Modeling User Contextual Behavior Semantics with Geographical Influence for Point-Of-Interest Recommendation

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***Abstract*—Point-Of-Interest (POI) recommendation assists users to find their preferred places and helps businesses to attract potential customers. However, the data sparsity and the complexity of user check-in behavior pose a big challenge to POI recommender systems. To tackle this challenge, we propose a POI recommendation method named HeteGeoRankRec based on user contextual behavior semantics. First, to mine the fine-grained user behavioral features, we employ the meta path of Heterogeneous Information Network (HIN) to represent the complex semantic relationship among users and POIs and integrate the context constraints (such as time and weather) into the meta paths. Secondly, we propose a weighted matrix factorization model considering the influence of geographical distance to obtain semantic preference through the user-POI semantic correlativity matrixes generated by multiple meta paths. Finally, we introduce a ranking-based fusion method, which unifies the recommendation results of different meta paths as the final preference of users. Experiments on the real data collected from Foursquare show that HeteGeoRankRec has the better performance than the state-of-the-art baselines.**

***Keywords*—location-based social network; heterogeneous information network; context information; point-of-interest recommendation; behavior semantics.**

I. Introduction

In recent years, thanks for the widespread of Internet and mobile devices, Location-Based Social Networks (LBSNs) have become increasingly popular. Users explore their preferred locations, such as libraries, restaurants and stores, through the "check-in" behavior provided by the LBSN services. For example, more than 50 million people use Foursquare every month [1]. The personalized POI recommendation service is designed to improve the LBSN service experience by mining user preferences through check-in data.

However, POI recommendation faces serious challenges. First, the number of POIs visited by a user usually accounts for only a small portion of all the POIs, which results in the highly sparse user-POI check-in data. In addition, the decision-making process for user check-in behavior is very complex and prone to be affected by rich context information [1]. For example, user's mobility is significantly affected by geographical distance [2,3]. In other words, users are more inclined to visit closer locations. Meanwhile, user's visiting preference might be affected by their social relationships [4], meaning a user may follow the suggestions from his friends or some influential people. Besides, the user's preference may also be affected by the time [5] and the weather [6]. Taking Fig. 1 as an example, Mary may prefer to visit the library on rainy days, while Skye may like to go to the restaurant for lunch. Unfortunately, most existing works lack deep mining of user behavior semantics and suffer from the much worse data sparsity problem.

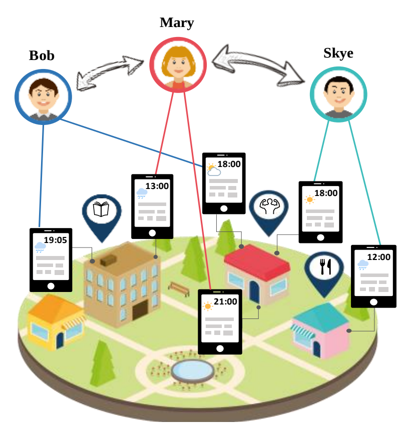

Figure 1. An example of LBSN.

In this paper, we propose a novel POI recommendation model named HeteGeoRankRec, based on user contextual behavior semantics. First, we employ the meta path of Heterogeneous Information Network (HIN) to represent the complex semantic relationships of LBSN. Afterwards, to mine fine-grained user behavioral features, we integrate the context constraints, such as time and weather, to the meta paths. Furthermore, we propose a weighted matrix factorization

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[1] https://foursquare.com/about

considering geographical distance, from which we obtain the semantic preference through the user-POI semantic correlativity matrixes. Finally, we introduce a ranking-based fusion method, which unifies the recommendation results obtained from different meta paths as the final user preference.

The rest of the paper is organized as follows. After presenting related work in Section II, we introduce the related concepts and problem definition in Section III. Our proposed model is given in Section IV, followed by its experimental evaluation in Section V. Finally, Section VI concludes this paper and outlines the future work.

II. RELATED WORK

The POI recommendation plays an important topic in the field of recommendation systems, attracting the attention from both the academic and industrial fields. The context information, such as geographical influence, has always been regarded as a very significant impact on the recommendation performance [7]. For example, Li et al. [8] considered the user’s general interests as a mixture of intrinsic and extrinsic interests, where the former is personal-taste driven and the latter is environment driven. Wang et al. [9] modeled the POI-specific geographical influence between two POIs using three factors: the geo-influence of POI, the geo-susceptibility of POI, and their physical distance. However, only considering the geographical influence is not always enough to represent the user's behavior characteristics.

User’s social relationships may affect the user check-in behavior. For example, in [4], Gao et al. held that the social relationships and check-in sequences significantly affect the user's behavior and proposed a fusion model to combine two features to predict user’s preference. Besides, Li et al. [10] learned potential locations from three types of friends and incorporated potential locations into matrix factorization model to overcome the cold-start problem. In addition, there are some works considering temporal effect [5] and content information [11]. Although the aforementioned works improve the recommendation performance to some extent by modeling the context information, they lack deep mining of user behavior semantics and suffer from the data sparsity problem.

In recent years, some researches [12,13,14] attempted to apply HIN to the recommendation tasks to integrate more information and represent user behavior semantics. For example, Zhao et al. [13] proposed a HIN-based recommendation method, which uses matrix factorization and factorization machine to solve the information fusion problem. Wang et al. [14] utilized the meta-path-based approach to extract implicit relationships between a user and a POI, and applied logistic regression to establish a prediction model for recommendation. However, they simply regarded the location that the user has not visited as a negative sample, without considering LBSN actually lacks the explicit feedback of POI preferences.

III. THE PRELIMINARY

As an abstract representation of the real world, the information network [15] focuses on the connection between the different types of objects, which is usually defined as follows:

Definition 1. Information Network. *An information network is a directed graph $G = (V, E)$, where V is a set of objects and E is a set of links, with an object type mapping function $\emptyset: V \rightarrow A$ and a link type mapping function $\varphi: E \rightarrow R$. In other words, each object $v \in V$ belongs to one particular object type $\emptyset(v): \in A$, and each link $e \in E$ belongs to one particular relation $\varphi(e): \in R$. When there exists more than one type of object, i.e., $|A| > 1$, or one type of relation, i.e., $|R| > 1$, the network is called a **heterogeneous information network**. Otherwise, it is a **homogeneous information network**.*

Definition 2. Network Schema. *The network schema is a meta template of information network, denoted as $T_G = (A, R)$, with the object type mapping $\emptyset: V \rightarrow A$ and the link mapping $\varphi: E \rightarrow R$.*

Fig. 2 shows an example of LBSN heterogeneous information network schema. The network schema serves as a template for a network and tells how many types of objects there are in the network and where the possible links exist, thereby making the heterogeneous information network semi-structured.

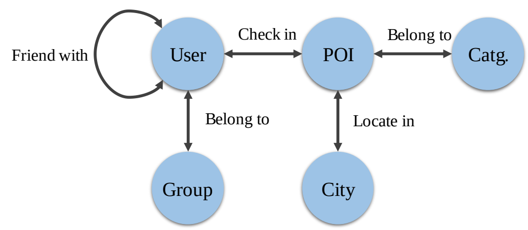

Figure 2. LBSN heterogeneous information network schema.

Definition 3. Meta Path. *A meta path M is a path defined on the graph of network schema $T_G = (A, R)$, denoted as $M = A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \cdots \xrightarrow{R_{l-1}} A_l$.*

For simplicity, we denote the meta path as $M = A_1 A_2 \cdots A_l$. As shown in Fig. 2, in a LBSN heterogeneous information network, the co-check-in relationship between users can be represented by a meta path $U \xrightarrow{check-in} P \xrightarrow{checked-in\ by} U$, abbreviated as UPU, where U and P represent the user objects and location objects respectively.

Definition 4. Context-constrained Meta Path. *A context-constrained meta path is a meta path with the context attribute constraints on relations, denoted as $M_c = A_1 \xrightarrow{\delta_1(R_1)} A_2 \xrightarrow{\delta_2(R_2)} \cdots \xrightarrow{\delta_l(R_{l-1})} A_l\ |S$, where $\delta(R)$ represents a set of context attribute values on relation R, S defines the context of the meta path and the corresponding attribute value constraints.*

For example, suppose the whole day is divided into multiple time slices $T_1, T_2, \cdots, T_n$, and the check-in relationship between user U and POI P can occur in multiple time slices. We use $U \xrightarrow{\{T_1,T_2\}} P \xrightarrow{T_1} U$ to indicate that two users check in P at T_1, and one of them makes a check-in at the T_2 again. Moreover, the path $U \xrightarrow{T_i} P \xrightarrow{T_j} U|\{S: Context \in \{Time\}, T_i = T_j\}$ means that two users check in the same POI at the same time slice. Taking Fig. 1 as an example, we can easily find that although three people all go to the gym, the temporal preferences for Bob and Skye are more similar.

Definition 5. Counting Matrix. *For a meta path* $M = A_1 A_2 \cdots A_l$ *, we define its counting matrix as* $C_M = W_{A_1A_2} W_{A_2A_3} \cdot \ldots \cdot W_{A_{l-1}A_l}$*, where* $W_{A_iA_j}$ *is the adjacency matrix between* A_i *and* A_j*. The values in the counting matrix represent the number of times the interactions occur between objects.*

Problem Definition. *Given an LBSN heterogeneous information network* G*, and a check-in record set* S *with context information, the problem we try to resolve is to build a personalized recommendation model, and return the Top-K unvisited POIs for each user* u.

IV. THE FRAMEWORK

In this section, we present the proposed POI recommendation method, called HeteGeoRankRec, in detail (Fig. 3).

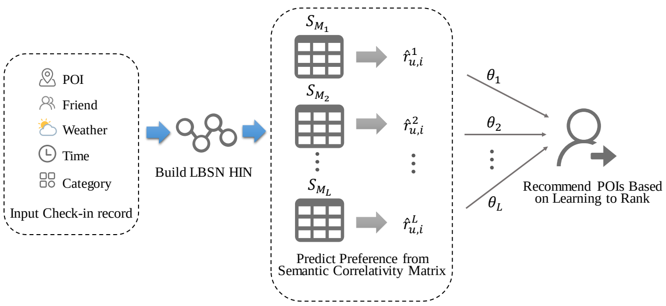

Figure 3. The Framework of HeteGeoRankRec.

A. Build Semantic Correlativity Matrixes Based on Context-constrained Meta Path

1) Design Meta Paths: We first employ the meta path to build the semantic relationship sequences for further analysis of user preferences. Taking the path $UPUP$ as an example, it may indicate that users prefer locations where people with common check-in records have checked in, which is a user-based collaborative recommendation. Moreover, the UUP path represents that users prefer the locations checked in by their friends, which is a social recommendation. Therefore, we can make the recommendation more explainable by designing reasonable meta paths to represent different user behavior semantics. Table I lists the meta paths and their corresponding semantics, where C represents the category of POI.

In addition, the context-constrained meta path is used to capture the user's preferences in different contexts (e.g. time, weather). For the meta path like $U * UP$ (e.g. M_3 and M_5 in Table I), we add context constraints as follows:

$$M_c: U \xrightarrow{i} P * P \xrightarrow{j} U \xrightarrow{k} P | \{S: Context \in Z, i = j = k\} \quad (1)$$

where $Z = \{Time, Weather\}$ represents a set of context types. Note that weather indicators, such as cloud cover and temperature, can also be divided into multiple numerical segments. Here, $i = j = k$ indicates that the behavior occurs in same context.

TABLE I. THE META PATHS AND ITS SEMANTICS

Symbol	Meta path	Semantic
M_1	UP	Users prefer locations they have checked in
M_2	UUP	Users prefer locations where their friends have checked in
M_3	$UPUP$	Users prefer locations where people with common check-in records have checked in
M_4	$UPCP$	Users prefer the same category of locations they have checked in
M_5	$UPCPUP$	Users prefer locations where people having checked in the POIs of the same category have checked in

2) Build Semantic Correlativity Matrix: We employ the counting matrix defined above as a counting-based correlativity matrix between user objects and location objects, denoted as S_M. This can effectively alleviate the sparsity of the user-POI relation matrix by computing the correlativity through meta path. The counting-based correlativity reflects the idea of high correlativity between nodes with high visibility in the LBSN heterogeneous information network. Such an idea is intuitive and suitable for recommendation task. Taking the time context as an example, the semantic correlativity matrix is built according to Eq. (2), which involves three steps: (a) Divide the time of day into multiple slices $T_1, T_2, \cdots, T_n$, and obtain user check-in records for each slice; (b) Obtain the correlativity matrixes $S_{M_{T_i}}$ by calculating the correlativity from meta paths within each time slice; (c) Add the correlativity matrixes to construct the semantic correlativity matrix S_{M_c} of the context-constrained meta path.

$$S_{M_{T_i}} = \left(W_{A_1A_2} W_{A_2A_3} \cdots W_{A_{l-1}A_l}\right)^{T_i}, S_{M_c} = \sum S_{M_{T_i}} \quad (2)$$

B. Predict POI Preference Based on Weighted Matrix Factorization

In this section, we extend the weighted matrix factorization algorithm based on implicit feedback proposed in [16] and optimize the objective function by adding geographical influence factor to make it suitable for POI recommendation.

1) Calculate User-POI Check-in Probability: Users are more inclined to visit closer locations. The check-in probability of the user from one location to another $x\,(km)$ away approximately follows the power law distribution [2], as the following:

$$y = Pr_u(i, j) = a \cdot x^b \quad (3)$$

Let $a = 2^{w_0}$, $b = w_1$, and Eq. (3) is then transformed into Eq. (4) by taking the logarithm:

$$log\, y = w_0 + w_1\, log\, x \quad (4)$$

Let $y' = log\, y, x' = log\, x$. We then use the linear regression method to optimize the following loss function to obtain the regression coefficient:

$$L = \frac{1}{2}\sum_{n=1}^{N}(y' - p_n)^2 + \frac{\lambda}{2}||\boldsymbol{w}||^2 \quad (5)$$

where w_0 and w_1 are regression coefficients, denoted together by $\boldsymbol{w}$, p_n is real check-in probability to the x', and the regularization parameter λ is used to prevent the model from overfitting.

Then the check-in probability from POI i to j for user u is normalized by Eq. (6):

$$Pr_u^G(i,j) = \frac{Pr_u(i,j)}{Max(Pr_u)} \quad (6)$$

where the denominator represents the maximum check-in probability of two POIs among the user records.

2) Incorporate Geographical Influence: Suppose the corresponding value in the meta-path-based semantic correlativity matrix is represented as $S_{M_{u,i}}$. We define the user implicit preference as follows:

$$r_{u,i} = \begin{cases} 1 & S_{M_{u,i}} > 0 \\ 0 & S_{M_{u,i}} = 0 \end{cases} \quad (7)$$

In other words, $r_{u,i}$ indicates whether there is a value greater than 0 in the correlativity matrix. Furthermore, we introduce $c_{u,i}$ to measure our confidence in $r_{u,i}$. In general, as $S_{M_{u,i}}$ grows, there is a stronger indication that user indeed prefers the location. Eq. (8) defines $c_{u,i}$, where α controls the rate of increase.

$$c_{u,i} = 1 + \alpha S_{M_{u,i}} \quad (8)$$

We believe that the user's preference for unvisited POIs is limited by the distance between the candidate POIs and the POIs that the user has checked in. Thus, based on matrix factorization, the new user preference can be defined as Eq. (9):

$$\hat{r}_{u,i} = \beta x_u^T y_i + \frac{(1-\beta)}{|D_u|}\sum_{k\epsilon D_u} Pr_u^G(i,k) x_u^T y_k \quad (9)$$

where β is geographical influence factor, D_u represents a set of POIs that user u has checked in, x_u and y_i represents the latent feature vectors under same dimension f for user u and POI i.

Then, we solve the low-dimensional feature vector corresponding to the user and the POI by minimizing the loss function defined as Eq. (10) where λ is used to prevent the model from overfitting.

$$min_{x_*,y_*} \sum_{(u,i)\in T} c_{u,i}(r_{u,i} - \hat{r}_{u,i})^2 + \lambda(\|x_u\|^2 + \|y_i\|^2) \quad (10)$$

The alternating least squares method is used to optimize the above loss function. For simplicity, we define the following variable:

$$\tilde{y}_i = \beta y_i + \frac{1-\beta}{|D_u|}\sum_{k\epsilon D_u} Pr_u^G(i,k) y_k \quad (11)$$

The updating equations for x_u and y_i are obtained as:

$$x_u = (\sum_i c_{u,i}\tilde{y}_i\tilde{y}_i^T + \lambda I)^{-1} \cdot \sum_i c_{u,i} r_{u,i}\tilde{y}_i \quad (12)$$

$$y_i = (\beta^2 \sum_u c_{u,i} x_u x_u^T + \lambda I)^{-1} \times \\ \beta \sum_u c_{u,i}(r_{u,i} x_u + \frac{1-\beta}{|D_u|}\sum_{k\epsilon D_u} Pr_u^G(i,k) x_u^T y_k x_u) \quad (13)$$

C. Recommend POIs Based on Learning to Rank

Suppose we have designed F meta paths and G context-constrained meta paths, and have obtained $L = F + G$ user-POI semantic correlativity matrixes S_M^1, S_M^2,..., S_M^L. Each matrix generates the user semantic preference $\hat{r}_{u,i}^l$ through the matrix factorization algorithm described above. After combining the different semantic features, the final preference of user u for POI i can be formulated as:

$$r_{u,i}^* = \sum_{l=1}^{L} \theta_l \cdot \hat{r}_{u,i}^l \quad (14)$$

where θ_l represents the weight of the preference obtained by meta path l.

LBSN often lacks negative feedback, because we regard the POIs that the user has checked in as the positive samples. However, the POIs where the user has not visited yet does not simply mean that they are not interested in (they may not find this location). Therefore, a direct and effective recommendation model should be able to better rank the POI pairs for users, indicating that the user's preference for the POI with high correlativity is greater than the POI with low correlativity in user semantic correlativity matrix. Here, we adopt the idea of pair-wise learning. More specifically, we use the relative orders of POIs as the samples to learn the weights in Eq. (14).

Based on the method proposed in [17], we use the Eq. (15) to express the probability that user u prefers POI i instead of j:

$$p(i >_u j|\theta) = \frac{1}{1+e^{-(r_{u,i}^* - r_{u,j}^*)}} \quad (15)$$

where $\theta = \{\theta_1, \theta_2 \cdots \theta_L\}$ is a weight vector, $>_u$ represents the ordering relationship of two POIs.

According to the Bayesian formula, if we want all the POIs to be sorted correctly, we need to maximize the following posterior probability:

$$p(\theta| >_u) \propto p(>_u |\theta)p(\theta) \quad (16)$$

Assuming that the user's ranking preference for POI pairs is independent, the likelihood function can be defined by:

$$p(R|\theta) = \prod_{u\in U} p(R_u|\theta) = \prod_{u\in U}\prod_{(i>_u j)\in R_u} p(i >_u j|\theta) \quad (17)$$

where R represents a set of ordering relationships of the POI pairs.

We assume that $p(\theta)$ follows a Gaussian distribution with zero mean and variance-covariance matrix $\sum_\theta = \lambda_\theta I$. Thus, the objective function of ranking optimization can be formulated as:

$$O(\theta) = -\ln p(\theta| >_u) = -\ln p(>_u |\theta)p(\theta) \\ = -\sum_{u\in U}\sum_{(i>_u j)\in R_u} \ln p(i >_u j|\theta) - \lambda_\theta \left||\theta|\right|^2 \quad (18)$$

We employ stochastic gradient descent (SGD) to optimize the above objective function. After obtaining θ, the predicted value of user u for all POIs can be calculated by the Eq. (14). Finally, we select K POIs that user has not visited with the highest predicted value and recommend them to the user.

V. EXPERIMENTS

A. Experimental Setup

1) Dataset: The experiments are based on the Foursquare dataset[2] provided by the author of literature [10], including the real-world check-in data from 2010 to 2011. Each check-in record includes a user ID, a location ID, and a timestamp, where each location has its latitude, longitude and category, and each user is associated with her friends. In addition, we used the API of darksky.net[3] to collect the weather information for each <*latitude, longitude, timestamp*> record, including temperature, humidity and cloud cover. To evaluate the performances of the proposed method HeteGeoRankRec[4], implemented based on LibRec [18], we construct two datasets via extracting the check-in records generated from Los Angeles and San Diego. The detailed statistics of the datasets are shown in Table II.

TABLE II. STATISTICS OF DATASETS

	#Users	#POIs	#Check-ins	Sparsity
Los Angeles	2,026	8,270	51,917	99.83%
San Diego	916	4,919	26,762	99.71%

In order to make the experiments more consistent with real situation, we split training data D_{train} and testing data D_{test} as follows: for each individual user, (a) aggregating her check-ins for each location; (b) sorting the location according to the first time that the user checked in; (c) selecting the earliest 80% to train the model and using the next 20% as testing.

2) Evaluation Metrics: We employ two widely used metrics to evaluate the performance of different recommendation methods, namely precision and recall, denoted by Pre@K and Rec@K, where K is the number of recommended POIs. We compute Pre@K and Rec@K as follows:

$$Pre@K = \frac{1}{|D_{test}|}\sum_{u\in D_{test}}\frac{|R_u \cap T_u|}{|R_u|} \tag{19}$$

$$Rec@K = \frac{1}{|D_{test}|}\sum_{u\in D_{test}}\frac{|R_u \cap T_u|}{|T_u|} \tag{20}$$

where R_u represents the Top-K recommendation results for user u, and T_u is a set of POIs visited by user u in D_{test}.

3) Parameters Settings: We use the meta paths listed in Table I to calculate the semantic correlativity matrixes and add time and weather context constraints to M_3 and M_5. We divide the time of day into three slices and the weather indicators into three segments in tertile, and build the semantic correlativity matrixes by the method described in Section IV.A. The parameters of check-in probability are obtained through learning. In particular, we set the latent feature number f of the matrix factorization model to 10, the geographical influence factor β to 0.8, and the regularization parameter λ to 0.01.

4) Baseline Methods: We compare the proposed method with the following baseline methods:

- WRMF [16]: A matrix factorization model for implicit feedback.
- BPRMF [17]: A matrix factorization model which optimizes the ordering of the preference for the observed location and the unobserved location.
- GMF: A matrix factorization model based on that proposed in Section IV.B and check-in matrix (correlativity matrix generated from *UP* meta path) directly for recommendation.
- USG [2]: A model combining user preferences, social relationships, and geographical influence with collaborative filtering.
- RankGeoMF [3]: A matrix factorization model based on ranking and geographical influence for POI recommendation.
- ASMF [10]: A model which learns a set of user's potential locations from her three types of friends, and then incorporates them into matrix factorization.

B. Experimental Result

1) Performance Comparison: The comparisons between the HeteGeoRankRec and other methods in terms of Pre@K and Rec@K is shown in Fig. 4. Both WRMF and BPRMF are recommendation methods for implicit feedback data. Due to the severe data sparsity problem of LBSN, these two methods do not perform well. However, we observe GMF improves WRMF by 55.7% and 19.5% in terms of Pre@5 on Los Angeles and San Diego datasets, respectively, due to the incorporation of geographical influence. Besides, USG exhibits better performance than RankGeoMF on both datasets. One possible reason is that USG integrates geographical, social information and user preference, while RankGeoMF only uses geographical information. Most importantly, on average, the proposed HeteGeoRankRec outperforms its competitors WRMF, BPRMF, GMF, USG, RankGeoMF and ASMF, in terms of Pre@5, by 81.1%, 70.5%, 31.4%, 27.2%, 49.5% and 11.4% respectively.

2) Context Influence: The performance comparisons of HeteGeoRankRec with different contexts are shown in Fig. 5, which indicate the limited benefit when it only introduces one type of context information. However, combining the time and weather context will greatly improve the Pre@K and Rec@K on both datasets. Therefore, it can be easily concluded that considering various contexts to mine the user's behavior from multiple dimensions makes the model more accurate.

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[3] https://darksky.net/dev
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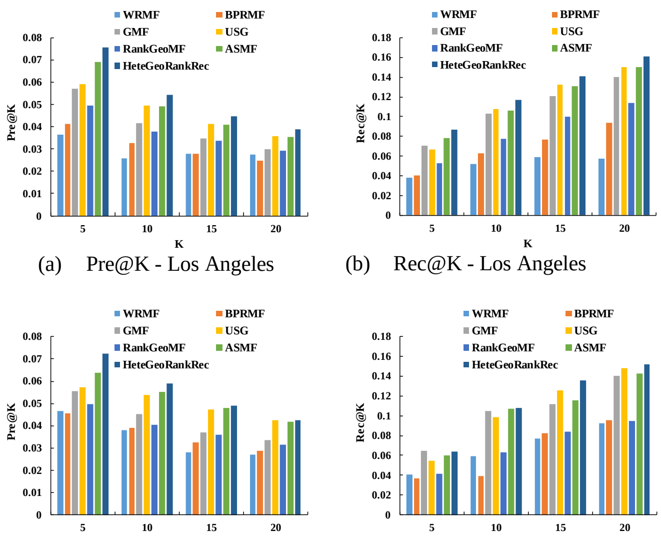
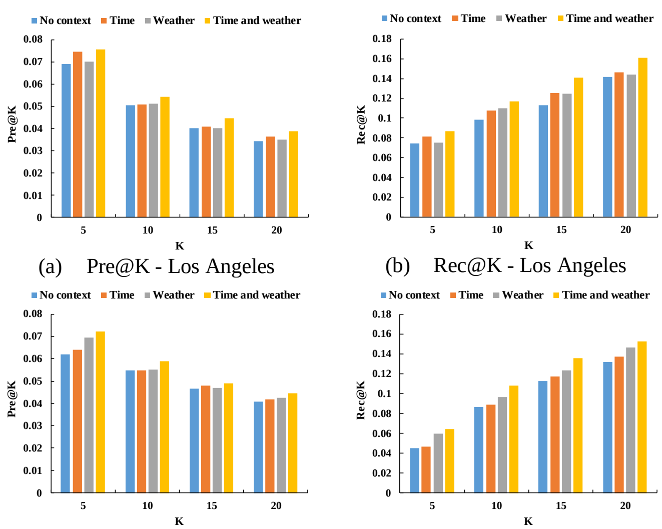


(a) Pre@K - Los Angeles (b) Rec@K - Los Angeles

(c) Pre@K - San Diego (d) Rec@K - San Diego

Figure 4. Performance comparisons of different methods.



(a) Pre@K - Los Angeles (b) Rec@K - Los Angeles

(c) Pre@K - San Diego (d) Rec@K - San Diego

Figure 5. Performance comparisons of different contexts.

VI. CONCLUSION

In this paper, we propose a POI recommendation method called HeteGeoRankRec based on the contextual behavioral semantics. It employs meta paths to represent the complex semantic relationship of user behavior, and combines social relationships, location categories, time and weather contexts, and geographical distance to mine the fine-grained user behavioral characteristics. In the future, we will further study the following issues: (a) deeply explore the influence factors of user behavior in LBSN; (b) express more information on the LBSN heterogeneous information network; and (c) study POI recommendation at specific contexts (e.g. time, weather).

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