A Deep Learning Approach for Next Location Prediction

Xiaoliang Fan[1,2], Lei Guo[1], Ning Han[1], Yujie Wang[1], Jia Shi[1], Yongna Yuan[1,*]
[1] School of Information Science and Engineering, Lanzhou University, Lanzhou, China
[2] Fujian Key Laboratory of Sensing and Computing for Smart Cities, Xiamen University, Xiamen, China
Email: {fanxiaoliang, guol15, hann15, wangyujie15, shij2016, yuanyn}@lzu.edu.cn

***Abstract*—Next location prediction plays an essential role in location-based applications. Many works have been employed to predict the next location of an object (e.g. a vehicle), given its historical location records. However, existing methods have not fully addressed the importance of contextual features, such as the short-term traffic flows. In this paper, we propose a deep learning-based model to incorporate contextual features into next location prediction. First, we conduct the similarity mining among candidate locations. Second, we model contextual features among trajectories, including both periodical patterns and dynamic features of trajectories. Third, we adopt both CNN and bidirectional LSTM networks to predict next location in each trajectory with contextual information. Intensive experiments on 197 million vehicle license plate recognition (VLPR) records in Xiamen, China, demonstrate that the proposed method outperforms several existing methods.**

Keywords—next location prediction, deep learning, trajectory mining

I. Introduction

Location-based services have been widely used in our lives, such as food delivery, taxi-service, real-time bus system, and advertisement posting [1-2]. The next location prediction plays a major role in these applications. And also, predicting the vehicle's future location has attracted much attentions due to its essential role in Intelligent Transportation Systems.

With the rapid development of the city leads to the geometric growing of motor vehicles. For example, the number of vehicles in Xiamen City has been increasing enormously, from 300,000 in 2010 to 1.3 million in 2015, and it is expected to reach 1.8 million by 2018[1]. A large number of motor vehicles [23] brings a great challenge for urban traffic management. Therefore, the accurate prediction of vehicles' location could benefit many scenarios, such as detecting illegal vehicles for police officers [3], notifying congested areas for citizens [4], etc.

Nowadays, with the widely deployment of Vehicle License Plate Recognition (VLPR) Devices [5], the volume of the vehicle passing records could represent a historical mobility patterns of vehicles. Many approaches have been proposed in next location prediction. The earlier models include the Variable-order Markov model (VMM) [6], hidden Markov model (HMM), and Auto-regressive integrated moving average (ARIMA) [8], etc. Recently, a large number of models based on deep learning have been used, such as BP neural network, convolution neural network (CNN) [9], recurrent neural network (RNN) [10], etc.

Existing methods for next location prediction is two-fold: 1) mining trajectory patterns of a single-user [11]. However, the single-user method tends to suffer from the data sparsity problem, where an object might have little historical trajectory; and 2) mining trajectory patterns of multiple users. If trajectories of vehicle_1 and vehicle_2 are similar and they share the identical sequence (loc_1, loc_2, loc_3, loc_4). Therefore, to make the prediction for vehicle_2, could be helpful. However, many previous methods tend to use previous travel behaviors of vehicle_1 directly in order to make the prediction for vehicle_2, without the consideration of dynamic contexts (i.e., traffic flows, weather). Therefore, the prediction results may be not accurate.

To address the problems above, this paper proposes a Deep Learning Approach for Next Location Prediction (DLNLP) to incorporate contextual information into the vehicle movement prediction in the city level. First, we obtain the location relationship by Loc2vec, which replaces a discrete location with a continuous vector to retrieve context features among locations. Second, we model the contextual characteristics between trajectories based on both periodic trends and dynamic features. Third, we build a deep learning model, which integrates both multiple Convolution Neural Networks (CNNs) and bidirectional Long Short-Term Memory (bi-LSTM) networks. Finally, we conducted intensive experiments on the next location prediction of 197 million VLPR records in Xiamen City, and the proposed method outperforms several existing methods.

The rest of paper is organized as follows. Section II discusses the related works on next location prediction. Section III describes the preliminary and observations of dataset. Section IV describes the algorithm that has been used to predict the next location. Section V shows experiment results and evaluations. Finally, we conclude our work in Section VI.

II. Related Works

Comprehensive works have been investigated to predict the next location based on vehicle passing data in two categories: 1) individual-based (single-user), and 2) trajectory-based (multi-user).

First, in methods based on individual, most of them are based on Markov. Xue et al. [11] used taxi traces to construct a

* Corresponding author.
[1] http://xm.lanfw.com/2015/0826/337970.html

Probabilistic Suffix Tree and predicted short-term routes with Variable-Order Markov models. Simmons et al. [7] built a hidden Markov models (HMM) for every driver, which predicts the future destination and route of each target. Lin et al. [22] introduced a hierarchical Markov model that infers a user's daily movements through an urban community. All these above methods focus on predicting the destinations of specific individuals based on their own historical trajectory patterns. However, in these approaches, each trajectory is considered as a whole, and when the all historical trajectories of a vehicle are limited and insufficient to cover all locations, some locations will never be predicted. Then, the cold start problem is not solved well, when a new object (i.e., a vehicle) joined or an object gets to a new location.

Second, trajectory-based methods use the related and external information from the trajectory, so that predicting the next location. Mining the movement patterns with the historical trajectories of all moving objects has been widely studied. Monreale et al. [21] built a T-pattern Tree with all the trajectories to predict future location. Morzy [14] used all the moving objects' locations to discover frequent trajectories and movement rules with the PrefixSpan algorithm. And, Chen et al. [6] trained an integrated Markov model with different trajectory sets to mine both individual and common movement patterns to predict next location. Especially, Meng et al. [15] proposed a weighted Markov model (WMM) with incorporating the object similarity and considering the trajectory similarity. There are also many studies that focus on dynamic environments and improving the prediction performance with external information. Zhang et al. [10] extracted the underlying correlation between human mobility patterns and cellular call patterns and used it for the location prediction from temporal and spatial perspectives.

With development of Intelligent Transportation System, as well as the equipment cost is reduced, makes the mass surveillance cameras (VLPR devices) are deployed in the corners of the city. All kinds of positioning device such as the Global Positioning System Device (GPS) have been on a large-scale deployment in mobile vehicle [20]. Through the VLPR devices and positioning devices, we can obtain mass vehicle passing records. Researchers can study the movement patterns in citywide with the records, analyze the behavior rules of vehicles, predict the vehicle next location, and monitor the running state of the whole traffic [18].

Deep learning is the application of deep neural network technology (i.e., neural network architecture with multiple hidden layers) to solve machining learning problems. The success of artificial intelligence in deep learning involves all aspects, such as voice, text, and autonomous driving. Especially, CNN [9] and RNN [10] are often associated with next location prediction, which uses the big data technologies to mine the inherit correlations among a large number of trajectories.

In summary, existing methods do not fully address the contextual features (such as the short-term traffic flow and weather condition) in mining mobility patterns. Instead, in this paper, we extract the features with contextual information that could affect the next location prediction.

III. Preliminary and Features Analysis

A. Preliminary

Definition 1 (Vehicle License Plate Recognition Record): A VLPR Record is a vehicle passing record captured by VLPR Device. Each record can be denoted as $VR_{i,k}$ = (b_k, v_i, $time_{i,k}$, lo_k, la_k), where b_k is the ID of the VLPR device, v_i denotes the recognized vehicle license plate number, $time_{i,k}$ is the time stamp of the record, and lo_k and la_k refer to the longitude and latitude of b_k, respectively.

Definition 2 (Location): A vehicle passes through a set of locations where the VLPR devices deployed.

Definition 3 (Vehicle Trajectory): A vehicle trajectory *TRA* is represented by the sequence of VLPR records for a vehicle, i.e. TRA= $\{loc_i,\ 1 \le i \le n\}$, which is a sequence of locations ordered by vehicle passing time. Therefore,$\{loc_i = (b_i, t_i) | 1 \le i \le n\}$, where t_i is the vehicle passing timestamp, and b_i represents the location of VLPR device.

Definition 4 (Candidate Next Locations): If a vehicle is passing the location loc_i, and the next location is loc_j as a candidate next location without passing another location. We can obtain the set of candidate next location by the vehicles' historical trajectories and the locations deployed VLPR devices.

B. Problem Definition

There is a vehicle track TRA, that made up of n historical vehicle passing records, TRA=$\{ loc_i ,\ 1 \leq i \leq n \}$.

The problem is to predict the location loc_{n+1} that the vehicle will arrive at, based on the TRA and related contextual information.

C. Data Description

The VLPR devices as smart cameras can recognize a vehicle's license plate number with advanced techniques. Meantime, they can record the vehicle passing information. Recently, VLPR devices have been widely deployed and used in city traffic applications, such as road traffic monitoring, traffic law enforcement, and so on. There are over 329 VLPR devices in Xiamen, China, which is a coastal city with 3.8 million populations and 1.4 million local vehicles. Thus, by hundreds of VLPR devices on city-wide road networks we can get a large-scale mobility dataset.

The VLPR dataset includes vehicles passing records and device information. TABLE I shows a sample of VLPR records. Explicitly, a record contains attributes as follows: 1) DID: Device ID, which is an identifier for each device; 2) DIR: driving direction of the vehicle; 3) LPN: vehicle license plate number; 4) Color: the color of vehicle license plate; 5) LN: lane number; and 6) TS: timestamp. Specifically, license plate numbers have been redacted for privacy-protection issues. Furthermore, the VLPR device information is described by DID, Device Location, Longitude, and Latitude. An example of VLPR information is "620115, 0304, North Hubin Road and Yuxiu Road (East to West), 118.117, 24.488".

TABLE I. SAMPLE OF VLPR RECORDS FOR PASSING VEHICLES.

DID	DIR	LPN	Color	LN	TS
62068	2A	000001	2	2	2017-3-11-07:04:57
62078	2B	000002	2	1	2017-3-11-07:05:11
62098	2A	000005	2	3	2017-3-11-07:05:59

D. Features Analysis

The features describe the vehicle behaviors and the movement patterns as follows. And n is the length of each vehicle trajectory.

1) *Spatial feature*, based on the location where VLPR device deployed, we can generate the vehicle trajectory sequence, and the sequence is ordered by the vehicle passing time. It is just like the Definition 3 defined the trajectory, as, B={ b_i , $1 \leqslant i \leq n$ }.

2) *Temporal feature*, the vehicle trajectory patterns occur with strong periodicity. First, based on rush hour and usual hour, we group the VLPR dataset, like morning rush hour (7:00 a.m. to 9:30 a.m.), evening rush hour (5:00 p.m. to 8:00 p.m.) and usual hour. Second, we quantify the vehicle passing time recorded by VLPR. We divide 24 hours a day into 288 periods, and each period has five minutes (experiments show optimal choice) and unique identification number. Then, we convert the vehicle passing time in trajectory to the period id number, for a vehicle, a time sequence can be obtained, as, T={ t_i , $1 \leq i \leq n$ }.

3) *Direction feature*, the trajectory changes dynamically with the change of its direction. The feature is a sequence organized by the VLPRs' direction attributes. When a vehicle passes the VLPR device, the direction can be obtained by the VLPR device. And the direction has 8 classes, such as north, south, east, west, southeast, northeast, southwest and northwest. The direction is quantified, each direction is numbered. Therefore, based on a vehicle trajectory, we can form a sequence of direction feature, as: D= {d_i , $1 \leq i \leq n$}.

4) *Vehicle feature*, the information of vehicle (e.g. license plate number and color), it can reflect the vehicle condition, such as the blue license plate represents the small vehicle and the yellow license plate represents the large vehicle, each type of vehicles has different movement patterns.

E. Context Features Analysis

The contextual characteristics related to the vehicles movement behaviors, are described as follows.

1) *Traffic Flow feature*, is described by the traffic flow of the VLPR device in a period (five minutes). The influence of short-term traffic condition on vehicle trajectory is considerably essential, it reflects the behavior of the driver in traffic. For instance, when a VLPR device has large traffic flow, the driver maybe choose a road with less flow. It is a sequence, as, F= {f_i , $1 \leq i \leq n$}.

2) *Weather Condition feature*, the traffic condition always is affected by the weather condition, TABLE II shows a sample of weather condition dataset. Based on a vehicle passing time, this feature of the vehicle can be formed as, W= {w_i , $1 \leq i \leq n$}.

TABLE II. SAMPLE OF WEATHER CONDITION DATASET.

Time	Temperature	Humidity	Visibility
201703011200	14.0 °C	51%	6.0 KM
201703011400	16.0°C	49%	7.2KM
201703011800	12.0°C	52%	9.2KM

IV. NEXT LOCATION PREDICTION

The general architecture of our proposed method for next location prediction is presented in Fig. 1. In this section, we firstly describe data processing of the system, and then the proposed algorithm.

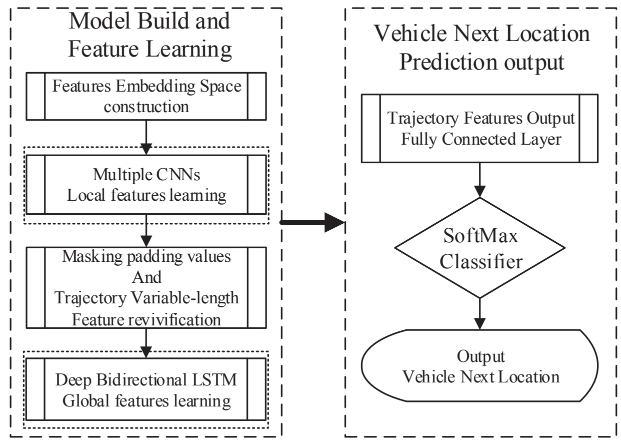

Fig. 1. Overview of the algorithm architecture

A. Data Preprocessing

Step 1. Data Acquisition.

First, we obtain the raw VLPR data (namely the vehicle passing record) from VLPR server database and delete the record that the vehicle license plate format is incorrect, for example, the license plate "MIN DT1111" ("MIN" is short for Xiamen). The task of data cleaning is to remove the irrelevant and redundant passing records. Then, we select the filtered VLPR records and generate the VLPR dataset.

Second, we extract the key attributes related on the vehicle trajectory in the VLPR dataset and update the dataset. The attributes include the ID of VLPR, the type of VLPR, latitude and longitude, the direction, the license plate number, the color of license plate, the lane number, as well as the vehicle passing time. Based on the peculiarity of traffic network, that vehicle trajectory pattern is in cyclical change, so we set the time period, such as morning peak (from 7 am to 9:30 am) and evening peak (from 5 pm to 8 pm). Then, we group the VLPR dataset into rush period and usual period, and respectively build model.

Step 2. Data Pre-processing.

According to characteristics mentioned in Section III.D and III.E, we process the data from VLPR dataset and the weather dataset before training. First, based on the key attribute license plate number, we generate the vehicle trajectory, mentioned in Section III.B. And the trajectory is arranged by the vehicle passing time with an increasing order. Then, we generate the vehicle trajectory dataset.

Second, we filter out the redundant location in trajectory, for example, the trajectory "2, 2, 3, 4, and 6" only remain "2, 3, 4, and 6". Then, in vehicle trajectory dataset we judge the unable-predict vehicle, whose trajectory's length is less than 3, based on the predictability of traffic network patterns. We delete the trajectory of unable-predict vehicle and update the vehicle trajectory dataset.

Third, on the basis of Section III, we convert the data formats of the characteristics. More specifically, considering the importance of spatial feature in vehicle trajectory, we extract spatial features by obtaining the relationship between locations in traffic network. Specifically, 1) we extract all locations in vehicle trajectories formed in the road network and generate the location information database; 2) we use the trajectories information to analyze the location relationship. We use the principle of Word2vec [16] to build our Loc2vec model, and Word2vec was created by a team of researchers led by Tomas Mikolov at Google, it is a neural network model; 3) we train Loc2vec model and reconstruct traffic context of locations. Location vectors are positioned in the vector space such that locations that share common contexts in the trajectories are located in close proximity to one another in the space. Finally, the discrete location data is transformed into a continuous embedding space location vector. As a result, we can obtain the similarity of locations, the adjacent locations have high similarity, and there is a below 0 similarity between no adjacent locations.

B. The Proposed Algorithm

We adopt the multiple-classification methodology based on deep learning, which is capable of incorporating heterogeneous features to effectively predict the next location. The proposed algorithm includes three modules, multiple CNNs, Deep Bidirectional LSTM, and the prediction module which outputs the next locations of the vehicles.

Module 1. Multiple CNNs

By using the embedding layer, we can convert the relevant features of vehicle trajectory into the feature vectors in the embedding vector space. And then, we fuse these features with vehicle trajectory spatial feature. The list of embedding size used in the proposed method is given in Table III.

TABLE III. METADATA VALUES AND ASSOCIATED EMBEDDING SIZE

Metadata	Direction	Time granularity	Vehicle ID
Number of possible values	8	288	3170546
Embedding Size	12	12	12

We construct multiple convolution neural networks (CNNs). Using the CNN feature detection layer, we can avoid extracting features explicitly and learn movement patterns implicitly from vehicle trajectories. Thus, we can learn the local characteristic of vehicle trajectory feature sequence.

Module 2. Deep Bi-LSTM

With the mask layer, we can mask the padding values and retrieve the variable-length feature sequence of vehicle trajectory. The LSTM can easily integrate external variables and provide automatic feature extraction capabilities with end-to-end modeling features. Its unit typically contains four complex components: an input gate, an output gate, a forgotten gate, and a memory controller. The unit basically determines which information is useful and holds useful information. Because the presence of each location depends on its previous location and the latter location, the LSTM can better handle this situation.

As shown in Fig. 2, each bidirectional LSTM is composed of two LSTM neural networks, one is the forward propagation (left to right), and the another one is backward propagation (right to left).In this way, we use deep bidirectional LSTM to obtain the past and future states of vehicle trajectory feature sequence. With this structure, we fully obtain the movement patterns of vehicles on time dependency.

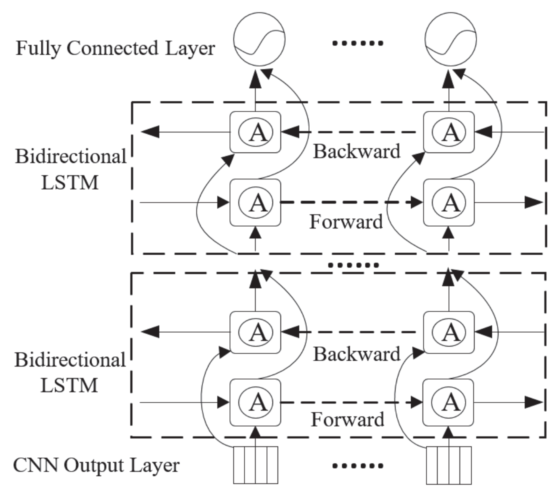

Fig. 2. The Deep Bidirectional LSTM structure

Module 3. Prediction

After feature learning in Module 2, we can obtain the final location vector features. The fully connected layer (In Keras, it is the Dense) disposes the vector features. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. Every two nodes have a weight value. The network output will be decided by the node connection, weight value and activation function. Then the state vector of the hidden layer is sent to a SoftMax classifier.

$$\hat{y}_i = \frac{\exp(z_i^L)}{\sum_{j=1}^{C} \exp(z_j^L)}$$

where $\hat{y}_i$ is the predicted next location vector, z_i^L (z_j^L) is the activation of the previous layer. And C is the number of the candidate locations plus 2, which is equal to the number of last hidden layer neurons in this paper.

Finally, the system can output the prediction result by the prediction function of Keras, which can convert a location vector to an Index of location. The prediction module structure is presented as Fig. 3.

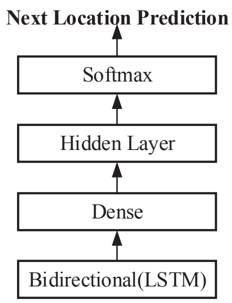

Fig. 3. The prediction module structure

V. EXPERIMENTS AND EVALUATIONS

In this section, we present experiments and evaluations with our proposed method. First, we describe the experimental environment and the detail of datasets. Then we demonstrate the effectiveness of our method. In addition, we compare the performance of six methods including DPNLP on real-word traffic datasets by evaluation metrics.

A. Experimental Settings

We conduct our experiments on a real-world traffic dataset containing nearly 197,021,276 vehicle passing records of over 6.5 million vehicles generated by 329 VLPR devices deployed in Xiamen in March 2017. It means that the number of next candidate locations is 329. To evaluate the effectiveness of our proposed approach, the dataset is divided into two subsets: the first 25 days are used for training, and the remaining 6 days are used for testing. In addition, we use Keras [17] and TensorFlow [19] to implement the proposed algorithm. TensorFlow is the deep learning open-sourcing framework developed by Google, which is used to express the interface of machine learning algorithms and implement the algorithms. Keras is a high-level neural networks API, and capable of running on the top of TensorFlow.

B. Evaluation Metrics

We evaluate the next location prediction performance by *ACC* (*Accuracy*), recall and F1-score. They are all frequently used to measure the performance of different classified models.

C. Baselines

We conducted intensive experiments to compare the proposed method with the following four methods.

- MM [6]. Next location prediction based on Markov Model, which is a variable Markov model considering different time periods. The Markov order we use is 3.
- WMM [15]. It is also based Markov model, using the weighted similarity object, and predicts the next location with taking the trajectories similarity into account.
- CNN [12]. Convolution Neural Network (CNN), which can learn each trajectory characteristics.
- LSTM [13]. Long short-term memory (LSTM) network, is a specific RNN, which is able to learn time series with long time dependencies. Especially, it is adapting to predict the next location in vehicle trajectories.
- NC. We set this baseline which is the proposed method DLNLP in this paper without considering the contextual information (short-term traffic flow and weather condition).

D. Results Summary

For further study the effectiveness of the proposed approach, we evaluate the performance of our framework with baselines. The results show that the top-5 ACC and other metrics are improved when the trajectory contextual characteristics mentioned in Section III are used together.

TABLE IV. PARAMETER VALUES

Parameter	Number of neurons	Momentum	Learning Rate	Epochs
Value	331	0.2	0.2	100

Table II shows several key parameters of the proposed approach in experiments: 1) the number of neurons in last hidden layer is more than 2 of the number of candidate VLPR devices; 2) the default Momentum Rate and Learning Rate are 0.2; 3) the optimal number of training epochs is 100 as shown in Fig. 4. , as the curves are gradually smooth from 80 to 100.

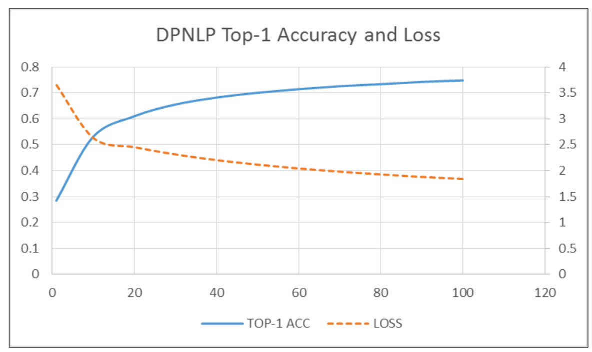

Fig. 4. The improvement in the DPNLP on top-1and the reduction in loss

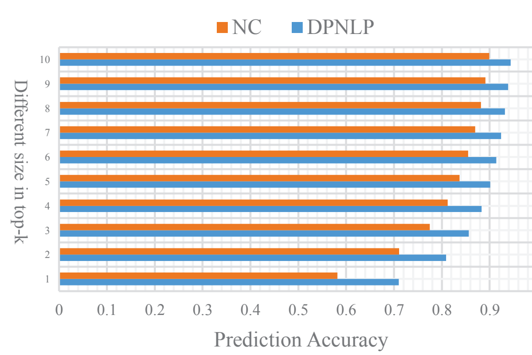

Fig. 5. The comparison of DLNLP and NC in different k of top-k accuracy

Table V. Performance Results of Each Method

Metrics	**MM**	**WMM**	**CNN**	**LSTM**	**DPNLP**
ACC	0.4307	0.4751	0.5151	0.6069	**0.721**
Top-5 ACC	0.8307	0.8065	0.815	0.8367	**0.901**
Recall	0.5272	0.5987	0.5371	0.6117	**0.6458**
F1-score	0.6635	0.7195	0.6717	0.7287	**0.7523**

We could conclude that: 1) when the number k(the length of predicted next location list) increases in Fig. 5, the performance of the proposed DPNLP is better than NC. This proves the importance of contextual information in predicting the next location; 2) as shown in Table V, the top-k accuracy of all methods increase when k increases and 3) in general, the results of Fig. 6 demonstrates that the significant performance of the proposed DPNLP method compared with the other methods.

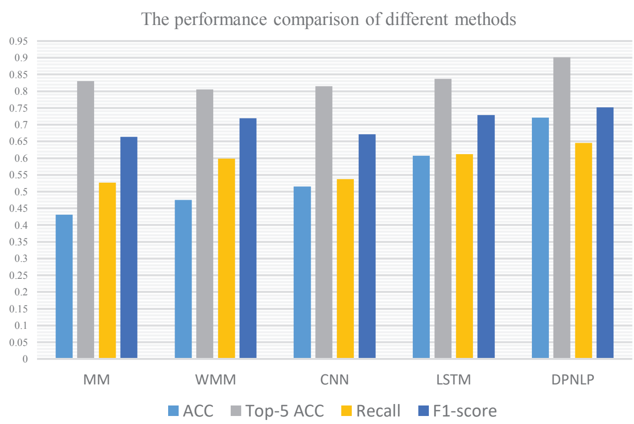

Fig. 6. The comparison of DLNLP with baselines in different metrics

VI. Conclusion

In this paper, we proposed a deep learning approach (DPNLP) to predict the next location with a large number of vehicle historical trajectories. The DPNLP method incorporates contextual features into next location prediction. Experimental results on a real-world vehicles dataset show that the method outperform several existing methods.

In the future, our work can be extended, for example: 1) the learning phase of the model can be further enhanced, and 2) we will fuse additional datasets (e.g., parking lot records) to further interpret vehicle trajectory patterns in the city.

Acknowledgment

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