Integrating Personalized Spatio-Temporal Clustering for Next POI Recommendation

Chao Song, Zheng Ren, Li Lu

School of Computer Science and Engineering, University of Electronic Science and Technology of China
chaosong@uestc.edu.cn, renzheng@std.uestc.edu.cn, luli2009@uestc.edu.cn

Abstract

Location-Based Social Networks (LBSNs) offer a rich dataset of user activity at Points-of-Interest (POIs), making next POI recommendation a key task. Traditional algorithms face challenges due to broad searching scopes, affecting recommendation accuracy. Users tend to visit nearby POIs and show temporal concentration in their activities, reflecting personalized spatio-temporal clustering. However, individual user data may be insufficient to capture these clustering effects for personalized recommendations. In this paper, we propose an integrated Personalized Spatio-Temporal Clustering Model (iPCM) for next POI recommendation. The model learns this kind of personalized spatio-temporal clustering effect by using global historical trajectory data in conjunction with user feature embeddings. It integrates the features of personalized spatio-temporal clustering with the user's trajectory, and completes the user's POI recommendation through a Transformer encoding and MLP decoding. To enhance the accuracy of predictions, we add a module of probability adjustment. The experimental results on multiple datasets show that with the help of personalized spatio-temporal clustering, the proposed iPCM is superior to existing methods in various evaluation metrics.

Introduction

With the rapid development and application of mobile devices and network applications, Location-Based Social Networks (LBSNs) such as Foursquare, Gowalla, and Yelp are capable of recording a large amount of rich activity trajectories of users at different Points-of-Interest (POIs), such as shopping centers, restaurants, or gyms. The vast historical check-in data provides valuable information for service providers to understand users' preferences for the next visit behavior, as historical trajectories reveal the behavioral patterns of users when making every decision (Luo, Liu, and Liu 2021; Long et al. 2023; Dai et al. 2022; Song, Wen, and Li 2019; Gutowski et al. 2019; Cranshaw et al. 2012). Based on this information, service providers can make more accurate recommendations for users and provide more personalized services, thereby improving user satisfaction with the service; this information can also serve as an auxiliary factor to help businesses or service providers make wiser decisions, which has potential commercial value. Therefore, recommending the next POI for users based on historical check-in data is one of the most important tasks in the research of location-based social networks (Huang et al. 2022; Yin et al. 2023; Wang et al. 2023a; Ou et al. 2023).

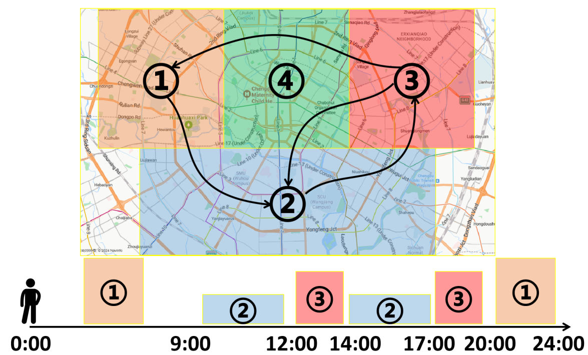
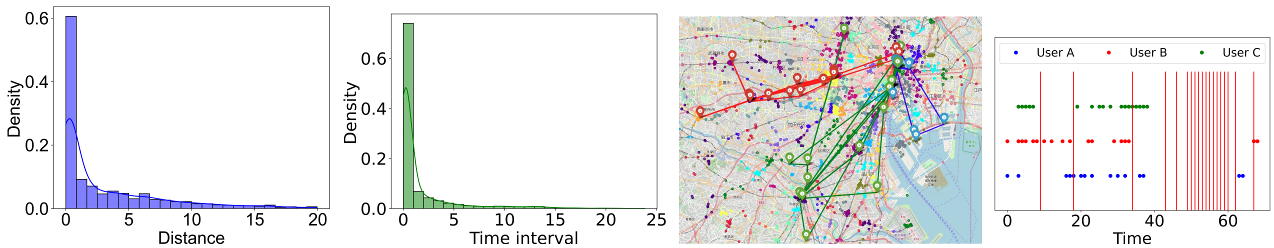


Figure 1: Personalized spatio-temporal clustering

Next POI recommendation is a critical task in location-based services, aiming to predict users' future visits based on their historical data. Traditional algorithms struggle with vast searching scopes, encompassing whole cities and all times, leading to decreased accuracy due to increased computational load and noise. Limiting the spatio-temporal searching range is essential to improve recommendation quality. As shown in Fig. 1, the occurrence of POIs exhibits spatial and temporal clustering effects. In terms of time, user behavior tends to be concentrated within specific time periods, while in terms of space, the clustering effect of geographical locations is reflected in the tendency of users to visit nearby places. Combined with personal habits and preferences, each user has their own unique lifestyle and preferences, which leads to clustering behavior in specific times and places. We term the combination of temporal and spatial clustering effects and personalized recommendation as *personalized spatio-temporal clustering*. For each user, such personalized spatio-temporal clustering also exhibits a distribution of their individual characteristics, hence we need to learn this for personalized POI recommendations. However, learning such effect from an individual's historical trajectory data can be challenging due to insufficient data volume.



(a) Spatial distribution (b) Temporal distribution (c) Spatial trajectories (d) Temporal trajectories

Figure 2: The effects of spatial-temporal clustering.

This necessitates the use of global historical trajectory data, combined with user feature embeddings, to learn this kind of personalized spatio-temporal clustering effect. How to integrate the global historical trajectories and the personalized spatio-temporal clustering has become a challenging issue.

In this paper, we propose the integrated Personalized Spatio-Temporal Clustering Model (iPCM) for next POI recommendation. The model analyzes the spatio-temporal regional distribution of users' mobile preference POIs, clusters the spatio-temporal regions, learns and aggregates them separately, and then predicts the next POI. To enhance the POI recommendation model, we focus on integrating spatio-temporal user visit data more effectively. Spatially, we adopt a k-means based clustering approach for POIs to reflect geographical relationships, avoiding the shortages of traditional grid divisions (Lim et al. 2022). Temporally, we employ an ordered sample clustering method to segment the day based on user visit patterns to different POIs, rather than equal time intervals. Additionally, we leverage more accurate predictions of the next region and time period to narrow down the searching scope for POI recommendations, thus enhancing recommendation accuracy. We summarize the primary contributions of our work as follows:

- To integrate the personalized spatio-temporal clustering effect, we propose the iPCM model that clusters the POIs appearing in the user's historical trajectory in both time and space, and incorporates user features.
- The iPCM model employs Transformer encoding and MLP decoding for next POI recommendation, and introduces a module of Probability Adjustment to enhance the accuracy of predictions.
- We conduct extensive experiments on four real-world LBSN datasets, and the experimental results reveal that with the help of personalized spatio-temporal clustering, iPCM consistently outperforms the state-of-the-art POI recommendation methods.

Related Work

In early research on POI recommendation, some only recommended a few popular POIs for users to choose from (Cheng, Ye, and Zhu 2013), which is too simplistic and cannot meet user demands very well. Other works are based on the assumption of Markov chains (Cheng et al. 2013), focusing on predicting the transition probabilities between POIs to recommend the next visit, but this method finds it difficult to handle high-order sequence patterns. Some researchers have also proposed many POI recommendation models, such as the classic collaborative filtering model (Xiong et al. 2010) and matrix factorization models (Salakhutdinov and Mnih 2007). Collaborative filtering can combine influences from different users, while matrix factorization can consider the context and social information of POI visits, but these models are quite limited in their ability to model sequential data.

In recent years, researchers have begun to focus on using deep learning methods, such as POI recommendation methods based on RNN and self-attention mechanisms, because they have superior capabilities for modeling sequential patterns from different perspectives. STRNN (Liu et al. 2016) incorporates time feature matrices and distance feature matrices into traditional RNN models to capture the influence from time and space. Spatio-temporal information has also been applied to LSTM models; STGN (Zhao et al. 2022) adds additional spatio-temporal gates to LSTM units to obtain the user's long and short-term preferences. (Yang et al. 2020) calculates weights using the spatio-temporal intervals between current and historical visits, with the aim of identifying historical RNN hidden states similar to the context, and then aggregating them for prediction. In addition, some recent studies have also explored new methods using self-attention mechanisms. SGRec (Li et al. 2021) proposes an attention-based model to aggregate POI representations learned through sequence-to-graph reinforcement learning. STAN (Luo, Liu, and Liu 2021) enhances the effect of the attention mechanism by explicitly utilizing spatial and temporal matrices. There are also studies that take additional related information into account; HMT-GRN (Lim et al. 2022) adopts a grid partitioning method to consider regional influences between POIs, GETNext (Yang, Liu, and Zhao 2022) incorporates the category information of POIs included in the dataset into the representation of check-ins. AGRAN (Wang et al. 2022) dynamically learns the structure of the graph to replace the traditional pre-defined graph.

HMT-GRN (Lim et al. 2022) method divides the entire area into several grids, thereby adding additional regional attributes to POIs. However, this division method can disrupt the original geographical relationships between POIs, and the divided areas lack actual physical significance. The GETNext (Yang, Liu, and Zhao 2022) method divides the time of day into the same intervals, but does not use explicit predictive information about time to assist in predicting POIs. In general, existing methods have significantly improved in capturing the sequential relationships of POI visits compared to the past and have also considered many additional pieces of information. However, they have not divided factors such as time and space in a more reasonable way and integrated them into the representation of check-in information and predictions for POIs.

Problem Formulation

Problem

The set of N POIs is denoted by $L = \{l_1, l_2, \cdots, l_N\}$, and the set of M users is denoted by $U = \{u_1, u_2, \cdots, u_M\}$. Next, we introduce the definitions for the problem of next POI recommendation.

DEFINITION 1 (check-in) *A check-in is denoted by $c = (u, l, t)$, which denotes that the user u visits the location (i.e., POI) l at the timestamp t.*

DEFINITION 2 (user trajectory) *A user trajectory of user u_i is orderly composed of one or several check-ins denoted by $T_{u_i} = \{c_1, c_2, \cdots, c_s\}$, where s denotes the index of the last check-in of the trajectory.*

DEFINITION 3 (next POI recommendation) *Given the current trajectory of user u_i, i.e. $T_{u_i} = \{c_1, c_2, \cdots, c_s\}$, the objective of next POI recommendation is to recommend a list of top-ranked POIs that the user is most likely to visit at the next timestamp with probabilities.*

Motivation

To analyze the spatial distribution of POIs, we conducted experiments using a dataset of Foursquare[1], selecting data from Tokyo city (TKY). For each check-in record in the trajectories, we calculated the distance between the next POI and the currently visited POI, and plotted a histogram of the distance distribution. The statistical results are shown in Fig. 2(a). To analyze the temporal distribution of POI visits, we calculated the time interval between the next POI and the currently visited POI, and plotted a histogram of the time interval distribution. The statistical results are shown in Fig. 2(b). We can see from the distribution of check-in records in global historical trajectories that both the spatial and temporal distributions observed appear to follow a Power-Law Distribution. This means that more next POIs tend to be chosen in proximity in space and time, exhibiting an clustering effect in their spatio-temporal distribution.

We analyzed the spatio-temporal clustering effects of different user trajectories using the TKY dataset and found variations in the clustering effects. As shown in Fig. 2(c), we selected trajectory data from three users in the TKY training dataset, plotted the POIs in the user trajectories, and connected them in the order of check-ins. The user trajectories were projected onto the latitude and longitude plane and displayed on the map. In Fig. 2(d), the horizontal axis represents the time of day (with 20 minutes as the basic unit), the red vertical lines indicate the division lines for temporal clustering, and points of different colors represent the distribution of different users' trajectories in time. From the results, it can be seen that the time and space distribution of POIs in different user trajectories exhibit both aggregation and their own characteristics. This is what we refer to as *personalized spatio-temporal clustering*. There are personalized differences in the spatio-temporal clustering effects of different user trajectories, which can help achieve personalized POI recommendations.

[1]https://sites.google.com/site/yangdingqi/home

Method

Overview

We propose the integrated Personalized Spatio-Temporal Clustering Model (iPCM) for next POI recommendation, and Fig. 3 shows the overall structure. Initially, for POIs, we construct a global POI graph based on the check-in dataset and obtain the POI embeddings using a Gated Graph Neural Network (GGNN) on the graph. For users, we establish a user-POI bipartite graph based on the user's check-in records to obtain user embeddings. We employ clustering methods to cluster POIs and access times to obtain embeddings for regions and time periods. Subsequently, we combine the POI, user, region, and time period embeddings from the check-in data through a fusion module and input them into the Transformer encoder module. Finally, an MLP (Multi-Layer Perception) layer is used to make predictions. Thus, iPCM is partitioned into three modules: embedding module, encoding and decoding module, and probability adjustment.

Embedding Module

The embedding module includes POI embedding, user embedding, region embedding, time period embedding and fusion module.

POI embedding We constructed a global POI graph based on the check-in dataset, which is defined as follows:

DEFINITION 4 (POI graph) *The POI graph is a homogeneous graph denoted as $G_l = \{L, E_l\}$, where L and E_l represent a set of POIs and a set of edges, respectively. An edge $< l_i, l_j >$ is the frequency of a visit to l_i followed by a visit to l_j in the POI visit history of a user.*

After constructing the POI graph, it is necessary to embed the POIs. We use the GGNN model to embed the POIs (Li et al. 2016). This results in the POI embeddings represented as $e^l \in \mathbf{R}^d$. Here, d refers to the dimension of the vector, and is set to 128.

User embedding We constructed a global user-POI graph based on the check-in dataset as follows:

DEFINITION 5 (user-POI graph) *The user-POI graph is a bipartite graph denoted as $G_u = \{U, L, E_u\}$, where U, L and E_u represent a set of users, POIs and edges, respectively. If a user u_i has visited POI l_j in his/her travel history, a user-POI edge $< u_i, l_j >$ exists.*

After constructing the user-POI graph, we utilize a mean function as the aggregation function to aggregate the embeddings of POI nodes adjacent to the user. Let e_i^{u-} denote the

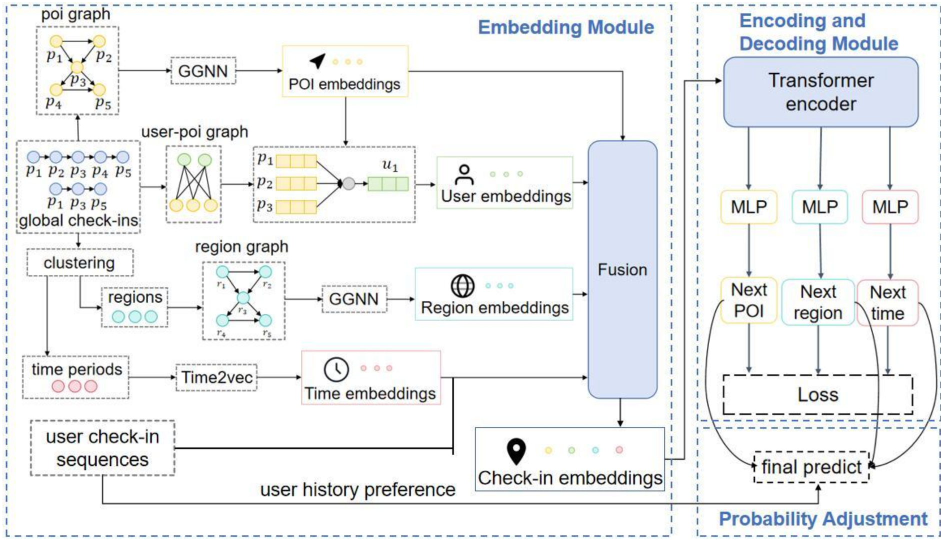


Figure 3: Overview of integrated personalized spatio-temporal clustering model (iPCM) for next POI recommendation.

initial embedding of u_i, and $\mathcal{N}_i$ is the set of POIs adjacent to user u_i. The final user embedding obtained is denoted as $e_i^u \in \mathbf{R}^d$,

$$e_i^u = LeakyReLU(\mathbf{w}_u \times (e_i^{u-} + AGG(e_j^l | j \in \mathcal{N}_i) + b_u)).$$

where $\mathbf{w}_u \in \mathbf{R}^{d \times d}$ is a learnable weight vector and b_u is the bias.

Region embedding A spatial region, in the context of clustering POIs based on global user trajectory data, can be defined as a geographical area that contains a group of POIs which have been clustered together due to their proximity to one another. This clustering is intended to reflect the spatial distribution and patterns of user visits, with the assumption that POIs within the same region are more likely to be visited consecutively by users due to their relative closeness in space.

DEFINITION 6 (region) *A spatial region is a geographical zone that encapsulates a cluster of POIs identified through clustering techniques, based on their spatial closeness within the scope of location-based services and recommendation systems.*

We adopt the k-means algorithm to cluster POIs based on their latitude and longitude information. The result of the clustering, that is, the set of POIs, is defined as a region. Let G denote the set of regions. We follow the method of constructing the POI graph to build a region-region graph and similarly use the GGNN method to obtain the embeddings of the regions, denoted by $e^g \in \mathbf{R}^{d/2}$.

Time embedding A temporal period, in the context of clustering POIs based on the sequence and intervals of their occurrences throughout a day, can be defined as a specific segment of time within the 24-hour day that contains a cluster of POIs which have been grouped together due to similar visitation patterns or time intervals.

DEFINITION 7 (time period) *A time period within a day is defined by clustering analysis, encompassing a set of POIs that exhibit usage patterns or are visited within similar timeframes. This periodization is based on the aggregation of user activity data, reflecting the temporal distribution of visits and identifying distinct phases of user engagement with POIs throughout the day.*

In iPCM, we divide a day into 72 time slices, each 20 minutes long. From the global historical trajectories, each time slice contains the check-in records. We utilize the method of ordered sample clustering (Fisher 1958) to cluster these time slices into multiple time periods, and the set of periods is denoted by T. We then obtain the embeddings of time periods, denoted by $e^t \in \mathbf{R}^{d/2}$, through the time2vec method (Kazemi et al. 2019).

Fusion Module After obtaining the embeddings for POI, user, region, and time period from the check-in records, we use a fusion module to concatenate these four embeddings together, and then pass them through a fully connected layer to output them as the embedding for the check-in record, denoted by $e^c \in \mathbf{R}^{3d}$,

$$e^c = \sigma(\mathbf{w}_c[e^l; e^u; e^g; e^t] + b_c),$$

where $\mathbf{w}_c \in \mathbf{R}^{3d \times 3d}$ is a learnable weight vector and b_c is the bias. Thus, each input trajectory $(c_1, c_2, \cdots, c_s)$ can be represented by $(e^{c_1}, e^{c_2}, \cdots, e^{c_s})$. Therefore, these check-in embeddings additionally contains the features of personalized spatio-temporal clustering.

Transformer Encoding and MLP Decoding Module

Transformer encoder The Transformer (Vaswani et al. 2017) is a core architecture in natural language processing models that uses a self-attention mechanism. Given our goal of predicting the next POI based on the provided sequence, we only utilize the encoder part of the Transformer model to process the input sequence. For an input user trajectory of length s, we encode the s check-in locations with positional encoding, and stack the embeddings of the s check-ins together, adding them to the positional encoding as the input tensor $X^{[0]} \in \mathbf{R}^{s\times 3d}$ for the encoder. We stack multiple encoder layers (l layers, $l = 2$), with each encoder layer consisting of a multi-head self-attention module and a feed-forward neural network, resulting in the output tensor $X^{[l]}$.

MLP decoder Through the Transformer encoder layers, we have extracted the effective features of the input trajectory embeddings. To predict the next POI, we use a MLP (Multi-Layer Perception) to decode the features output by the encoder layers. For the prediction of the next POI (Y_{poi}), the next time period (Y_{time}), and the next region (Y_{region}), we have used three different MLP heads to process the features output by the encoder layer respectively:

$$\begin{aligned} Y_{poi} &= X^{[l]}\mathbf{w}_{poi} + b_{poi}, \\ Y_{time} &= X^{[l]}\mathbf{w}_{time} + b_{time}, \\ Y_{region} &= X^{[l]}\mathbf{w}_{region} + b_{region}, \end{aligned}$$

where $\mathbf{w}_{poi} \in \mathbf{R}^{3d\times|L|}$, $\mathbf{w}_{time} \in \mathbf{R}^{3d\times|T|}$ and $\mathbf{w}_{region} \in \mathbf{R}^{3d\times|G|}$ are the learnable weights in MLP. Here, $|L|$, $|T|$ and $|G|$ denote the numbers of POIs, time periods and spatial regions, respectively. b_{poi}, b_{time} and b_{region} are the biases in MLP.

Loss function We use the cross-entropy function as the loss functions for predicting the next POI (L_{poi}), the next time period (L_{time}), and the next region (L_{region}). The total loss function (L_{total}) is the sum of these loss functions,

$$L_{total} = L_{poi} + L_{time} + L_{region}.$$

Probability Adjustment

We have obtained the prediction results for the next POI, next region, and next time period. The next step is to use the prediction results of the region and time period to assist in predicting the next POI.

If we directly modify the prediction probabilities of POI using the prediction results of the region, the experimental results do not improve. The reason is that although the prediction results of the region are relatively accurate, a region often contains dozens of POIs or more. This would introduce a lot of noise, which might reduce the original recommendation effect.

In other words, the prediction probability of the next region is higher than that of the next POI, but predicting the next region does not ensure 100% coverage of the correct next POI. So when selecting multiple next regions, there is a certain probability of covering the correct next POI, and this probability increases with the number of next regions selected, until it covers the whole city. We hope to reduce the number of selected next regions to minimize the noise impact, but this would lead to a decrease in the accuracy of predicting the next POI.

Based on this issue, attempts are made to further narrow the screening range or reduce noise from other perspectives: Since users tend to visit POIs they have already visited, the focus is on narrowing the scope to the POIs that the user has visited and introducing the user's preference information for POIs. The situation of users visiting POIs in various regions during different time intervals is statistically analyzed from the training data, serving as the user's preference for each POI.

We extracted the following tensor from the training dataset: *user-period-poi*, where a value of 1 in the tensor indicates that the user has visited a specific POI in a specific time period, otherwise it is 0. Another tensor is *user-region-poi*, where a value of 1 indicates that the user has visited a specific poi within a specific region, otherwise 0. A threshold is set for filtering regions and time periods, such as selecting the top 40 regions and top 5 time periods. After the MLP layer, based on the user's current test data and the set spatio-temporal threshold, the corresponding vectors are extracted from the two tensors, multiplied by the corresponding positions of the two, and added to the POI prediction result as the final prediction result.

Dataset	#user	#POI	#check-in	#trajectory
NYC	1083	5132	106919	32541
TKY	1181	3566	93692	22637
SIN	1526	4311	119491	34912
OSK	938	2954	105567	25281

Table 1: Foursquare Datasets

Experiments

Experimental Parameters

The numbers of dimensions for POI embedding ($poi\_embedding$), user embedding ($user\_embedding$), region embedding ($region\_embedding$) and time embedding ($time\_embedding$) are 128, 128, 64 and 64, respectively.

The number of encoder layers in Transformer module (denoted by $encoder\_layers$) is 2. The dimensions of the feed-forward network in the Transformer encoder layer (denoted by $encoder\_hidden$) is 1024. The number of attention heads in the multi-head attention module ($encoder\_head$) is 2.

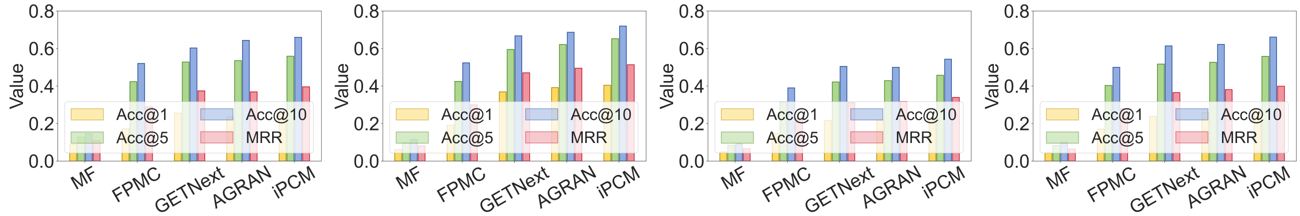
The Adam optimizer is used, with the initial learning rate (lr) set to 1e-3. The batch size ($batch\_size$) is set to 100, and the model is trained for 100 epochs, with the best-performing epoch on the validation set metrics being used to calculate the test set metrics.

We develop iPCM[2] based on PyTorch framework with Python 3.9. We conduct experiments on hardware platform (CPU: 11^{th} Gen Intel(R) Core(TM) i7-11700 @ 2.50GHz 2.50GHz, RAM: 16.0 GB), and the operating system is Windows 11.

Dataset

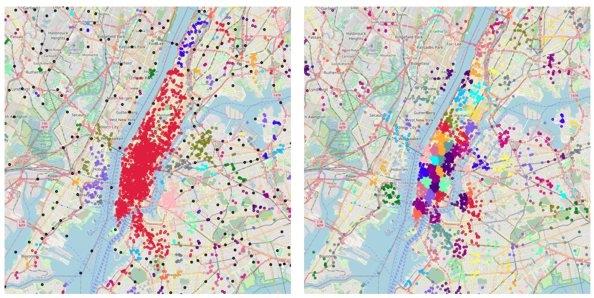
Experiments were conducted on four public datasets of Foursquare collected from location-based service platform

[2]https://github.com/songchaocn/iPCM



(a) NYC (b) TKY (c) SIN (d) OSK

Figure 4: Comparison with different models.



(a) DBScan (b) k-means

Figure 5: Spatial clustering into regions in NYC.

introduced in the Problem Formulation section, and the details are shown in Table 1. NYC collects check-in data from New York City from April 2012 to February 2013, and TKY collects check-in data from Tokyo during the same period. SIN and OSK are collected the check-in data from Singapore and Osaka during the same period, respectively. Each record contains information on the user, POI, POI category, GPS coordinates, and timestamp. For all datasets, POIs that appear less than 10 times and are unpopular are excluded. Users who have checked in less than 20 times are also excluded. Regarding the division of the dataset, each user's check-in data is sorted by time, with the first 80% as the training set, the middle 10% as the validation set, and the last 10% as the test set. Regarding the division of trajectories, a day-based division method is adopted, where check-in data from the same user on the same day is considered as one trajectory. If the length of a trajectory exceeds 50, only the last 50 check-ins of the trajectory are taken.

Metrics

Accuracy@k ($Acc@k$) and Mean Reciprocal Rank (MRR) are common metrics used in recommendation systems. Accuracy@k indicates whether the true POI appears in the top-k recommended POIs. Given a dataset with m samples (trajectories), Accuracy@k is calculated as: $Acc@k = \frac{1}{m}\sum_{i=1}^{m} \mathbf{1}(rank \leq k)$. Since $Acc@k$ treats the top-k recommendations as an unordered list and ignores the order of correct predictions, MRR is used to measure the index of the correctly recommended POI in the ranked list of recommendations, i.e., $MRR = \frac{1}{m}\sum_{i=1}^{m} \frac{1}{rank_i}$.

Baseline Models

To evaluate the effectiveness of the proposed iPCM model, we compare it with the following state-of-the-art methods in the experiments: (1) **MF** (Koren, Bell, and Volinsky 2009): A traditional matrix factorization model for next POI recommendation. (2) **FPMC** (Rendle, Freudenthaler, and Schmidt-Thieme 2010): A model integrates personalized Matrix Factorization with Markov Chains by leveraging a transition cube factorization approach. (3) **GETNext** (Yang, Liu, and Zhao 2022): A Transformer-based model that integrates global transition patterns, spatial-temporal contexts, and category embeddings. (4) **AGRAN** (Wang et al. 2023b): A model that enhances next POI recommendation by adaptively learning graph structures to capture dynamic geographical dependencies.

Comparisons with Models

Fig. 4 shows the recommendation performance of iPCM and baseline models on the four datasets. We take Acc@1, Acc@5, Acc@10 and MRR as the evaluation metrics. From the statistical table of the dataset, it can be seen that the average number of check-ins per user (total number of check-ins / number of users) in the SIN dataset is the lowest, far below NYC and OSK, and slightly lower than TKY. Moreover, compared with the TKY dataset, the average trajectory length in the SIN dataset (total number of check-ins / number of trajectories) is significantly smaller. These reasons may lead to the recommendation algorithm's performance on the SIN dataset being lower than on other datasets.

The experimental results show that our proposed model iPCM outperforms all other state-of-the-art baseline models. On all the four datasets in terms of all evaluation metrics, the iPCM model has achieved an average improvement of **452.96% over MF, 49.13% over FPMC, 8.29% over GETNext, and 5.88% over AGRAN**. MF is an early classic recommendation algorithm that learns vector representations of users and POIs through matrix factorization for subsequent recommendations. However, the user-POI matrix on which the MF algorithm relies is often very sparse, and it is entirely based on the interaction between users and POIs, ignoring other factors. These reasons lead to poor performance of the MF algorithm. Compared to various baselines, our model iPCM not only takes into account spatio-temporal and user-specific information but also utilizes the predictive results of spatio-temporal clustering information to recommend the next POI, thus outperforming the other baselines.

	$Acc@1$	$Acc@5$	$Acc@10$	MMR
POI	0.2236	0.485	0.5698	0.3364
POI+user	0.2486	0.553	0.6370	0.3825
w/o period	0.2513	0.5456	0.6536	0.3825
w/o region	0.2577	0.55	0.6503	0.3915
iPCM	**0.2604**	**0.5589**	**0.66**	**0.3962**

Table 2: Ablation studies on NYC dataset.

	$Acc@1$	$Acc@5$	$Acc@10$	MMR
POI	0.2556	0.4784	0.5738	0.3617
POI+user	0.3691	0.6358	0.7149	0.488
w/o period	0.3818	0.6433	0.7151	0.4981
w/o region	0.4007	0.6418	0.7129	0.5088
iPCM	**0.4044**	**0.6524**	**0.7198**	**0.5136**

Table 3: Ablation studies on TKY dataset.

Spatial Clustering

We compare the effects of the clustering algorithms of DB-Scan and k-means on spatial regions, as shown in Fig. 5. From the experimental results, the difference in performance between the two is not very significant. The k-means method doesn't produce noise points and makes it easier to control the number of clusters, hence in this paper we utilize the k-means method for clustering POIs into regions.

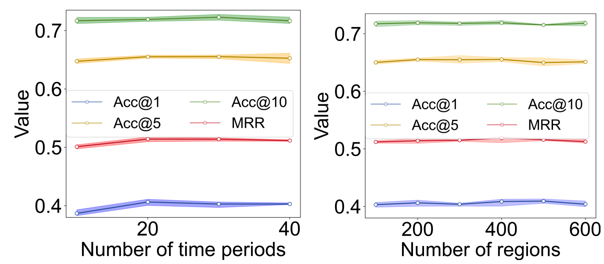
Ablation Study

To evaluate the contributions of each component in our model iPCM, we conduct an ablation study on Foursquare dataset. The results on the NYC and TKY datasets are shown in Tables 2 and 3, respectively.

In this ablation study, the first method (POI) constructs the POI graph using only POI information for next POI recommendation as the baseline method. The second method (POI+user) introduces user information (i.e., user embedding) on the basis of this baseline method, thereby implementing a personalized POI recommendation approach.

Following the personalized spatio-temporal clustering approach proposed in this paper, the third method (*w/o* period) considers personalized spatial clustering, while the fourth method (*w/o* region) only considers personalized temporal clustering. The last model (iPCM) is a method that takes into account both spatial and temporal clustering effects. For the baseline POI method, its performance is the lowest. When we consider user information, making it a more personalized POI+user method, its performance is better than the baseline POI method. From the experimental results, we can also see that under two datasets, after introducing time clustering or space clustering respectively, the performance of the algorithm has been improved, both for the basic POI method and the personalized POI+user method. The experimental results show that across various metrics and datasets, the iPCM model we proposed has the best performance.

Therefore, through this experiment, we can see that, starting from a baseline recommendation method like POI, it is necessary to consider both personalized recommendations and personalized clustering in time and space. When these features are integrated together, a very good effect can be achieved. This ablation experiment reflects the contribution and role of user features, time clustering, and spatial clustering in the entire model.



(a) Number of periods (b) Number of regions

Figure 6: Sensitivity analysis.

Sensitivity Analysis

To validate the personalized spatio-temporal clustering model proposed in this paper, we conducted sensitivity experiments on two key parameters in the personalized spatio-temporal clustering, i.e., the number of periods and the number of regions. In the experiment, we used the TKY dataset, changing the number of divisions in time, from 10 periods to 40 periods, and the number of divisions in space, dividing the space into 100 regions to 600 regions, to test the changes in the values of different test metrics under our proposed iPCM model. The results are shown in Fig. 6.

We notice that the values of metrics do not fluctuate much with the parameter of the number of periods. There is a slight improvement in the test metrics as the count increases, followed by a slight decline. The metric $Acc@1$ ranks the lowest, $Acc@5$ is next, and $Acc@10$ is the highest, which is understandable since as the number of candidates increases, the prediction accuracy also improves. Spatially, it is the same; the impact of the parameter of the number of regions, on the metrics is not significant, with some minor fluctuations.

Conclusion

This paper found that to achieve more effective next POI recommendations, we need to consider the effects of personalized spatio-temporal clustering. Therefore, we constructed a model iPCM that aggregates features from four aspects: POI embedding, user embedding, period embedding, and region embedding. The model then integrates these features, combines them with the user's trajectory, and completes the user's POI recommendation through a Transformer module. In the experiments, we verified the proposed iPCM model method by comparing existing methods on different datasets and different test metrics, thereby validating the performance of iPCM. In addition, we conducted ablation studies and parameter sensitivity experiments to further validate the effectiveness of the proposed model method.

Acknowledgments

This work is supported by the National Natural Science Foundation of China under Grant No. 62472070, 82241060, 62020106013; the Sichuan Science and Technology Program No.2024NSFSC0492; the National Key R&D Program of China under Grant 2021YFB3101303 and 2021YFB3101302; the Full-Time Postdoctoral Research and Development Fund of West China Hospital of Sichuan University No. 2023HXBH129.

References

Cheng, C.; Yang, H.; Lyu, M. R.; and King, I. 2013. Where You Like to Go Next: Successive Point-of-Interest Recommendation. In *Proceedings of the 23rd International Joint Conference on Artificial Intelligence (IJCAI)*, 2605–2611.

Cheng, H.; Ye, J.; and Zhu, Z. 2013. What's Your Next Move: User Activity Prediction in Location-based Social Networks. In *Proceedings of the 13th SIAM International Conference on Data Mining*, 171–179.

Cranshaw, J.; Schwartz, R.; Hong, J. I.; and Sadeh, N. M. 2012. The Livehoods Project: Utilizing Social Media to Understand the Dynamics of a City. In *Proceedings of the Sixth International Conference on Weblogs and Social Media*.

Dai, S.; Yu, Y.; Fan, H.; and Dong, J. 2022. Spatio-Temporal Representation Learning with Social Tie for Personalized POI Recommendation. *Data Science and Engineering*, 7(1): 44–56.

Fisher, W. D. 1958. On Grouping for Maximum Homogeneity. *Journal of the American Statistical Association*, 53: 789–798.

Gutowski, N.; Camp, O.; Chhel, F.; Amghar, T.; and Albers, P. 2019. Improving Bandit-Based Recommendations with Spatial Context Reasoning: An Online Evaluation. In *31st IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*, 1366–1373.

Huang, Z.; Ma, J.; Dong, Y.; Foutz, N. Z.; and Li, J. 2022. Empowering Next POI Recommendation with Multi-Relational Modeling. In *Proceedings of the 45th International Conference on Research and Development in Information Retrieval (SIGIR)*, 2034–2038.

Kazemi, S. M.; Goel, R.; Eghbali, S.; Ramanan, J.; Sahota, J.; Thakur, S.; Wu, S.; Smyth, C.; Poupart, P.; and Brubaker, M. A. 2019. Time2Vec: Learning a Vector Representation of Time. *CoRR*, abs/1907.05321.

Koren, Y.; Bell, R. M.; and Volinsky, C. 2009. Matrix Factorization Techniques for Recommender Systems. *Computer*, 42(8): 30–37.

Li, Y.; Chen, T.; Luo, Y.; Yin, H.; and Huang, Z. 2021. Discovering Collaborative Signals for Next POI Recommendation with Iterative Seq2Graph Augmentation. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence (IJCAI)*, 1491–1497.

Li, Y.; Tarlow, D.; Brockschmidt, M.; and Zemel, R. S. 2016. Gated Graph Sequence Neural Networks. In *Proceedings of the 4th International Conference on Learning Representations (ICLR)*.

Lim, N.; Hooi, B.; Ng, S.; Goh, Y. L.; Weng, R.; and Tan, R. 2022. Hierarchical Multi-Task Graph Recurrent Network for Next POI Recommendation. In *Proceedings of the 45th International Conference on Research and Development in Information Retrieval (SIGIR)*, 1133–1143.

Liu, Q.; Wu, S.; Wang, L.; and Tan, T. 2016. Predicting the Next Location: A Recurrent Model with Spatial and Temporal Contexts. In *Proceedings of the Thirtieth Conference on Artificial Intelligence (AAAI)*, 194–200.

Long, Z.; Wang, L.; Liu, Q.; and Wu, S. 2023. Personalized Interest Sustainability Modeling for Sequential POI Recommendation. In *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management (CIKM)*, 4145–4149.

Luo, Y.; Liu, Q.; and Liu, Z. 2021. STAN: Spatio-Temporal Attention Network for Next Location Recommendation. In *Proceedings of International World Wide Web Conference (WWW)*, 2177–2185.

Ou, J.; Jin, H.; Wang, X.; Jiang, H.; Wang, X.; and Zhou, C. 2023. STA-TCN: Spatial-temporal Attention over Temporal Convolutional Network for Next Point-of-interest Recommendation. *ACM Transactions on Knowledge Discovery from Data*, 17(9): 124:1–124:19.

Rendle, S.; Freudenthaler, C.; and Schmidt-Thieme, L. 2010. Factorizing personalized Markov chains for next-basket recommendation. In *Proceedings of the 19th International World Wide Web Conference (WWW)*, 811–820.

Salakhutdinov, R.; and Mnih, A. 2007. Probabilistic Matrix Factorization. In *Proceedings of the Twenty-First Annual Conference on Neural Information Processing*, 1257–1264.

Song, C.; Wen, J.; and Li, S. 2019. Personalized POI recommendation based on check-in data and geographical-regional influence. In *Proceedings of the 3rd International Conference on Machine Learning and Soft Computing (ICMLSC)*, 128–133.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is All you Need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems*, 5998–6008.

Wang, E.; Xu, Y.; Yang, Y.; Jiang, Y.; Yang, F.; and Wu, J. 2023a. Zone-Enhanced Spatio-Temporal Representation Learning for Urban POI Recommendation. *IEEE Transactions on Knowledge and Data Engineering*, 35(9): 9628–9641.

Wang, Z.; Zhu, Y.; Liu, H.; and Wang, C. 2022. Learning Graph-based Disentangled Representations for Next POI Recommendation. In *Proceedings of the 45th International Conference on Research and Development in Information Retrieval (SIGIR)*, 1154–1163.

Wang, Z.; Zhu, Y.; Wang, C.; Ma, W.; Li, B.; and Yu, J. 2023b. Adaptive Graph Representation Learning for Next POI Recommendation. In *Proceedings of the 46th International Conference on Research and Development in Information Retrieval (SIGIR)*, 393–402.

Xiong, L.; Chen, X.; Huang, T.; Schneider, J. G.; and Carbonell, J. G. 2010. Temporal Collaborative Filtering with

Bayesian Probabilistic Tensor Factorization. In *Proceedings of the SIAM International Conference on Data Mining (SDM)*, 211–222.

Yang, D.; Fankhauser, B.; Rosso, P.; and Cudré-Mauroux, P. 2020. Location Prediction over Sparse User Mobility Traces Using RNNs: Flashback in Hidden States! In *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence (IJCAI)*, 2184–2190.

Yang, S.; Liu, J.; and Zhao, K. 2022. GETNext: Trajectory Flow Map Enhanced Transformer for Next POI Recommendation. In *Proceedings of the 45th International Conference on Research and Development in Information Retrieval (SIGIR)*, 1144–1153.

Yin, F.; Liu, Y.; Shen, Z.; Chen, L.; Shang, S.; and Han, P. 2023. Next POI Recommendation with Dynamic Graph and Explicit Dependency. In Williams, B.; Chen, Y.; and Neville, J., eds., *Thirty-Seventh AAAI Conference on Artificial Intelligence (AAAI)*, 4827–4834.

Zhao, P.; Luo, A.; Liu, Y.; Xu, J.; Li, Z.; Zhuang, F.; Sheng, V. S.; and Zhou, X. 2022. Where to Go Next: A Spatio-Temporal Gated Network for Next POI Recommendation. *IEEE Transactions on Knowledge and Data Engineering*, 34(5): 2512–2524.