Towards Semantic Travel Behavior Prediction for Private Car Users

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***Abstract*—The urban private car as convenient transportation plays an essential role in daily human life, which accordingly produces massive trajectory data by built-in GPS tracking devices. These data offer a new opportunity to mine and explore travel behavior for private car users. Existing works mining travel behavior mainly focus on modeling the sequential contexts while seldom considering the semantic information of the travel behavior, which led to a shallow understanding of users' travel regularity. To capture valuable information on users' travel mode, we design a semantic-aware method named as Semantic Long Short-Term Memory(Sem-LSTM). Specifically, we exploit an LSTM network as the foundation of a unified travel behavior prediction framework and introduce two types of semantic information, including area of interest (AOI) properties and user interests. We aim to explore individual travel behavior for a single private car user and conduct extensive experiments on real-life private car datasets. The experimental results demonstrate that Sem-LSTM is very suitable for capturing semantic content and improve prediction performance on private car users. In detail, for the travel behavior prediction, achieve average prediction $accuracy$ of 0.82, $recall$ of 0.80 and $F1$-$score$ of 0.81.**

***Index Terms*—Private car, Location prediction, Semantic information, Sequential contexts, Long Short-Term Memory**

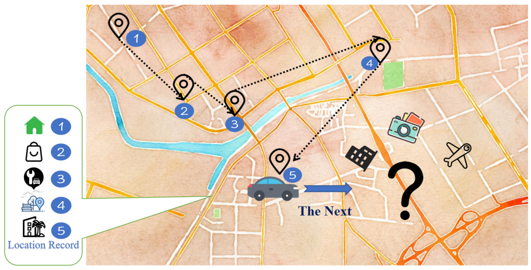

Fig. 1. An example of semantic travel behavior: to predict the next location for a private car user

I. Introduction

With the development of economic society, private cars as popular transportation enter people's daily life. Due to the flexibility and convenience of private cars, the number of urban private car owners increases yearly [1]–[3]. While the limited street and parking facilities are not adapt to the increasing usage of vehicles, various traffic troubles also follow, such as environmental pollution, traffic jam, severe traffic congestion, etc [4]. Fortunately, in the background of the intelligent transportation system (ITS), a large amount of trajectory data is produced [5]. These trajectory data offer a new opportunity to percept, mine, and explore travel behavior for private car users, provide a key solution to address these urban traffic problems [6], [7].

Fig.1 depicts an example of the travel behavior of private car users: given the previous location records, to predict which location the users will go? The number 1-5 stands for the last five location points of the private car user just visited, meaning the users' travel sequence patterns. By analyzing the long term location sequence of the individual user, we can infer that the next location of the private car.

To understand private car users' travel behavior, considering the sequential contexts of trajectory is necessary because the successive location is usually correlated [8]. Recurrent neural networks (RNNs) (e.g.,long short-term memory (LSTM) networks [9]) usually are employed to model and mine the sequential contexts of travel behavior [10]–[12]. Studies in [13] exploited an extended RNN model to capture the correlation of successive trajectory records, and in [14] proposed a multi-modal embedding RNN to model the complicated sequential transitions. Recently, with the advantage of LSTM is suitable for modeling long term dependence, researchers in [15] designed a variant of LSTM to find the sequential context, in [16] combined dimensionality reduction algorithm and LSTM to model spatiotemporal sequence feature. The various existing work of travel behavior prediction focus on exploring the sequential contexts for users, which have been proven to be effective for improving the model's performance. Moreover, we observe that the semantic information, including AOI properties and user interests, are key factors that affect users' travel behavior. For example, users always work in a fixed office building every day and relax in a park weekly. The semantic information provides new insight into understanding the users' daily travel behavior. However, all previous travel bahavior prediction models usually ignore the semantic information of trajectory, which motivates this paper.

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To bridge this gap, we systematically study the two types of semantic information and exploit them to improve the performance of the next location prediction task. Specifically, inspired by the success of LSTM for modeling the sequential contexts in location prediction [17], we design a unified framework: a semantic LSTM (Sem-LSTM) for users' travel behavior prediction. To consider the influence of AOI properties, we design an AOI extraction method to label the AOI tag for all trajectory points. To consider the influence of user interest, we design evaluation factors to measure the degree of user interest. Then we are incorporating the extracted semantic information into an extended LSTM to capture the semantic contents dynamically. In our work, all trajectory records of a user are feed into the Sem-LSTM network to model mobility regularity and user interest. In summary, the main contributions are as follows:

- To better understand the semantic information of the trajectory data, we present a clustering algorithm to label the AOI tag for each trajectory point and design an evaluation factor to indicate the user interests of every location.
- We propose a unified framework named Sem-LSTM for mining travel behavior by considering semantic information. The network is naturally incorporating semantic content in the neural network to capture more details of the users' travel patterns.
- We compare the Sem-LSTM with six baseline models. Empirical results on five different users' datasets perform excellent prediction competence for different evaluation metrics.

The remainder of this study is organized as follows. First, we present a brief review of related works in Section II. Following that, we introduce the definitions and concepts for the private car trajectory in Section III. In Section IV, we detail the proposed Sem-LSTM. Then we introduce real-life private car datasets and evaluate the Sem-LSTM in Section V. Finally, we conclude our work and describe future work.

II. Related work

In this section, we briefly outline the works related to our research.

Firstly, to model the mobility regularity, various existing work focuses on the spatiotemporal information. For example, Huang $et\ al.$ explored the spatiotemporal information for location records, designed an ST-LSTM to predict users' next location [18]. Zhao $et\ al.$ considered that neighbor check-ins and spatio-temporal intervals are essential for modeling user behaviors, propose a Spatio-Temporal Gated Network (STGN). Specifically, they introduced a spatio-temporal gate to capture the spatio-temporal relationships [19]. Yang $et\ al.$ focused on human convergence patterns to predict people's travel mode, monitor urban mobility, and extract eight distinct human mobility patterns [20]. Cao $et\ al.$ proposed a framework based on hierarchical spatiotemporal data under a location-based environment. [21]. However, these methods merely consider the spatiotemporal correlation and ignore the semantic contents.

Secondly, there is plenty of work aim to the sequential patterns of collected data. For example, Tang $et\ al.$ considered that sequential patterns play an important role in Top-N item recommendation, and proposed a unified network structure to capture general preferences and sequential patterns [22]. He $et\ al.$ focused on the sparse sequential data in personalized prediction, designed a similarity-based method for item recommendation [23]. Lonjarret $et\ al.$ focused on the frequent sequences, which is employed to identify the most relevant part in historical records for sequential recommendation [24]. However, unlike news and music, the interactions between private car users and location point require people to arrive at an actual place. Hence, it's important to consider spatial contextual information. Recently, an increasing number of work-related to spatial sequence data. Such as Zhao $et\ al.$ utilized a pairwise preference ranking method to incorporate the geographical influence. Furthermore, it captures the contextual check-in information, proposed a temporal embedding model [25]. Cui $et\ al.$ considered that different users demonstrate a different spatial preference. Thus, they designed a Distance-to-Preference network to model spatial influence [26].

In summary, to model the mobility of private car users, both spatiotemporal information and sequential pattern are adopted. Additionally, we also incorporate the semantic information into our model, capable of our mobility prediction task for private car users.

III. Preliminaries

In this section, we introduce related definitions and concepts for users' travel behavior prediction.

A. Definitions

Definition 1: **Spatio-temporal Point**: Let the couple P = (l, t) stands for the spatio-temporal point P, where t represents the time a user visit location l = (x, y) . Under the coordinate reference system (GCJ), x and y are the spatial coordinates.

Then according to couple P, we can obtain the AOI tag after calling the api interface of the reverse address encoding of Amap [27]. Finally, we obtain the trajectory with semantic information as shown in Definition2.

Definition 2: **Semantic Spatio-temporal Point**: Let the triple P_s = (l, t, a) stands for the semantic spatio-temporal point P_s, a is the AOI tag which is from Amap api.

A private car's duration time represents that the car stay in an area for a while, which is defined as S_t. Let t_s be the start time of stay behavior and t_e be the end time of stay behavior, the S_t=t_e-t_s.

Definition 3: **Private Car Trajectory**: Let U stands for a driver. A private car trajectory $T = P_1, P_2, \ldots, P_k$ is a series of spatio-temporal points, describing the stay location of driver U. When it takes semantic and stay time information into consideration, the trajectory T is created as T_s = (l_1, t_1, a_1, s_1), (l_2, t_2, a_2, s_2), . . . , (l_k, t_k, a_k, s_k).

B. *Problem Statement*

The travel behavior prediction problem is formulated as follows: if U is a car driver, T_u stands for his/her trajectory. According to $T_u \cup p_k$, being p_k the current location, the purpose is to predict the next location p_{k+1}.

IV. METHODOLOGY

This section introduces the entire framework for Sem-LSTM. An efficient process is constructed to collect, process, and mine the data in Fig.2. The whole framework focuses on semantic information, which mainly includes two parts, namely AOI property, user's interest. The proposed Sem-LSTM network can dynamically capture the semantic information and spatio-temporal contexts for predicting the next location. A detailed description of as follows.

A. *AOI Property Match*

In this section, we aim to label the AOI tag for all location point. The raw trajectory is made up of coordinate points, merely include longitude and latitude. So we employ the Amap [27] interface to match an AOI tag for each coordinate point. To solve the problem efficiently, two main preprocessing steps for AOI match are described in detail as follows:

Firstly, to deal with the location drift [28], a traditional density-based clustering algorithm (DBSCAN) is adopted to gather these adjacent coordinate points. DBSCAN has the capability of discovering clusters with arbitrary shapes. After clustering, all locations in each cluster stand for the same location.

Secondly, based on the previous step, We obtain the clustering result of the raw data. Using the AOI tag of the coordinate point, noise points or clusters with the same AOI can be merged in the same cluster. AOI refers to the area of interest in the electronic internet map. It contains four necessary information, name, address, category, latitude, and longitude coordinates. Generally, a residential area, a university, and an office building, an industrial park, are regarded as an AOI [27]. Through the reverse address coding interface of Amap, we can obtain the AOI information to which each coordinate point belongs. AOI type and AOI name are the Semantic information, as shown in table I. Given the raw location point, this API interface will return the name of the AOI. If two coordinate points belong to the same AOI, the two coordinate points are merged into a location record.

B. *User Interest Extraction*

User interest indicates the user's preference for different visit locations, including the duration and frequency of a car user visit a place. In this section, we design an evaluation factor of M to measure the degree of user interest. Fig.3 illustrates an example for user interest in a different place:

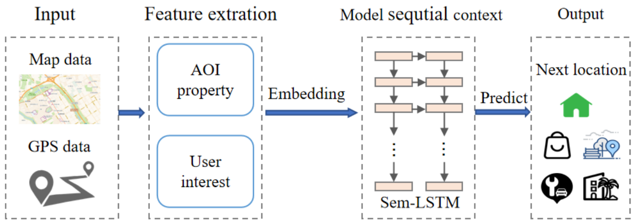


Fig. 2. Overview of framework.

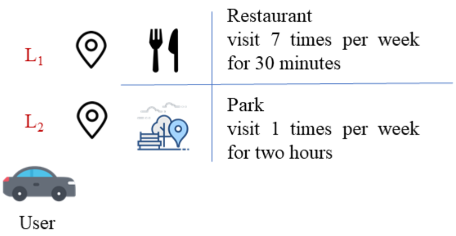


Fig. 3. An example of semantic information for a private car user.

the location of L_1 is a restaurant; the user visits it seven times every week and stays with half an hour. The location of L_2 is a park. The user visits it once a week and stays with two hours. User interest is a key factor in understanding the mobility of users. A detailed description of user interest extraction as follows.

1) Duration of Visit: One signal to infer the importance of a location is the duration of the visit; the value of duration indicates a user's preference of the location [29]. For example, a user usually stays in a company for 3 hours, while a convenience store for 15 minutes. The company may be where car users go to work, and the convenience store is just a place visited occasionally. Earthly, we think that this company is a frequent destination for the user. It is enlightening to analyze the importance of different location given an aspect of stay time. For each user, we define P_t to indicate the degree of the duration of the visit, which can be obtained by equation (1). where R_i represents the user's $i-$th visit location, S_{end} and S_{start} are the starting and ending time of visiting respectively. The P_t ratio represents the proportion of $i-$th duration to 24 hours a day, n represents the number of all locations visited by the user.

$$P_t\left(R_i\right) = \left(S_{\text{end}} - S_{\text{start}}\right)/24 * 60, \quad \text{i} \in [0, n] \qquad (1)$$

2) Visit Frequency: Users' visit frequency is also a key factor of the user's interest. If a user visits more in a location, He/She frequency more often [29]. For example, a car user would go to the supermarket for shopping every three days, while a playground once a month. If calculated in one month, visiting the supermarket is 10, while the playground is only 1. We may think that the supermarket is more important than the playground. It's essential to consider visit frequency to our model. Similarly, as an

TABLE I
AOI PROPERTY FOR RAW COORDINATE POINT

Latitude,longitude	AOI Property	
	AOI name	AOI type
112.962039,28.186914	Orange islet scenic spot	park
112.978751,28.192424	Changsha International Finance Square	shop
112.93642,28.1835431	Yuelu Mountain	tourist attraction
112.981153,28.192347	The People's Bank Of China	bank
112.987576,28201759	Changsha No.1 Middle School	school

indicator of stay time weight, P_f can be obtained by (2). Where $N(R_i)$ is the number of car stay in $i-$th location. N_{all} is the total number of user's location records.

$$P_f(R_i) = N(R_i)/N_{all}, i \in [0, n] \tag{2}$$

For these reason, it is important to consider the user inrerest on the prediction task. We formulate equation (3) to measure the importance of users interest.

$$M(R_i) = \mathrm{w_t} * P_\mathrm{t}(R_i) + \mathrm{w_f} * P_f(R_i) \tag{3}$$

Where the w_f and w_t are adjustable variables denoting the weights on duration and visit frequency. $M(R_i)$ is the factor denotes user interest.

C. Semantic LSTM

This section consists of two sub-sections: (1) we introduce a standard LSTM network as our base network; (2) we then detail the proposed semantic-based LSTM network (Sem-LSTM).

1) Standard LSTM: The stay data of a private car is a sequence with temporal and spatial features. Generally, in the early stage, Recurrent Neural Network(RNN) is usually used to process sequence data because of its recurrent network structure can achieve memory function. RNN is an extension of a conventional feed-forward neural network, but standard RNN has the gradient vanishing or exploding problems. To solve this problem, a Long Short-term Memory network(LSTM) was proposed and achieved superior performance. Additionally, LSTM has three gates and a cell memory state; these gates can filter data and only keep important information. With the help of these gates, the LSTM network can capture long-range dependencies in a sequential pattern. Thus, in this work, we employ it as a module to predict the next location.

In an LSTM network, the update process of each cell can be computed as follows:

$$X = \left[\begin{array}{c} h_{t-1} \\ x_k \end{array} \right] \tag{4}$$

$$f_t = \sigma(W_f \cdot X + b_f) \tag{5}$$

$$i_t = \sigma(W_i \cdot X + b_i) \tag{6}$$

$$o_t = \sigma(W_o \cdot X + b_o) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c \cdot X + b_c) \tag{8}$$

$$h_t = o_t \odot \tanh(c_t) \tag{9}$$

where W_f,W_i,$W_o \in \mathbb{R}^{d\times 2d}$ are weighted matrices. b_f,b_i,b_o $\in \mathbb{R}^d$ are bias vectors during training of LSTM network. The x_k indicates the embedding vector of location in input gate. Here, σ stands for the sigmoid function, and $\odot$ denotes the element-wise multiplication. The vector of hidden layer is h_t.

Finally, the last hidden vector $\mathbf{h}_{t_N}$ is a representation of input location sequence. In this work, we use LSTM to automatically capture user inner preferences. The probability result of a user u visit location x_k at time point as followed:

$$o^u_{t_{N+1},x_k} = \left(\mathbf{h}^u_{t_N}\right)^T \mathbf{x}_k \tag{10}$$

2) Sem-LSTM: The semantic information of location is vital when modeling users' travel patterns. We can get more accurate modeling results if the semantic aspects information are considered. To make use of semantic information, we propose a base network called semantic LSTM (Sem-LSTM), Which can learn the non-linear dependency representation from historical location records. In this model, we define a AOI property feature vector $\mathbf{a}^u_{t_i}$ and a user interest vector $\mathbf{l}^u_{t_i}$ to incorporate semantic information.

At time point t_i, we first embed location informantion into a latent space. Then, Sem-LSTM takes the embedded vector with the AOI property feature and user interest vector, a triple $\left(\mathbf{x}^u_{t_i}, \mathbf{a}^u_{t_i}, \mathbf{l}^u_{t_i}\right)$, as input at each time step. Hence, the output of Sem-LSTM represents the accumulated influence of AOI property and user interest contexts from the past location records. Fig.4 illustrates the architecture of Sem-LSTM.

In the hidden layer of Sem-LSTM, we update each hidden vector $\mathbf{h}^u_{t_i}$ after receiving the current input and the memory $\mathbf{h}^u_{t_{i-1}}$ from the past location activities. In Sem-LSTM, we have

$$\mathbf{h}^u_{t_i} = \mathrm{LSTM}\left(\mathbf{W}_x\mathbf{x}^u_{t_i} + \mathbf{W}_a\mathbf{a}^u_{t_i} + \mathbf{W}_l\mathbf{l}^u_{t_i}, \mathbf{h}^u_{t_{i-1}}\right) \tag{11}$$

where $\mathbf{W}_x \in \mathbb{R}^{d\times d}$, $\mathbf{W}_a \in \mathbb{R}^{d\times d}$ and $\mathbf{W}_l \in \mathbb{R}^{d\times d}$ are transition matrices. The learned hidden vector $\mathbf{h}^u_{t_i}$ is a dynamic component of Sem-LSTM and can be regarded as the representation of user u at time point t_i. In nature,

TABLE II
DETAILS OF EACH CAR DATA SET

Car ID	#Stay	#Time	#Latitude	#Longitude	#City
107737	923	2015/7/1-2017/2/27	37.17-42.24	114.76-119.52	Beijing
108470	930	2015/7/1-2016/11/30	39.75-39.82	116.33-116.56	Beijing
116853	1770	2015/7/1-2017/9/30	30.33-30.59	113.94-114.41	Wuhan
125870	1539	2015/7/1-2016/6/16	23.13-23.54	116.40-117.13	Shantou
379972	996	2015/8/3-2016/7/27	30.08-33.43	116.24-120.90	Yangzhou

it reflects dynamic user preferences for visit location under different semantic contexts.

We also design a stationary component $\mathbf{m}_u$ to represents the long term user interest, and can be obtained by equation (3): $\mathbf{m}_u = (m_{R_1}, m_{R_2}, \ldots, m_{R_n})$. Therefore, in this work, the user semantic information is defined as a function of both dynamic state $\mathbf{h}^u_{t_i}$ and stationary state $\mathbf{m}_u$. We then to predict the next location for target users by computing the dot-product of user and semantic representations. Lastly, the predicted probability that user u visits a location x_k at time point t_{N+1} can be obtained by the following operation:

$$o^u_{t_{N+1},x_k} = \left(\mathbf{W}_N \mathbf{h}^u_{t_N} + \mathbf{W}_m \mathbf{m}_u\right)^T \left(\mathbf{W}_x \mathbf{x}_k + \mathbf{W}_a \mathbf{a}^u_{N+1} + \mathbf{W}_l \mathbf{l}^u_{N+1}\right) \quad (12)$$

where $\mathbf{W}_N \in \mathbb{R}^{d\times d}$ and $\mathbf{W}_m \in \mathbb{R}^{d\times d}$ are the parameters of the output layer, $\mathbf{W}_N \mathbf{h}^u_{t_N} + \mathbf{W}_m \mathbf{m}_u$ represents the user representation, and $\mathbf{W}_x \mathbf{x}_k + \mathbf{W}_a \mathbf{a}^u_{N+1} + \mathbf{W}_l \mathbf{l}^u_{N+1}$ represents the AOI representation. Note that $\mathbf{m}_u$ is determined by the P_t and P_f According to equation (1) and equation (2).

V. EXPERIMENT AND RESULT

A. Data Set

The evaluation is conducted over real-world private car trajectory datasets, which are obtained in [30], [31]. The data contains users' located-in information, including geographical coordinates, timestamps, etc. We utilize the inverse address encoding interface of Amap to obtain the AOI for each coordinate point in the dataset. In this study, a located-in record is a quadri-tuple composed of a user, an AOI, the geographical location of the AOI, and the corresponding located-in timestamp. All the located-in records in these datasets were treated as user sequences. Also, we performed a preprocessing step on these datasets to filter out inactive users and unpopular AOIs.

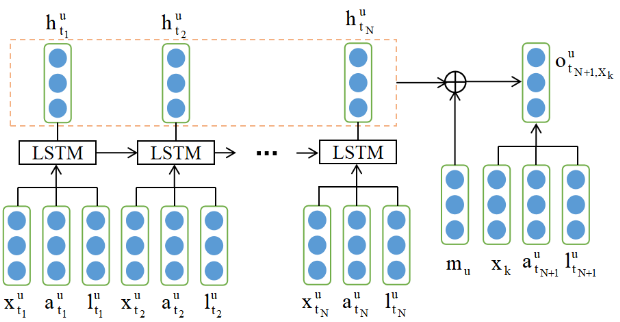


Fig. 4. The architecture of Sem-LSTM.

To protect the privacy of private car owners, all sensitive information was removed from the raw trajectories. All researchers are subject to a strict non-disclosure license. For the private car trajectory dataset, instructions, and Python code packet, please see https://github.com/HunanUniversityZhuXiao/PrivateCarTrajectoryData.

In our prevous work of [7], designing an evaluation factor to measure users' mobility regularity for private car users. The factor is a spatial-temporal entropy rate represented by H. If the value of H is greater than 2.5, the car's travel pattern is hard to identify. Therefore, to verify our model, we selected a five-car trajectory whose value of H less than 2.5. Table II details the five cars quantity information. where $Car\ ID$ stands for the number of the car trajectory data set, #$Stay$ stands for the number of stays reflected from the data. #$Time$ stands for the time range of car trajectory. #$Latitude$ and #$Longitude$ stand for the area range of stay point. #$City$ stands for the user's permanent residence.

B. Baselines

Considering the spatio-temporal characteristics of private car trajectory data, we compared our method with several baselines, including SVM, RF, RNN, LSTM, GRU, and ST-GRU.

SVM: Support Vector Machine(SVM) is a generalized linear classifier by supervised learning, which perform well in time series problem.

RF: Random Forest(RF) is a classifier containing multiple decision trees, which is flexible, easy to use. But it is prone to overfitting.

RNN: Recurrent Neural Networks (RNN) are a class of Artificial Neural Networks that can process a sequence of inputs in deep learning, which is usually used for time series forecasting problems. But for long-term sequences of data, it usually has a gradient explosion problem, resulting in low output.

LSTM: Long Short-Term Memory(LSTM) is a variation of the recurrent net, aims to solve the vanishing gradient problem. By helping preserve the error that can be back-propagated through time and layers, LSTM can retain data over many time steps(over 1000).

GRU: Gated Recurrent Unit can be considered a variation of the long short-term memory (LSTM) unit because both have a similar design and produce equal results in some cases.

ST-GRU: ST-GRU is a GRU-based model for next location prediction, which can improve the performance of prediction by incorporating both the geographical and temporal context information within the recurrent architecture.

C. Metrics

we emploied three standard metrics called Accuracy, Recall and F1_score to assess the performance of all above methods.

$$\text{Accuracy } = (\mathrm{TP}+\mathrm{TN})/(\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}) \quad (13)$$

$$\text{Precision } = \mathrm{TP}/(\mathrm{TP}+\mathrm{FP}) \quad (14)$$

$$\text{Recall} = \mathrm{TP}\,/(\mathrm{TP}+\mathrm{FN}) \quad (15)$$

$$\text{F1-score} = 2*\mathrm{P}*\mathrm{R}/(\mathrm{P}+\mathrm{R}) \quad (16)$$

For our work, the next location prediction task is a multi-classification problem. We applied Accuracy metric to measure global performance of all methods. But Accuracy is not a fair measure for unbalanced data sets. Therefore Recall and F1-score are needed for our work. For every location in the test dataset, take a lacation called $West\ Lake\ Park$ as a example, the TP is True Positive ration corresponds to the proportion of $West\ Lake\ Park$ correctly predicted $West\ Lake\ Park$. The FN is False Negative ratio refers to the proportion of $West\ Lake\ Park$ is incorrectly predicted other location. The FP is False Positive ratio refers to the proportion of Other location incorrectly predicted $West\ Lake\ Park$. The TN is True Negative ratio refers to the proportion of other location correctly predicted other location. For the two metrics, final value is equals to every location's average value.

D. Results and Discussions

1) AOI property Match: The purpose of the property Match is to match the AOI label for all stay points. For example, taking the car ID=125870, 1539 stay points correspond to 326 AOIs in Shantou, China, Fig.5 shows the clustering result. On the left of this figure, the clustering result of all stay point of the car is represented here. The detailed results of the area 'Local A' is showed in the right of Fig.5. These colorful points mean that they have been merged into the same AOI; the same color stands for the same AOI. But these gray points indicate that they have not merged and match an exclusive AOI label for themselves.

2) Performance of Sem-LSTM: The proposed Sem-LSTM incorporates semantic and sequence information to improve the model performance. We evaluate our method with the baseline methods on five private car users datasets. Table III details the result of these methods:

Firstly, we can find all neural network-based methods, including RNN, LSTM, GRU, ST-GRU, and Sem-LSTM, which focus on modeling temporal sequence information, usually have better performance on prediction precision than SVM and RF. Such as the results of datasets ID=107737, the accuracy of Sem-LSTM, ST-GRU, GRU, LSTM, and RNN improved approximately 52.42%, 44.36%, 31.29%, 23.56%, and 56.18%, compared with the SVM, and recall improved approximately 80%, 70.42%, 48.95%, 48.13%, and 39.3%. Compared with RF, the accuracy improved 33.33%, 25.27%, 12.2%, 4.47% and 37.09%, and recall improved 49.06%, 39.4%, 17.93%, 17.11% and 8.28%. This is mainly because SVM and RF are difficult to model complicated, nonstationary temporal sequence data, and other neural network-based methods can better deal with this problem.

Secondly, to verify whether the Sem-LSTM can model semantic information. We compared the Sem-LSTM and ST-GRU model. Taking data sets ID=108470 and ID=125870 as an example, The ID=108470 has 930 stay point records for 17 months, and ID=125870 has 1539 stay point records for 11 months. Thus the former is sparser than the latter. For the stationary dataset ID=125870, Sem-LSTM and ST-GRU performed almost the same performance. While for the sparser data set ID=108470, we can find Sem-LSTM outperformed the ST-GRU model significantly by a large margin, the accuracy of Sem-LSTM improved 21.3%, the recall improved 33.2% than ST-GRU, indicating that Sem-LSTM benefits from considering semantic information. Besides, we discover that LSTM outperformed the RNN on datasets ID=116853 and 125870, which may be due to the advantage of LSTM over RNN. For the two denser datasets, LSTM has the advantage of dealing with long term dependencies and solving gradient vanishing problem.

3) Sensitive of context window size: We further studied how the context window size affects the performance of the Sem-LSTM model. Generally, a larger context window of input can model a more comprehensive target location's

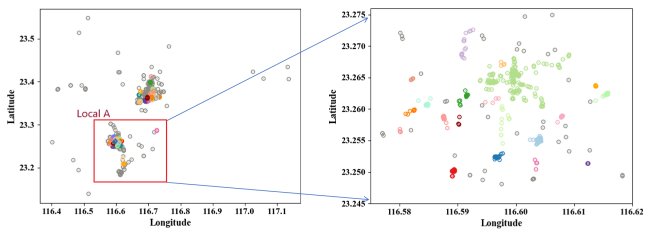
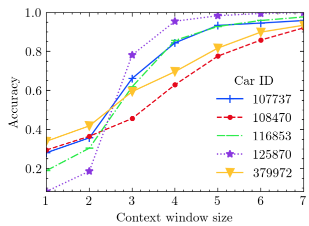


Fig. 5. Clustering result of original stay data of car ID=125870 in Shantou. The 'local A' is the detailed presentation of AOI cluster result.

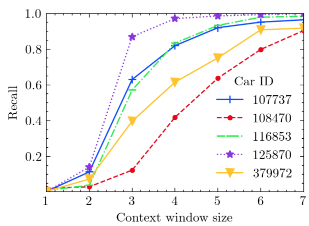
TABLE III
THE PREDICTION RESULTS OF SEM-LSTM MODEL AND OTHER NASELINE METHODS ON DIFFERENT CAR USER DATASETS

Data set	Metric	Random Baseline*	SVM	RF	RNN	LSTM	GRU	ST-GRU	Sem-LSTM
107737	Accuracy	0.0969	0.2993	0.4902	**0.8611**	0.5349	0.6122	0.7429	0.8235
	Recall	0.0021	0.0289	0.3391	0.4219	0.5102	0.5184	0.7331	**0.8297**
	F1-score	0.0021	0.0255	0.2781	0.4368	0.4879	0.5103	0.7151	**0.8147**
108470	Accuracy	0.1859	0.2992	0.3702	**0.8932**	0.5027	0.6086	0.4238	0.6368
	Recall	0.0183	0.0222	0.0821	0.4357	0.3052	0.4706	0.2017	**0.5391**
	F1-score	0.0183	0.0102	0.0727	0.4899	0.3328	0.4747	0.2093	**0.5559**
116853	Accuracy	0.0618	0.1469	0.3516	0.8291	0.8544	0.5994	0.8737	**0.9286**
	Recall	0.0053	0.0059	0.1284	0.3231	0.9126	0.5225	0.9077	**0.9194**
	F1-score	0.0054	0.0015	0.1038	0.3318	0.9142	0.5333	0.9113	**0.9274**
125870	Accuracy	0.0254	0.0897	0.2926	0.7740	0.8807	0.6591	0.9739	**0.9883**
	Recall	0.0056	0.0137	0.1987	0.3071	0.9565	0.3032	0.9811	**0.9931**
	F1-score	0.0046	0.0078	0.1745	0.2794	0.9433	0.2956	0.9811	**0.9918**
379972	Accuracy	0.1503	0.3427	0.5176	**0.8574**	0.5116	0.6186	0.7447	0.7326
	Recall	0.0032	0.0222	0.2124	0.2507	0.4314	0.5028	0.7110	**0.7115**
	F1-score	0.0031	0.0167	0.1892	0.2571	0.4368	0.5341	**0.7217**	0.7155

* Means that randomly select a location as current prediction result.



(a) Accuracy



(b) Recall

Fig. 6. Performance with vary context window size of Sem-LSTM model

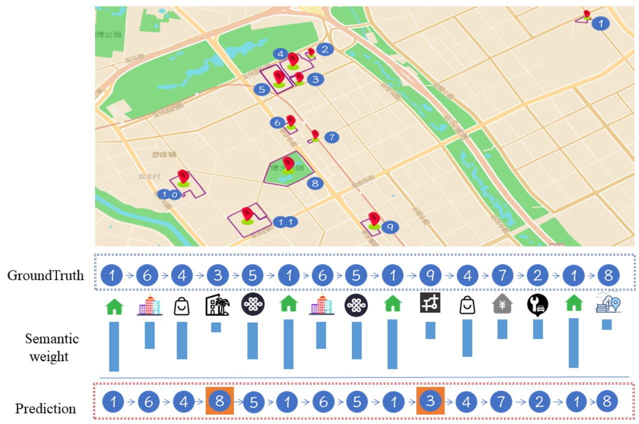


Fig. 7. An example of prediction result. The comprision of location suquence between ground truth and prediction.

contexts. However, it needs more compute resources and time. Here, We varied the context window size from 1 to 7 and used Accuracy and Recall Metrics to observe our model. In Fig.6, we first find that both Accuracy and Recall increase with the broader context window size; when window size from 2 rises to 3, the performance improves significantly; from 3 rises to 6, shows a constant increase trend; From 6 rise to 7, the performance of our model is stable. Unlike large-scale datasets, location records are relatively sparse, so a small context window such as 5 is suitable to model the location's context influence.

4) Case Study: For a better understanding of the user's interest used in Sem-LSTM. Fig.7 describes a case that shows the excellent performance of user ID=108470's randomly-selected fifteen constant visit records in five days. In the upper of the picture, we visualized the location sequence on Amap. The purple polygon stands for AOI's boundary; all stay points lie in the same boundary belong to the same AOI. Obviously, due to the embedding of semantic information, the prediction result is approaching accurate location records. Fig.7, we also observe that the lower weight means that a lack of a location's stay time and frequency, which makes it challenging to model the semantic information. Such as the NO.3 and NO.9 are hotel and park respectively, as a result of the user is seldomly visit this type of location, the weight value of them is lower than other location with higher semantic weight. Therefore, two error prediction locations emerged in the prediction sequence. At the same time, other locations with higher weight have a stable prediction result. In conclusion, Our model is capable of modeling users' sequential patterns more effectively via embedded semantic information.

VI. Conclusion

In this study, we design a semantic LSTM network to model private car users' mobility regularity. Besides modeling the spatiotemporal contexts, we employ AOI property and users' interest to mine the users' travel patterns further, contribute to improving the performance of the prediction model. Compared to baseline methods, we proposed the Sem-LSTM model perform excellent prediction results on five real-life users' datasets. In future work, we will study the correlation between private cars and other vehicles on the road to further mine the mobility of the entire city.

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