FGCRec: Fine-Grained Geographical Characteristics Modeling for Point-of-Interest Recommendation

Yijun Su[1,3], Xiang Li[1,2,3], Baoping Liu[1,3], Daren Zha[3 *], Ji Xiang[3], Wei Tang[1,2,3], Neng Gao[2,3]
[1]School of Cyber Security, University of Chinese Academy of Sciences
[2]State Key Laboratory of Information Security, Chinese Academy of Sciences
[3]Institute of Information Engineering, Chinese Academy of Sciences
Beijing, China
{suyijun, lixiang9015, liubaoping, zhadaren, xiangji, tangwei, gaoneng } @iie.ac.cn

***Abstract*—With the popularity of location-based social networks (LBSNs), Point-of-Interest (POI) recommendation has become an essential location-based service to help people explore novel locations. Although the massive check-in data bring a good opportunity, there are still many challenges in building personalized POI recommender systems based on geographical information. First, current coarse-grained geographical models provide considerably limited improvements on POI recommendations and fail to capture the overall impact of fine-grained geographical characteristics in LBSNs. Second, previous methods such as matrix factorization always give equal weight to each positive example and may not distinguish between their different contributions in learning the objective function. To cope with these challenges, we develop a fine-grained POI recommendation framework that makes full use of the geographical characteristics from both users' and locations' perspectives. For capturing the fine-grained geographical influence, we present a unified probability distribution model based on four key geographical characteristics. For mining more contribution information from positive examples, we assign a higher weight to highlight the contribution of a higher check-in frequency by employing a logistic matrix factorization. Finally, experimental results on two real-world datasets demonstrate the effectiveness and superiority of the proposed method.**

***Index Terms*—POI Recommendation; Geographical Characteristics; Location-based Social Network**

I. Introduction

With the popularity of smart mobile devices and advances in location acquisition and wireless communication technologies, location-based social networks (LBSNs), which bridge the gap between the physical world and online social networking services, have become prevalent. Online LBSNs such as Foursquare and Yelp are attracting millions of users to use and share information. On these platforms, users can post their physical locations and share experiences of visiting Point-of-Interests (POIs), e.g., restaurants, shopping malls, and theaters via check-in behaviors. Fig. 1 gives an overview of a typical LBSN. A tremendous volume of check-in data provide an unprecedented opportunity to understand human mobility patterns [1], benefiting a series of location-based services such as urban computing and POI recommendation [2]. In this paper, we aim to provide a systematic POI recommendation service with the help of large-scale individual trajectory data in LBSNs.

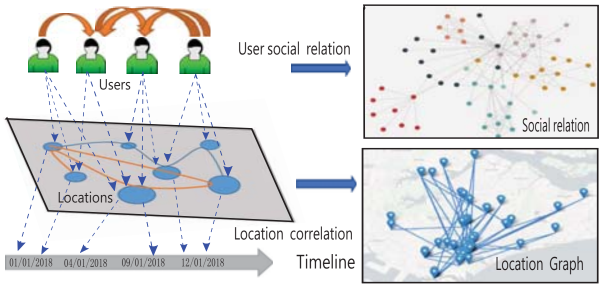

Fig. 1. A location-based social network. In the LBSN, users can establish social relationships with others to share their experiences of visiting some POIs through making check-ins at these POIs via their mobile devices.

Currently, various types of contextual information provide a good chance for improving the quality of POI recommendations. A series of studies have been focused on incorporating geographical [3], social [4] and temporal [5] information into the recommendation process. Among these contextual information, geographical characteristics of users and POIs (e.g., *activity ranges of users* and *geographical coordinates of POIs*) play a prominent role. In particular, several representative models, such as power-law distribution [6], multi-center Gaussian distribution [7], kernel density estimation [8], and graph embedding methods [3], [9], [10], are proposed to capture the geographical influence in POI recommendations. Building personalized POI recommendations based on geographical influence is a very challenging problem due to two important reasons. First, geographical information contains two POI attributes from a location perspective: *geographical coordinates of POIs* and *the distance among POIs*. It also includes two user attributes from a user perspective: *activity ranges of users* and *the distance between user centers (e.g., user home and work place) and POIs*. However, these methods utilizing geographical information [3], [6]–[10] rarely consider the impact of such fine-grained geographical characteristics from both users' and locations' perspectives. Moreover, these methods model the above two distance distributions separately and may not catch the interaction of the two types of distance and activity ranges of users. Second, user-generated check-in data in LBSNs is indeed a kind of implicit feedback

* Corresponding author.

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data, which means only positive observations are available in practice. Most traditional recommendation methods such as Matrix Factorization (MF) [7], [11]–[13] give equal weight to each positive example and may not distinguish between their different contributions in learning the objective function. However, in POI recommendations, a higher check-in frequency corresponds to a larger confidence of preference for the POI.

To address the aforementioned challenges, we propose a fine-grained POI recommendation framework which makes full use of the geographical characteristics from both users' and locations' perspectives. The framework is composed of two modules: **geographical module** and **check-in module**. They are used to capture the geographical influence and explore check-in frequency contributions, respectively. For capturing the geographical influence, we estimate a unified probability distribution on geographical characteristics, i.e., *geographical coordinates of POIs, the distance among POIs, activity ranges of users* and *the distance between user centers and POIs*. For mining more contribution information from positive examples, we assign a higher weight to highlight the contribution of a higher check-in frequency. More specifically, we employ a logistic matrix factorization (an effective probabilistic model for implicit feedback data) [14] to model the probability of the event that users have chosen to interact with POIs by a parameterized logistic function. Next, we integrate the two modules into a unified POI recommendation framework to enhance the performance of recommendations. Finally, experimental results on two real-world datasets demonstrate that a significant improvement of our proposed method in terms of various metrics, compared with the state-of-the-art methods.

In summary, the main contributions are listed as follows:

- We propose a fine-grained POI recommendation framework based on geographical characteristics, which captures the geographical influence from both users' and locations' perspectives and explores check-in frequency contributions.
- To model the fine-grained geographical influence, we present a unified probability distribution model based on four key geographical characteristics.
- To mine the frequency contribution, we employ a logistic matrix factorization to model the probability of the event that users interact with POIs by assigning a higher weight to a larger check-in frequency.
- To evaluate our POI recommendation framework, we conduct it on two large-scale real-world datasets and the results show that our framework works efficiently.

The rest of this paper is organized as follows. Section II presents the related work. Section III formalizes our research problem and presents the proposed model in details. Section IV reports the experimental results. We finally conclude this study in Section V.

II. Related Work

POI recommendation as an important location-based service in LBSNs has been drawn great research attention from both academia and industry in recent years. In order to enhance the performance of POI recommendation, advanced techniques are leveraged to capture more influences, including geographical, social and temporal influences [15]. Among these, geographical influence (e.g., distances among POIs) is a basic and indispensable. Many previous studies [2], [3], [6], [7], [9], [16] learned user preference for POI recommendation using geographical information. For example, the distance distribution among POIs and the distance distribution between user centers and POIs are commonly used to capture geographical influence [6]–[8]. Besides, other researchers employed graph embedding techniques such as bipartite graph learning [10] and neural networks [16], [17] to get location embeddings in a low-dimension vector space. Unfortunately, these methods utilizing geographical information rarely consider the impact of such fine-grained geographical characteristics from both users' and locations' perspectives. Moreover, these methods [6]–[8] model the above two distance distributions separately and may not catch the interaction of the two types of distance and activity ranges of users.

Also, some studies [6], [11] have applied traditional recommendation methods to POI recommendation. These techniques can be grouped into two categories, namely memory-based and matrix factorization. Memory-based method [6] mainly found similar users or items to the target user or item based on their check-in records by using a similarity measure, such as Cosine similarity or Pearson correlation. Matrix factorization methods [7], [11], [13] learned users' and POIs' latent factors that represent inherent features of users and locations. However, these methods always give the equal weight to each positive example and may not distinguish between their different contributions in learning the objective function.

In this paper, comparing our work with these existing ones, there are many differences. First, we estimate a unified probability distribution using such fine-grained geographical characteristics, including two POI attributes from a location perspective and two user attributes from a user perspective. Second, the geographical module not only captures the above two distance distributions simultaneously but also catch the interaction of the two types of distance and activity ranges of users. Finally, we mine more useful information from positive examples by placing a higher weight to highlight the contribution of a larger check-in frequency.

III. Proposed Model

A. Problem Definition

Let $\mathcal{U} = \{u_1, u_2, \ldots, u_n\}$ be a set of users, where each user u checked in some POIs $\mathcal{L}_u$. For each user u, there exists some check-in centers $\mathcal{M}_u$ such as the user's home and work place. Let $\mathcal{L} = \{l_1, l_2, \ldots, l_m\}$ be a set of POIs, where each POI l has a geographical coordinate $l = \{lon, lat\}$ represented by longitude and latitude. We denote the user-POI check-in matrix by $\mathcal{C} \in \mathbb{R}^{m \times n}$, in which each entry c_{ul} represents the check-in frequency of user u on POI l.

Given user-POI check-in matrix $\mathcal{C}$, the geographical coordinates of POIs, and a user's check-in centers $\mathcal{M}_u$, the task of POI recommendation is to predict the preference score $r_{u,l}$ for the user u to an unvisited POI l, and then return the top-N POIs with the highest recommendation score $r_{u,l}$ to user u.

B. Geographical Module

Distinctly from traditional items, such as book, film and music recommendations, in LBSNs users are quired to physically interact with POIs to check in. Thus, geographical coordinates of POIs (i.e., latitude and longitude) are the most essential and helpful information in LBSNs. Indeed, the Toblers First Law of Geography states that *Everything is related to everything else, but near things are more related than distant things*. Based on this, we can infer many contributing geographical attributes from a user perspective and a location perspective. First, combining users' check-in records, the study [7] clustered users' whole historical check-ins and found users' behavior exists several centers (e.g., home and work place). Inspired by this, activity ranges of users and distances between users' check-in centers and POIs should be taken into account because they measure the cost of users checking in POIs. That is, one tends to visit POIs near his centers instead of the distant ones that exceed his activity ranges. Second, according to the distance distribution among POIs that users visited historically, the research [6] demonstrated that users may be interested in exploring nearby POIs of the POI that users like, even though they are far away from users' centers. For instance, one has a high probability to watch the film at the nearby cinema after eating with friends. Therefore, modeling such fine-grained geographical characteristics has a significant on capturing the geographical influence.

In view of the above geographical nature, we propose a personalized geographical model to estimate a unifed probability distribution on fine-grained geographical characteristics. The geographical model is the linear combination of the User model and POI model as follows:

$$P_G(u,l) = \alpha P_U(u,l) + (1-\alpha) P_P(u,l) \tag{1}$$

where α is a parameter that balances the influence of User and POI models. $P_U(u,l)$ and $P_P(u,l)$ are the predicted probability distributions by User and POI models, respectively.

The User model is designed for capturing the impact of activity ranges of users and distances between users' check-in centers and POIs. New POIs close to users' centers are likely to be recommended:

$$P_U(u,l) = \frac{\sum_{l_i \in \mathcal{M}_u} exp(-\frac{\Upsilon_u}{2}||l_i - l||^2)}{\sum_{l_j \in \mathcal{L}} \sum_{l_i \in \mathcal{M}_u} exp(-\frac{\Upsilon_u}{2}||l_i - l_j||^2)} \tag{2}$$

where $||.||$ denotes the Euclidean norm in the geographical space, $\sum_{l_j \in \mathcal{L}} \sum_{l_i \in \mathcal{M}_u} exp(-\frac{\Upsilon_u}{2}||l_i - l_j||^2)$ is the normalization constant, and Υ_u is a parameter describing the width of user u activity area. Here, we define it by considering the distance between POI and a user's home: $\Upsilon_u = max\left\{||l_k - h_u||^2\right\}, l_k \in \mathcal{L}_u$, where h_u represents the user's home.

The POI model aims at capturing the impact of the distance among POIs that users visited. New POIs near POIs that users checked in are possible to be recommended:

$$P_P(u,l) = \frac{\sum_{l_i \in \mathcal{L}_u} exp(-\frac{\Phi_u}{2}||l_i - l||^2)}{\sum_{l_j \in \mathcal{L}} \sum_{l_i \in \mathcal{L}_u} exp(-\frac{\Phi_u}{2}||l_i - l_j||^2)} \tag{3}$$

where $\sum_{l_j \in \mathcal{L}} \sum_{l_i \in \mathcal{L}_u} exp(-\frac{\Phi_u}{2}||l_i - l_j||^2)$ is the normalization constant, and Φ_u is an adaptive bandwidth that depicts average visiting distance of user u: $\Phi_u = mean\left\{||l_j - l_k||^2\right\}, l_j, l_k \in \mathcal{L}_u$.

C. Check-in Module

In LBSNs, the user-generated check-in data is a kind of implicit feedback data, which means we only obtain positive examples. Some traditional recommendation methods [7], [11]–[13] often give the equal weight to each positive example and may not distinguish between their different contributions in learning the objective function. However, the check-in frequencies of a user on POIs reflect the confidences of being fond of them. The check-in patterns of higher frequencies indicate the preferences of higher confidences. For fully mining the contributions of check-in frequencies in the check-in module, we place a higher weight to highlight the importance of a larger check-in frequency.

More specifically, we employ a logistic matrix factorization that is an effective probabilistic model for implicit feedback data [14] to model the probability of the event that users have chosen to interact with POIs by a parameterized logistic function. The model learns user low-dimensional matrix $\mathcal{P} \in \mathbb{R}^{m \times d}$ and POI low-dimensional matrix $\mathcal{Q} \in \mathbb{R}^{n \times d}$ by factorizing the user-POI matrix $\mathcal{C}$. Column vectors p_u and q_l represent user-specific and POI-specific latent factor vectors, respectively. Thus, the probability of the check-in event is given by,

$$P_C\left(x_{ul}|p_u, q_l, \beta_u, \beta_l\right) = \frac{exp(p_u q_l^T + \beta_u + \beta_l)}{1 + exp(p_u q_l^T + \beta_u + \beta_l)} \tag{4}$$

where x_{ul} denotes the event that user u checks in POI l. β_u and β_l represent user and POI biases, which are meant to account for variation in behavior across both users and POIs. For example, some users are active users that tend to visit a diverse assortment of POIs while others only check in a limited number of POIs. Likewise, some POIs are very popular and attract a broad visitors to check in while other POIs are less popular and have a niche group.

By placing a higher weight to highlight the contribution of a higher check-in frequency, we use a log scaling function such as:

$$w_{ul} = 1 + \gamma log(1 + c_{ul}), \tag{5}$$

where γ is a tuning parameter.

Given parameters $\mathcal{P}$, $\mathcal{Q}$ and β, the likelihood over check-in frequencies can be inferred:

$$\begin{aligned} P(\mathcal{C}|\mathcal{P}, \mathcal{Q}, \beta) = \prod_{u,l} & P_C\left(x_{ul}|p_u, q_l, \beta_u, \beta_l\right)^{w_{ul}} \\ & \left(1 - P_C\left(x_{ul}|p_u, q_l, \beta_u, \beta_l\right)\right) \end{aligned} \tag{6}$$

TABLE I
STATISTICAL INFORMATION OF THE TWO DATASETS

Statistical item	Foursquare	Gowalla
Number of users	7,642	5,628
Number of POIs	28,484	31,803
Number of check-ins	512,523	620,683
User-POI matrix density	0.13%	0.22%

A zero-mean Gaussian prior is placed to on the user and POI latent spaces. Furthermore, the log of posterior distribution over $\mathcal{P}$ and $\mathcal{Q}$ can be derived by utilizing the method of maximum a posterior (MAP). We get the objective function as follows:

$$\begin{aligned} J(\mathcal{P}, \mathcal{Q}, \beta; \mathcal{C}) &= \sum_{u,l} w_{ul}(p_u q_l^T + \beta_u + \beta_l) \\ &- (1 + w_{ul}) log(1 + exp(p_u q_l^T + \beta_u + \beta_l)) \\ &- \frac{\lambda}{2}(||p_u||^2 + ||q_l||^2) \end{aligned} \tag{7}$$

where λ is the regularization constant that avoids overfitting.

Finally, we use an alternating gradient ascent to update latent factor vectors p_u, q_l and biases β.

D. Recommendation Framework

The aim of recommendation is to predict the preference score $r_{u,l}$ of a user u on an unvisited POI l, and then recommend a top-N POIs according to preference scores. Hence, the score can be computed by integrating the geographical module with check-in module.

$$r_{u,l} = P_G(u, l) \cdot P_C(x_{ul}|p_u, q_l, \beta_u, \beta_l) \tag{8}$$

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we empirically evaluate the performance of our proposed recommendation method. Extensive experiments are performed on two real-world LBSN datasets, Gowalla and Foursquare.

A. Datasets Description

In this study, we perform our experiment on two public datasets, which are collected from Gowalla and Foursquare [15], [18]. Gowalla contains check-in data ranging from February 2009 to October 2010 while Foursquare includes check-in data ranging from April 2012 to September 2013. Each check-in record in the datasets provides a user ID, a location ID and a timestamp, where each location has latitude and longitude. We empirically select users who have at least 15 check-in POIs and remove POIs that have fewer than 10 visitors on Gowalla. Similarity, we filter out those users who have fewer than 10 check-in POIs and those POIs which are visited by less than 10 users on Foursquare. We summarize the data statistics for all datasets in Table I.

In our experiments, we divide the dataset into training set, tuning set and test set in terms of the user's check-in time. For each user, the earliest 70 % check-ins are selected as training data, the most recent 20 % check-ins as test data and the remaining 10 % as the tuning data.

B. Evaluation Metrics

We utilize two widely-used metrics to evaluate the performance of the model we proposed: precision (Pre@N) and recall (Rec@N) [15], where N is the number of recommended POIs.

Pre@N and Rec@N. Pre@N defines the ratio of discovered POIs to the total number N of recommended POIs, and Rec@N measures the ratio of discovered POIs to the number of visited POIs in the testing set. Given the top-N recommendation list of POIs $\mathbb{R}_u(N)$ for user u, they are formally defined as follows:

$$Pre@N = \frac{1}{|\mathcal{T}|} \sum_{u \in \mathcal{T}} \frac{|\mathbb{R}_u(N) \cap \mathbb{V}_u|}{N} \tag{9}$$

$$Rec@N = \frac{1}{|\mathcal{T}|} \sum_{u \in \mathcal{T}} \frac{|\mathbb{R}_u(N) \cap \mathbb{V}_u|}{|\mathbb{V}_u|} \tag{10}$$

where $\mathcal{T}$ denotes the set of users in the testing data, and $\mathbb{V}_u$ represents the set of visited POIs in the testing set.

C. Baseline Methods

To illustrate the performance of our proposed POI recommendation framework, we thus introduce the following baseline methods to compare.

- **Pop**: Pop method recommends the top-N most popular POIs to users.
- **LMF** [14]: This is an effective probabilistic model for matrix factorization with implicit feedback.
- **USG-G** [6]: This is a typical POI recommendation approach that uses the Power-law distribution to capture the geographical influence.
- **GS2D** [19]: This is a typical geographical model that provides a personalized geographical influence using a kernel density estimation.
- **FMFMGM** [7]: This is a recommendation framework based on Poisson factor factorization, which exploits geographical influence with Multi-center features.
- **GeoSoCa-G** [20]: This is a geographical module of GeoSoCa recommendation framework, which uses check-in distribution to build an adaptive kernel estimation.
- **L-WMF** [21]: This is a location neighborhood-aware weighted probabilistic matrix factorization method that exploits geographical relationships among POIs.

D. Experiment Setup

For all baseline methods, we use the optimal setting reported in the corresponding papers. In our experiments, all critical parameters are tuned via cross-validation. Empirically, for the check-in module, the regularization parameter λ is set by 0.6. In Foursquare data, the balance parameter α is set to 0.9, the tuning parameter γ is set to 50 and the latent factor dimension $d = 10$. In Gowalla data, the balance parameter α is set to 0.95, the tuning parameter γ is set to 70 and the latent factor dimension $d = 10$. For the parameters α, γ, d, we will discuss the effect of them in the Section IV-F.

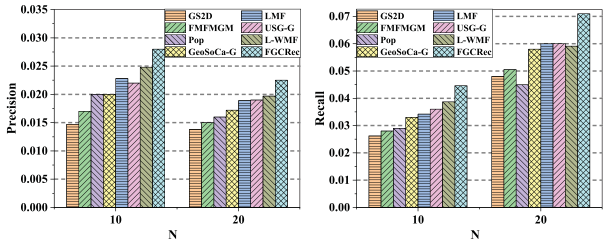
E. Performance Comparison

The performance of our framework and baseline methods in terms of Pre@N and Rec@N on Foursquare and Gowalla data are shown in Fig. 2 and Fig. 3. From the results, we can see that FGCRec consistently outperforms the relevant POI recommendation methods on the two datasets. Firstly, we compare the performances of the proposed method FGCRec and four coarse-grained geographical models (i.e., GS2D, FMFMGM, GeoSoCa-G, and USG-G). On the one hand, USG-G outforms GS2D, FMFMGM, and GeoSoCa-G in terms of Pre@N and Rec@N metrics on all datasets. On the other hand, FGCRec has a significantly large improvement over the second best coarse-grained geographical model USG-G. Particularly, as shown in Fig. 2(a) and Fig. 3(a), FGCRec attains 27.27% and 32.2% better performance than USG-G over all datasets, in terms of Pre@10. One possible reason is that coarse-grained geographical approaches only model the two types of distance (i.e., distances among POIs and distances between user centers and POIs) separately, but ignore the impact of fine-grained geographical characteristics, e.g., activity ranges of users and the interaction of them. Secondly, compared with Pop method, our recommendation algorithm presents an absolute advantage. For example, in terms of Pre@10, the improvments of FGCRec over Pop are 30.23% and 74.38% respectively, on Foursquare and Gowalla. This indicates that FGCRec is an appropriate choice to provide personalized POI recommendations. Thirdly, our framework significantly outperforms the other two state-of-the-art algorithms LMF and L-WMF for implicit feedback data. For instance, in terms of Rec@20, as shown in Fig. 2(b) and Fig. 3(b), FGCRec outperforms LMF and L-WMF by 30.4%, 12.3% and 15.24%, 4.28%, on average. The possible reason is that placing a higher weight to highlight the contribution of a higher check-in frequency in logistic matrix factorization works effectively for utilizing check-in data in POI recommendations.

In addition, comparing the performance on Foursquare against Gowalla, we can clearly see that the metrics of FGCRec on Gowalla is better than Foursquare. Especially, the performance of FGCRec achieves 0.028 and 0.0354 over Foursquare and Gowalla datasets, in terms of Pre@10. The possible reasons are three-fold: (1) The user-POI matrix density on Gowalla is larger than on Foursquare, which is reflected in Table I. (2) The number of visited POIs per user on Gowalla is more than on Foursquare. (3) The activity area of the Foursquare users is wider than the Gowalla users.

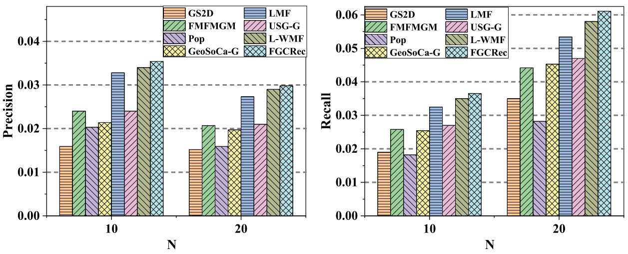
F. Parameter Selection

Tuning model parameters is critical to the performance of the proposed FGCRec. In the geographical module of FGCRec, the impact of fine-grained geographical characteristics in User and POI models is controlled by the balance parameter α. In the check-in module of FGCRec, the impacts of log scaling function and latent vector dimension are controlled by the parameters γ and d, respectively. Due to limited space and similar results, we only present the parameter selection process on Foursquare data.



(a) Pre@N on Foursquare (b) Rec@N on Foursquare

Fig. 2. Top-N Performance on Foursquare



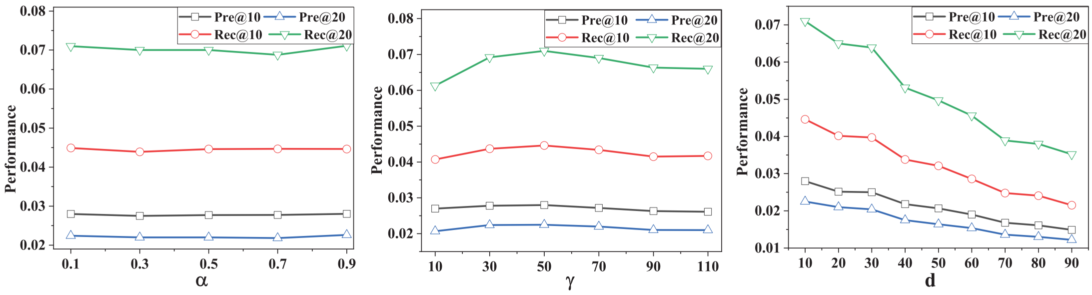
(a) Pre@N on Gowalla (b) Rec@N on Gowalla

Fig. 3. Top-N Performance on Gowalla

Impact of Balance Parameter α**.** Fig. 4(a) reports the impact of parameter α. By observing the results, we find that the recommendation performances of FGCRec first decrease with the increasing number of parameter α, and then it increases gradually when the number of α is larger than 0.3. Finally, it hits the best performance when α= 0.9. It is the best weight of User model and POI model. This is an interesting change, indicating that User model is more important than POI model in the geographical module. One possible explanation is that the recommendation process is primarily to infer users' intent, so geographical characteristics associated with users play a dominant role.

Impact of Tuning Parameter γ**.** Fig. 4(b) depicts the impact of parameter α. From the experimental results, we observe that the performances of FGCRec first improve quickly with the increase of the value of parameter γ and then drop down rapidly when it is larger than 50. When γ = 50, the performance hits the highest prediction accuracy. It is the optimal value to scale check-in frequencies of users on POIs. This indicates that assigning higher weights to highlight the importance of higher check-in frequencies by employing logistic matrix factorization is effective for POI recommendations.

Impact of Latent Factor Dimension d**.** Fig. 4(c) investigates the impact of latent factor dimension d. In our experiment, following the existing work [14], we set a differing number of latent factors d ranging from 10 to 90 with an increment of 10 to observe the impact. From the results, it is observed that d = 10 is the most suitable setting in Foursquare dataset. We also find that the performances of FGCRec drop drastically by increasing d from 10 to 90. We speculate this is because that the learned suitable latent factors dimension can better reflect the underlying relationships, but when it exceeds the threshold, the reconstruction of users' preferences on POIs



(a) Impact of Balance Parameter α (b) Impact of Tuning Parameter γ (c) Impact of Latent Factor Dimension d

Fig. 4. Impact of Parameters α, γ and d on Foursquare Data

are insufficient to provide accurate POI recommendations.

V. Conclusion

In this paper, we propose a fine-grained POI recommendation framework, named FGCRec, which takes full advantage of the geographical characteristics from both users' and locations' perspectives. The FGCRec consists of two modules: geographical module and check-in module. The geographical module is used to capture the geographical influence by estimating a unified probability distribution using fine-grained geographical characteristics. The check-in module is to mine more contributions from positive examples by assigning a higher weight to highlight the contribution of a higher check-in frequency employing a parameterized logistic function. Finally, extensive experimental results on two real-world LBSNs data validate the effectiveness of the proposed FGCRec.

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