# Successive POI Recommendation with Category Transition and Temporal Influence

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***Abstract*—With the popularization of mobile devices and wireless networks, people are able to share their experience on points of interest (POIs) in social networks through "check-ins." Therefore, the problem of successive POI recommendation has been proposed to recommend some POIs to users so that the users are likely to check in at these POIs in the near future. In this paper, we propose a two-phase method to solve the problem of successive POI recommendation. First, we utilize the Matrix Factorization technique to analyze the interaction of users and their sequential check-in behavior with time influence and POI categories, and select the candidate categories that the user will visit. Then, after removing those POIs not belonging to the candidate categories, we fuse user preferences, temporal influence and geographical influence together and finally recommend the POIs with high scores to users. The experimental results on a real check-in dataset show that our recommendation method is better than several state-of-the-art methods in terms of precision and recall.**

***Index Terms*—Successive POI recommendation, matrix factorization, recommendation**

## I. Introduction

With the prevalence of mobile devices and wireless networks, more and more people share their life styles with others through social networks. Moreover, the growing popularity of smart phones gives rise to the emergence of location-based social networks (LBSNs) such as Foursquare, Gowalla, Facebook, and Instagram. As shown in [8], until June 2011, Gowalla has recorded more than 36 million check-ins with 300 thousand users and 2.8 million points of interest (POIs). These check-in records provide an opportunity for third party companies to develop more personalized services such as point of interest (POI) recommendation for users.

The purpose of POI recommendation is to recommend a user some POIs which the user is interested in according to the user's historical check-in records. However, traditional POI recommendation only considers users' check-in preferences and does not consider the current time and the distances among users and POIs. Thus, it is possible that a traditional POI recommendation method recommends a user some POIs far away from the user's current location. Such recommendation is not informative for the user since it is difficult for the user to check in at a distant POI.

In view of this, the problem of successive POI recommendation has been proposed in [3] and attracted more attention in recent years. The goal of successive POI recommendation is to recommend POIs that users will visit in the near future (say several hours). Thus, the successive POI recommendation method should consider users' successive check-in behavior, the current time and the current locations of users. Some studies on successive POI recommendation have been proposed to utilize Markov chain [3][14], Matrix Factorization (MF) [2], or Tensor Factorization (TF) [15][1] to analyze users' successive check-in behavior.

However, these prior studies do not consider temporal influence and the categories of POIs which have great influence on users' check-in preferences. Thus, these studies may not be able to capture the successive check-in behavior of users. Consider a user usually goes to bars after dinner. The user's check-in records will have a lot of check-in sequences like "Restaurant A then Bar C," "Restaurant A then Bar D," "Restaurant B then Bar C," and "Restaurant B then Bar D," increasing the difficulty to discover the user's check-in preference. If the categories of POIs are considered, the user's check-in records will be transformed into "Restaurant then Bar." Considering the categories of POIs will simplify the problem to capture users' successive check-in preference. Besides, since the number of categories is much smaller than the number of POIs, such transformation will further relieve the problem resulting from the sparseness of the dataset.

Moreover, current time usually has great influence on check-ins. Suppose a user usually goes to a coffee shop before going to work in the afternoons and goes to a bar after having dinner at night. Without considering the current time, it is also possible that a traditional POI recommendation method recommends the user some coffee shops when the user has finished his/her dinner at night. To achieve better recommendation performance, in this paper, we consider four specific factors, namely, category transition, temporal influence, user preference, and geographical influence to build our successive POI recommendation method.

Motivated by [1], our successive POI recommendation method consists of the following two phases: the category prediction phase and the POI recommendation phase. In the category prediction phase, our method predicts the categories of the POIs where a user may check in by two MF models based on successive category transitions and the user's check-in time of categories, respectively. In the POI recommendation phase, the POIs belonging to these predicted candidate categories are ranked according to user-based collaborative filtering or user-time-based collaborative filtering with geographical influence. By predicting the categories first, we can not only learn users' preference more comprehensively and

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more precisely but also reduce the spareness of the check-in records and the computation complexity. We evaluate our successive POI recommendation method on a real world LBSN dataset, Gowalla, and the experimental results show that the performance of successive POI recommendation is better than the other state-of-the-art methods.

The rest of this paper is organized as follows. The related work is introduced in Section II. The analysis of the Gowalla dataset and the problem definition are given in Section III. Section IV describes our proposed successive POI recommendation method in details. In Section V, we evaluate our method and other prior methods. Finally, we make a short conclusion in Section VI.

## II. Related Work

In this section, we will briefly introduce several state-of-the-art works on traditional POI recommendation and successive POI recommendation.

### A. POI Recommendation

Due to the success of collaborative filtering (CF) in other recommendation problems, lots of works in POI recommendation use CF to perform POI recommendation based on the following two factors [11][13][10][12].

- Geographical influence: Geographical influence is an important factor in POI recommendation. Ye et al. [11] were the first to perform an analysis on distances between sequential check-ins and found out users tend to visit the POIs close to their current locations. After analyzing real check-in records, they observed that the probabilities of visiting POIs usually follow the power-law distribution. Instead of power-law distribution, Cheng et al. [2] observed that users usually visit the POIs around several specific locations, such as home or offices. They adopted a Multi-center Gaussian Model (MGM) to catch the geographical influence on POIs. However, the above two works applied a universal model for all users. Zhang et al. [13] argued that the distance distribution of each user should be personalized. Therefore, they deployed the kernel density estimation with a personalized distance distribution to model the geographical influence.
- Temporal influence: People usually show up at coffee shop in the morning and go to a bar at night. This kind of daily behavior heavily impacts on where we are going. Gao et al. [5] were the first to consider temporal influence on POI recommendation. They adopted a MF model to capture the non-uniformness property since users behave differently in hours of the day. They also adopted another CF model to represent the consecutiveness property since users will have similar check-in preferences in close time slots. Yuan et al. [12] assumed that if two users have similar temporal behavior, they are likely to visit similar POIs at the same time. Therefore, they simply combined temporal influence into user-based collaborative filtering, and then performed POI recommendation.

### B. Successive POI Recommendation

Unlike (traditional) POI recommendation, successive POI recommendation focuses on users' recent locations and patterns among successive check-ins. Cheng et al. [3] were the prior study which defined the problem of successive POI recommendation. They proposed the FPMC-LR model based on the assumption that a user's next check-in will be influenced by the user's current location. They used a first-order Markov chain to model the successive relation of checks-in and considered the localized region constraints since the previous works have showed that distance is an important factor in POI recommendation. Rather than considering the latest check-in location, Zhang et al. [14] proposed an $n$th-order additive Markov chain model to capture the successive influence based on all successive check-ins of users. However, Feng et al. [4] argued that it's not suitable to use matrix factorization on sparse POI data. They proposed a Ranking based Metric Embedding (RME) model to utilize the Euclidean distances among POIs to model their transition probabilities. The shorter the distances, the larger the transition probabilities. By making use of the unobserved data, RME model is able to reduce the sparseness and hence increase the accuracy of recommendation. Besides, using distance as an indicator of transition probability can learn the potential relation that FPMC will ignore. For example, if successive check-ins $l_i \rightarrow l_j$ and $l_j \rightarrow l_k$ were observed, $l_i \rightarrow l_k$ should be expected to be a potential transition. Gau et al. [6] suggested that users' interest may be influenced by the regions where the POIs are located. POIs located around several famous POIs (i.e., in a popular region) are more likely to be visited than those in a unpopular region.

Most studies in successive POI recommendation directly recommend the POIs without considering the categories of the POIs and hence tend to suffer from the sparseness of the dataset. Thus, Chen et al. [1] argued that utilizing the categories of the POIs are able to improve the performance of recommendation. They divided the successive POI recommendation process into two parts: group-based category recommendation and categroy-based location recommendation. They first clustered the users into groups according to their residence locations and preferences on location categories and adopted a pairwise interaction tensor factorization model (PITF) [9] to model the interaction of users, current location categories and the next location categories. Given the obtained predicted categories, they proposed a distance-weighted HITS algorithm to recommend the POIs belonging to the predicted categories to users. With the smaller number of categories and the two-layer structure, the sparseness problem can be relieved.

Unfortunately, most of these works did not directly consider the relation between successive check-in behavior and users. Besides, it is obvious that temporal influence has critical impact on POI recommendation. However, Chen et al. [1] did not put it into consideration. The above phenomena motivate us to develop a novel successive POI recommendation method by considering time influence and the relation between successive

TABLE I
STATISTICS OF THE GOWALLA DATASET

| Users | Locations | Categories | Check-ins | Periods |
|---|---|---|---|---|
| 12,459 | 25,460 | 133 | 2,561,710 | Aug. 2010 - Aug. 2011 |

check-in behavior and users.

## III. PRELIMINARIES

In this section, we first present the statistics of the dataset we use (i.e., the Gowalla dataset) and the process of data pruning in Section III-A. The problem of successive POI recommendation is then defined in Section III-B.

### A. Dataset

We use the Gowalla dataset [8] in the following analysis and experiments. The check-in records we use are from August 2010 to August 2011. Besides, we remove the inactive users with the number of check-ins less than 300 and the unpopular POIs with the number of visits less than 80 times. Table I shows the statistics of the Gowalla dataset after data pruning.

### B. Problem Definition

**Definition 1 (Check-in sequence)** A check-in sequence of user $u$ is denoted by $S_u = \langle(l_1, t_1), (l_2, t_2), \cdots, (l_n, t_n)\rangle$ meaning that user $u$ has checked in at POI $l_i$ at time $t_i$. The check-in records in $S_u$ are assumed to be sorted according to the occurrence time in ascending order (i.e., $t_1 \leqslant t_2 \leqslant \cdots \leqslant t_n$).

**Definition 2 (Category transition)** Given a check-in sequence $S_u = \langle(l_1, t_1), (l_2, t_2), \cdots, (l_n, t_n)\rangle$ and a time threshold $\tau$, for any two check-in records in $S_u$, if $t_j - t_i \leqslant \tau$, a category transition is denoted by $c_{l_i} \to c_{l_j}$ where $c_{l_i}$ is the category of $l_i$ and $c_{l_j}$ is the category of $l_j$. It is possible that $c_{l_i}$ and $c_{l_j}$ are the same category.

**Definition 3 (Time-category pair)** Given a check-in record $(l_i, t_i)$ and the category of $l_i$, say $c_{l_i}$, the time-category pair of the check-in record is denoted by $(c_{l_i}, t_i)$.

Let $U$ be the set of users, $L$ be the set of POIs and $S$ be the set of check-in sequences of all users. Given a user $u \in U$, his/her current POI $l_c \in L$, and the current timestamp $t_c$, the successive POI recommendation aims to recommend $N$ POIs where he/her has never been and will check in within the time period $[t_c, t_c + \tau]$.

## IV. PROPOSED METHOD

Figure 1 shows the architecture of our successive POI recommendation method. As shown in Figure 1, our successive POI recommendation method consists of two phases: the category prediction phase and the POI recommendation phase. In the category prediction phase, our method first predicts the categories through the category transition matrix, the time-category pair matrix, the users' current POIs and the current time. Then, in the POI recommendation phase, our method ranks the POIs based on user-based CF (or user-time-based CF) and the geographical influence and recommends the top $N$ POIs. The details of the category prediction phase and the POI recommendation phase are described in Section IV-A and Section IV-B, respectively.

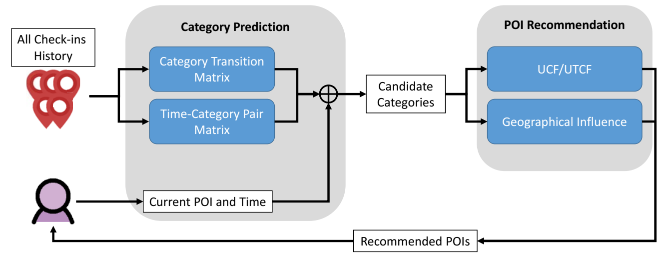



Fig. 1. Architecture

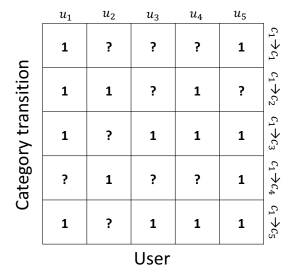



Fig. 2. Category Transition Matrix

### A. Category Prediction

*1) Category Transition Matrix:* Most of the previous works model the users' successive check-in behavior indirectly and hence cannot really find the relation between the successive check-in behavior and users. Besides, transitions between POIs are usually too sparse to build an effective prediction model. By analyzing the real dataset, we observe that users usually prefer some specific category transitions, and such observation gives us a new perspective on modelling users' successive behavior.

Figure 2 shows the matrix of category transitions and users. The matrix cell is labeled as "1" if we observe the user has this transition in the dataset, or "?" otherwise. We adopt a matrix factorization model to represent the interaction of users and category transitions. Let $n$ be the number of users, $m$ be the number of category transitions, $f$ be the number of latent factors, $R \in M^{m \times n}$ be the category transition matrix, and $P \in M^{m \times f}$ and $Q \in M^{n \times f}$ be the matrices of latent factor of category transition and user's preference on the latent factor of category transition, respectively. The objective function is as follows:

$$argmin_{P,Q} \Sigma_{i=1}^{m} \Sigma_{j=1}^{n} w_{ij} (P_i Q_j^T - R_{ij})^2 + \lambda_r \|P\|^2 + \lambda_r \|Q\|^2,$$
$$where\ w_{ij} = \begin{cases} 1 & \text{if the transition is observed} \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

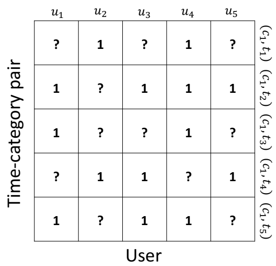



Fig. 3. Time-Category Pair Matrix

where $\lambda_r$ is the regularization constants. $w_{ij}$ is an indicator function which equals 1 if the category transition is observed, and equals 0, otherwise. We assume that users have positive preference on the observed category transitions. But an unobserved category transition does not imply that the users are not interested in the category transition. Besides, there will be some category transitions that only few users have. For example, after watching a baseball game, people usually go to have some food at restaurants or go home, and only few users will go to museums. Hence, the category transition "Arena then Museum" will not be significant in predicting users' successive check-in behavior. Those rare category transitions will be seen as outliers and will be removed from the category transition matrix. Thus, after parameter tuning, we order all category transitions according to their occurrences in descending order and keep only top 8000 category transitions to form the category transition matrix.

*2) Time-Category Pair Matrix:* Users tend to visit specific types of POIs in specific time. For example, users usually go to lunch at noon and have fun at bars in the midnight. We separate the time influence from category transition because we argue that time has more impact directly on the categories of POIs.

Figure 3 shows the matrix of time-category pairs and users. The matrix cell is labeled as "1" if we observe the user has this time-category pair in the dataset, or "?" otherwise. We adopt a matrix factorization model to represent the interaction of users and their time-category pairs. Let $n$ be the number of users, $o$ be the number of time-category pairs, $f$ be the number of latent factors, $V \in M^{o\times n}$ be the time-category pair matrix, and $W \in M^{o\times f}$ and $H \in M^{n\times f}$ be the matrices of the latent factor of time-category pair and user's preference on the latent factor of time-category pair, respectively. The objective function is as follows:

$$argmin_{W,H} \Sigma_{i=1}^{o} \Sigma_{j=1}^{n} w_{ij} (W_i H_j^T - V_{ij})^2 + \lambda_v \|W\|^2 + \lambda_v \|H\|^2,$$
$$where\ w_{ij} = \begin{cases} 1 & \text{if the time-category pair is observed} \\ 0 & \text{otherwise} \end{cases}, \tag{2}$$

where $\lambda_v$ is the regularization constants.

*3) Learning Algorithm:* In our proposed method, the matrices $P$, $Q$, $W$, and $H$ are learned by solving the objective functions shown in Eq. (1) and Eq. (2). In this paper, we adopt the Alternating Least Squares (ALS) method [7] to compute each latent factor matrix by fixing the other in two MF models, respectively, to minimize the objective functions. The updating formulas of $P$, $Q$, $W$, and $H$ are as follows:

$$P_i = (\Sigma_{j=1}^{n} w_{ij} Q_j Q_j^T + \lambda_r I)^{-1} (\Sigma_{j=1}^{n} w_{ij} R_{ij} Q_j), \tag{3}$$

$$Q_j = (\Sigma_{i=1}^{m} w_{ij} P_i P_i^T + \lambda_r I)^{-1} (\Sigma_{i=1}^{m} w_{ij} R_{ij} P_i), \tag{4}$$

$$W_i = (\Sigma_{j=1}^{n} w_{ij} H_j H_j^T + \lambda_v I)^{-1} (\Sigma_{j=1}^{n} w_{ij} V_{ij} H_j), \tag{5}$$

$$H_j = (\Sigma_{i=1}^{o} w_{ij} W_i W_i^T + \lambda_v I)^{-1} (\Sigma_{i=1}^{o} w_{ij} V_{ij} W_i), \tag{6}$$

where $I$ is an f-dimension unit matrix.

*4) Linear Aggregation:* Given the learned $P$, $Q$, $W$, and $H$, we can compute the next POI category preference for each user by the following equations:

$$S_{u,x}^{transition} = P_u Q_x^T, \tag{7}$$

$$S_{u,y}^{time} = W_u H_y^T, \tag{8}$$

where $S_{u,x}^{transition}$ is the score of user $u$ having the category transition $x$ and $S_{u,y}^{time}$ is the score of user $u$ having the time-category pair $y$.

Finally, we adopt the linear aggregation on the scores of category transition and time-category pair. The score of the preference of the user $u$ on the category $c$ is formulated as

$$S_{u,c} = \alpha S_{u,x}^{transition} + (1-\alpha) S_{u,y}^{time}, \tag{9}$$

where $\alpha \in [0,1]$ is a parameter to control the importance of category transition. The top $k$ categories are selected and passed to the POI recommendation phase.

### B. POI Recommendation

In the POI recommendation phase, the POIs belonging to the predicted categories are considered as the candidate POIs, and our method combines the collaborative filtering models and geographical influence to recommend $N$ POIs from the candidate POIs. In this section, we introduce two proposed CF models, *User-based Collaborative Filtering* (UCF) and *User-Time-based Collaborative Filtering* (UTCF).

*1) UCF: User-Based Collaborative Filtering:* Motivated by [11], users' preference on items can be computed by aggregating users who have similar behavior through collaborative filtering. First, we compute the similarity of user $u$ and user $v$ by the following equation:

$$w_{u,v} = \frac{\Sigma_{l=1}^{|L|} c_{u,l} c_{v,l}}{\sqrt{\Sigma_{l=1}^{|L|} c_{u,l}^2} \sqrt{\Sigma_{l=1}^{|L|} c_{v,l}^2}}, \tag{10}$$

where $c_{u,l} = 1$ means user $u$ has a check-in in POI $l$ and $c_{u,l} = 0$, otherwise. If two users share more common check-ins, their similarity will be higher and we can assume that they have similar preference on POIs. Then, we compute all users' similarity with the target user $u$ and the preference of user $u$

on POI $l$ is calculated as follows:

$$p_{u,l} = \frac{\Sigma_{v=1}^{|U'|} w_{u,v} c_{v,l}}{\Sigma_{v=1}^{|U'|} w_{u,v}} \tag{11}$$

where $U'$ is the set of users $h$ similar to the target user $u$.

*2) UTCF: User-Time-Based Collaborative Filtering:* We now propose a user-time-based collaborative filter method by integrating time influence and user preference. Similar to [12], we split the time into hours and extend the user-based collaborative filtering by considering temporal influence as follows:

$$w_{u,v} = \frac{\Sigma_{t=1}^{|T|} \Sigma_{l=1}^{|L|} c_{u,l,t} c_{v,l,t}}{\sqrt{\Sigma_{t=1}^{|T|} \Sigma_{l=1}^{|L|} c_{u,l,t}^2} \sqrt{\Sigma_{t=1}^{|T|} \Sigma_{l=1}^{|L|} c_{v,l,t}^2}}, \tag{12}$$

$c_{u,l,t} = 1$ means user $u$ has a check-in in POI $l$ at time $t$ and $c_{u,l,t} = 0$, otherwise. If two users visit the same POI at the same time, their similarity will be higher. The preference of user $u$ on the POI $l$ at time $t$ can be calculated as follows.

$$p_{u,l,t} = \frac{\Sigma_{v=1}^{|U'|} w_{u,v} c_{v,l,t}}{\Sigma_{v=1}^{|U'|} w_{u,v}} \tag{13}$$

*3) Geographical Influence:* Based on previous works and our observation on the Gowalla dataset, geographical influence plays an important role on POI recommendation since users tend to visit somewhere close to them.

Similar to [2], the geographical influence is modelled by a power law distribution. In addition, the POIs of distances to a user's current location longer than 5 km cannot be the candidate POIs for the user. Given a user $u$ and the user $u$'s current POI $l_c$, the preference that user $u$ will visit POI $l$ is formulated as follows:

$$dist\_prob(u, l_c, l) = a \cdot d^b, \tag{14}$$

where $a$ and $b$ are the constants of the power law distribution and $d$ is the Euclidean distance between POI $l$ and POI $l_c$.

Finally, the score that user $u$ will visit POI $l$ in $\tau$ hours when the current time is $t$ can be obtained by the following equation.

$$s_{u,l,t} = \frac{\Sigma_{i=0}^{\tau} p_{u,l,t+i}}{dist\_prob(u, l_c, l)} \tag{15}$$

## V. Experiments

### A. Experimental Settings

The experiments are conducted on the Gowalla dataset and the statistics of the Gowalla dataset is given in Table I. The first 80% data are selected for training and the rest 20% data are used for testing. The parameters $f$, $\lambda_r$, and $\lambda_v$ are set to 5, 0.01, and 0.02, respectively. The number of iterations of ALS for solving the category transition matrix and the time-category pair matrix are set to 10 and 20, respectively. $Precision@N$ and $Recall@N$ are used to evaluate the performance of successive POI recommendation:

$$Precision(L)@N = \frac{|R_{q_i^u} \cap V_{q_i^u}|}{N}, \tag{16}$$

$$Recall(L)@N = \frac{|R_{q_i^u} \cap V_{q_i^u}|}{V_{q_i^u}}, \tag{17}$$

where $R_{q_i^u}$ is the set of POIs recommended by the recommended method, and $V_{q_i^u}$ is set of POIs where the user $u$ checks in within $\tau$ hours.

We compared our proposed method with the state-of-the-art method PITF-WHITS [1]. In addition, several variations of our proposed methods are also implemented for comparison purposes. The methods used in our experiments are listed as follows.

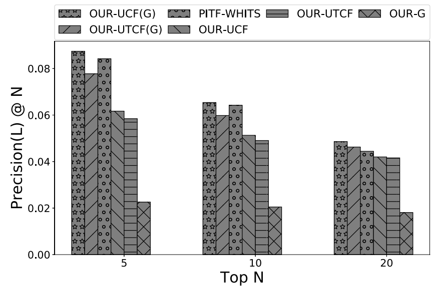
- **PITF-WHITS** [1]: This method is a two-step method with PITF for category prediction and WHITS for location recommendation.
- **OUR-G**: A variation of our proposed method, considering geographical influence on POI recommendation only.
- **OUR-UCF**: A variation of our proposed method, considering user-based collaborative filtering on POI recommendation only.
- **OUR-UTCF**: A variation of our proposed method, considering user-time-based collaborative filtering on POI recommendation only.
- **OUR-UCF(G)**: A variation of our proposed method, considering user-based collaborative filtering and geographical influence on POI recommendation.
- **OUR-UTCF(G)**: A variation of our proposed method, considering user-time-based collaborative filtering and geographical influence on POI recommendation.

### B. Experimental Results

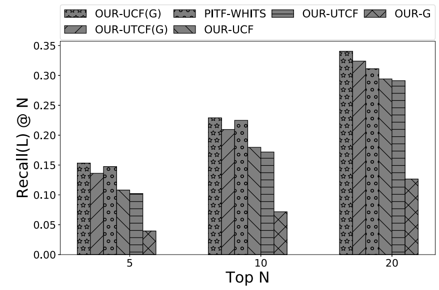
Figure 4(a) and Figure 4(b) show the experimental results when $\tau$ is set to 1 hour. The experimental results show that our method, OUR-UCF(G), outperforms others significantly. First of all, OUR-UCF(G) outperforms PITF-WHITS because of the advantage of the direct modelling of the successive check-in behavior. However, OUR-UTCF(G) is worse than PITF-WHITS. We argue that it is because the time threshold $\tau$ is set too short (only 1 hour) to capture the temporal influence on users' check-in preference since the temporal influence on users' behavior is usually not able to be observed within a short time period. For example, users may have dinner during 17:00 to 20:00, depending on how hungry he/she is or whether he/she has a social event or not. Thus, setting $\tau$ to a long period makes OUR-UTCF(G) able to capture temporal check-in behavior of users. As shown in Figure 4(c) and Figure 4(d), OUR-UTCF(G) performs well when $\tau$ is set to 6 hours. In our experiments, OUR-UTCF(G) is of the best performance when $\tau$ is set to 6 hours and $N$ is set to 5.

## VI. Conclusion

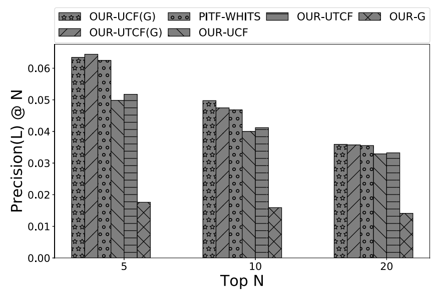
In this paper, we proposed a two-phase method for successive POI recommendation. In the category prediction phase, our method predicts a set of candidate categories that users will be interested in using the MF technique on the category transition matrix and the time-category pair matrix. In the POI recommendation phase, our method combines user preference,



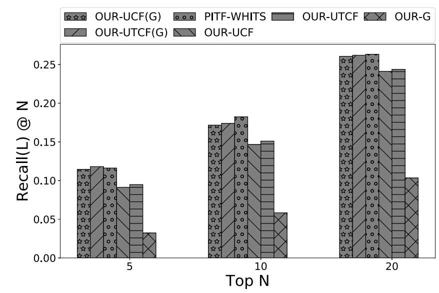

(a) Evaluate $\tau = 1$ on precision




(b) Evaluate $\tau = 1$ on recall




(c) Evaluate $\tau = 6$ on precision




(d) Evaluate $\tau = 6$ on recall

Fig. 4. The Performance Comparison of different time threshold in POI Recommendation

temporal influence, and geographical influence together to rank the candidate POIs. Experimental results on the Gowalla dataset showed that our method is of the best recommendation performance.

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## REFERENCES

[1] Jialiang Chen, Xin Li, William K. Cheung, and Kan Li. Effective successive poi recommendation inferred with individual behavior and group preference. *Neurocomput.*, 210(C):174–184, October 2016.

[2] Chen Cheng, Haiqin Yang, Irwin King, and Michael R. Lyu. Fused matrix factorization with geographical and social influence in location-based social networks. In *Proceedings of the 26th AAAI Conference on Artificial Intelligence*, AAAI'12, pages 17–23. AAAI Press, 2012.

[3] Chen Cheng, Haiqin Yang, Michael R. Lyu, and Irwin King. Where you like to go next: Successive point-of-interest recommendation. In *Proceedings of the 23rd International Joint Conference on Artificial Intelligence*, IJCAI '13, pages 2605–2611. AAAI Press, 2013.

[4] Shanshan Feng, Xutao Li, Yifeng Zeng, Gao Cong, Yeow Meng Chee, and Quan Yuan. Personalized ranking metric embedding for next new poi recommendation. In *Proceedings of the 24th International Conference on Artificial Intelligence*, IJCAI'15, pages 2069–2075. AAAI Press, 2015.

[5] Huiji Gao, Jiliang Tang, Xia Hu, and Huan Liu. Exploring temporal effects for location recommendation on location-based social networks. In *Proceedings of the 7th ACM Conference on Recommender Systems*, RecSys '13, pages 93–100, New York, NY, USA, 2013. ACM.

[6] H. Y. Gau, Y. S. Lu, and J. L. Huang. A grid-based successive point-of-interest recommendation method. In *2017 10th International Conference on Ubi-media Computing and Workshops (Ubi-Media)*, pages 1–6, Aug 2017.

[7] Yehuda Koren, Robert Bell, and Chris Volinsky. Matrix factorization techniques for recommender systems. *Computer*, 42(8):30–37, August 2009.

[8] Yong Liu, Wei Wei, Aixin Sun, and Chunyan Miao. Exploiting geographical neighborhood characteristics for location recommendation. In *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management*, CIKM '14, pages 739–748, New York, NY, USA, 2014. ACM.

[9] Steffen Rendle and Lars Schmidt-Thieme. Pairwise interaction tensor factorization for personalized tag recommendation. In *Proceedings of the 3rd ACM International Conference on Web Search and Data Mining*, WSDM '10, pages 81–90, New York, NY, USA, 2010. ACM.

[10] Mao Ye, Peifeng Yin, and Wang-Chien Lee. Location recommendation for location-based social networks. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, GIS '10, pages 458–461, New York, NY, USA, 2010. ACM.

[11] Mao Ye, Peifeng Yin, Wang-Chien Lee, and Dik-Lun Lee. Exploiting geographical influence for collaborative point-of-interest recommendation. In *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '11, pages 325–334, New York, NY, USA, 2011. ACM.

[12] Quan Yuan, Gao Cong, Zongyang Ma, Aixin Sun, and Nadia Magnenat Thalmann. Time-aware point-of-interest recommendation. In *Proceedings of the 36th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '13, pages 363–372, New York, NY, USA, 2013. ACM.

[13] Jia-Dong Zhang and Chi-Yin Chow. igslr: Personalized geo-social location recommendation: A kernel density estimation approach. In *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, SIGSPATIAL'13, pages 334–343, New York, NY, USA, 2013. ACM.

[14] Jia-Dong Zhang, Chi-Yin Chow, and Yanhua Li. Lore: Exploiting sequential influence for location recommendations. In *Proceedings of the 22nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, SIGSPATIAL '14, pages 103–112, New York, NY, USA, 2014. ACM.

[15] Shenglin Zhao, Tong Zhao, Haiqin Yang, Michael R. Lyu, and Irwin King. Stellar: Spatial-temporal latent ranking for successive point-of-interest recommendation. In *Proceedings of the 30th AAAI Conference on Artificial Intelligence*, AAAI'16, pages 315–321. AAAI Press, 2016.