual and visual content of microblog posts. Experiments on real Twitter data sets demonstrate the sentiments expressed in textual content and visual content are correlated.

2.4. Discussion on the differences

The core differences between our work and previous research are presented as follows. (1) Our work leverages users' sentiment to represent sentimental attributes of locations for POI mining, while previous research does not consider sentimental attributes of locations in POI mining. (2) Previous research utilizes user sentiment information to measure the preference distance between users and POIs, but our work proposes a sentiment similarity between POIs by regarding the sentiment information as an attribute of the POI. (3) Previous research utilizes the mean/popular locations of user check-ins to be as the user's location, but our work mines multi-activity centers for each user to get the recommendations with more accuracy.

The differences with our previous work [11] in details are reported as follows. (1) In Section 2, we conduct comprehensive survey on related works. Several new references are cited and introduced, and the major methodologies used by recommender systems in location-based social networks are reported. (2) In Section 3, we improve the SPM method with considering to remove the redundant and noisy microblogs by incorporating spatial and temporal information. Experiments in Section 5.4 demonstrate the effectiveness of this improvement. (3) In Section 4, we improve the study on the factor of geographical distance by considering the truth that users' usually have more than one activity centers, such as their homes and work places. For a user, her check-ins are clustered to find out individual multi-activity centers. Then the shortest geographical distance between user's multi-activity centers and POIs are utilized to optimize our SPR model. Experiments in Section 5.4 demonstrate the effectiveness of this improvement. (4) In Section 4, we introduce the details of SPR model training, including the gradients of the objective function with respect to the variables and the learning process during each iteration. The whole procedure of SPR is summarized carefully in Algorithm 1, and the time complexity and space complexity analysis are given. (5) In Section 5, more experiments and comparisons are implemented. We add four existing methods for performance comparison including our previous work [11] and a state-of-the-art method DeepMF [47]. our dataset is extended from 3 cites, 0.39 million users, and 1.2 million microblogs to 6 cites, 1.4 million users, and 5.13 million microblogs. The impact of bandwidth on the performance of POI mining and the impact of the factors of noise reduction and multi-activity centers on the performance of POI recommendation are discussed. We also show the presentation of the mined POIs.

Taken together, approximately six pages of new content can be found in this work, which covers more supplementary of related works, the improvements of SPM and SPR methods, the detailed procedure of our model, the larger dataset, more experiments and discussions, as opposed to the preliminary nature of the work [11].

3. Our sentimental–spatial POI mining method

Fig. 2 shows the overview of our SPM method which incorporates POIs' geographical attributes and sentimental attributes. In Fig. 2, the red, green, and blue dot represents the microblog posts with high, fair, and low sentiments respectively. There are two steps in SPM method. First, the sentimental features of locations are discovered by calculating the sentiment of posts in these locations. Second, based on sentiment values and GPS positions of these microblog posts, the locations which have a high density of users and similar sentiments of posts are mined and regarded as POIs.

3.1. Sentiment analysis of microblog posts

The first step of SPM is performing the sentiment analysis of posts. The microblogs posted in a particular area carry not only the information about users' preferences and behaviors but also their sentiments like happiness, and sadness. This information can be leveraged to represent the sentimental attributes of this location. For example, if happiness is more frequent than other sentiments in the microblogs posted in a location, it implies that this place has a sentimental attribute of making people happy. Through analyzing the sentiment of the posts, the specific sentimental attributes of this location can be discovered.

We analyze the sentiment of posts based on the lexicon-based method. HowNet Sentiment Dictionary was used to compute sentiment as in [10], which is a popular sentiment dictionary in

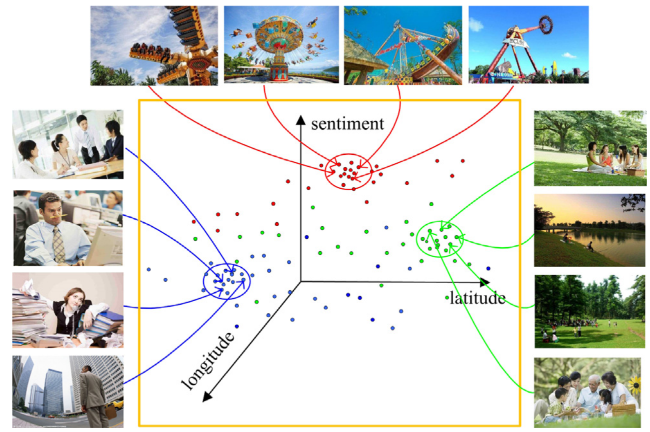

Fig. 2. The overview of SPM method. The red, green, and blue dot represent the microblog posts with high, fair, and low sentiments respectively.

the area of Chinese and English sentiment classification. As the method in [10], we extract fifty topics from the microblog posts using LDA model. Every topic contains twenty feature words. Thus, given a text, according to the distribution of its feature words on topics, we can get the topic representation. Then we analyze the sentiment on topics by using a lexicon-based method. We utilize $\mathbf{v}_i$ to represent the sentiment value for the post i as follows.

$$\mathbf{v}_i = [v_{i,1},\ v_{i,2}, \dots,\ v_{i,n}] \tag{1}$$

Above formula is the representation of topic-based sentiment value for the post i, where n is the number of topics and $v_{i,n}$ denotes the sentiment on the nth topic. Note that, $v_{i,n}$ is the product of the probability of this post on the nth topic and the sentiment value of the post. The details of this procedure can be found in [10]. We expect as the research in sentiment analysis advances, the performance of our model can further improve as well.

3.2. POIs clustering with combining sentimental features

The second step is to discover the POIs which have similar sentimental features. In traditional Meanshift algorithm for POI mining [8,48], if microblog posts are dense in a location such as a shopping center, a school or a scenic spot, it implies that this place has high population density and can be regarded as a POI. Our SPM method improves it by exploring sentimental attributes of locations. That means, besides the GPS coordinates, the sentiment of the microblog post is also exploited in the feature space. For a microblog, its 3-dimension feature space can be represented by:

$$\mathbf{x}_i = [lon_i,\ lat_i,\ \mathbf{v}_i] \tag{2}$$

where lon_i and lat_i denote the GPS coordinates of the ith microblog. $\mathbf{v}_i$ indicates its topic-based sentiment values as shown in Eq. (1).

However, there is some redundant and noisy information as shown in Fig. 3. In location A, a user posted many microblogs in a short time, which would affect the result of POI clustering. Because our work prefers to mine the POIs that many users checked rather than one user checked many times, e.g. location B in Fig. 3. To filter out the redundancy and noise, for a user who posted more than one microblog in one hour, we incorporate these posts into one, and its features set to the average of the features of these posts. The purpose is to make sure that the POI

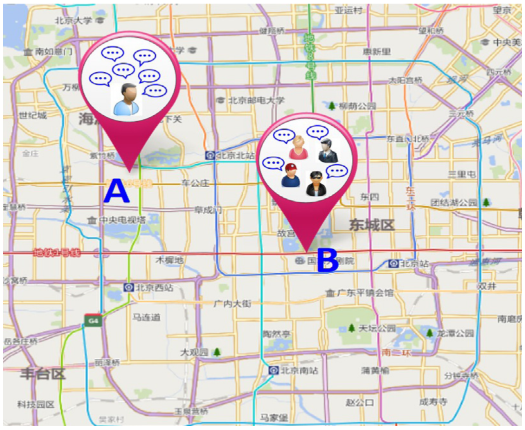

Fig. 3. Our work aims to mine the POIs that many users checked such as location B rather than one user checked many times such as location A.

we find has a high density of users rather than the microblog posts.

Given n microblog posts $\mathbf{x}_i$, $i = 1, \ldots, n$ in a 3-dimension space, the multivariate kernel density estimator obtained with kernel $K(\mathbf{x})$ and bandwidth h is:

$$f(\mathbf{x}) = \frac{1}{nh^d} \sum_{i=1}^{n} K(\frac{\mathbf{x} - \mathbf{x}_i}{h}) \tag{3}$$

For the radial basis function, it suffices to define the profile of the kernel $k(x)$ satisfying:

$$K(\mathbf{x}) = c_{k,d} k(\|\mathbf{x}\|^2) \tag{4}$$

where $c_{k,d}$ is a normalization constant which assures $K(x)$ integrates to 1. Kernel is a kind of weighting functions. The samples near to the cluster centers would be given high weights, and the samples far away would be given low weights. The mean shift vector always points toward the direction of the maximum increase in the kernel density by analyzing the gradient of the density estimator. It is expressed by:

$$\mathbf{m}_h(\mathbf{x}) = \frac{\sum_n^{i=1} \mathbf{x}_i g(\|\frac{\mathbf{x} - \mathbf{x}_i}{h}\|^2)}{\sum_n^{i=1} g(\|\frac{\mathbf{x} - \mathbf{x}_i}{h}\|^2)} - \mathbf{x} \tag{5}$$

where $g(x) = -k'(x)$.

4. Our sentimental–spatial POI recommendation model

In this section, the SPR model will be introduced in details. This recommendation model utilizes low-rank probabilistic matrix factorization [7] to figure out how much a user prefers a POI. Let $U = \{u_1, u_2, \ldots, u_M\}$ be the set of users and $P = \{i_1, i_2, \ldots, i_N\}$ be the set of POIs, where M and N denote the number of users and POIs respectively. $\mathbf{R} = [R_{u,i}]_{M \times N}$ is a user-POI matrix with $R_{u,i}$ representing the number of check-ins made by user u at POI i. In this paper, a user's preference on a POI is represented by the number of check-ins. Let $\mathbf{U} \in \mathbb{R}^{k \times M}$ and $\mathbf{P} \in \mathbb{R}^{k \times N}$ as user and POI latent features matrices, in which column vectors $\mathbf{U}_u$ and $\mathbf{P}_i$ represent k-dimensional user and POI latent feature vectors. Certainly k is much less than M and N. Moreover, $\mathbf{U}_u$ and $\mathbf{P}_i$ can be seen as a brief characterization of user u and POI i. The task of matrix factorization is to learn these latent features and exploit them for POI recommendation.

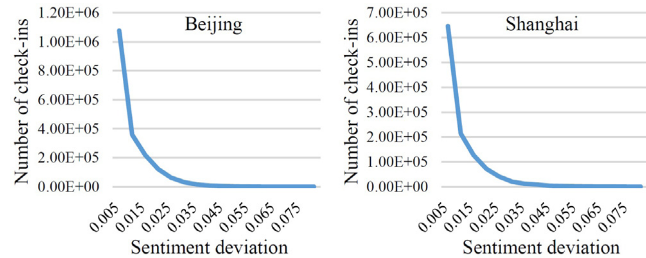

Fig. 4. The relevance between the number of check-ins and the sentiment deviation of POIs that have been visited by users on our Beijing and Shanghai dataset.

4.1. Matrix factorization

Our proposed model is based on the latent factor model realized by matrix factorization [7,37,38,49–51]. Using user and POI latent feature vectors $\mathbf{U}_u$ and $\mathbf{P}_i$, the basic location recommendation model approximates user's preference via solving the following optimization problem:

$$\min_{\mathbf{U},\mathbf{P},\mathbf{b}} \frac{1}{2} \sum_u \sum_{i \in H_u} (R_{u,i} - \hat{R}_{u,i})^2 + \frac{\lambda_1}{2}\|\mathbf{U}\|_F^2 + \frac{\lambda_2}{2}\|\mathbf{P}\|_F^2 + \lambda_3(b_u^2 + b_i^2) \tag{6}$$

where $\hat{R}_{u,i}$ denotes the number of check-ins predicted by:

$$\hat{R}_{u,i} = r + \mathbf{U}_u^T \mathbf{P}_i + b_u + b_i \tag{7}$$

where r is an offset value, which is empirically set as users' average check-in value. $\|\cdot\|_F$ is the Frobenius norm. It is used to avoid over-fitting [37,49]. b_u and b_i are the user and POI biases. This objective function can be minimized by using gradient descent method [37,38,49]. Once the low-rank matrices $\mathbf{U}$ and $\mathbf{P}$, and the bias $\mathbf{b}$ are learned, the number of check-ins can be predicted according to Eq. (7) for any user-POI pairs.

4.2. The factor of sentiment similarity between POIs

The sentimental attribute plays a significant role in affecting users' decision on where they prefer to visit. Fig. 4 illustrates the relevance between the number of check-ins and the sentiment deviation of POIs that have been visited by users. The X-axis indicates the sentiment deviation of POIs, and the Y-axis implies the number of users' check-ins. It suggests that users often visit the POIs which have similar sentiments. With the concept of item based collaborative filtering, the view of sentiment similarity can be inferred because the POIs which bring similar sentiments to users are relevant. Therefore, sentiment similarity can be exploited to optimize POI latent feature vector $\mathbf{P}_i$.

The sentiment value of the mined POI is represented by the mean sentimental value of involved micro-blogs, which are ranging from 0 to 1. Exponential function is utilized to compute the un-linear sentiment similarity as follows:

$$E_{i,j} = \exp(-|Avg.(i) - Avg.(j)|) \tag{8}$$

where

$$Avg.(i) = \frac{\sum_{n=1}^{N_i} \mathbf{x}_{i,n}}{N_i} \tag{9}$$

where $Avg.(i)$ denotes the mean of the topic-based sentiments for all the posts in POI i. $\mathbf{x}_{i,n}$ is the topic-based sentiment for the nth post in POI i. N_i is the number of posts in the POI i. $E_{i,j}$ is the sentiment similarity between POIs i and j.

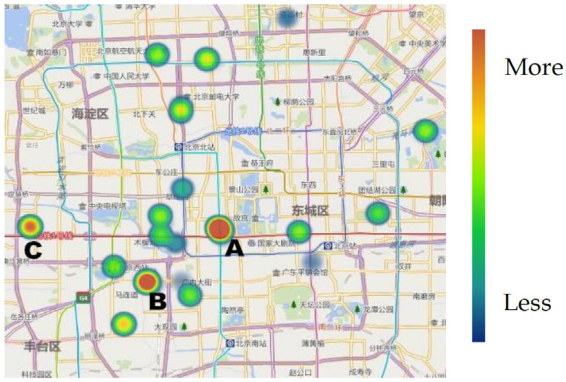

Fig. 5. A real user's multi-activity centers mined in our Sina Weibo dataset. The color temperature indicates the number of check-ins. The warm color implies more check-ins. The cool color means fewer check-ins. It shows that the Top 3 activity centers often visited by this user are A, B, and C.

Considering sentiment similarity $E_{i,j}$ between POIs, the optimization must perform the following term:

$$\min_{\mathbf{P}} \sum_i [(\mathbf{P}_i - \sum_j E^*_{i,j}\mathbf{P}_j)^T(\mathbf{P}_i - \sum_j E^*_{i,j}\mathbf{P}_j)] \tag{10}$$

where $\mathbf{P}_i$ is the latent vector of POI i. $E^*_{i,j}$ is the normalization value for the topic-based sentiment similarity $E_{i,j}$, where $\sum_j E^*_{i,j} = 1$. This term is utilized to optimize the latent vectors of POIs via exploiting sentiment similarity.

4.3. The factor of geographical distance between user's multi-activity centers and POIs

The geographical attribute is another main concern of this study. It also plays a significant role in affecting users' decision on where they would like to go. The study states that the activity radiuses of 45% users are no more than 10 miles [51]. It indicates users would like to visit the closer POIs to their activity centers [6,11,36]. For a user, we collected his/her all check-ins. These check-ins reveal his/her activities in geographic space. Intuitively, the locations with high dense check-ins are this user's activity centers. Then we utilized the points with longitude and latitude as the input of Mean shift method. In addition, mean shift is a nonparametric feature-space analysis technique for locating the maxima of a density function. The numbers of output clusters may be varied for different users. However, usually, users have multi-activity centers in their daily life, such as their homes and workplaces. It is sufficient for us to find two or three activity centers for each user. Thus, we rank the user's Top 5 activity centers and calculate the average check-in number of them. We set the activity centers that have more check-ins than their average as the user's final multi-activity centers. If the count of original centers is less than three, we directly assign them as the finally multi-activity centers. Fig. 5 shows an example of a real user's multi-activity centers mined in our Sina Weibo dataset. The color temperature indicates the number of check-ins. The warm color implies more check-ins. The cool color means fewer check-ins. It shows that the Top 3 activity centers often visited by this user are A, B, and C.

Geographical distances between user's multi-activity centers and POIs can be utilized to optimize user and POI latent feature vectors $\mathbf{U}_u$ and $\mathbf{P}_i$. The basic idea is that the number of check-ins becomes larger with the decreasing distance. Exponential function is leveraged to compute the un-linear factor of geographical distance as:

$$L_{u,i} = \exp[-Distance(u,i)] \tag{11}$$

where $Distance(u,i)$ denotes the geographical distance between user u and POI i via their latitude/longitude coordinates. Note that, it is the shortest distance between user u's multi-activity centers and POI i. The geographical distance between two latitude/longitude coordinates is calculated by using the Haversine geodesic distance equation [52].

Considering the factor of geographical distance between users and POIs, the optimization must contain the following term:

$$\min_{\mathbf{U},\mathbf{P}} \sum_u \sum_{i \in H_u} (L^*_{u,i} - \mathbf{U}_u^T\mathbf{P}_i)^2 \tag{12}$$

where $L^*_{u,i}$ is the normalization value based on the number of POIs, resulting $\sum_i L^*_{u,i} = 1$. This term is utilized to optimize the latent feature vectors via exploiting the factor of geographical distance between user's multi-activity centers and POIs.

4.4. Model training

Incorporating the factors of sentiment similarity between POIs and geographical distance into matrix factorization, our objective function is given by:

$$\begin{aligned}\Psi =& \frac{1}{2}\sum_u \sum_{i \in H_u}(R_{u,i} - \hat{R}_{u,i})^2 + \frac{\lambda_1}{2}\|\mathbf{U}\|_F^2 + \frac{\lambda_2}{2}\|\mathbf{P}\|_F^2 \\ &+ \frac{\lambda_3}{2}(b_u^2 + b_i^2) \\ &+ \frac{\beta}{2}\sum_i (\mathbf{P}_i - \sum_j E^*_{i,j}\mathbf{P}_j)^T(\mathbf{P}_i - \sum_j E^*_{i,j}\mathbf{P}_j) \\ &+ \frac{\gamma}{2}\sum_u \sum_{i \in H_u}(L^*_{u,i} - \mathbf{U}_u^T\mathbf{P}_i)^2\end{aligned} \tag{13}$$

where H_u is the set of items rated by user u. Once we get the objective function, it can be minimized by the gradient decent approach as in [7,37,38,51]. The gradients of the objective function with respect to the variables $\mathbf{U}_u$, $\mathbf{P}_i$, b_u, b_i are:

$$\begin{aligned}\frac{\partial \Psi}{\partial \mathbf{U}_u} =& \sum_{i \in H_u}(\hat{R}_{u,i} - R_{u,i})\mathbf{P}_i + \lambda_1\mathbf{U}_u \\ &+ \gamma \sum_{i \in H_u}(\mathbf{U}_u^T\mathbf{P}_i - L^*_{u,i})\mathbf{P}_i\end{aligned} \tag{14}$$

$$\begin{aligned}\frac{\partial \Psi}{\partial \mathbf{P}_i} =& \sum_u I_{u,i}(\hat{R}_{u,i} - R_{u,i})\mathbf{U}_u + \lambda_2\mathbf{P}_i \\ &+ \beta(\mathbf{P}_i - \sum_j E^*_{i,j}\mathbf{P}_j) - \beta\sum_j E^*_{j,i}(\mathbf{P}_j - \sum_l E^*_{j,l}\mathbf{P}_l) \\ &+ \gamma\sum_u I_{u,i}(\mathbf{U}_u^T\mathbf{P}_i - L^*_{u,i})\mathbf{U}_u\end{aligned} \tag{15}$$

$$\frac{\partial \Psi}{\partial b_u} = \sum_{i \in H_u}(\hat{R}_{u,i} - R_{u,i}) + \lambda_3 b_u \tag{16}$$

$$\frac{\partial \Psi}{\partial b_i} = \sum_u I_{u,i}(\hat{R}_{u,i} - R_{u,i}) + \lambda_3 b_i \tag{17}$$

where $I_{u,i}$ is the indicator that is equal to 1 if user u has rated item i, and equal to 0 otherwise. The initial values of $\mathbf{U}$ and $\mathbf{P}$ are sampled from the normal distribution with zero mean.

Once we get the gradients, we update coefficient matrices during each iteration as follows:

$$\mathbf{U}_u^{(t)} = \mathbf{U}_u^{(t-1)} - \alpha^{(t)}\frac{\partial \Psi^{(t-1)}}{\partial \mathbf{U}_u} \tag{18}$$

$$\mathbf{P}_i^{(t)} = \mathbf{P}_i^{(t-1)} - \alpha^{(t)} \frac{\partial \Psi^{(t-1)}}{\partial \mathbf{P}_i} \tag{19}$$

$$b_u^{(t)} = b_u^{(t-1)} - \alpha^{(t)} \frac{\partial \Psi^{(t-1)}}{\partial b_u} \tag{20}$$

$$b_i^{(t)} = b_i^{(t-1)} - \alpha^{(t)} \frac{\partial \Psi^{(t-1)}}{\partial b_i} \tag{21}$$

where α is the learning rate, which is set to 0.0005 initially. It decreases by a factor of 0.9 after each iteration, and the iteration count is 50.

The whole procedure of our algorithm is summarized in Algorithm 1. Moreover, the time complexity is $O(T \times (4M \times N + N^3) \times k)$, where M is the number of users, N is the number of POIs, T is the number of iterations, and k is the dimension of latent feature. The space complexity is $O(2M \times N + N^2 + (k+1) \times (M \times N))$. Since the rating matrix is usually sparse and $M, N \gg k$, the time complexity is $O(T \times N^3)$ and the space complexity is $O(M \times N + N^2)$.

Algorithm 1. The proposed Sentimental–Spatial POI Recommendation (SPR) model

```
Input: The rating matrix R in training dataset.
    Sentiment similarity E calculated by Eq. (8).
    Geographical distance L calculated by Eq. (11).
    Setting the parameters, including iteration count T, learning
    rate α and tradeoff parameters λ1, λ2, λ3, β, γ.
Output: The accuracy validation and the rank of POIs.
Initialize latent feature matrices U, P and biases b_u, b_i.
for t = 1 : T do
  for each user u and POI i parallel do
    Calculate ∂Ψ/∂U_u, ∂Ψ/∂P_i, ∂Ψ/∂b_u, and ∂Ψ/∂b_i by Eqs. (14), (15), (16),
    and (17) respectively.
    Update U_u, P_i, b_u, and b_i by Eqs. (18), (19), (20) and (21).
  end for
end for
for each test user u do
  for each test POI i do
    Predict the probability of visiting by user u by Eq. (7).
  end for
  Rank the test POIs in descending order of probability.
end for
Output the accuracy validation results RMSE and MAE
  calculated by Eqs. (24) and (25).
```

5. Experiment

Adopting the data of Sina Weibo as the dataset, the proposed models are verified by experiments. We compare the performance of our SPM method with Meanshift method [53], K-means, and Gaussian Mixture Model (GMM). They are traditional popular clustering methods. Then our SPR model is compared with BaseMF [7], Bias-MF [54], CF-MF [49], LBSMF [35], and IRenMF [32], DeepMF [47] and CSPR [11]. In addition, we present POIs mined by SPM on the map.

5.1. Dataset introduction

The dataset utilized for experimental verification is crawled from Sina Weibo, i.e., the Twitter of China. The number of the microblog posts of Sina Weibo is 5.1 million from 1.4 million users. Microblogs can be treated as check-ins according to their GPS positions. Table 1 shows the statistics of our Sina Weibo

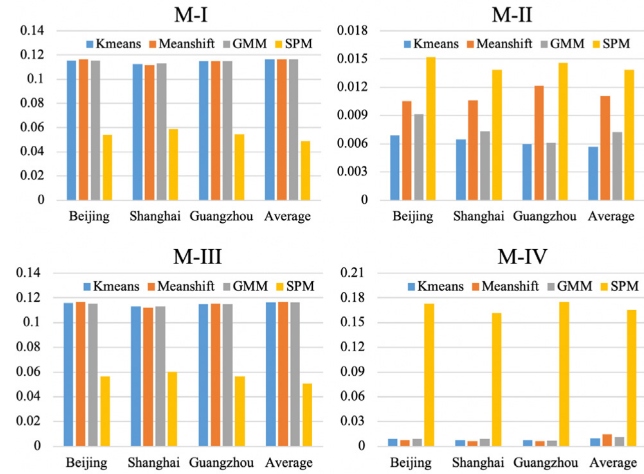

Fig. 6. The performance comparison of different methods on POI mining. For M-I, M-II and M-III, the lower, the better. For M-IV, the higher, the better.

dataset. Our code and data are released.[3] Six cities are involved in our dataset, including Beijing, Shanghai, Guangzhou, Xi'an, Kunming, and Urumchi. Weibo API is employed to crawl these data. We set a GPS position as the center of a city. Generally, it is the administration center. Therefore, it is not assured that the center is the most prosperous area in the city. Then the authorized API is applied to crawl the microblogs posted in the covered area within radius 11.132 km.

5.2. Performance measurements

5.2.1. POI mining

For a POI, (1) its interior posts should have fewer variances on sentiment, (2) the interior posts should distribute tightly in geographical space, and (3) the sentiments of different POIs should have wide variances. Thus, two kinds of measurements are utilized for performance validation of mining results.

The first measurement shown in Table 2 is represented by *Measure*$_1$:

$$Measure_1 = \frac{1}{M} \sum_{j=1}^{M} \sqrt{\sum_{i \in POI(j)}^{N_j} \frac{\varepsilon D_{i,j}^2 + \theta (V_i - \bar{V}_j)^2}{N}} \tag{22}$$

where j denotes the jth POI, i indicates the ith microblog in the jth POI. $\bar{V}_j$ is the average sentiment of the posts in jth POI. $D_{i,j}$ is the geographical distance between the GPS position of the ith microblog and the geographical center of the jth POI.

Measure$_1$ is employed to evaluate the distribution of sentiment values and geographical positions of microblog posts in POIs, of which the symbols are M-I, M-II, and M-III. The lower M-I, M-II, and M-III are, the better the performance is.

The second measurement is represented by *Measure*$_2$:

$$Measure_2 = \sqrt{\sum_{j=1}^{M} \frac{(\bar{V} - \bar{V}_j)^2}{M}} \tag{23}$$

Measure$_2$ is expressed by M-IV. $\bar{V}_j$ denotes the sentiment of the jth POI. $\bar{V}$ is the average sentiment of all POIs. The bigger M-IV is, the larger the gap of sentiments between different POIs is. Thus

[3] https://github.com/rushing-snail/Sentimental-Spatial-POI-Recommendation.

Table 1
Statistics of Sina Weibo Dataset.

City	Beijing	Shanghai	Guangzhou	Xi'an	Kunming	Urumchi	Total
Number of users	478,614	329,590	289,790	140,588	93,040	65,489	1397,111
Number of micro-blogs	1901,801	1151,048	971,012	512,299	320,421	270,189	5126,770
Number of GPS positions	637,709	546,298	513,179	252,432	195,579	153,806	2299,003
Center	39°54′27″N 116°23′17″E	31°13′46.86″N 121°28′24.17″E	23°7′44.99″N 113°15′51.97″E	34°20′29.64″N 108°56′24.63″E	25°3′0″N 102°43′59.99″E	43°49′32.13″N 87°37′0.65″E	–
Coverage radius	11.132 km						–

Table 2
Performance Measurements on POI Mining.

Measures	Parameter setting	Description	Symbol	Note
$Measure_1 = \frac{1}{M}\sum_{j=1}^{M}\sqrt{\sum_{i\in POI(j)}^{N_j}\left[\varepsilon(D_{ij})^2+\theta(V_i-\overline{V}_j)^2\right]/N}$	$\varepsilon=0,\theta=1$	The average error of each POI on sentimental values of the POI's inner social media data.	M-I	The lower, the better.
	$\varepsilon=1,\theta=0$	The average fluctuation of each POI on geographic distance from the locations of POI's inner social media data to POI's center.	M-II	
	$\varepsilon=1,\theta=1$	The average comprehensive fluctuation of each POI on sentimental values and geographic distance.	M-III	
$Measure_2 = \sqrt{\sum_{j=1}^{M}(V_i-\overline{V}_j)^2/M}$	–	The RMSE of sentimental values of every POI.	M-IV	The higher, the better.

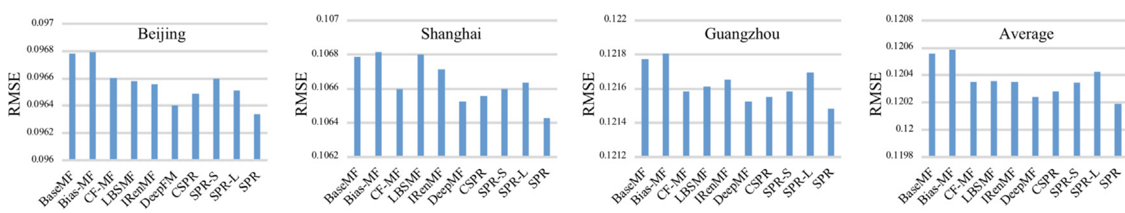

Fig. 7. The performance of POI recommendation of different methods in terms of RMSE. The lower, the better.

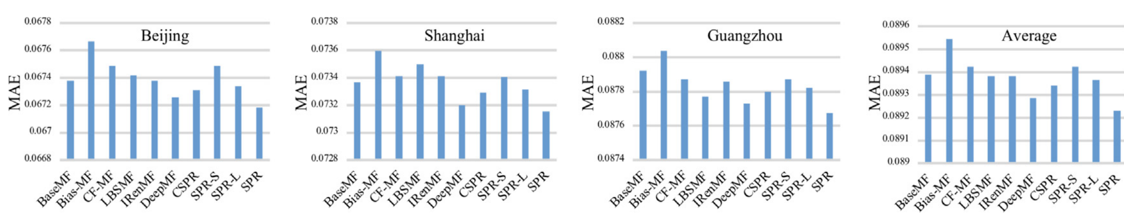

Fig. 8. The performance of POI recommendation of different methods in terms of MAE. The lower, the better.

adopting this measurement can discover the POIs which have different sentimental attributes and lead to a better mining result. The higher M-IV is, the better the performance is.

5.2.2. POI recommendation

The evaluation metrics of the prediction accuracy utilized in our experiments are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). They are the most popular accuracy measures in recommender systems [7,36–38,49,55,56]. They are defined by:

$$RMSE = \sqrt{\sum_{(u,i)\in\Re_{test}} \frac{(R_{u,i}-\hat{R}_{u,i})^2}{|\Re_{test}|}} \tag{24}$$

$$MAE = \sum_{(u,i)\in\Re_{test}} \frac{|R_{u,i}-\hat{R}_{u,i}|}{|\Re_{test}|} \tag{25}$$

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

Note that, logistic function $\frac{1}{1+e^{-x}}$ is commonly used in recommender systems [55] to map each matrix element into [0, 1]. But in our dataset, some check-in frequencies of a location are large while the function e^{-x} would result in very small and indistinguishable values [57]. Therefore, as in [57], the logistic function is defined as $\frac{1}{1+x^{-1}}$.

5.3. Evaluation

5.3.1. Performance of POI mining

We compare the performance of our method and the traditional popular methods, including Meanshift, K-means, and Gaussian Mixture Model (GMM). These methods only exploit the GPS position of the data point rather than its sentimental attribute.

We combine the results under various measures for a comprehensive validation. As shown in Fig. 6, the performance in terms

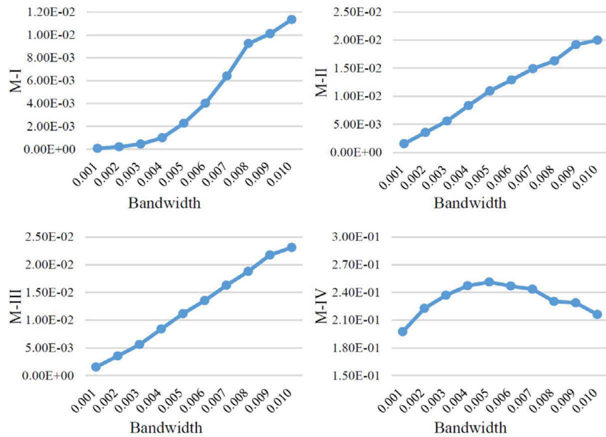

Fig. 9. Discussion on the impact of bandwidth h on Beijing dataset.

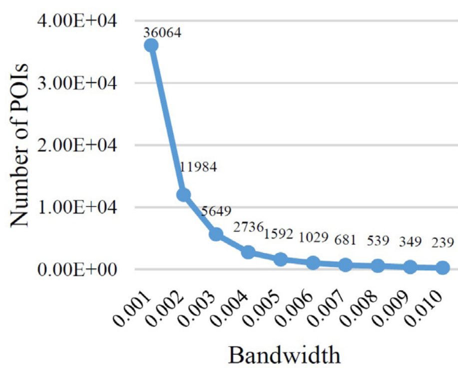

Fig. 10. Discussion on the impact of bandwidth h on the mined POI count in Beijing.

of the M-I, M-II, M-III, and M-IV are given on the Sina Weibo dataset. The smaller M-I, M-II, and M-III are and the larger M-IV is, the better the method is. Compared with these methods, the performance of our SPM method on M-I and M-III is better. It indicates that by using our method, the posts in the same POI have similar sentimental attributes. However, regarding M-II, the performance of our SPM method is worse than others. The reason for the low performance is that the M-II is used to measure the geographic density of the clusters. It does not consider the factor of other attributes. Thus, the K-means and GMM, which only use GPS information for clustering, are better than our multi-attributes fused method. In Fig. 6, we observe that our SPM is much better than other methods on M-IV. It implies that SPM can discover the POIs with obviously different sentimental attributes. In a word, our SPM is more effective to mine the POIs with sentimental attributes.

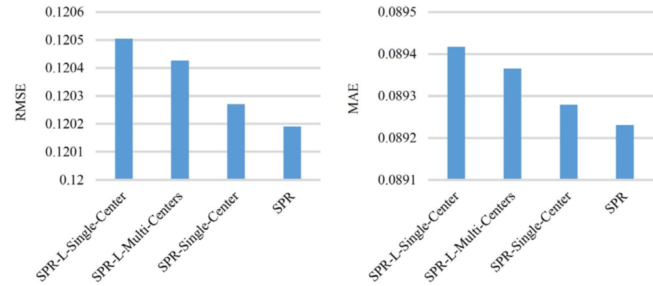

Fig. 12. Discussion on the performance comparison between considering multi-centers and single-center.

5.3.2. Performance of POI recommendation

In this section, we compare the performance of our SPR model with the existing methods including BaseMF [7], Bias-MF [54], CF-MF [49], LBSMF [35], IRenMF [32], DeepMF [47] and CSPR [11]. The compared methods are reviewed:

- Basic Probabilistic Matrix Factorization Model (BaseMF): This approach [7] learns the latent features by minimizing the objective function based on the observed rating data. We adopt it for POI recommendation.
- Bias based Matrix Factorization Model (Bias-MF): User Bias and item bias are utilized in matrix factorization models [54].
- Collaborative Filtering based Matrix Factorization Model (CF-MF): Collaborative filtering method is used to compute the similarity between POIs. We adopt it for latent factor model to recommend POIs as in [49].
- Location Based Social Matrix Factorization Model (LBSMF): This method proposed in [35] extracts check-ins and text-based tips to analyze users' location preference by considering the factor of users' sentiment towards the venues.
- Instance-Region Neighborhood Matrix Factorization (IRenMF): This method proposed in [32] exploits both instance and region-level geographical neighborhood characteristics for location recommendation.
- DeepMF [47] is a state-of-the-art method which combines the power of factorization machines for recommendation and deep learning for feature learning in a new neural network architecture.
- CSPR [11] is our conference version of this work. It can be seen as a short version of our SPR model. The main differences with this work have been discussed in Section 2.4.
- Sentiment based Matrix Factorization Model (SPR-S): This is a short version of our SPR model. It just employs the factor of sentiment similarity.
- Location based Matrix Factorization Model (SPR-L): This is a short version of our SPR model. It just considers the factor of geographical distance.
- Sentimental–Spatial POI Recommendation Model (SPR): This is our SPR model. It exploits two factors including sentiment similarity and geographical distance.

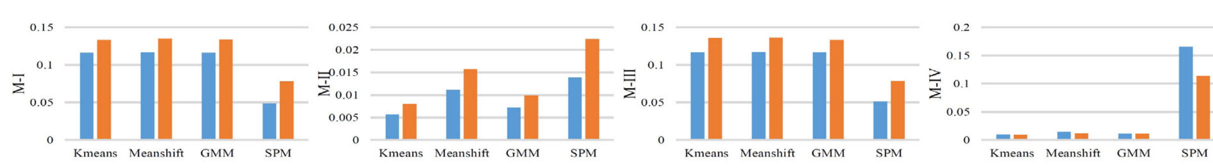

Fig. 11. Discussion on the performance comparison between with and without noise reduction.

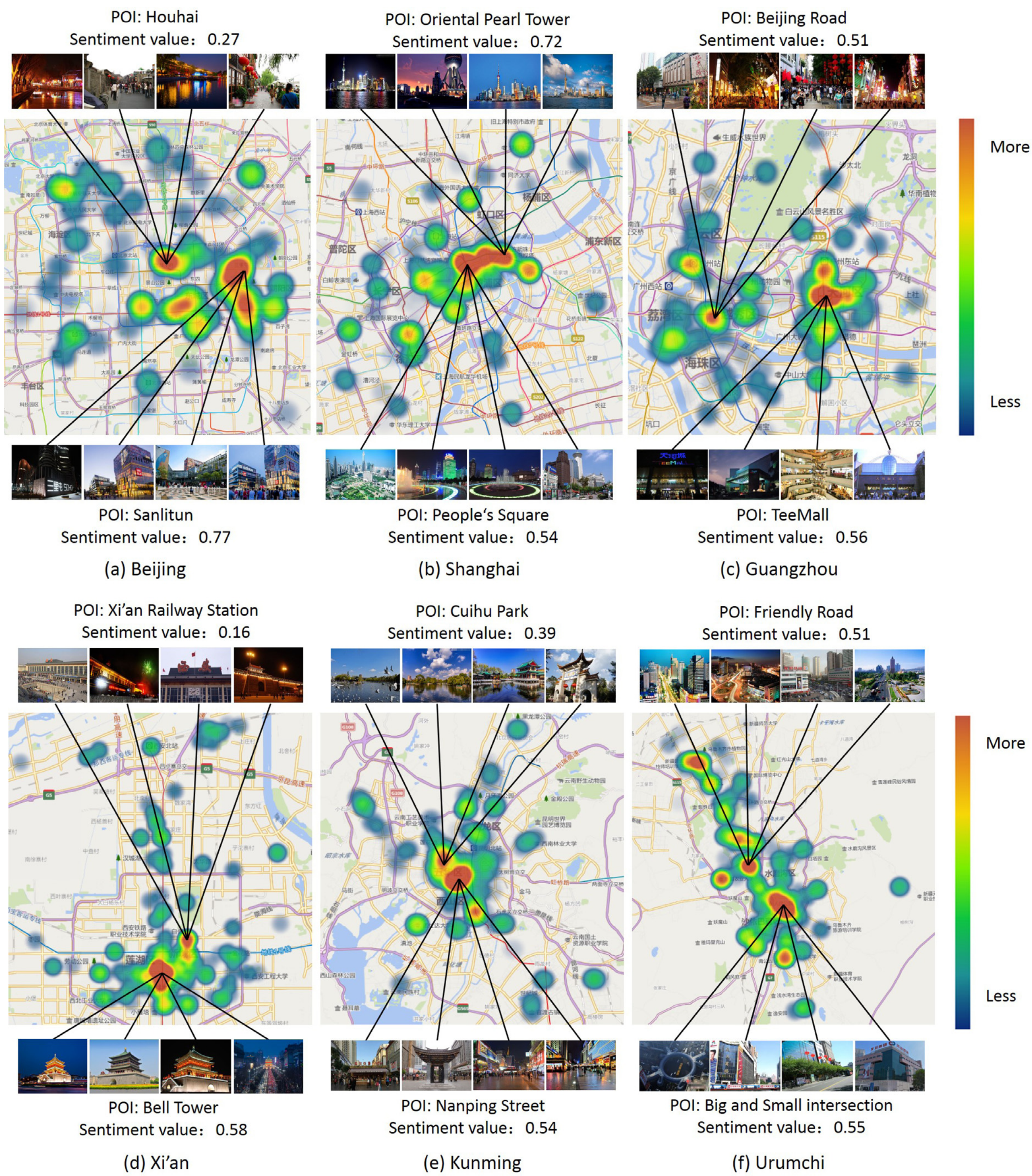

Fig. 13. The presentation of the POIs mined by SPM method in Beijing, Shanghai, Guangzhou, Xi'an, Kunming and Urumchi. The color temperature indicates the number of check-ins. The warm color represents more check-ins. The cool color means fewer check-ins. Sentiment values are normalized to [0, 1] by Min–Max Normalization.

We select 20% of our dataset as the testing data randomly and the other 80% as the training data. We use 5-fold cross-validation to demonstrate the effectiveness of our experiments. Figs. 7 and 8 report the comparison results on RMSE and MAE. It can be observed that our SPR model performs better than existing methods including the conference version method CSPR and the state-of-the-art method DeepMF. In these existing methods, DeepMF achieves the best performance and CSPR is the second best method. It can be concluded that our SPR model achieves the state-of-the-art performance and the contributions proposed in this work significantly improve the performance of our previous work CSPR.

We also show the quantitative results of ablation study for our SPR method. SPR-S is a short version of our SPR model. It just employs the factor of sentiment similarity. SPR-L is another short version of SPR model, and it just considers the factor of geographical distance. From Figs. 7 and 8, we can see SPR method which exploiting both of the two factors obtains better performance than SPR-S and SPR-L. It demonstrates the combination of the two factors is effectiveness.

5.4. Discussion

This section reports three discussions on our method: (1) the impact of bandwidth on the performance of POI mining, (2) the impact of the factors of noise reduction and multi-activity centers on the performance of POI mining.

5.4.1. The impact of bandwidth

The main limitation of the Meanshift method is that the value of the bandwidth parameter h is unspecified. Thus, the discussion on the impact of the bandwidth h on the performance of POI mining is necessary. SPM method performs with different h ranging from 0.001 to 0.01. Cheng et al. [58] set the bandwidth as 0.001, which indicates 100 meters in real life. It is roughly the radius of a landmark. POIs are larger than landmarks. That is the reason why we range h from 0.001 to 0.01. Fig. 9 shows the performance of SPM with different h on M-I, M-II, M-III, and M-IV. It shows that M-I, M-II, and M-III increase with the increase of bandwidth h. In Fig. 10, when bandwidth h is set to 0.001, the number of POIs is more than 30k, and when h sets to 0.01, the number of POIs is about 200. It shows that the coverage area of a POI becomes larger with the increase of h, and accordingly, the number of POIs becomes smaller. That is to say, the number of points in a POI increases with h. It can be concluded that a small POI is more homogeneous than a big one.

5.4.2. The impact of the factors of noise reduction and multi-activity centers

We perform some experiments to verify the improvements of considering noise reduction and multi-activity centers. Experiment results are given in Figs. 11 and 12. Fig. 11 shows the performance comparison between with and without noise reduction. For M-I, M-II, and M-III, the lower the value, the better the performance. However, for M-IV, the higher, the better. We can see that the noise reduction works well in our method. Fig. 12 shows the performance comparison between considering multi-centers and single-center. SPR-L-Single-Center is the method considering the factor of geographical distance with single-center. SPR-L-Multi-Centers is the method considering the factor of geographical distance with multi-centers. SPR-Single-Center is our SPR method with the single-center. SPR is our normal method with multi-centers. The performance comparison shows the effectiveness of considering multi-centers.

5.5. Presentation

The POIs mined by our SPM method are shown in Fig. 13. The color temperature indicates the number of check-ins. The warm color represents more check-ins. The cool color means fewer check-ins. Sentiment values are normalized to [0, 1] by Min-Max Normalization $f(x) = \frac{x - min}{max - -min}$. The values below 0.5 show that the sentiment of the POI is peace or negative and the values above 0.5 show that of POI is positive.

Fig. 13 presents the POIs mined by SPM method in Beijing, Shanghai, Guangzhou, Xi'an, Kunming and Urumchi. It can be observed that our SPM mines not only the POIs with high sentiment values such as Sanlitun in Beijing and Oriental Pearl Tower in Shanghai whose sentiment attributes are happiness and joy, but also the POIs like Houhai in Beijing and Railway Station in Xi'an whose sentimental attributes are down. For Beijing, most of the mined POIs are nearby the Houhai, Beijing Central Business District (CBD), and Sanlitun. All of the three areas are the most flourishing in Beijing. More specifically, Beijing CBD is the location of headquarters of many Fortune 500 enterprises in China and the location of many high-end enterprises in China, while Houhai and Sanlitun have more leisure and entertainment places, e.g. their bar streets are the most prosperous entertainment streets in Beijing. In the SPM results, the sentiment value of Houhai is 0.27 while it is 0.77 for Sanlitun. It can be observed that the sentiment values of Houhai and Sanlitun are very different even both of them are famous for their bar streets. A plausible reason is that there is no noisy music but melodious songs and unique cultural atmosphere of Beijing in Houhai bar street, but Sanlitun is the landmark of Beijing fashion, and its bar street is full of loud music and frantic songs. They are so different that the calculated sentiment values are also distinct. The example of Houhai and Sanlitun demonstrates that considering the sentiment value of POIs is significant for deep perception of the POI characteristics.

6. Conclusion

Existing location recommender systems mainly focus on physical characteristics of locations rather than the sentimental attributes of locations. The SPM and SPR methods are proposed in the paper. According to our methods, the POIs with obvious sentimental attributes are mined and recommended to users. We conducted extensive experiments on a large real-world dataset and demonstrated that the proposed methods have better effectiveness than existing approaches.

In our future work, check-in behaviors of users will be explored by combining the spatial–temporal and sentimental attributes. Users have various behaviors at different times. Additionally, POI tagging may be interesting and useful for the explainable recommendation. It can not only intuitively show why to recommend them to users, but also help users for independent travel. In a word, we would like to schedule a thorough travel scheme by solving the problems of when, where, and why.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Guoshuai Zhao: Conceptualization, Methodology, Visualization, Writing - original draft, Formal analysis. **Peiliang Lou:** Methodology, Software, Data curation, Writing - original draft, Formal analysis. **Xueming Qian:** Resources, Supervision. **Xingsong Hou:** Writing - reviewing & editing.

Acknowledgments

This work was supported in part by the NSFC, China under Grants 61902309, 61732008, 61772407, and 1531141; in part by the World-Class Universities (Disciplines) and the Characteristic Development Guidance Funds for the Central Universities, China (PY3A022); in part by the Fundamental Research Funds for the Central Universities, China; in part by China Postdoctoral Science Foundation; and in part by the National Postdoctoral Innovative Talents Support Program, China for G. Zhao.

References

[1] J. Bao, Y. Zheng, D. Wilkie, M.F. Mokbel, Recommendations in location-based social networks: a survey, GeoInformatica 19 (3) (2015) 525–565.

[2] H. Li, Y. Ge, D. Lian, H. Liu, Learning user's intrinsic and extrinsic interests for point-of-interest recommendation: A unified approach, in: Proc. IJCAI, 2017, pp. 2117–2123.

[3] H. Wang, H. Shen, W. Ouyang, X. Cheng, Exploiting POI-specific geographical influence for point-of-interest recommendation, in: Proc. IJCAI, 2018, pp. 3877–3883.
[4] Z. Yao, Exploiting human mobility patterns for point-of-interest recommendation, in: Proc. WSDM, 2018, pp. 757–758.
[5] Y. Zheng, X. Xie, Learning travel recommendations from user-generated GPS traces, ACM TIST 2 (1) (2011) 2.
[6] E. Cho, S.A. Myers, J. Leskovec, Friendship and mobility: user movement in location-based social networks, in: Proc. ACM SIGKDD, 2011, pp. 1082–1090.
[7] R. Salakhutdinov, A. Mnih, Probabilistic matrix factorization, in: Proc. NIPS, 2007, pp. 1257–1264.
[8] S. Jiang, X. Qian, J. Shen, Y. Fu, T. Mei, Author topic model-based collaborative filtering for personalized POI recommendations, IEEE Trans. Multimedia 17 (6) (2015) 907–918.
[9] M. Munezero, C.S. Montero, E. Sutinen, J. Pajunen, Are they different? Affect, feeling, emotion, sentiment, and opinion detection in text, IEEE Trans. Affect. Comput. 5 (2) (2014) 101–111.
[10] X. Lei, X. Qian, G. Zhao, Rating prediction based on social sentiment from textual reviews, IEEE Trans. Multimedia 18 (9) (2016) 1910–1921.
[11] P. Lou, G. Zhao, X. Qian, H. Wang, X. Hou, Schedule a rich sentimental travel via sentimental POI mining and recommendation, in: Proc. IEEE BigMM, 2016, pp. 33–40.
[12] X. Xiao, Y. Zheng, Q. Luo, X. Xie, Inferring social ties between users with human location history, J. Ambient Intell. Humaniz. Comput. 5 (1) (2014) 3–19.
[13] M. Ye, D. Shou, W. Lee, P. Yin, K. Janowicz, On the semantic annotation of places in location-based social networks, in: Proc. ACM SIGKDD, 2011, pp. 520–528.
[14] J. Zhang, C. Chow, iGSLR: personalized geo-social location recommendation: a kernel density estimation approach, in: Proc. ACM SIGSPATIAL, 2013, pp. 324–333.
[15] Y. Zheng, L. Zhang, X. Xie, W. Ma, Mining interesting locations and travel sequences from GPS trajectories, in: Proc. WWW, 2009, pp. 791–800.
[16] R. Raymond, T. Sugiura, K. Tsubouchi, Location recommendation based on location history and spatio-temporal correlations for an on-demand bus system, in: Proc. ACM SIGSPATIAL, 2011, pp. 377–380.
[17] G. Zhao, X. Lei, X. Qian, T. Mei, Exploring users' internal influence from reviews for social recommendation, IEEE Trans. Multimedia 21 (3) (2019) 771–781.
[18] G. Zhao, X. Qian, X. Lei, T. Mei, Service quality evaluation by exploring social users' contextual information, IEEE Trans. Knowl. Data Eng. 28 (12) (2016) 3382–3394.
[19] J. Sang, T. Mei, J. Sun, C. Xu, S. Li, Probabilistic sequential POIs recommendation via check-in data, in: Proc. ACM SIGSPATIAL, 2012, pp. 402–405.
[20] L. Wei, Y. Zheng, W. Peng, Constructing popular routes from uncertain trajectories, in: Proc. ACM SIGKDD, 2012, pp. 195–203.
[21] G. Zhao, H. Fu, R. Song, T. Sakai, Z. Chen, X. Xie, X. Qian, Personalized reason generation for explainable song recommendation, ACM TIST 10 (4) (2019) 41:1–41:21.
[22] Z. Gao, Y. Fan, C. Wu, W. Tan, J. Zhang, Y. Ni, B. Bai, S. Chen, SeCo-LDA: Mining service co-occurrence topics for composition recommendation, IEEE Trans. Serv. Comput. 12 (3) (2019) 446–459.
[23] G. Zhao, Z. Liu, Y. Chao, X. Qian, CAPER: Context-aware personalized emoji recommendation, IEEE Trans. Knowl. Data Eng. (2020) 1, [Online]. Available: http://dx.doi.org/10.1109/TKDE.2020.2966971.
[24] Y. Si, F. Zhang, W. Liu, An adaptive point-of-interest recommendation method for location-based social networks based on user activity and spatial features, Knowl.-Based Syst. 163 (2019) 267–282.
[25] C. Cui, J. Shen, L. Nie, R. Hong, J. Ma, Augmented collaborative filtering for sparseness reduction in personalized POI recommendation, ACM TIST 8 (5) (2017) 71:1–71:23.
[26] S. Wang, Y. Wang, J. Tang, K. Shu, S. Ranganath, H. Liu, What your images reveal: Exploiting visual contents for point-of-interest recommendation, in: Proc. WWW, 2017, pp. 391–400.
[27] G. Zhao, T. Liu, X. Qian, T. Hou, H. Wang, X. Hou, Z. Li, Location recommendation for enterprises by multi-source urban big data analysis, IEEE Trans. Serv. Comput. (2017) 1, [Online]. Available: http://dx.doi.org/10.1109/TSC.2017.2747538.
[28] S. Zhao, T. Zhao, I. King, M.R. Lyu, Geo-teaser: Geo-temporal sequential embedding rank for point-of-interest recommendation, in: Proc. WWW, 2017, pp. 153–162.
[29] X. Qian, Y. Wu, M. Li, Y. Ren, S. Jiang, Z. Li, LAST: Location-appearance-semantic-temporal clustering based poi summarization, IEEE Trans. Multimedia (2020) 1, [Online]. Available: http://dx.doi.org/10.1109/TMM.2020.2977478.
[30] Y. Wu, K. Li, G. Zhao, X. Qian, Long- and short-term preference learning for next POI recommendation, in: Proc. CIKM, 2019, pp. 2301–2304.
[31] K. Li, Y. Wu, Y. Xue, X. Qian, Viewpoint recommendation based on object oriented 3d scene reconstruction, IEEE Trans. Multimedia (2020) 1, [Online]. Available: http://dx.doi.org/10.1109/TMM.2020.2981237.
[32] Y. Liu, W. Wei, A. Sun, C. Miao, Exploiting geographical neighborhood characteristics for location recommendation, in: Proc. ACM CIKM, 2014, pp. 739–748.
[33] H. Yin, B. Cui, Y. Sun, Z. Hu, L. Chen, LCARS: A spatial item recommender system, ACM Trans. Inf. Syst. 32 (3) (2014) 11:1–11:37.
[34] S. Zhao, T. Zhao, H. Yang, M.R. Lyu, I. King, STELLAR: spatial-temporal latent ranking for successive point-of-interest recommendation, in: Proc. AAAI, 2016, pp. 315–322.
[35] D. Yang, D. Zhang, Z. Yu, Z. Wang, A sentiment-enhanced personalized location recommendation system, in: Proc. ACM HT, 2013, pp. 119–128.
[36] C. Cheng, H. Yang, I. King, M.R. Lyu, Fused matrix factorization with geographical and social influence in location-based social networks, in: Proc. AAAI, 2012.
[37] X. Qian, H. Feng, G. Zhao, T. Mei, Personalized recommendation combining user interest and social circle, IEEE Trans. Knowl. Data Eng. 26 (7) (2014) 1763–1777.
[38] G. Zhao, X. Qian, X. Xie, User-service rating prediction by exploring social users' rating behaviors, IEEE Trans. Multimedia 18 (3) (2016) 496–506.
[39] J. Zhang, C. Chow, Y. Zheng, ORec: An opinion-based point-of-interest recommendation framework, in: Proc. ACM CIKM, 2015, pp. 1641–1650.
[40] F. Benamara, C. Cesarano, A. Picariello, D.R. Recupero, V.S. Subrahmanian, Sentiment analysis: Adjectives and adverbs are better than adjectives alone, in: Proc. ICWSM, 2007.
[41] Y. Wang, M. Wang, H. Fujita, Word sense disambiguation: A comprehensive knowledge exploitation framework, Knowl. Based Syst. 190 (2020) 105030.
[42] E. Cambria, S. Poria, D. Hazarika, K. Kwok, SenticNet 5: Discovering conceptual primitives for sentiment analysis by means of context embeddings, in: Proc. AAAI, 2018, pp. 1795–1802.
[43] J. Zhao, L. Dong, J. Wu, K. Xu, MoodLens: an emoticon-based sentiment analysis system for chinese tweets, in: Proc. KDD, 2012, pp. 1528–1531.
[44] X. Hu, L. Tang, J. Tang, H. Liu, Exploiting social relations for sentiment analysis in microblogging, in: Proc. ACM WSDM, 2013, pp. 537–546.
[45] Q. You, J. Luo, Towards social imagematics: sentiment analysis in social multimedia, in: Proc. MDMKDD, 2013, pp. 3:1–3:8.
[46] T. Hayashi, H. Fujita, Word embeddings-based sentence-level sentiment analysis considering word importance, Acta Polytech. Hung. 16 (7) (2019) 7–24.
[47] H. Guo, R. Tang, Y. Ye, Z. Li, X. He, DeepFM: A factorization-machine based neural network for CTR prediction, in: Proc. IJCAI, 2017, pp. 1725–1731.
[48] M. Lichman, P. Smyth, Modeling human location data with mixtures of kernel densities, in: Proc. ACM KDD, 2014, pp. 35–44.
[49] Y. Koren, Factorization meets the neighborhood: a multifaceted collaborative filtering model, in: Proc. ACM SIGKDD, 2008, pp. 426–434.
[50] L. Hu, A. Sun, Y. Liu, Your neighbors affect your ratings: on geographical neighborhood influence to rating prediction, in: Proc. ACM SIGIR, 2014, pp. 345–354.
[51] G. Zhao, X. Qian, C. Kang, Service rating prediction by exploring social mobile users' geographical locations, IEEE Trans. Big Data 3 (1) (2017) 67–78.
[52] M.J. Strickland, C. Siffel, B.R. Gardner, A.K. Berzen, A. Correa, Quantifying geocode location error using GIS methods, Environ. Health 6 (1) (2007) 1–8.
[53] Y. Cheng, Mean shift, mode seeking, and clustering, IEEE Trans. Pattern Anal. Mach. Intell. 17 (8) (1995) 790–799.
[54] Y. Koren, Collaborative filtering with temporal dynamics, Commun. ACM 53 (4) (2010) 89–97.
[55] H. Ma, H. Yang, M.R. Lyu, I. King, SoRec: social recommendation using probabilistic matrix factorization, in: Proc. ACM CIKM, 2008, pp. 931–940.
[56] X. Yang, H. Steck, Y. Liu, Circle-based recommendation in online social networks, in: Proc. ACM SIGKDD, 2012, pp. 1267–1275.
[57] H. Gao, J. Tang, X. Hu, H. Liu, Exploring temporal effects for location recommendation on location-based social networks, in: Proc. ACM RecSys, 2013, pp. 93–100.
[58] A. Cheng, Y. Chen, Y. Huang, W.H. Hsu, H.M. Liao, Personalized travel recommendation by mining people attributes from community-contributed photos, in: Proc. ACM MM, 2011, pp. 83–92.