Social Personalized Ranking Embedding for Next POI Recommendation

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Abstract. As the increasing popularity of the applications of location-based services, points-of-interest (POI) recommendation has become a great value part to help users explore their surrounding living environment and improve the quality of life. Recently, some researchers proposed next POI recommendation, which not only exploiting the users personal interests but also considers the sequential information of users check-ins. There are some next POI recommendation models exploit Metric Embedding method to improve recommendation performance and efficiency. However, these approaches not consider social relations in next POI recommendation, which is challenging due to social relations are noisy and sparse. To this end, in this paper, we proposed a Social Personalized Ranking Embedding (SPRE) model, which integrates user personalization and social relations into consideration, to learn the social relations by social embedding for next POI recommendation. Our experiments on a real-world large-scale dataset (Foursquare) results show that our model outperforms the state-of-the-art next POI recommendation methods.

Keywords: Next POI recommendation · Metric embedding · Social relations influence

1 Introduction

As the rapid increasing popularity of the applications of location-based services, location-based social networks (LBSNs), such as Foursquare, Facebook Places, Gowalla and Yelp, have attracted the large amount of users to check in at points-of-interest (POIs), e.g., bars, restaurants and sighting sites, and share their experience of visiting these POIs with friends. POI recommendation is has a great value to help users explore their surrounding living environment and improve the quality of life, which has attracted a significant amount of research interest in developing recommendation techniques [2,4]. Recently, there are a lot of recommendation models that were put forward for POI recommendation by developing and integrating geographical influence [21], social influence [6],

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context influence [19], the effect of temporal cyclic information [7,25] and their joint effect [13,22,24].

Some researchers proposed a natural extension of general POI recommendation, i.e., next POI recommendation [3]. Comparing to POI recommendation, next POI recommendation has more challenges and fewer studies are on this new problem. In addition to the user's personal interests, the next POI recommendation additionally considers the sequential information of users' check-ins. On the one hand, there are some researchers proposed Markov chain-based recommender model [26] to capture the sequential patterns of POIs for next POI recommendation. On the other hand, some researchers proposed a hybrid model [3] for next POI recommendation by combining temporal cyclic effect, social relations influence and others. However, because of the sparseness of the data, it is difficult for Markov chain-based models and others to accurately and effectively estimate the probability of visiting next POI for users. Recently, many various recommender models utilize the social relations influence to improve the recommended accuracy. However, social links are also sparse and noisy [27]. The traditional recommendation methods (such as MF and Markov chain) of recommended accuracy will be hurt since the sparsity and noise.

Recently, embedding the item in the low-dimensional Euclidean space has been widely used in various fields, especially in natural language processing and data mining. Embedding model is often used to deal with some sparse data and mine the data that has not been observed. Tang et al. [18] proposed a Large-scale Information Network Embedding model (LINE), which suits arbitrary types of information networks and easily scales to millions of nodes by using the metric embedding. Feng et al. [5] proposed a Personalized Ranking Metric Embedding (PRME) model to map each user and POI to some point in a latent Euclidean space for next new POI recommendation. However, they did not take into account some influences, such as social relations influence, context influence and temporal cyclic information, into the model.

In this paper, we proposed a new embedding model by embedding the social relations and user preference for next POI recommendation. In the real-world social relations graph, some users have no direct links, but their social network structure is similar, such as users 5 and 6 in Fig. 1. But the implicit relationships are ignored by the existing methods. In our model, we map the per-user to an object in a low-dimensional Euclidean latent space, and use the metric embedding algorithm to effectively calculate the social relationships. By social embedding method, we can be the implicit social relations in the European space. Intuitively speaking, the distance between two objects measures the intensity of the similar relationship. Since embedding model is often used to deal with sparse data and mines the data which has not been observed [5], social embedding can solve the sparse social relational data. That is, we can use the social embedding model to find the user's more similar friends even their social relations graph is sparse or unobserved, so we can utilize the social embedding model to more accurate and effective calculate the user relations, which can better to do next POI recommend. In the other words, our embedding method respectively encodes the personal preference and social dimensions in low-dimension latent space to effectively address the issues of data sparsity. According to our model, we are efficient and accurate to calculate user's preference and social relation parameters. As far as we know, we are the first of using social embedding in the next POI recommendation. Experimental results show that our Social Personalized Ranking Embedding (SPRE) model outperforms competitive baselines in terms of both effectiveness and efficiency. The primary contributions of our research are summarized as follows.

- We propose a Social Personalized Ranking Embedding (SPRE) model to joint personalized embedding and social embedding for next POI recommendation. To best our knowledge, this is first work that uses social embedding for the next POI recommendation.
- We evaluate our method with a real-world dataset. Our extensive experimental results show that our method outperforms baselines in terms of different metrics.

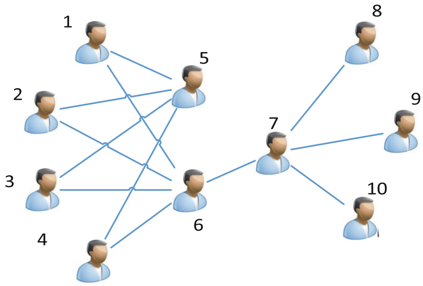


Fig. 1. Social graph

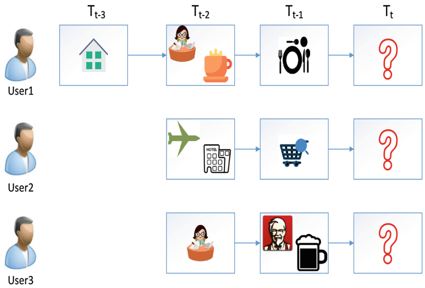


Fig. 2. Users check-in sequences

The rest of the paper is organized as follows. We introduce the related work in Sect. 2. In Sect. 3, we list notations used in the following paper and provide the formal definition of next POI recommendation with considering user personalization and social relations. Some related models contributing to our model are explained in detail in Sect. 4. Our proposed method and the model parameter Learning is discussed in Sect. 5. Our experimental results are shown in Sect. 6. Finally, we conclude our work in Sect. 7.

2 Related Work

POI recommendation has attracted many researchers and many different recommendation technologies have been developed [17,21,23,25]. Recently, some researchers pay attention to next POI recommendation, which is a natural extension of general POI recommendation. It needs timely to provide satisfactory advice based on the POIs that users access recently and their personal preferences. Most of the research is based on the Markov chain-based method to capture the POI sequential pattern and to predict the next check-ins. Zhang et al. [26] predicted the next location probability through an additive Markov chain, and assumed that the POIs that a user recently visited have more impact than the POIs that the users visited a long time ago. Liu et al. [15] exploited the transition pattern of POI categories to predict future check-ins. However, their method fails to describe the unobserved transition probability or highly depends on the category information for calculating accuracy. In this paper, we estimate the European distance between users and POIs in latent European space, so we can through the distance in space to show their transition probability.

Recommendation with social dimensions focuses on using social networks to improve the accuracy and the efficiency of recommendation [8,9,14,16]. Most existing methods are based on Metric Factorization with regularization. For example, Golbeck [8] and Massa and Avesani [16] assumed that a user's preference is similar to or influenced by their directly connected friends. experimentally, this assumption is rough. Their estimation of user's preference is not accurate because of the highly sparse directly linked lines in social networks. To overcome the sparsity of directly connected data, Krohn-Grimberghe et al. [11] recently employed a twice matrix factorization approach, and used potential social relations as regularization for users. However, their method just used *first-order proximity* to construct a Laplacian matrix for regularizing the preference of users. Our work differs from the aforementioned studies in that we can incorporate *first-order proximity* and *second-order proximity* in a unified embedding for calculating social relations.

Embedding methods have been studied for a long time and their wide applications showed that they can effectively capture latent semantic interactions. Tang et al. [18] learned words embedding to make document classification, and showed that their method is efficient with a high accuracy. Recently, some music recommendation research adopted metric embedding into optimization recommendation. Chen et al. [1] proposed a Logistic Markov embedding (LME) for generating the playlists by using metric embedding in the music playlist prediction. And then, there is some research take advantage of metric embedding in the field of next POI recommendation. GE [20] used graph-based metric embedding, and joined four embedding models (i.e., POI-POI, POI-Time, POI-Region, and POI-Word) for POI recommendation. And the PRME [5] is using metric embedding for next new POI recommendation, which is most related to ours. The research proposed a model embedded user preferences and sequential transition into two different spaces. However, this research did not use some useful characteristics, such as social relations of users. Our work differs from the studies mentioned above in that we exploit social embedding scheme to learn the user social relations and adapt Metric Embedding for the next POI recommendation by incorporating user preference and social relations influence.

3 Problem Definition and Notations

In this section, we formulate several definitions for next POI recommendation, and provide notations used in this paper.

Let us assume that there is a user u_i in a M users set $U = \{u_1, u_2, u_3, \ldots, u_M\}$, who just visited a POI l_j in the N POIs set $L = \{l_1, l_2, l_3, \ldots, l_N\}$ and checked-in at this POI at time t. And we defined the social relations set $G = (U, E)$., and U is the set of users and E is the set of edges between users. In general, if the user u_i have a friend u_j, there is an edge between u_i and u_j, the e_ij is defined as the set value of 1 to represent the relationship between them. Then, the user wants to know where she/he like to go next. Based on the user's sequential activities within a short time $\triangle T$ and the social relations G, we need to recommend u_i a POI to go next, which u_i may be interested in. According to this scenario, we formally define the next POI recommendation problem as follows.

Definition 1 (*Next POI Recommendation*). *For a user set U and a POI set L, l^c is the current POI of the user u, the next POI recommendation goal is to recommend a list of POIs that u would be interested in the next, denoted as S^{u,l^c},* which is defined as follows*.*

$$S^{u,l^c} = \{l \in L\} \tag{1}$$

For example, the next POI recommendation may tell where a user goes to play after dinner, or suggest which place can be affordable for a lunch near shops where he/she is shopping, as illustrated in Fig. 2. Note that our next POI recommendation model uses the visited POIs and the social relation of a user to predict his/her next POIs. Therefore, we provide the definitions of social embedding for next POI recommendation as follows.

Definition 2 (*First-Order Proximity*). *The **first-order** proximity in a social network is the local pairwise proximity between two users (i.e., two vertices in the social network). Each pair of users is linked by an edge (u, v) with a weight w_uv. The weight indicates the first order proximity between u and v. The first-order proximity is 0, if no edge is observed between u and v.*

In a real-world network, the *first-order* proximity often represents the similarity of two nodes. Such as, between each other are friends who want to share a similar interest in the social network, such as users 6, 7 in Fig. 1. However, the links observed are only a small proportion in a real-world information network, and with many others missing [12]. Therefore, we define the *second-order* proximity to complement the first-order proximity and save it in the network structure.

Definition 3 (*Second-Order Proximity*). *The **second-order** proximity between two users (u, v) in a social network is the similarity between their neighborhood network structures. The first-order proximity of u with all other users* *is denoted* $p_u = (w_{u,1}, \ldots w_{U,|v|})$*, and the second-order proximity between* u *and* v *is resolved by the similarity between* p_u *and* p_v*. If no vertex is linked from/to both* u *and* v*, the second-order proximity between* u *and* v *is 0.*

In the social graph, some users have no direct links, but their social network structure is similar, such as users 5 and 6 in Fig. 1. Their *second-order* proximity is high. In our paper, we utilize both *first-order* and *second-order* proximity for social embedding. We will introduce our social embedding model in detail in next section. Notations used in this article are shown in Table 1.

Table 1. Notations

Symbols	Interpretation
U, L	The set of users and POIs
O_{ij}	Distance of point i and j in the latent European space
$X(i)$	Location of i in the latent European space
G	The graph of the user social information
K	The number of dimensions of the latent space
$\triangle T$	The time period threshold

4 Preliminary Models

4.1 Metric Embedding Technology

The Metric Embedding (ME) model is often used to deal with some sparse data and mine the data which has not been observed [5]. To help understand the specific meaning of metric embedding, we use POI embedding as an example to explain metric embedding. In the POI embedding model, we present each POI as one point in a latent Euclidean space. We also use the Euclidean distance of POIs in the latent Euclidean space to estimate the transition probability, no matter the transition information have been unobserved.

In the POI Embedding model, each POI l has a position $X(l)$ in the latent space. Given a pair of POIs l_i and l_j, we can use the Euclidean distance of the pair of POIs l_i and l_j to estimate their transition probability. The larger the distance, the lower the transition probability is. That is, the transition probability is defined as follows.

$$\hat{P}(l_j|l_i) = \sigma(\|X(l_i) - X(l_j)\|^2) \tag{2}$$

where $\|X(l_i) - X(l_j)\|^2 = \sum_{k=1^K}(X_K(l_i) - X_K(l_j))^2$, K is the number of dimensions of the latent space and the $\sigma(z) = 1/(1 + exp(-z))$ is the logistic function as the method for normalization, which is in accordance with our hypothesis about the relationship between the distance and the transition probability.

4.2 Personalized Embedding Model

Here we will present the PRME [5], the state-of-the-art Personalized Ranking Embedding Model to utilize two latent spaces, i.e., the *sequential transition space* and the *user preference* space.

In the Personalized Embedding Model, each POI l has one latent position $X^S(l)$ in the sequential transition space, This is similar to the ME, and $O^S_{l_i,l_j} = \|X(l_i)^S - X(l_j)^S\|^2$ on behalf of the Euclidean distance of the POIs i and j. In the user preference space, each POI l has one latent position $X^U(l)$ and each user u has one latent position $X^U(u)$, and the Euclidean distance of user u and POI l in the user preference space is defined as $O^U_{u,l} = \|X(l_i)^U - X(l_j)^U\|^2$.

In the above spaces only the observed check-ins are exploited to learn the latent position of each POI and each user. Since the observed data is very sparse, we fit the rankings for the POI transition for learning the latent position. Consequently, we can additionally make use of the unobserved data to learn the parameters. We assume that the observed under a POI compared with current POI more relevant than was not observed. For example, POI l_i is observed, and next POI l_j is not. We can compare the Euclidean distance with the user current location $X(u)$. In other words, we use Euclidean distance to rank the POIs instead of utilizing the exponential function, which is used in previous studies. The ranking can be defined as follows.

$$\begin{aligned}\hat{P}(l_i|u) > \hat{P}(l_j|u) =& \sigma(\|X(u) - X(l_j)\|^2) > \sigma(\|X(u) - X(l_i)\|^2) \\ &\Rightarrow \|X(u) - X(l_j)\|^2 < \|Xl_u) - X(l_i)\|^2 \\ &\Rightarrow O_{u,l_i} - O_{u,l_j} > 0\end{aligned} \tag{3}$$

We model personalized sequential transition by integrating two kinds of metrics for a candidate POI l. Given current location l_c of user u in sequential transition space, we can use a linear interpolation to weight the two metrics.

$$O_{u,l_c,l} = \alpha O^U_{u,l} + (1-\alpha) O^S_{l_c,l} \tag{4}$$

where $\alpha \in [0, 1]$ controls the weight of different kinds of spaces.

5 Social Personalized Ranking Embedding (SPRE)

In this section, we will present the social embedding model in Sect. 5.1. And in Sect. 5.2, we propose our model: Social Personalized Ranking Embedding (SPRE) model, which jointly incorporates personalized embedding and social embedding. In the end, we will be detailed introduce our model parameter learning.

5.1 Social Embedding Model

Based on this fundamental assumption, the goal of social embedding is to describe relations between users, regardless whether a link between two users is observed or not. To achieve the goal, formally, given the user-user graph $G = (U, E)$, where U is the set of users and E is the set of edges between users. Each edge $e_{i,j}$ in the graph has a source node (u_i) and a target node (u_j). In this section, we propose a novel solution as a variant of LINE [18] to combine both first-order and second-order proximities in a unified framework for depicting the social relations.

The first-order proximity refers to the local pairwise proximity between the vertices in the network. Thus, we define the joint probabilities of any pair of nodes as the models of the first-order proximity.

$$p_1(u_i, u_j) = \frac{1}{1 + exp(-q_i^T \cdot q_j)} \tag{5}$$

where q_i is the embedding vector of vertex u_i, and q_j is the embedding vector of vertex u_j. Equation 5 defines a distribution $p(\cdot, \cdot)$ over the space $U \times U$ and its empirical probability, which can be defined as $\hat{p}(i, j) = \frac{w_{ij}}{W}$, where $W = \Sigma_{(i,j) \in E}$. The way to preserve the first-order proximity is to minimize the following objective function.

$$O_1 = d(\hat{p_1}(\cdot|\cdot), p_1(\cdot|\cdot)) \tag{6}$$

where $d(\cdot, \cdot)$ is the distance between two distributions. By omitting some constants and replacing $d(\cdot, \cdot)$ with KL-divergence, we can have:

$$O_1 = -\sum_{(i,j) \in E} w_{ij} log\ p_1(U_i|U_j) \tag{7}$$

We can present each vertex in the K-dimensional space by finding $\{q_i\}_{1...|U|}$ that minimizes Eq. 7.

In the second-order proximity, we suppose similar context nodes tend to have similar meanings. This supposition leads to a more reliable way to measure the relations between users, which could solve the social link sparsity well. Based on the above assumptions, we define the conditional probability of vertex u_j generates vertex u_i as follows.

$$p_2(u_j|u_i) = \frac{exp(q_j^T \cdot q_i)}{\sum_{k=1}^{|v|} exp(q_k^T \cdot q_i)} \tag{8}$$

where q_i and q_j are the embedding vector of vertex U_i and U_j, Respectively. Equation 8 defines a conditional distribution $p(\cdot|u_i)$ over all the vertices.

We make the conditional distribution $p(\cdot|u_i)$ close to its empirical distribution $\hat{p}(\cdot|u_i)$ for preserving the weight w_{ij} on edge e_{ij}. The empirical distribution can be defined as $\hat{p}(u_j|u_i) = \frac{w_{ij}}{deg_i}$. Then, we minimize the following objective function.

$$O_2 = \sum_{i \in U} \lambda_i d(\hat{p_2}(\cdot|u_i), p_2(\cdot|u_i)) \tag{9}$$

where $d(\cdot,\cdot)$ is the distance between two distributions, and λ_i is the prestige of vertex u_i in the network, which can be measured by the degree $deg_i = \sum_j w_{ij}$. Omitting some constants, the objective function Eq. 9 can be calculated by replacing $d(\cdot,\cdot)$ with KL-divergence as follows.

$$O_2 = -\sum_{(i,j) \in E} w_{ij} log\ p_2(\cdot|u_i) \tag{10}$$

By learning $\{u_i\}_{i=1...|U|}$ to minimize Eq. 10, we are able to present every user u_i with a K-dimensional space.

5.2 Social Personalized Ranking Embedding (SPRE) Model

In Personalized embedding model we assume that if the time interval between two adjacent check-ins is larger than the threshold $\triangle T$, we just consider the user preference. Then we recount the distance metric $O_{u,l_c,l}$ as follows.

$$O_P = O_{u,l_c,l} = \begin{cases} O^U_{u,l} & \text{if } \triangle(l, l_c) > \triangle T, \\ \alpha O^U_{u,l} + (1-\alpha) O^S_{l_c,l} & \text{otherwise.} \end{cases} \tag{11}$$

where $\triangle(l, l_c)$ is the time difference of the successive POIs (l and l_c).

And in social model we linearly combine the first-order and second-order proximities together to preserve both proximities with interest propagation for embedding the social networks.

$$O_S = \beta O_1 + (1-\beta) O_2 \tag{12}$$

where $\beta \in [0, 1]$ is the strength weight; O_1 and O_2 are the first-order objective and second-order objective respectively. According to Eq. 12, we can obtain a better result to represent the distance between users.

In the above two embedding model, we have a detailed description of the personalized embedding and the social embedding. In this section, we normalize O_S and O_P by using Min-Max scaling to avoid the impacts of excessive value, which could lead to inaccurate results.

Given a current location l^c of user u and the user social relation links, we define the distance metric O as follows.

$$O = \mu O_S \cdot O_P + (1-\mu) O_P \tag{13}$$

where $\mu \in [0, 1]$ is the coefficient to control the proportion of the personalized embedding and social embedding. With the primary assumption in Sect. 4.1, (i.e., the larger the distance, the lower the transition probability is), we can rank the TOP-n next POI recommendation for user u.

5.3 Optimization Learn

By using maximum a posterior (MAP) based Bayesian Personalized Ranking (BPR) [17] approach for personalized embedding, and maximizing a criterion for social embedding, we develop the SPRE Model as follows.

$$\Theta = \underset{\Theta}{\operatorname{argmax}} \prod_{u \in U} \prod_{l^c \in L} \prod_{l_i \in L} \prod_{l_j \in L} \prod_{(i,j) \in E} P(>_{u,l^c} |\Theta) P(G|\Theta) P(\Theta) \tag{14}$$

where the major parameters of personalized embedding are $\Theta = \{X_L^S, X_L^U, X_U^U, X_U^G\}$ and $P(>_{u,l^c} |\Theta)$. The social embedding is denoted $P(G|\Theta)$.

By using the logistic function to calculate the above two probabilities, the two probabilities can be further estimated as follows.

$$P(>_{u,l^c} |\Theta) = \sigma(O_{u,l^c,l_j} - O_{u,l^c,l_i}) \tag{15}$$

$$P(G|\Theta) = \sigma(O_S) \tag{16}$$

Then, we have the final objective function in Eq. 17 with Gaussian priors on the parameters Θ. ω is a regularization term parameter.

$$\begin{aligned} \Theta &= \underset{\Theta}{\operatorname{argmax}} \ln \prod_{u \in U} \prod_{l^c \in L} \prod_{l_i \in L} \prod_{l_j \in L} \prod_{(i,j) \in E} \sigma(O_{u,l^c,l_j} - O_{u,l^c,l_i}) \sigma(O_S) P(\Theta) \\ &= \underset{\Theta}{\operatorname{argmax}} \sum_{u \in U} \sum_{l^c \in L} \sum_{l_i \in L} \sum_{l_j \in L} \sum_{(i,j) \in E} (\ln(\sigma(O_{u,l^c,l_j} - O_{u,l^c,l_i})) \\ &\quad + \ln(\sigma(O_S)) - \omega \|\Theta\|^2 \end{aligned} \tag{17}$$

We adopt a widely used stochastic gradient descent (SGD) algorithm to optimize the objective function in Eq. 18. Based on the previous check-in records and the social graph, we can construct the training tuples. And the updating procedure is defined as follows, where η is the learning rate.

$$\Theta \leftarrow \Theta + \eta \frac{\partial}{\partial \Theta} (\ln(\sigma(O_{u,l^c,l_j} - O_{u,l^c,l_i})) + \ln(\sigma(O_S)) - \omega \|\Theta\|^2) \tag{18}$$

6 Experiments

6.1 Experimental Settings

Datasets. In the experiments, we use a publicly available real-world large-scale LBSNs dataset Foursquare to evaluate our proposed SPRE model. The statistics of the dataset is shown in Table 2. The whole dataset covers 483,813 check-in histories and 121,142 POIs in the local scope. There are 4,163 users in this dataset, who live in the California, USA. There are 32,512 friendship links, and the average number of friends per user is 6.7.

Table 2. Description of our dataset Foursquare

Statistics	Counts
Number of users	4,163
Number of POIs	121,142
Number of the whole check-ins	483,813
Friendship links	32,512
Average friends per user	6.7

Baselines. We compare our SPRE model with the following three methods.

- **SocialMF:** This system combines both a user-item matrix and positive links for recommendation [10], which is a special case of the proposed framework with only positive links. It utilizes the user-item matrix and a user-user matrix.
- **MESocial:** This method joints the user preference embedding and the social embedding together as a baseline. It does not include the POI sequential transition, and is like traditional POI recommendation. However, it is an embedded method.
- **PRME:** PRME [5] is a personalized ranking metric embedding algorithm by integrating the sequential transition of POIs and user's preference. It maps the POI-POI and the POI-user to two different spaces. One is the sequential transition space, and the other is the user preferences space. It also exploits the metric embedding method for the next POI recommendation.

Evaluation Metrics. The performance of our SPRE model and the three comparison methods is measured in terms of two well known measure metrics, namely Recall@N and Precision@N, which are defined as follows.

$$Recall@N = \frac{\#hit@N}{N_v} \tag{19}$$

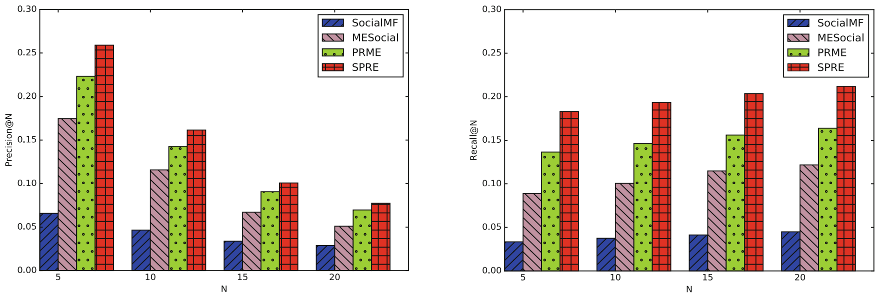
$$Prescision@N = \frac{\#hit@N}{N} \tag{20}$$

where $\#hit@N$ denotes the number of POIs that user u visited after the time t in Top-n recommended, and N_v is the total number of POIs that user u have visited after the time t.

6.2 Experimental Results

The experimental results of our SPRE model and the three baselines are shown in Fig. 3. All the methods are running with well-tuned parameters for their effectiveness. Note that we usually ignore a large N in top-n recommendation tasks. We only show the performance for $N = \{5, 10, 20, 30\}$ respectively. In our proposed methods, we set $k = 80, \triangle T = 6\,h$. Besides, we set personalized embedding component weight α as 0.2, and the social embedding component weight β as 0.6. The learning rate η is set as 0.0025, and the SPRE component weight μ is set as 0.3.

In accordance with the time each user visits, we use the first ten months of data as a training set when comparing with the other three baselines. From the results, as shown in Fig. 3, we observe that our method generally outperforms two baselines. SocialMF has a lower precision and recall. This indicates that the traditional MF method is not suitable for the next POI recommendation since it does not make use of sequential information and can't solve the sparsity issue of both POI check-ins and social links. By comparing SocialMF and MEsocial in Fig. 3, we can find out the metric embedding technology can effectively solve the problem of data sparseness, both in POI check-ins and social links. Sequential transition has an important effect in next POI recommendation by observing the differences between ME-social and SPRE. Figure 3 also show that our proposed SPRE model obviously outperforms PRME. This is because our proposed SPRE model joints the social influence to the model. This shows that the social influence indeed improves the accuracy of next POI recommendation.

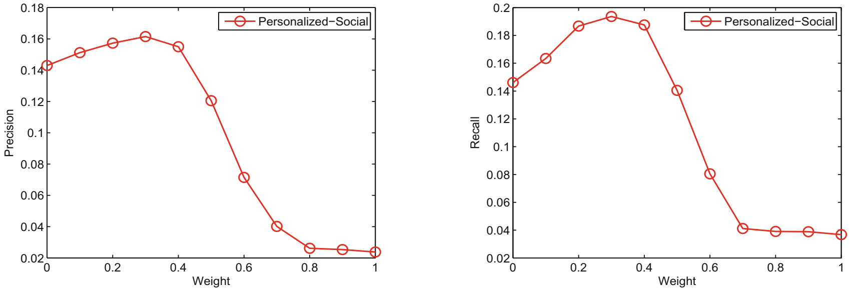


(a) Prescision@N (b) Recall@N

Fig. 3. The result of methods.

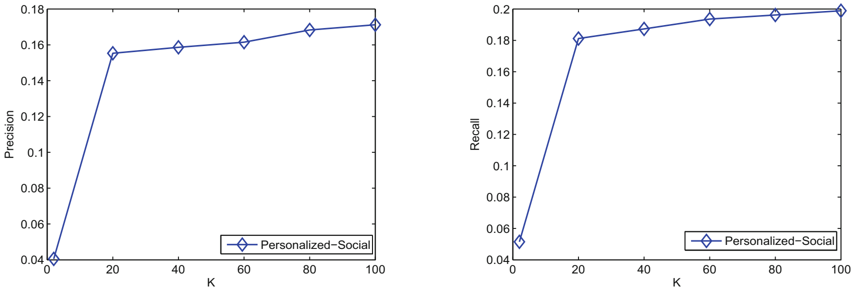
6.3 Impact of Different Parameters

Impact of the Component Weight μ. Figure 4 shows the impact of the component weight μ. The performance at $\mu = 0$ (only personalized embedding) is much better than $\mu = 1$ (only social embedding). That is, user preference is more important than social influence in the next POI recommendation. The best results are obtained at $\mu = 0.3$. Hence, we set the $\mu = 0.3$ in our following experiments. We also notice that there is a sharp drop when we change the weight μ from 0.3 to 0.8. This shows that too much social dimension factors can degrade the performance of the next POI recommendation.



(a) Prescision@10 (b) Recall@10

Fig. 4. Effect of component weight μ.



(a) Prescision@10 (b) Recall@10

Fig. 5. Effect of the number of dimension K.

Impact of Metric Dimensions K. Figure 5 shows the experimental results under different metric dimensions K (including the personalized embedding and social embedding metric dimensions). When $K > 20$, the recommendation quality growth becomes smooth. The performance increases with the increment of K.

This is because a high dimension can reflect the potential measurement better. Figure 5 also shows that it is less helpful to improve the performance by increasing K, when the number of dimensions is larger than 80. Empirically, we chose $K = 80$ in our experiments because we simultaneously consider both the model quality and the running time.

7 Conclusion

In this paper, we studied the next POI recommendation problem. We proposed a Social Personalized Ranking Embedding (SPRE) model to joint personalized embedding and social embedding together, which can learn the user preference and social relations in a low-dimension latent space. As far as we know, we are the first to integrate personalized embedding and social embedding in the next POI recommendation. Experimental results on the real-world LBSNs data Foursquare validated the performance of our proposed SPRE method. Our extensive experimental results also show that our method outperforms baselines regarding Top-n recommendation. In the future, we will integrate other dimensions into the model for next POI recommendation, such as semantic information, context information, and temporal cyclic information.

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