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STGCN: A Spatial-Temporal Aware Graph Learning Method for POI Recommendation

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***Abstract*—Point-of-Interest (POI) recommendation helps users find their interested places to visit based on the time and user location. Unlike traditional recommendation tasks, POI recommendation is personalized, spatial-aware, and temporally dependent. Although many previous works have tried modeling spatial and temporal characteristics, most of them suffer from the following two limitations: For the spatial aspect, existing works only consider the user-POI distance or POI-POI distance. However, we find that a user prefers different regions at different times, which is known as *user-region periodic pattern*. For the temporal aspect, most works treat user and time as two independent factors. However, different users may prefer the same POI in different time periods, which is known as *user-POI periodic pattern*. To address the limitation of existing works, we propose a novel *S*patial-*T*emporal aware *G*raph *C*onvolutional *N*eural *N*etwork (STGCN) for POI recommendation. Specifically, we first design a *user record multigraph* to fuse all the context information into a unified graph. Then, we propose a time-based neighborhood sampling algorithm and take advantage of the flexible propagation mechanism of GCNs to learn the representations of each node at a specific time. Furthermore, multiple scoring functions are proposed to exploit *user-region periodic pattern* and *user-POI periodic pattern*, respectively. We also develop a time smoothing strategy to alleviate the data sparsity problem. Extensive experiments are conducted on two real-world datasets, and the experimental results demonstrate the effectiveness of our method.**

***Index Terms*—POI Recommendation, Spatial-Temporal, Graph Convolutional Networks**

I. Introduction

With the popularity of mobile devices and the advancement of locating technologies, Location-based Services (LBSs) such as Foursquare[1], Yelp[2], and Dianping[3], have attracted millions of users. To address the information explosion problem and improve user experience, POI recommendation is the key technique in LBSs and has attracted extensive research attention from both industry and academia [1].

Different from general item recommendation only focus on users' preference (e.g., movie [2]), POI recommendation are associated with the *spatially-aware* and *temporally-dependent* [3] querying context, i.e. user's location and present time. For example, a user tends to have a quick breakfast at cafe nearby house on a weekday morning, but prefers a further downtown bar for a drink in the evening. To exploit the spatial and temporal characteristics, previous studies in POI recommendations treated these two factors respectively:

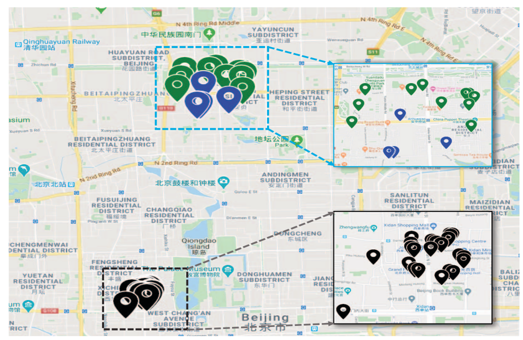

Fig. 1. The distribution of visited POIs of a randomly selected user. Different colors represent POIs visited by the user at different time: blue denotes 6:00-12:00, green denotes 12:00-18:00, and black denotes 18:00-24:00.

On the one hand, for the spatial aspect, existing solutions usually make use of user-POI distance or POI-POI distance based on the spatial clustering phenomenon [4], and they usually assume user's check-in behavior follows particular spatial distributions, for example, multi-center Gaussian distribution [5]. However, a fundamental limitation of existing works is that they neglect the *user-region periodic pattern* in realistic scenarios, i.e., a user prefers different regions at different times. To demonstrate this, we made statistics for each user's frequently visited regions in different times on Dianping dataset. According to the result, more than 67% of users prefer different regions at different times. We additionally sample a user and provide an illustrating example in Figure 1. This finding indicates that a user's frequently visited POIs exhibit high temporal pattern, which should be carefully taken into consideration in POI recommendation algorithms.

On the other hand, for the temporal aspect, prior methods assumed users prefer to visit similar POIs during the same

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[1]https://foursquare.com/
[2]https://www.yelp.com/
[3]http://www.dianping.com/

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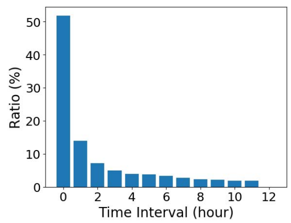
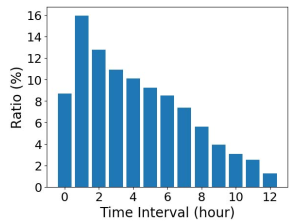


(a) Same users



(b) Most similar user pairs

Fig. 2. Distribution of time difference of (a) a user visiting the same POI, and (b) the most similar user pair visiting the same POI. The difference between the two distributions means that user and time are two dependent factors.

period [6]. However, we argue that user and time factors are not independent but exhibit *user-POI periodic pattern*, which means users opt for the same interested POI at different times, for instance, some users prefer noodles in the morning while others at noon. For demonstration, we adopt the daily pattern and calculate the time difference of every single user's behavior and between most similar user pairs. Figure 2(a) shows more than 73% of each user's consecutive visits on the same POI occur within 2 hours. While in Figure 2(b), the distribution of visiting time variance on the same POI by user pairs sharing common interests differs greatly from Figure 2(a), indicating even the most similar users have different time preferences. Therefore, we can infer that user and time are dependent factors and they exhibit *user-POI periodic pattern*.

In this paper, we investigate the problem of spatial-temporal aware POI recommendation with the two periodic patterns above that are not explored by existing works. This task is challenging in that, (1) it is not straightforward to fuse both spatial and temporal information properly while considering the user periodic patterns, and (2) user interaction data is very sparse in real-world scenarios, especially at a specific time. To address the challenges above, we propose a novel graph-based method, *Spatial-Temporal aware Graph Convolutional Neural Networks* (STGCN), for POI recommendation. Specifically, we first build a *user record multigraph* to fuse all the context information into one unified graph. The difference between our work and the literature is that, we model time as edge relations rather than nodes to emphasize that user and time are two dependent factors. Then we propose a time-based sampling algorithm and take advantage of the flexible propagation mechanism of GCN to learn the representations of each node at a specific time. Moreover, we apply different scoring functions to exploit the *user-region periodic pattern* and *user-POI periodic pattern*. Finally, to solve the data sparsity problem, we assume that users have similar preferences at adjacent time intervals, and develop a time smoothing strategy. Extensive experiments on two real-world datasets show the effectiveness of our method.

II. Related Work

A. POI recommendation

POI recommendation is a special case of recommender systems which is spatial-aware, and temporal depended. There are many works that consider spatial and temporal effects [7]–[9]. In particular, more and more works use graph-based methods [10], [11] in POI recommendation. Although great successes have been achieved, *user-region periodic pattern* and *user-POI periodic pattern* are still largely under-exploited.

B. Graph Convolutional Networks

Graph Convolutional Networks (GCNs) that extend Convolutional Neural Networks (CNNs) to non-Euclidean domains have received great attention recently [12], [13]. In recent years, GCNs also have achieved success in recommender systems [14]. However, to the best of our knowledge, there are no works that apply GCNs in POI recommendation, which is profoundly affected by spatial and temporal effects.

III. Problem Formulation

The purpose of personalized POI recommendation is to recommend POIs to users based on their locations and the current time. Let $\mathcal{U} = \{u_1, u_2, ..., u_M\}$ be a set of users, $\mathcal{P} = \{p_1, p_2, ..., p_N\}$ be a set of POIs, $\mathcal{L} = \{l_1, l_2, ..., l_Z\}$ be a set of regions that divided by GPS coordinates, and $\mathcal{T} = \{t_1, t_2, ..., t_H\}$ be a set of times which is divided by a specific pattern. Each POI corresponds to a region and users may be in different regions because of the users' mobility.

We focus on two scenarios. The first one is to find POIs online, such as Dianping, where users search POIs and decide which one they would like to go based on their locations. In this scenario, we use click as implicit feedback, and we know the user's current location. The other is "check-in", such as Gowalla, where users share POIs by checking-in. And we don't know the user's original location. Without loss of generality, we define the task as follows:

Definition 3.1. (**User Record**) A user record $r = (u_i, l_u, p_j, l_p, t)$ is five-tuple that represents the context of interactions. It means that the user u_i at location l_u and time t click or visit the POI p_j that locates in region l_p. Note the user location l_u may be unavailable.

Definition 3.2. (**POI Recommendation**) Given a set of user records $\mathcal{R}$ and a new query $q = (u_i, t, l_u)$, where $u_i \in \mathcal{U}, l_u \in \mathcal{L}$ and $t \in \mathcal{T}$, POI recommendation aims to recommend POIs $p \in \mathcal{P}$ that the user u_i would be interested at time t and location l_u.

IV. Our Approach

In this section, we first present the design of user record multigraph that fuses both spatial and temporal information, and then introduce technical details of STGCN model.

A. User Record Multigraph

To fuse the spatial-temporal context information, we propose the user record multigraph, as shown in Figure 3. As analyzed before, user and time are two dependent factors. We inventively treat users, POIs, and regions as nodes while regarding time as the relation in edges. Edges in inter-layer or intra-layers not only represent different relations but also contain various information. In the following, we give explanations for each type of edges.

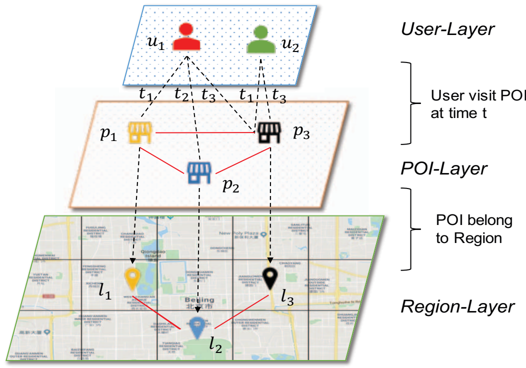


Fig. 3. The user record multigraph

User-POI edge $e_{i,j,t}$ represents the user u_i has been to the POI p_j at a time t. If user u_i has visited POI p_j at different times, then there will be multiple edges between i and j, and each one represents a time slot. The weight w of each edge is set to the number of visits in the time.

POI-POI edge $e_{i,j}$ connect p_i and p_j if users visit POI p_i and POI p_j during a time period t [3]. The weight w of the edge $e_{i,j}$ is the number of co-visits p_i and p_j in a time period t. The POI-POI edges point the proximity between the POIs.

POI-Region edge $e_{i,j}$ represents POI p_i located in region l_j. The POI p_i and p_k in the same region l may be different types, so to avoid the information propagation along the path $p_i \to l \to p_k$, there are only edges from POIs to regions and information propagate from regions to POIs.

Region-Region edges connect region nodes if two regions are geographically close to each other. As users are likely going to the neighbor POIs, and region-region edges make sure the adjacent regions have similar representations.

B. STGCN Model Architecture

The whole framework is shown in Figure 4, here we give explanations of each part.

1) Time-based Neighborhood Sampling Algorithm.

To capture the user periodic patterns, we need to get the representation of each node at time t. Therefore, we propose a time-based neighborhood sampling algorithm to get a fixed number of neighbors relevant to time t for every node. Furthermore, the fixed number of neighbors allows us to control memory footprint and reduce computation overhead [15].

As the neighbors of a node may have different distributions, we define normalization to edges to balance the sampled nodes' type as:

$$c_{i,r} = 1/\sum_{k\in N_i^r} w_{i,k}, \tag{1}$$

where N_i^r denotes the set of neighbors of node i under relation r and $w_{i,k}$ is the weight of edge $e_{i,k}$. Then we can define the sample weight for each edge at time t as:

$$w_e = w_{i,k} * c_{i,r} * w_t, \tag{2}$$

where $w_t = \mathbb{I}(e_t = t)$, e_t is the time in edge.

2) STGCN Layer.

After getting the multi-hops sampled neighbors of each node at time t, we design STGCN Layer to learn the representations of each node. By exploiting the idea of Relational Graph Convolution Network (RGCN) [16], we assign different transformation matrix to different relations of edges. Here we start by describing a single layer, including information propagation and information aggregation.

Information Propagation: As shown in Figure 4(c), for the first-order propagation, the user node interacted POIs provide direct evidence on the user's preference, the POI node gathers the representations of similar POIs, users and its own region, and the region node only propagates information among its adjacent regions. For the high-order propagation, taking the path $u_2 \xrightarrow{r_1} p_3 \xrightarrow{-r_1} u_1$ and $l_3 \xrightarrow{r_2} p_3 \xrightarrow{-r_1} u_1$ in Figure 3 as an example, where r_1 and $-r_1$ are two relations but they are both related to the same time t_3. The POI p_3 gathers the temporal u_2 preference that transformed by the transformation matrix of r_1 and the region embedding l_3 to enrich its own features, and then contribute to u_1 through relation $-r_1$. Furthermore, the path $u_2 \xrightarrow{r_1} p_3 \xrightarrow{-r_1} u_1$ can be viewed as user-based collaborative filtering [17].

Information Aggregation: After the propagation in the l-th layer, each node aggregates the information from its neighbors and generates a new representation. The representation can be represented as follows:

$$h_i^{(l+1)} = \sigma\left(\sum_{r\in\mathcal{R}}\sum_{j\in\mathcal{N}_i^r} w_e^{i,j}\mathbf{W}_r^{(l)}h_j^{(l)} + \mathbf{W}_0^{(l)}h_i^{(l)}\right), \tag{3}$$

where $h_i^{(l+1)}$ is the representation of node i at $(l+1)$ layer, $\mathcal{N}_i^r$ denotes the set of neighbors of node i under relation r, $w_e^{i,j}$ is the weight of edges $e_{i,j}$ calculated in algorithm 1, $\mathbf{W}_r^{(l)}$ is the transformation matrix assigned for relation r, and the σ denotes the activation function.

3) Prediction Layer.

After propagating L layers, we obtain the representations of users, POIs and regions at time t. To utilize the user periodic patterns for POIs and regions, while taking advantage of previous work, we propose the following score function:

$$y_{pred}(u,p,t) = \mathbf{e}_{u_t}^{\intercal}\mathbf{e}_{p_t} + \alpha\mathbf{e}_{u_t}^{\intercal}\mathbf{e}_{l_p} + \beta\mathbf{e}_{p_t}^{\intercal}\mathbf{e}_{l_u} + \gamma\mathbf{e}_{l_u}^{\intercal}\mathbf{e}_{l_p}, \tag{4}$$

where $\mathbf{e}_{u_t}$ and $\mathbf{e}_{p_t}$ is the embedding of the user u and the POI p at time t, $\mathbf{e}_{l_u}$ and $\mathbf{e}_{l_p}$ is the embedding of user and POI location, α, β, γ are the parameters that control the weight of each score function. The first part can represent *user temporal POI interests*, the second part can represent *User temporal region interests*, the third part is *POI influence areas* similar to [9], and the last part represent *user and POI distance*.

4) Time Smoothing Strategy.

To alleviate data sparsity when sampling the edges related to a specific time, we proposed a time smoothing strategy. As shown in Figure 2(a), users prefer to visit the same POI at the same or adjacent time, and the longer the interval, the less likely a user will visit. Based on this phenomenon, we relax

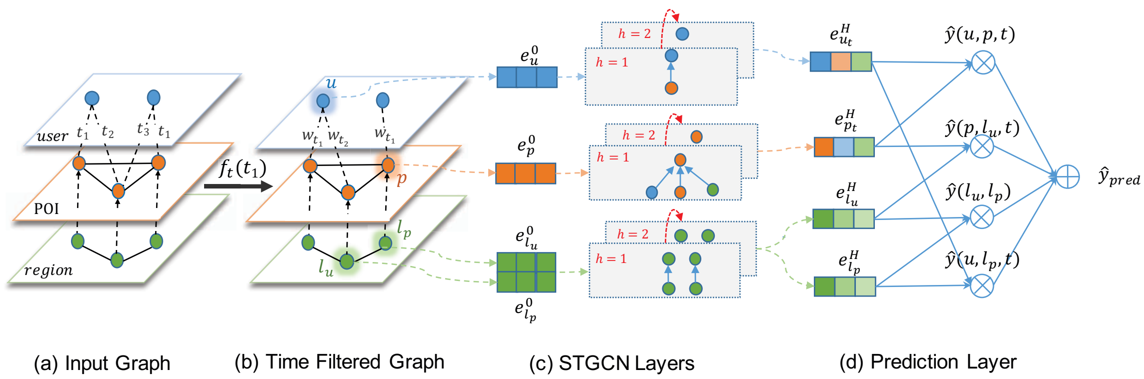


Fig. 4. Overview of our proposed STGCN model architecture. (a) shows the user record multigraph we proposed above. (b) is the graph transformed by time t_1, and the edges' time is t_1 or near t_1 are reserved and assigned to different time weights. (c) is the STGCN layers that propagate embeddings with H hops. (d) combines the final embeddings and integrates four scores to predict the result $\hat{y}_{pred}(u,p,t,l_u,l_p)$.

the time restrictions when sampling edges in Equation 2. We set the time weight w_t for each edge as follows:

$$w_t^{i,j} = \eta e^{\mu|t-t_0|}, \tag{5}$$

where t is the time on the edge $e_{i,j}$, t_0 is the sampling time and $\eta \geq 0, \mu \leq 0$ are parameters to control weight decay.

C. Optimization

To optimize our model, we first apply an unsupervised loss. Inspired by the skip-gram model [18], we define the unsupervised loss as:

$$\mathcal{L}_{unsup}(v) = -\log\sigma(\mathbf{e}_v^{\intercal}\mathbf{e}_w) - \sum_{z\in NEG(v)} \log\sigma(-\mathbf{e}_v^{\intercal}\mathbf{e}_z), \tag{6}$$

where $\mathbf{e}_v$ is the embedding of node v; w is the neighbor nodes of v and $NEG(v)$ is the negative sampling of node v.

Then, we adopt the BPR loss [19] for prediction loss as:

$$\mathcal{L}_{pred} = \sum_{\substack{(u,p,t)\in\mathcal{R},\\ (u,z,t)\in\mathcal{R}^-}} -\ln\sigma(y_{pred}(u,p,t) - y_{pred}(u,z,t)), \tag{7}$$

where $\mathcal{R}$ is the record set and $\mathcal{R}^-$ is the negative sampling set that we randomly replace the POIs and its regions.

Finally, we have the loss function as follows:

$$\mathcal{L}_{STGCN} = \mathcal{L}_{unsup} + \mathcal{L}_{pred} + \lambda\|\Theta\|_2^2, \tag{8}$$

where Θ is the model's parameters set, and λ is the parameter of L2 regularization.

V. Experiment

In this section, extensive experiments are conducted to verify the effectiveness of STGCN.

A. Dataset and Experimental setup

1) Dataset.

To evaluate the effectiveness of STGCN, we utilize two benchmark datasets:

- **Gowalla**[4] dataset [20] is a widely used benchmark dataset in POI recommendation. It only contains user, POI, time, and POI location. There are seven categories of POIs in Gowalla, and we choose the Gowalla-Food dataset due to the whole dataset is very large.
- **Dianping** is provided by Meituan-Dianping, and it contains the user location. We collect one month's data in Beijing, and each record represents a user click a POI at a specific location and time.

In this paper, we aim to study the daily pattern. We split time by 2 hours and choose Geohash length 6 to split space into regions for DianPing dataset and length 5 for Gowalla-Food dataset. Note that the time and space can be divided according to any granularity and further studies were recommended. To ensure the quality of the dataset, we use the 10-core setting in [21] that retaining users and POIs with at least ten interactions. The statistics of the two datasets are shown in Table I.

TABLE I
Statistics of the Gowalla-Food and Dianping Dataset

dataset	Gowalla-Food	Dianping
# of users	23,297	30,592
# of POIs	74,414	47,461
# of interactions	698,540	551,560
# of regions	21,238	4,358

2) Evaluation setup.

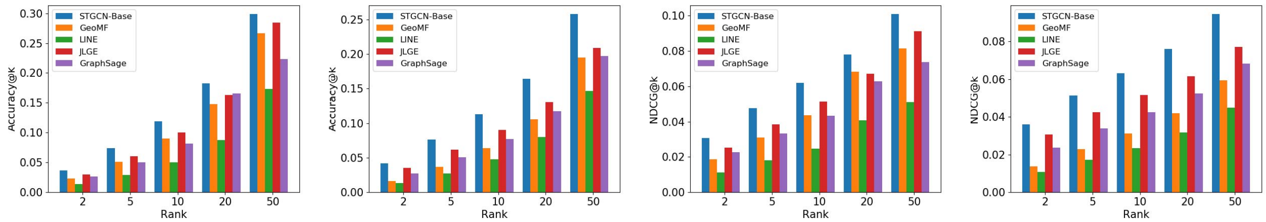
We randomly select 20% of interactions of each user as ground truth for testing and the remaining portions as the training set. We choose two of the most widely used evaluation metrics for the top k POI recommendation, including Accuracy@k and NDCG@k [7], [10]. Specifically, we calculate them using a single test record each time and then average.

3) STGCN Setup.

Since GCNs leverage node features to learn node representation, it's vital to provide valuable node features. Although we can easily utilize user profile and POI information [22] as node feature, to compare with other baselines without initial features, we adapt the LINE method [23] to get the initial representation. For simplicity, the embedding size of all vectors is set to 64. And we use 2 layers STGCN[5] with neighbor sampling size 5. For each positive record, we

[4]https://www.yongliu.org/datasets/

[5]https://github.com/ustchhy/stgcn



(a) Accuracy@k of Dianping (b) Accuracy@k of Gowalla-Food (c) NDCG@k of Dianping (d) NDCG@k of Gowalla-Food

Fig. 5. The results of Accuracy@k and NDCG@k.

randomly sample a negative POI with its corresponding region. The η and μ are set to 1 and -0.5, respectively.

B. Baselines

We compare the proposed STGCN model with several baselines for POI recommendation and remain their origin parameters as in papers. Specifically, these methods are:

- **GeoMF** [9] is a widely used MF baseline for POI recommendation, which augments latent factors with the user's activity region and POI's influence area.
- **LINE** [23] is an unsupervised graph embedding method which considers the first and second order proximity.
- **GraphSage** [15] is an inductive variant of GCNs and there is no time information in the input graph.
- **JLGE** [24] is a spatial-temporal graph-based model. It applies the LINE method on multiple bipartite graphs to jointly learn embeddings of every node.

C. Performance Comparison

As the baselines don't have the user location information, we only utilize the user temporal POI interests $\hat{y}(u, p, t)$ to train and predict. We call this model as **STGCN-Base**.

The results of all models are shown in Figure 5. We can see that our proposed STGCN-Base outperforms all the baselines on both two datasets and two metrics. Besides, we have the following observations:

- Our model has a better performance than GraphSage, whose edges have no time information, and it demonstrates that the time information plays an essential role in POI recommendation.
- Our model performs better than JLGE, who treats time as an independent node, especially in the Gowalla dataset. And it shows our hypothesis that user and time are two dependent factors can improve the performance.

D. Ablation Experiments

In this section, we conduct a series of ablation experiments to answer the question that how do spatial-temporal factors and different score functions affect STGCN. We list all the methods in Table II, and each method removes one or more components of spatial-temporal information and four score functions. The performance comparison results are presented in Table III. From the first three results, we can find both spatial and temporal factors are important in POI recommendation. And the next three results show each score function

TABLE II
THE METHODS IN ABLATION EXPERIMENTS.

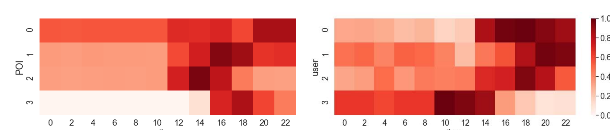
Method	Spatial	Temporal	U-P	U-LP	P-LU	LU-LP
ST-B	✓	✓	✓			
ST-B-S		✓	✓			
ST-B-T	✓		✓			
ST-ULP	✓	✓	✓	✓		
ST-PLU	✓	✓	✓		✓	
ST-LULP	✓	✓	✓			✓
STGCN	✓	✓	✓	✓	✓	✓

can improve performance. Finally, the STGCN that combines all factors has the best performance on all metrics.

E. Case Study

First, to explore the *user-POI periodic pattern*. We randomly select one user and four POIs visited by the user at different times, and randomly select a POI and four users who have visited the POI. We predict users preference for POIs at different times. As shown in 6(a), the user prefer different POIs at different times and from 6(b), we can tell that different users prefer the same POI at different times which proves the *user-POI periodic pattern*. Meanwhile, we can find that users also have a high preference near the visit time, and this phenomenon shows the efficiency of time smoothing strategy.

Then, to prove our model can capture the *user-POI periodic pattern*, we choose the same user as in Figure 1, and predict the user's most favorite regions at different times. As shown in Figure 7, we can easily find that it has a similar distribution with Figure 1.



(a) Different POIs (b) Different Users

Fig. 6. (a) A user's preference to different POIs, (b) Different users' preference to the same POI.

VI. Conclusion

In this paper, we presented a novel graph-based method for the spatial-aware and temporal dependent POI recommendation. By analyzing the real-world dataset, we find the *user-POI periodic pattern* and *user-region periodic pattern*. Considering the patterns, we first proposed a user record multigraph and

TABLE III
THE RESULTS OF ABLATION EXPERIMENTS.

Methods	Accuracy@k						NDCG@k					
	k=2	k=5	k=10	k=30	k=50	k=100	k=2	k=5	k=10	k=30	k=50	k=100
ST-B	0.0363	0.0742	0.1187	0.2300	0.2986	0.4071	0.0307	0.0475	0.0618	0.0879	0.1008	0.1184
ST-B-S	0.0358	0.0726	0.1174	0.2295	0.2979	0.4046	0.0303	0.0466	0.0610	0.0873	0.1001	0.1174
ST-B-T	0.0329	0.0647	0.1041	0.2041	0.2676	0.3692	0.0279	0.0420	0.05463	0.0781	0.0899	0.1064
ST-ULP	0.0376	0.0754	0.1214	0.2344	0.3045	0.4151	0.0318	0.0485	0.0632	0.0898	0.1029	0.1208
ST-PLU	0.0471	0.0953	0.1533	0.2974	0.3859	0.5207	0.0397	0.0610	0.0796	0.1135	0.1301	0.1519
ST-LULP	0.0526	0.1054	0.1690	0.3209	0.4119	0.5470	0.0441	0.0675	0.0879	0.1236	0.1407	0.1626
STGCN	**0.0530**	**0.108**	**0.1766**	**0.3494**	**0.4525**	**0.6038**	**0.0442**	**0.0681**	**0.0900**	**0.1307**	**0.1500**	**0.1746**

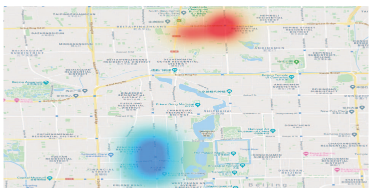


Fig. 7. Prediction heatmap of user prefers regions at different times. (The red and blue color represent 10-12 o'clock and 18-20 o'clock, respectively.)

then designed the STGCN model which was proved rationality and effectiveness in two real-world datasets. We hope this work could lead to more future studies.

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