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Exploiting Multi-Sources Information for Location Recommendation

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Abstract

In location-based social networks (LBSNs), user preference, social influence and geographical influence are three major factors that affect users' check-in behaviors. However, current studies tend to ignore the influence of the features from point-of-interest (POIs) to similar user groups. In this paper, we proposed a new approach named Base Item Attribute - Weighted Cosine Similarity (BIA-WCOS) to model social relationship of users, which consider the influence of location's popularity and check-in frequency on user similarity. The proposed Geographical - Base Location Attribute Social Relationship (G-BLAS) framework is to exploit personalized social and geographical influences on location recommendation. We conduct a comprehensive performance evaluation of our approach using two real datasets collected from Foursquare and Gowalla. Experimental results show the effectiveness and advantages of our proposed approach.

Keywords: Matrix Factorization; Geographical Influence; Item Attribute; User Similarity; Location Recommendation;

Introduction

With the advancement of mobile devices and the development of the GPS technique, we have witnessed the increasing popularity of location-based social networks (LBSNs) in recent years. In an LBSN, users can establish social links with their friends and share their experiences of visiting some locations they feel interesting, also known as POIs via "check-in", which can reflect their preferences. Further, users can share their feeling via commenting on the locations they visit. For example, Foursquare, one of the most popular LBSNs that have over 50 million users, 105 million places and 12 billion check-ins. Facing the huge amount of data, the personalized location recommendation systems can help users to explore new locations that they are interested in.

The most widely used approach to model user preference for location recommendation is collaborative filtering (CF) technique, where user's check-in data is modeled as user-location matrix with each entry representing the frequency of a user visiting a location. The personalized location recommendation system aims at predicting a user's preference on unvisited locations according to user check-in data and other contextual information, such as geographical influences [1-6], social relationship [7-10] and reviews [11, 12]. The features of POIs also have a certain influence on the social relationship. For example, compared to a popular location, users' visiting the unpopular locations often reflect the similarities between them. How to model these features more effectively becomes a research focus in our paper.

In this paper, a novel approach is proposed for determining weighted user-similarity, in which we explore the influence of POI's popularity and visit-frequency on social relationship according to user's historical check-in data, and then we propose a location recommendation framework by fusing multiple contextual information such as user preference, social influence, the geographical influence to social relationship and the personalized geographical influence of locations. The results show that the approach we proposed has significantly improved the recommendation accuracy.

The remaining section of this paper is structured as follows. Section 2 highlights related work and background introduction. Section 3 presents in detail our proposed approach. In Section 4, we reported and analyzed the experimental results. Finally, some concluding remarks are drawn in Section 5.

Related Work

In this section, we reviewed the related work and background knowledge of our study. These are organized in three parts, i.e. geographical recommendation, social recommendation and other contextual recommendation, as detailed below.

Geographical recommendation

Geographical information is the most important factor to POIs. Characterizing user's preference based on geographical features of locations is a widely used method in the POI recommendation system. [1] Considered that it is important to take implicit feedback characteristics of user mobility data into account as well as the location's spatial information, thus that a scalable and flexible framework GeoMF++ is proposed to recommend locations. [2, 3] found that the geographical influence of visiting the POI should be personalized for users, thus it is unreasonable to use power-law distribution to model user's check-in behavior. In order to prevent the fitting error caused by specific distributions, Zhang et al. proposed to use kernel density estimation method to estimate the distance distribution between any two POIs and to measure the geographical performance of the user check-in data.

In addition to the above-mentioned approach, there are also other methods proposed, such as the GeoMF model proposed in [13] to fuse geographical location information into weighted matrix factorization, and a rank-geoFM model proposed in [14] to sort the POIs based on pair wise sorting. These models can effectively model the characteristics of geographical information and can improve the accuracy of location recommendation.

Social recommendation

In addition to geographical influence, social network information also plays an important role in the location-based recommendation system. In real life, the user's visit to POI is largely influenced by the friends around him. For example, friends may go shopping together, thus we can assume that there are similar preferences among friends, and incorporating social network information into recommendation system has a corresponding gain effect.

Modeled and analyzed [7] the trajectory of user check-in location based on the HGSM (Hierarchical-graph-based Similarity Measurement) hierarchical similarity algorithm, which measured the similarity of user's behavior and ranked the highest ranked users as close neighbors recommended for the target user. [8] Used the two-hop random walk algorithm to exploit explicit social relationships and implicit social relationships between users based on the traditional matrix factorization model.

Other contextual information

Other context information of the user's visit to POI may also has a corresponding influence on the recommendation effect, such as the time of user's visit and the feature of picture published by the previous visitors. [15] Used the topic model (LDA) to exploit the topic attributes of POI based on its tag and to determine the user's preference according to these attributes. [16] Expanded the state-of-the art Rank-GeoFM POI recommender algorithm[[14] to include some features of weather-related. [17] Proposed a location-based recommendation algorithm that fuses temporal information. The algorithm models the user's check-in behavior as a fourth-order tensor containing time periods, and combines the geographical influence to recommend locations. [18] Believed that it is beneficial to analyze user preference by the pictures that they shared. Therefore, they proposed CNN based technique to extract feature vectors of pictures based on matrix factorization to improve the recommending accuracy.

In summary, the existing approaches have achieved certain results on predicting a user's preference to a location, but there are still many problems since the characteristics of locations cannot be fully utilized. In this paper, we explored the influence of the location's characteristics to social relationship. Further, we integrate the user preference, geographical influence and the social friendship of users into one framework for unified location recommendation.

The proposed approach

In this section, we first introduce the Matrix Factorization technique with different feedback data, and then introduce the model of geographical influence and social influence that we used in this paper. Finally, we present the unified framework with all these approaches integrated together.

The model of Matrix Factorization (MF)

There are currently two types of user-history-behavior data for recommendation systems, i.e. explicit feedback data and implicit feedback data. The explicit feedback can directly represent the user's preferences (such as the rating scores), while implicit feedback means that the feedback information does not reflect the user's preference directly (such as click and browsing). Here, we first introduce the matrix factorization that is suitable for explicit feedback data [19], and then introduce the matrix factorization that is suitable for implicit feedback data [20, 21] as used in this paper.

Collaborative filtering (CF) is one of the most widely used approaches in location recommendation, which describes user preferences on locations [22, 23]. Given m users ($u \in u_1, u_2, \cdots u_m$) and n locations ($l \in l_1, l_2, \cdots l_n$), the user's check-in data are modeled as a user-location matrix R∈Rmxn by CF, where each entry of R represents the frequency of a user visiting a location. CF aims to map the users and locations into a space with dimension k << min (m, n), and estimate users' preferences on locations by the dot product of them, which is shown below:

$$\hat{R} = U_i L_j^T \qquad (1)$$

where $\hat{R}$ denotes users' preferences on locations, U_i and L_j denote the ith row in U and the jth row in *L* respectively, $U \in R^{mxm}$ denotes the user matrix, $L \in R^{nxn}$ denotes the location matrix. In order to reduce the generalization error of the objective function, U and L can be used as the regularization terms. Thus, the function of minimize weighted square error loss is:

$$P=\min_{U,L} \frac{1}{2} \| W.(R-\hat{R}) \|_F^2 + \frac{\mu_1}{2} \| U \|_F^2 + \frac{\mu_2}{2} \| L \|_F^2 \quad (2)$$

where $W \in R^{mxn}$ is a weighting matrix that represents a confidence of R_{ij}. If the value of R_{ij} is larger than 0, we set W_{ij} to 1, otherwise, we set W_{ij} to 0. $\|\cdot\|_F^2$ Denotes the square of a matrix's Frobenius norm. μ_1 and μ_2 are regularization parameters.

On the other hand, when we try to estimate user preference according to the implicit feedback data, the user-location matrix will be modeled as a binary matrix $C \in R^{mxn}$. If u_i has checked-in location l_j at least once, the C_{ij} is set to 1; otherwise it is set to 0. Thus the function of the minimized weighted square error loss is given as follows:

$$P=\min_{U,L} \frac{1}{2} \| W.(C-\hat{R}) \|_F^2 + \frac{\mu_1}{2} \| U \|_F^2 + \frac{\mu_2}{2} \| L \|_F^2 \quad (3)$$

where the W_{ij} is set as:

$$W_{ij} = \begin{cases} \eta R_{ij} + 1, & R_{ij} > 0 \\ 1, & otherwise \end{cases} \quad (4)$$

The constant η denotes the rate of increase, in this paper we set η at 20.

Geographical influence

As aforementioned, MF can effectively estimate user preference and the relations associated with almost locations by mapping the check-in data into user-location rating matrix. However, the geographical influence plays an important role in location recommendation.

In our lives, it can be discovered that users would like to visit the locations that are close to each other in geography. For example, people usually visit nearby locations such as restaurants or shopping malls after watching the movies. Therefore, we consider using geographical neighborhood characteristic on locations to improve the recommendation accuracy. In this paper we define the user's preferences by fusing the geographical neighborhood characteristic [5] by:

$$\min_{U,L} \frac{1}{2}\|W.(C-UL^T G)\|_F^2 + \frac{\mu_1}{2}\|U\|_F^2 + \frac{\mu_2}{2}\|L\|_F^2 \quad (5)$$

where G=αH+ (1-α) S^T, H∈$R^{n\times n}$ is an identity matrix. $S \in R^{n\times n}$ for which $S_{jk} = Sim(l_j,l_k)/Z(l_j)$, and α∈[0,1] is a weighting parameter used to control the influence of the neighborhood locations; $D(l_j)$ is a set that represents the neighboring locations of l_j. $Sim(l_j,l_k)$ refers to the weight of geographical influence of the location l_k on l_j. Z(l_j) is a normalizing factor, which is defined as Z(l_j)= $\sum_{lk\in D(lj)} sim(l_j,l_k)$ where $sim(l_j,l_k)$ is a Gaussian function as follows:

$$\mathrm{Sim}\left(l_j,l_k\right) = e^{-\frac{\|x_j-x_k\|^2}{\sigma^2}} \quad \forall l_k \in D(l_j) \quad (6)$$

where x_j and x_k represent the longitude and latitude of the location l_j and l_k respectively. For the maximum distance between the two locations, we set a threshold as 10000, and l_k will not be considered if the distance is exceeded that threshold.

Social relationship

In our reality life, it can be found that people with similar interests are more likely to form relationships, such as friendships and emotional relationship. People often go to restaurants or other places recommended by friends, which reflects that the users' check-in behaviors are greatly affected by social relationship. Based on these observations, the social relationship has been modeled to improve the accuracy of location recommendation.

In this paper we believe that the social relationships between users are mutual, as shown in Figure 1. The cosine similarity [24, 25] is used here to measure the similarity between users. Given the individual user u_i and u_v, let *L* be a set of locations, and l_k denotes a location belonging to the *L*. The definition of the user similarity is defined by:

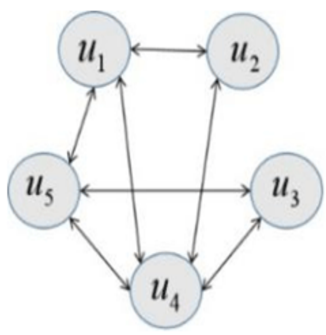


Figure 1: Social network

$$\mathrm{sim}(\mathrm{i},\mathrm{v}) = \frac{\sum_{l_k\in L} S_{ik}S_{vk}}{\sqrt{\sum_{l_k\in L} S_{ik}^2}\sqrt{\sum_{l_k\in L} S_{vk}^2}} \quad (7)$$

where sim(i,v) denotes the similarity between u_i and u_v. S_{ik} and S_{vk} indicate whether users u_i and u_v are checked in at location l_k or not. We set S_{ik} to one if the user u_i has checked-in at location l_k at least once, otherwise, we set S_{ik} to zero. The same processes are used for S_{vk}.

Generally, traditional similarity calculations suggest that each item has the same weights to influence each other, while in reality we discover that the higher frequency that users visit the same location, the greater impact on user similarity between them. For example, for location l_k, let users A, B and C visit it for 5, 2 and 6 times, respectively. Based on the theory, the higher frequency of visits represents the greater the user preference. Compared to user B, the user similarity between user A and user C should be larger because they have a higher degree of common visits [26]. On the other hand, we think that the factors that users visit the location can be divided into subjective factors and objective factors. The subjective factor is the user's own preference for the type of location, and the objective factor is the popularity of the location. For the location assuming that it has a high popularity, the number of users who visit the location will continue to increase, so the user's access to the location is not highly relevant to the type of itself. Then when the location l_k has been visited by many people, it is difficult to find a project similar to it. Therefore, the higher the popularity of the location that users access together, the weaker the influence on the similarity between users should be, and the corresponding weight should also be smaller. According to these observations, we proposed a novel approach to estimate the user similarity base on the cosine similarity as follow:

$$\lambda_k = \left(\frac{r_{ik}+r_{vk}}{2}\right)\ln\left|\frac{m}{I_k}\right| \quad (8)$$

where r_{ik} and r_{vk} indicate the frequency of user u_i and u_v visiting the location l_k respectively. In addition, l_k denotes the number of people who checked in at the location l_k, m denotes the total number of users. In this paper we use the ratio to denote the influence of the location popularity. We combined the two location characteristics as weighting parameter λ_k and fused it into the user similarity, which is modeled as follows:

$$sim^{new}(\mathrm{i},\mathrm{v}) = \frac{\sum_{l_k \in L} \lambda_k S_{ik} S_{vk}}{\sqrt{\sum_{l_k \in L} \lambda_k S_{ik}^2} \sqrt{\sum_{l_k \in L} \lambda_k S_{vk}^2}} \qquad (9)$$

Unified framework: G-BLAS

In this section, we introduce the integrated model of our approach. According to the Eq.(5) and Eq.(9), the proposed framework to combined three factors is shown as formula (10) below:

$$\mathrm{P} = \min_{U,L} \frac{1}{2} \| W.(C - UL^T G) \|_F^2 + \frac{\mu_1}{2} \| U \|_F^2 + \frac{\mu_2}{2} \| L \|_F^2$$
$$+ \frac{\mu_3}{2} \sum_{i=1}^{m} \sum_{v \in u} sim^{new}(i,v) \| u_i - u_v \|_F^2 \qquad (10)$$

where μ_1 and μ_2 are the weighting parameters that control the U and L respectively, and μ_3 denotes the weighting parameter that controls the influence of social relationship on recommendation. $\|U\|_F^2$ and $\|L\|_F^2$ are used as regularization terms to prevent over-fitting.

In this paper we used the gradient descent algorithm [15] to obtain the optimal solution of Eq. (10), the partial derivative of U and L is given by:

$$\frac{\partial P}{\partial L} = W.\left(UL^T G - C\right) GU + \mu_2 l_j \qquad (11)$$

$$\frac{\partial P}{\partial U} = W.(UL^T G - C) G^T L + \mu_1 u_i + \mu_3 \sum_{v \in U} sim^{new}(i,v)(u_i - u_v) \qquad (12)$$

Experimental Results and Analysis

In this section we first introduce the dataset, performance metrics and parameter settings that we used in the experiments, followed by detailed comparison of the results and analysis of the performance of each approach.

Dataset Description

The experimental data used in this study are collected from Foursquare and Gowalla , which are the two most popular LBSNs. Foursquare encourages users to share information such as their current locations, which contains 1,196,248 check-ins for 24,941 users to 28,593 POIs. Gowalla is a second check-in website after Foursquare. Users can share information about places, activities, travel routes, etc. among friends on it. It contains 6, 941,890 check-in data for 196,591 users to 950,327 POIs. Each of the check-in data includes userID, locationID, and the coordinate of POI and check-in time. We extracted some data for experimentation and the detailed statistics of the check-in data in the datasets are summarized in Table 1.

The Foursquare dataset for this experiment contains 496,488 check-in data for 13,805 users to 19,587 POIs. The Gowalla dataset contains 161, 553 check-ins for 5, 433 users to 9, 687

Table 1: Statistics of the two datasets

Datasets	No. of users	No. of locations	No. of check-ins	user-location matrix density
Foursquare	13805	19587	496488	1.83×10^{-3}
Gowalla	5433	9687	161553	3.06×10^{-3}

POIs. In our experiment, the data needs to be pre-processed due to the sparseness, we filtered out the users whose check-in times are less than 10 and the locations are visited by less than 10 users. Finally, based on the five-fold cross-validation method, we randomly split each dataset into training set and the testing set and the average of the test results is taken as the experimental result.

Performance Metrics

In this work, we use two widely used metrics (precision and recall) to evaluate the performance of the approach that we proposed. The precision and recall of the top-K location recommendations to a target user are denoted by P@K and R@K respectively. P@K defines the ratio of the discovered locations to the K recommended locations, and R@K defines the ratio of discovered locations to the set of locations that the target user has visited in the testing data. Generally, the higher the precision and recall values are, the better the performance is. P@K and R@K are defined as follows:

$$\text{Precision@K} = \frac{1}{|T|} \sum_{i=1}^{r} \frac{|R(u_i) \cap E(u_i)|}{K} \qquad (13)$$

$$\text{Precision@K} = \frac{1}{|T|} \sum_{i=1}^{r} \frac{|R(u_i) \cap E(u_i)|}{|R(u_i)|} \qquad (14)$$

where u_i denotes a user, $R(u_i)$ denotes the set of locations that the user u_i have visited in the testing data, $E(u_i)$ denotes the set of locations which is recommended to user u_i, T denotes the set of users in the testing data. In particular, users are more inclined to the results of high recommendation rankings; therefore we choose P@5, P@10, R@5, and R@10 as evaluation metrics in our experiments. For the regularization parameters μ_1 and μ_2 we set at 0.03. Furthermore, we set the instance weighting parameter α at 0.4. The weighting parameter that controls the social relationship μ_3 is set at 0.01 by cross-validation.

Benchmarking Algorithms

1) Base Matrix Factorization [27] (BaseMF): This is the based matrix factorization approach designed for explicit feedback datasets, which is used to predict a user's preference by considering the check-in data.

2) Weighting Matrix Factorization [22] (WMF): This is the weight matrix factorization approach designed for implicit feedback datasets. It predicts a user's preference without considering the geographical Influence, social relationship of users and other context information.

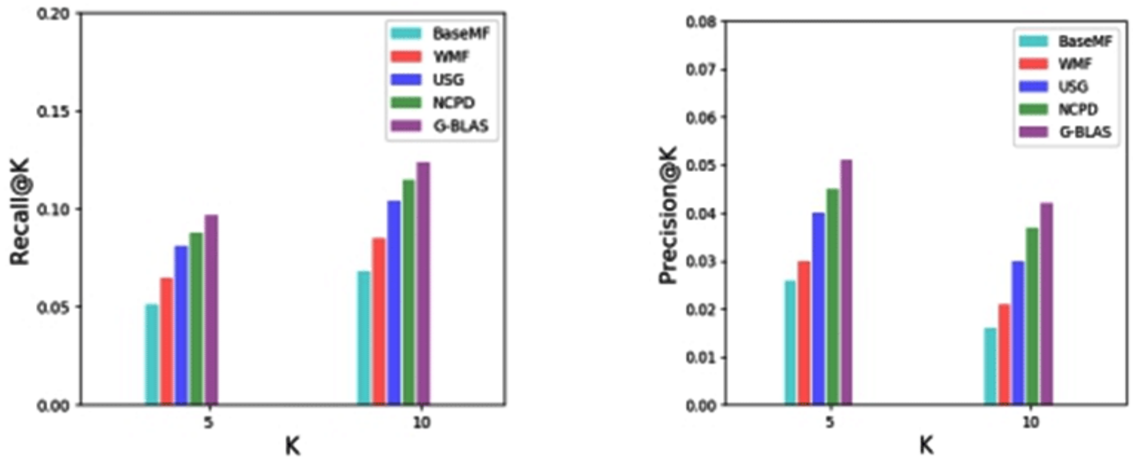
3) The approach in [28] is defined as USG in this paper: This approach is based on the observation that a user visiting a

location follows the power law distribution. A unified location recommendation framework is used to linearly combine the geographical influence and the user's preference.

4) The approach in [29] is defined as NCPD in this paper: This approach classifies the POIs by geographical neighborhood characteristics and fuses the location and popularity of POIs to predict a user's preference based on the Non-negative Matrix Factorization (NMF).

Experimental Results

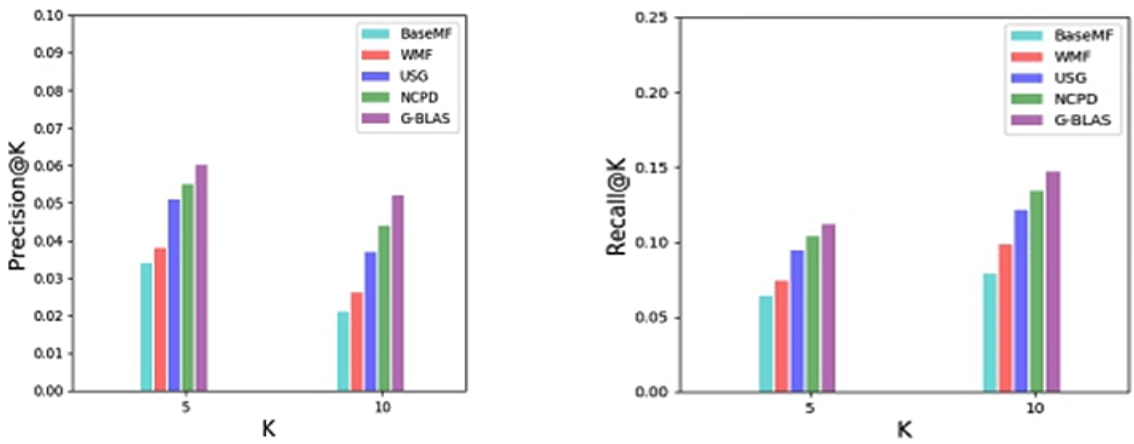
Figure 2 and Figure 3 depict the performance of the recommendation techniques based on the real dataset collected from Foursquare and Gowalla, using precision and recall measurements. Experimental results show that our framework G-BLAS outperforms the baseline matrix factorization model (i.e., BaseMF, WMF), which has not used any other contextual information, especially when compared to the approaches that utilize geographical characteristics or social relationship (i.e., USG, NCPD). The details are demonstrated as follows.



(a) Foursquare (Precision)

(b) Foursquare (Recall)

Figure 2: The performance of the recommendation techniques on Foursquare



(a) Gowalla (Precision)

(b) Gowalla (Recall)

Figure 3: The performance of the recommendation techniques on Gowalla

Figure 2(a) and 2(b) show the performance of a variety of recommendation techniques on the foursquare dataset. Taking P@5 as an example, it can be observed that the performance of WMF model is 19.23% which is higher than that of BaseMF model. This shows that the WMF model can more effectively model the user check-in data by assigning appropriate weights, which improves the recommendation performance. However, both WMF and BaseMF only consider the users' check-in data and the models are relatively simple, so the precision and recall rates of them are lower than other approaches. The USG fuses user preference, geographical influence, and social relationship to predict the users' preference on unvisited location, which outperforms BaseMF and WMF by 53.85% and 29.03% respectively. Similarly, NCPD also considers the user preference information and geographical influence of POIs, but its performance is only higher than the USG model by 15.14%. One possible reason is that USG considers that the power-law distribution is satisfied between the distance and the check-in probability, which is inconsistent with reality. Not all data sets are applicable to a specific distribution, and it also indicates that the influence of the user's social relationship is weaker than the geographical influence. In addition, from the result we can find that our approach always achieves the best result on the evaluation metrics, in terms of P@5, where the average improvements of G-BLAS over BaseMF, WMF, USG and NCPD are 95.15%, 61.52%, 27.51%, 10.87% respectively. It has demonstrated that the proposed G-BLAS can effectively mitigate the data sparsity and significantly improve the recommendation accuracy by fusing user preference and incorporating multiple context information.

Figure 3(a) and 3(b) show the performance of a variety of recommendation techniques on the Gowalla dataset. Because of the lower sparseness of the check-in data, the performance of each approach on the Gowalla dataset is better than that on the foursquare dataset. In general, compared with other approach that we have benchmarked with, the performances of our proposed approach again show significant improvements, which validate the effectiveness of our approach.

Parameter Tuning

In our proposed approach, the parameter α denotes the weight that the influence of geographical neighborhood characteristics to user preference, and the impact of social relationship on location recommendation is controlled by the parameter μ_3. In Figure 4 we tested the effect of different parameter α on recommended performance (setting the number of recommended locations as 5). As seen from the two figures, we have derived interesting findings: (1) our approach achieves the better results when the parameter α is set at 0.4; (2) if we don't consider the influence of geographical neighborhood characteristic, in other words the parameter α is set at 0, the recommendation accuracy will be degraded. It validates the importance of geographical influence in the process of location recommendation.

In Figure 5 we investigate the performance of our approach under different values of μ_3. A lager μ_3 indicates that the social relationship of users is more closely linked to location recommendation. As seen, $\mu_3 = 0.01$ is the most suitable setting in the two datasets. Furthermore, when parameter μ_3 is larger than 1, the fluctuation of performance becomes less obvious.

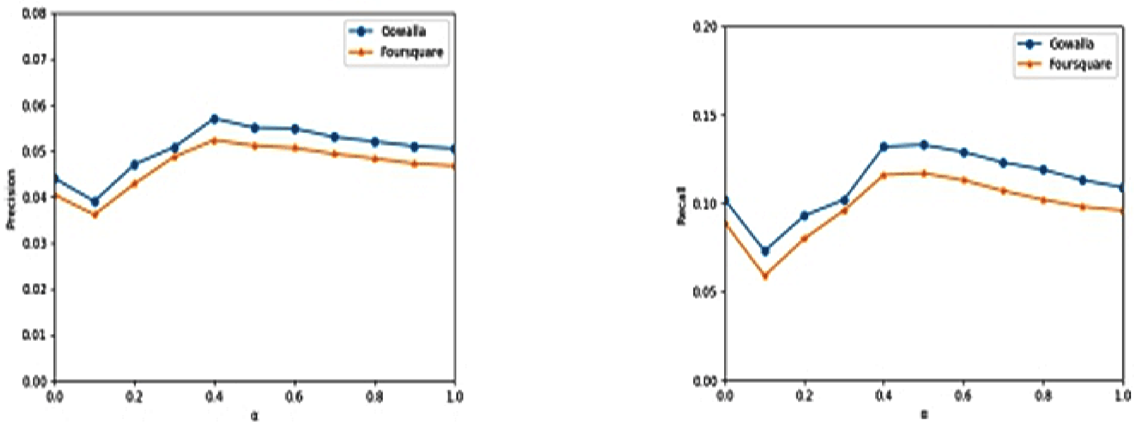


Figure 4: Effects of parameter α on recommendation accuracy (μ_3= 0)

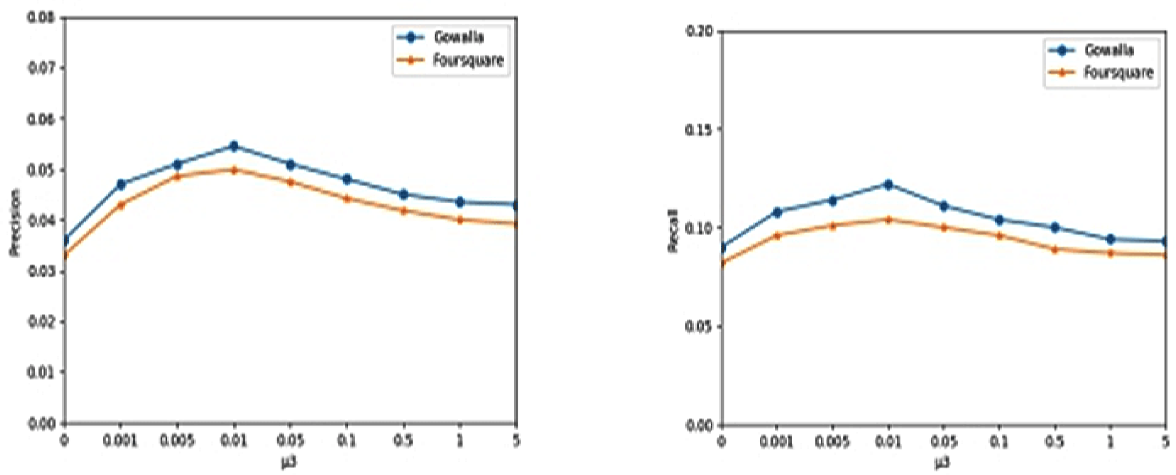


Figure 5: Effects of parameter μ_3 on recommendation accuracy(α= 1)

Table 2: Performance comparison of recommended technologies on Foursquare

	Other model performance improvements compared to BaseMF			
Foursquare (P@5)	WMF	USG	NCPD	G-BLAS
	19.23%	53.85%	76.92%	95.15%
	Other model performance improvements compared to WMF			
Foursquare (P@5)	USG	NCPD		G-BLAS
	29.03%	48.39%		64.52%
	Other model performance improvements compared to USG			
Foursquare (P@5)	NCPD	G-BLAS		
	15.14%	27.51%		
	Other model performance improvements compared to NCPD			
Foursquare (P@5)	G-BLAS			
	10.87%			

Conclusions

In this paper, we have explored the influence of the location characteristic on social relationship and then proposed a novel approach to measure the similarity between users. Furthermore, we proposed a framework to more accurately model user's preferences on location by fusing the geographical neighborhood characteristics and the social relationship of users. From the results, we can see that our approach achieves significantly higher recommendation performance than the state-of-the-art approaches, including Based, WMF, USG and NCPD.

There are two directions for future investigation:(1) how to fuse the influence of temporal information on user's preference to further extend our framework, and (2) how to capture more relationship between locations to improve the recommendation accuracy.

Author Contributions

Conceptualization and Methodology, HH.Y, WG.W; software, HH.Y. and GY.X; writing–original draft preparation, HH.Y; writing–review and editing, HM.Z and HH.Y.; supervision, WG.W.

Conflicts of Interest

The authors declare no conflict of interest.

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