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A User Location Prediction Method Based on Similar Living Patterns

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Abstract. With the development of fifth-generation mobile communication technology, a huge volume of mobile data have been generated which enable a wide range of location-based services. As a result, user location prediction has attracted attention from researchers. However, existing methods have low accuracy due to the sparsity of user check-ins. In order to address this issue, we propose a method for user location prediction based on similar living patterns. We first obtain a vector representation of each user's living habits to cluster users with similar living patterns. Then, embedded vectors of POI category and POI location are learned. Finally, we construct activity prediction model and location prediction model for each user cluster by using Gate Recurrent Unit (GRU). The experimental results for real user check-ins show that the proposed method outperforms the baseline methods in most cases.

Keywords. location prediction, living patterns, user check-ins, representation learning

1. Introduction

There is an inextricable relationship between activities and geographical locations in people's daily routines, and a person's general life style and regularity can be discovered from their location history [1]. With the popularization of location technology and personal mobile devices, large-scale semantic-rich trajectories of individuals check-ins on social networking sites are being recorded and accumulated at an unprecedented speed. Understanding the implied living patterns in these user check-ins can not only contribute to insights into their own lifestyles, but also provide support for POI recommendation, location prediction and other applications. This facilitates the provision of personalized and intelligent services to users and further promotes the development of location-based services network (LBSN). Additionally, this identifies the social roles of users and provides assistance to urban planners and decision makers. Even so, there have been few studies dedicated to living patterns recognition via semantic-rich trajectory data [2].

Existing studies show that user mobility has high-order space-time correlation and significant multi-level periodicity [3], which are also the challenges in location prediction. For instance, there is often multi-level periodicity that governs human mobility in the temporal aspect, involving daily routines, weekend leisure, and even other

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personal periodic activities [4]. The current location is often the same as the same location yesterday or one week ago. In the spatial aspect, two distant places may also attract users to visit because of similar functions.

Traditional user location prediction methods, such as those based on frequent patterns and Markov chains (MC), cannot effectively model high-order, multi-level spatial- temporal correlations, nor can they well solve the long-term dependencies of user movement trajectory. Because of the ability to capture complex and nonlinear temporal and spatial relationships, recurrent neural networks (RNNs) are extensively used in natural language processing [5], location prediction and other tasks, and achieve better results than traditional methods. However, there are some problems such as gradient disappearance, gradient explosion and historical information loss when dealing with long sequences. Long Short-Term Memory (LSTM) and GRU solve the above problems by introducing a gating mechanism to select or forget data features. They improve prediction accuracy and are widely used in location prediction.

In addition, an inherent challenge in location prediction is the sparsity of check-ins. Different from GPS data, user check-ins are sparse; some users have fewer POI types in check-in sequences and less context information that can be used in historical trajectories, making it difficult to train a movement model for each individual.

To tackle the aforementioned challenges, we propose a user location prediction method based on similar living patterns. Specifically, we first extract semantic information from all the check-ins, and cluster users with similar living patterns to alleviate the sparsity of check-ins. Then we use the clusters to train different activity prediction models and location prediction models, one for each cluster. Finally, by leveraging on GRUs for modeling the historical trajectory features, we concatenate trajectory features with similar life patterns and nearby locations and representations of recent mobility to predict a user's next location. Our main contributions are summarized as follows:

1. We cluster the users with similar living pattern, that is, engaging in similar behaviors at similar times, through the semantics information in user check-ins.
2. We incorporate the temporal information into POI types and POI locations embedding as the inputs of activity prediction and location prediction.
3. The experimental results for two public datasets validate that our model outperforms the baselines for both activity prediction and location prediction.

2. Related work

Location prediction, as one of the crucial tasks in LBSN, much research has been conducted in this area. In this section, we briefly introduce these research works from two perspectives:

Similar User Clustering Perspective. In order to alleviate the sparsity of user check-ins, many location prediction models based on social networks cluster similar users through different measurement criteria and then combine other trajectory information to predict the locations. [6] proposed a von Mises-Fisher mixture clustering for user grouping so as to learn a reliable and fine-grained model for groups of users sharing mobility similarity. [7] proposed a group-level mobility modeling method, which alternated between user grouping and mobility and characterized group-level movement patterns modeling, clustering users with similar movement behaviors. [8] proposed a location prediction algorithm combining semantic trajectory and location trajectory, which mined similar users according to semantic trajectory.

Although the above methods have improved the prediction accuracy or optimized the temporal and spatial complexity, there are still some problems, such as high time complexity, low efficiency and so on.

RNN-based Location Prediction Perspective. Compared with MC-based methods, RNN-based methods can capture long-term migration dependencies being able to process large-scale mobility data, which has been extensively used in location prediction. Earlier works directly utilizes RNNs to model human mobility.[9] proposed the ST-RNN model, which used the transfer probability matrix of positions at different time intervals in the user's historical spatial-temporal trajectory to model the local spatial-temporal sequence information and predict the user's location at a specific time. At present, numerous RNN-based methods aiming to improve location prediction from different perspectives have been proposed. [10] proposed ST-LSTM model, which combined spatial-temporal influence into LSTM model to alleviate the problem of data sparsity. [11] utilized bidirectional LSTM and convolutional neural network (CNN) to capture local and global features of user check-ins for location prediction. Moreover, some studies combine RNN with attention mechanisms for location prediction [3][12].

The above methods only consider the spatial-temporal factors of user trajectories or ignore the influence of semantic information on location prediction results, and they fail to provide insights as to why people move from one location to another.

3. Location Prediction Based on Similar Living Patterns

3.1. Problem description

Definition 1. (Check-In point) The check-in point can be denoted as a quadruple $c_t^u = (u, t, g, p)$, indicating that user u visits the POI type p located in grid location g at the timestamp t.

Definition 2. (Check-in trace) Check-in trace CT^u denotes a trajectory containing all check-in points generated by user u with chronological order in the light of timestamp, represented as a sequence $CT^u = \{c_{t_1}^u, c_{t_2}^u, ..., c_{t_u}^u\}$, where $t_1 < t_2 < ... t_u$.

Problem statement: Given the users' check-in trajectories $CT = \{CT^{u_1}, CT^{u_2}, ..., CT^{u_n}\}$ and given the historical trajectory sequence H of user u before time t_u, our goal is to train a model to predict the next activity intention p and grid location g for user u at time t_u.

3.2. Similar User Clustering

Due to the inherent characteristics of sparsity, periodicity and heterogeneity of check-in points, as in [13], we dynamically divided each user's daily check-in track into m time slices $\mathrm{T_1 < T_2 < \cdots < T_{m-1} < T_m}$, then convert the unequal user check-in track CT to an equal length time slice track $\mathrm{ST = \{s_{T_1}^u, s_{T_2}^u, ..., s_{T_m}^u\}}$ by setting a time influence threshold, where $\mathrm{s_{T_i}^u = \{c_{t_j}^u | c_{t_j}^u \in CT, t_j \in T_i\}}$.

In ST, $\mathrm{s_{T_i}^u}$ record all POI category visited by u in the time slice T_i. To some extent, the most frequently visited POI type reflects the living habits of u, that is, the POI that the user is accustomed to the POI type p during the time period. For instance, some users are used to going to the supermarket on weekends between 9 a.m. and 11 a.m.

Definition 3. (Users' living pattern) The most frequently POI type a user visits in each time slice is selected as his typical habit during that time slice. The sequence formed living habits of user u in m time slices is called his living pattern, in the format of $\mathrm{LP^u} = \{\mathrm{p^u_{T_1}}, \mathrm{p^u_{T_2}}, \dots, \mathrm{p^u_{T_m}}\}$.

In order to better capture the POI category and temporal information contained in the user's living patterns, and better measure the similarity between users based on the user's living patterns, this paper adopts a representation learning method based on Global Vectors for Word Representation(GloVe) [14] to embed the user's life pattern into the same vector space. This can extract more semantic information from user check-ins than the word2vec model. Algorithm 1 describes the process of similar user clustering.

Algorithm 1: Clustering of users based on similar living patternss
Input: CT
Output: Cluster_dataset
1. Initialize Cluster_dataset= Φ
2. For each check-in trajectory in CT do
3. Extract POI categories according to time slice length and time influence threshold
4. Use GloVe to train the POI categories to get the corresponding vectors
5. Cluster and tag user living habits
6. Add tags to ST
7. Cluster users using Kmeans++ algorithm and add clustering labels
8. Add user check-ins with tags to Cluster_dataset
9. End for
10. Return Cluster_dataset

3.3. POI Category and POI Location Embedding Incorporating Temporal Information

Considering the choice of the next activity or location for user has a strong correlation with the current activity type, current location, and current time. For instance, a user who chooses a place for lunch at noon on weekdays is inclined to choose a similar restaurant nearest to their workplace than a distant one they often go to on weekends. Therefore, we incorporate temporal information into POI category embedding and POI location embedding.

Inspired by [13], [15], we propose a model named the POI Type to Vector (PT2V) model incorporating time information based on Glove and hierarchical softmax strategy. According to the length of the different time slice length $l_{timeslice}$ and time influence span threshold $i_{threshold}$, the check-in traces of each group of users are allocated to m time slice($m = \lceil 24hours/l_{timeslice} \rceil$), and the POI type dictionary and co-occurrence matrix are constructed based on GloVe. Then, the Huffman tree is constructed according to the visited frequency of POI types in each time slice, and the root node of each Huffman tree is set as the corresponding time slice node. Finally, all time slice nodes are connected to build a multi-branches tree, namely, the Temporal-POI type tree.

A user's choice of the next location is largely related to the current time and location, in addition to being influenced by the activity intention. It is therefore crucial to mine the location sequence transfer pattern between user check-ins. The Continuous Bag-Of-

Words (CBOW) model can better approximate the embedding vectors of contextually similar locations in the potential space. Hence, the POI Location to Vector (PL2Vec) model incorporating temporal information is proposed based on CBOW, which combines clusters of the same class. The Temporal-POI location tree is similar to the Temporal-POI type tree, except that the leaf nodes of the Temporal-POI location tree correspond to the rasterized user check-ins geographical sequences.

Thus, given a check-in context visited by user u at time t, the probability of user u visiting the next activity type or the next location can then be calculated by the proposed Temporal-POI category tree or Temporal-POI location tree. Taking activity prediction as an example, maximizing the posterior probability of POI category p_j to be predicted leads to a POI category embedding incorporating temporal information, as shown in Eq.(1).

$$\Theta = \underset{\Theta}{\operatorname{argmax}} \prod_{(t,l_j)\in \mathrm{H}} P(t, p_j | C(t, p_j)) \tag{1}$$

Where $\Theta = \{\mathrm{Z}, \mathrm{M}, \Psi\}$ is the parameter sets of the model, Z is the embedding vectors set of Temporal-POI type tree, M is the parameter set of the root node, Ψ is the parameter set of the internal node of all Huffman trees, $P(t, p_j | C(t, p_j))$ can be computed by the hierarchical softmax. All parameters can be trained and learned by stochastic Gradient Descent .

3.4. User Activity Prediction and Location Prediction Based on GRU

Location prediction is divided into two tasks: activity prediction by using the POI type embedding vector and location prediction by using the POI location embedding vector. In order to obtain more contextual information about the location to be predicted, the current trajectory and several historical trajectories are jointly used as the current trajectory, and the proposed POI embedding method is used to obtain the current trajectory embedding vector incorporating temporal information and input to the GRU network. The output hidden vector is then fed into a fully connected layer to predict the user's next locations.

4. Experiments

In this section, we conduct experiments on two real-world datasets to compare the performance of the proposed methods against several baselines.

4.1. Experimental Setup

Datasets. This paper evaluates the proposed model on the FourSquare New York City (NYC) and Tokyo City (TKY) datasets [16], which record from April 2012 to February 2013. The dataset statistics are described in Table 1.

Table 1. Data Statistics

Dataset	Users	Check-ins	Locations	POI types	Locations per user	POI types per user
NYC	1083	227178	38333	251	84.05	40.28
TKY	2293	573126	61858	247	92.44	32.36

We apply the method of [17] to raster the location geographic information in the user check-ins, which merges user check-ins within a certain geographical range into the same grid and set the grid size as 200 meters . Additionally, we remove check-ins during holidays in the datasets and partition them by weekend and weekday.

Metrics. Following previous work [15, 18], we choose macro-F1 and Acc@K (Acc@K= $\sum_{(u,t,g,p)\in S} I\left(p \in \hat{V}_{u,t}^{K}\right)/N$) to evaluate the performance of our method, where macro-F1 is the harmonic mean of macro-P ($macro - P = (\sum_i^N (TP_i / TP_i + FP_i))/N$) and macro-R ($macro - R = (\sum_i^N (TP_i / TP_i + FN_i))/N$); N is the total number of test set samples, K = [1, 5, 10, 20] and $I(\cdot)$ is an indicator function.

Parameter settings. We set the embedding vector size to 128, the batch size to 30, the window size is 2, the hidden layer size to 256, and the initial learning rate of both the stochastic gradient descent algorithm and the Adam optimization algorithm to 0.001.

4.2. Experimental Results and Analysis

4.2.1. Location Prediction

We evaluate the impact of the user clustering on our location prediction model (PL2Vec) on the Foursquare NYC and Foursquare TKY datasets. Specifically, we adopt the none-clustering approach on RNN, Seq2seq and HSTLSTM [10]. We adopt user clustering approach on LSTM, DeepMove [4] and our method.

Table 2. Location prediction performance comparisons for NYC and TKY datasets

Dataset	Metrics	macro-F1	Acc@1	Acc@5	Acc@10	Acc@20
NYC	RNN	0.0258	0.1461	0.2889	0.3751	0.4946
	Seq2Seq	0.0294	0.1343	0.2763	0.3642	0.4844
	HSTLSTM	0.0265	0.1434	0.3046	0.3966	0.5071
	LSTM	0.0482	0.1973	0.3489	0.4522	0.5759
	DeepMove	0.0527	0.2080	0.3941	0.4931	0.6123
	PL2Vec	0.0572	0.2004	0.3597	0.4553	0.5910
TKY	RNN	0.0200	0.2669	0.4475	0.5498	0.6669
	Seq2Seq	0.0322	0.2630	0.4418	0.5413	0.6621
	HSTLSTM	0.0295	0.2510	0.4233	0.5178	0.6351
	LSTM	0.0415	0.2638	0.4567	0.5625	0.6940
	DeepMove	0.0508	0.2726	0.4877	0.5971	0.7152
	PL2Vec	0.0499	0.2660	0.4654	0.5708	0.7001

As can be seen from Table 2, our approach outperforms the none-clustering approaches in terms of the macro-Recall, macro-f1, and Acc@K. Moreover, Compared with DeepMove, one of the state-of-the-art location prediction models slightly better than our model in terms of macro-F1 and Acc@K. This demonstrates that the similar living pattern user clustering strategy is effective in improving the proposed prediction model.

4.2.2 Activity Prediction

We compare the PT2vec model with 5 baselines in the task of predicting the activity. (1) skip-gram and CBOW: variants of the Word2Vec model. (2) POI2Vec [15]: considering the influence of spatial relations between geographical locations and constructing an embedding model based on CBOW. (3) Geo-Teaser [19]: incorporating the effects of temporal influence into the location embedding based on skip-gram. (4) TALE [13]: training the time-aware location embedding model based on CBOW and designing a novel temporal tree incorporating temporal information for hierarchical softmax calculation.

Table 3 shows the performance of the user activity prediction model for each type of cluster under different POI type embedding methods.

Table 3. Performance comparison with different methods for activity prediction

Dataset	Metrics	macro-F1	Acc@1	Acc@5	Acc@10	Acc@20
NYC	Skip-gram	0.0263	0.1175	0.2755	0.3764	0.5039
	CBOW	0.0281	0.1229	0.2764	0.3832	0.5110
	Geo-Teaser	0.0268	0.1202	0.2750	0.3744	0.5141
	POI2Vec	0.0288	0.1207	0.2795	0.3911	0.5166
	TALE	0.0294	0.1212	0.2804	0.3839	0.5142
	PT2Vec	0.0303	0.1506	0.3252	0.4374	0.5635
TKY	Skip-gram	0.0282	0.2584	0.4559	0.5643	0.6832
	CBOW	0.0313	0.2570	0.4512	0.5518	0.6718
	Geo-Teaser	0.0320	0.2587	0.4547	0.5604	0.6839
	POI2Vec	0.0322	0.2598	0.4551	0.5631	0.6823
	TALE	0.0344	0.2589	0.4630	0.5707	0.6855
	PT2Vec	0.0362	0.2683	0.4715	0.5937	0.7234

As shown in Table 3, PT2Vec performs the best among all the methods. Taking the TKY dataset as an example, PT2Vec improves 19.72% in macro-F1 and 4.88%, 4.45%, 5.27%, and 5.46% in Acc@K, respectively, compared to TALE. This shows that GloVe-based methods can extract more information about living patterns than word2vec-based methods to improve activity prediction.

4.3. Effects of Parameters

The length of time slice $\mathrm{l}_{\mathrm{timeslice}}$ and time influence threshold $\mathrm{i}_{\mathrm{threshold}}$ will affect the quality of the POI embedding, and further affect activity prediction and location prediction. Therefore, we evaluate the effects of $l_{timeslice}$ and $i_{threshold}$.

Taking location prediction as an example, Figure 1 and Figure 2 show the experimental results for the hyper parameter tuning of $\mathrm{l}_{\mathrm{timeslice}}$ and $\mathrm{i}_{\mathrm{threshold}}$. The macro-R and macro-F1 obtained by the location prediction model are given with different time slice length and time influence threshold for NYC and TKY, where the solid line represents macro-F1 and the dotted line is for macro-R. From left to right, each subgraph represents the time influence threshold value: 10, 20, 30, 40, 50, and 60.

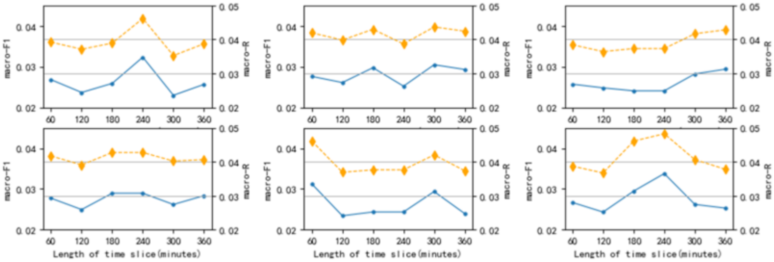

Figure 1. Effects of time slice length and time influence threshold on NYC

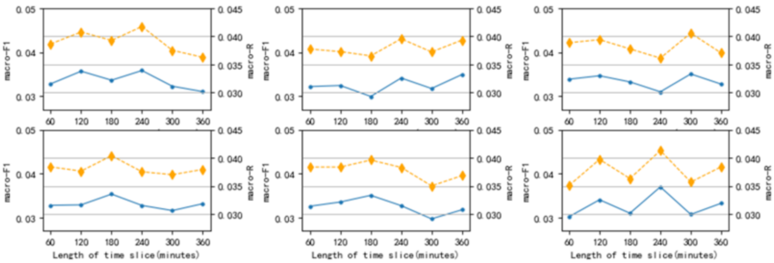

Figure 2. Effects of time slice length and time influence threshold on TKY

As can be seen from Figure 1 and Figure 2, when the length of time slice is 240 and the time influence threshold is 60, the value of macro-F1 and macro-R are relatively optimal.

5. Conclusion

In this paper, we propose a location prediction method based on the user similar living patterns. We learn these patterns through the semantics information in check-ins and cluster the users with the similar living patterns instead of geographically neighboring locations. This alleviates the sparsity of check-in data and enriches the user's historical trajectory characteristics. Additionally, we construct an activity prediction and a location prediction for each cluster. The experimental results for real data sets show that our method can improve the prediction performance compared to previous approaches.

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