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VEHICLE MOBILITY PREDICTION FOR INTELLIGENT APPLICATION BY USING RNN

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Abstract: A huge potential market for smart car applications is being created by recent advances in the vehicle industry and vehicle communication to everybody and mobility is very important in this area. This paper therefore proposes a new algorithm to support smart mobility applications for mobility of cars. First, a theoretical analysis reveals the predictability of mobility for vehicles quantitatively. Based on the knowledge gained from theoretical analyses, it is proposed to predict mobility of the vehicle in the future by using a deep recurrent neural network (RNN)-based algorithm known as Deep VM. The data has proved that Deep VM can significantly increase mobility forecast quality in comparison with other advanced algorithms and has proven the accuracy of its theoretical analysis. The results are also validated.

Index Terms: **Vehicle mobility, vehicle-to-everything (V2X), recurrent neural network, deep learning.**

I. INTRODUCTION

The recent advancements in the automotive technology have transformed the motor vehicle from a simple mechanical device into an intelligent platform, with different communication, computing and sensing functions. Future cars are expected to provide both an enjoyable and safe driving experience and diverse services, including multi-media infotainment and social interaction. Vehicle network systems, which enable cars to exchange information efficient through vehicle-to-vehicle, car-to-infrastructure, and vehicle-to-fedest communications, are among the most promising technologies to meet such expectations. Gartner estimates that networked vehicles will be produced in annual terms by 61 million by 2020 and this leads to a huge market for many smart vehicle applications, such as self-driving aid, vehicle-based collection of sensing data, traffic security, geo-advertising, inter-net vehicle access and pothole detection

The mobility of vehicles makes the topology of the V2X networks extremely dynamic, and this is one of V2X's main challenges. Therefore, the use of mobile vehicles for smart applications is of major importance. In a number of city smart applications, for example, the only thing you require is to regularly sensing data and tolerate delaying data transmission. Smart grid applications, for example, like advanced metering, are tolerant of a data delay from 10 minutes or several hours. Since it is rather costly to use so many cellular networks femtocell to transmit this sensing data generated by a large number of geo-distributed IoT devices, many scientists suggest using V2X communication with a short range to offload this tolerant delay data out of mobile networks. The IEEE 802.11 p and the LTE-V2X mode 4, which cover the communication from several hundred to very few kilometres, are two representative V2X short range standards. The example of the application of a prediction for vehicle mobility to support this application is shown in Figure 1. Assume that taxis A and B move around a city and collect sensor data in short distance when they meet the sensors deployed in the city (i.e., when vehicles enter the communication range of sensors). Both taxis want to supply these sensing data via short-range communication to a roadside unit (SSU) on the left, which is using wired broadband networks to forward sensing data back to a data centre. Taxi A can intelligently transmit its stored data to taxi B by means of short-distance contacts when two taxis meet each other, if taxi B are expected to move to the RSU. Thus, if Taxi B meet the RSU later, Taxi A data are delivered successfully, even where Taxi A never directly meets that RSU. The quality of vehicle-based sensing data collection could be greatly improved through such multi-hop mobility-based data transmission strategy [9, 10]. Geo-advertising using mobility for broad-casted promotion in a particular city region and mobile edge computing using mobility for encouraging the sharing of computational resources in V2X network are also other intelligent vehicle applications that may benefit from mobility predictions But as most vehicles are moving in their own right, a complete knowledge of their mobility is difficult. In order to prevent this high degree of uncertainty, existing works use either metrics such as time distributions for meeting and inter-recovery to implement rough-grained vehicle mobility predictions or simplify the problem in the Markov model to make precise predictions.

This paper therefore proposes a deep recurrent Network Network (RNN) algorithm known as DeepVM, which accurately predicts car mobility.

(1) The predictability of vehicle mobility is quantitatively shown through solid theoretical testing. As far as we know, DeepVM is the first in this field worldwide deeper learning technology.

2) Based on the knowledge gained from theoretical analyses, a deep RNN-based algorithm called DeepVM is proposed to predict vehicle mobility.

(3) extensive assessment results based on real taxi movement not only validated the accuracy of our theoretical analysis, but demonstrated that deepVM significantly improves vehicle prediction quality compared to the most advanced algorithms.

A conference paper presented a preliminary study of this work. This paper supplements an entropy-based theoretical analysis compared to its conference version in order to quantitatively assess mobility and the association between it and trajectory knowledge of vehicles. This analysis not only reveals the advantages of using profound learning for mobility predictions, but also explains why the DeepVM algorithm proposed. In addition, this paper provides complementary validation assessments. DeepVM from various aspects. An evaluation results presented in this article emphasise clarification of the theoretical factors that contribute to the superior performance of DeepVM, not simply comparing the performance of DeepVM and other state-of-the-art algorithms. This paper is first presented with over 75 percent analysis and evaluation results. Finally, the introduction and related work parts of the present paper are further improved so that the DeepVM scenarios and new points are better illustrated.

II. PROPOSED WORK

2.1 Basic Idea

Our work in this document thus validates both the theoretical and empirical evidence on the potential and superiority of this strategy. Compared to current prediction work on macro-level traffic statistics, our proposal helps smart vehicle applications driven by separate vehicle mobility and seeks to use the opportunistic communication window for providing new services between nearby vehicle and the Internet.

2.2 Recurrent Neural Networks (RNN)

Another type of neural network specialising in sequential data is a Recurrent Neural Network (RNN) model. The main difference compared to a FNN is the ability to handle sequential inputs that allow multiple inputs to be processed to predict. A RNN is able to predict future states by using historical information. RNNs consist of computer elements called RNN cells and each cell has a single entry and historical memory in the sequence. The elements are computerized and each cell takes one entry into the sequence and the historical memory. The model can thus capture the relationships or patterns between times. RNNs can also process inputs in various sizes because they are using a common parameter strategy in order to prevent parameter counts from changing their input size. Figure 2 shows xătą each input in the time-span sequential data, aătą is the activation that is transferred and processed via the cells.

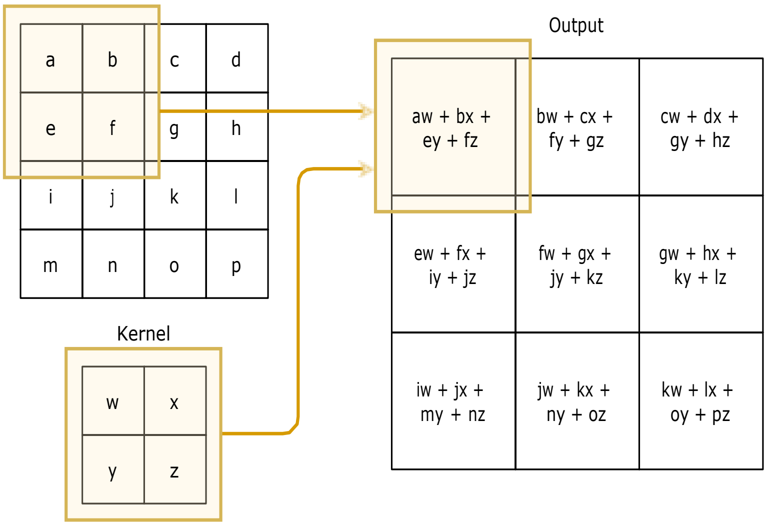


Figure 1: Convolution operations

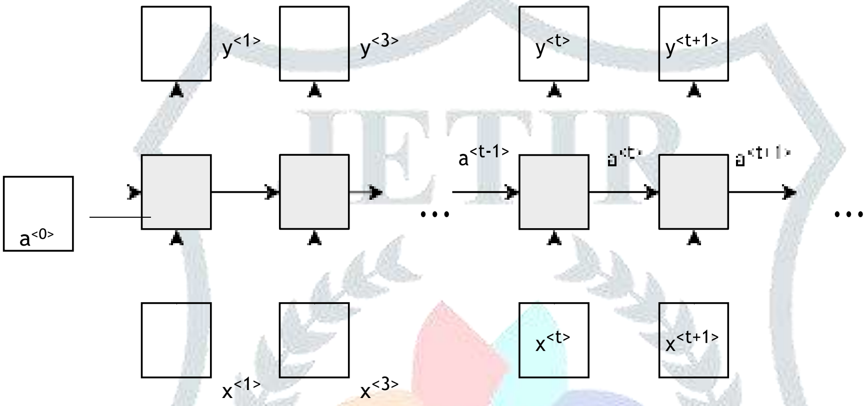


Figure 2: Recurrent Neural Network.

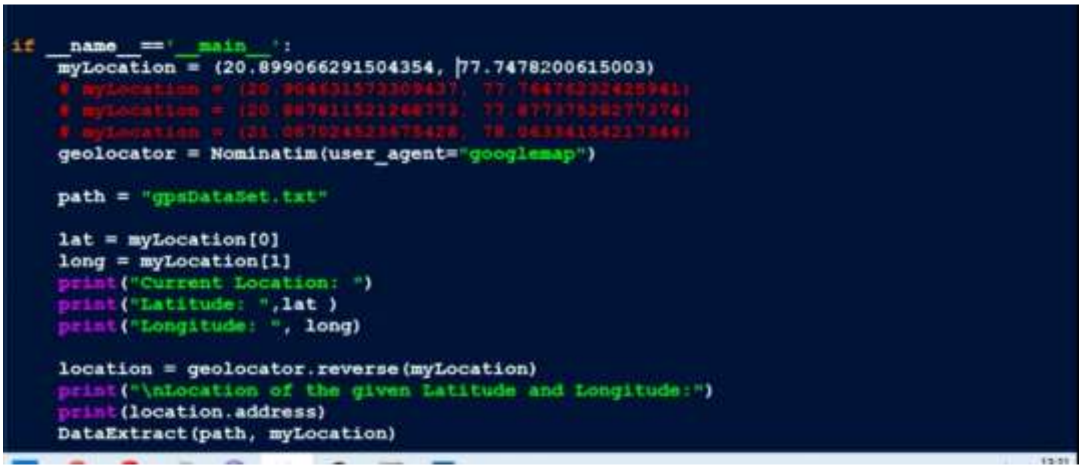
A significant drawback of RNNs is that they suffer from vanishing and exploding gradi ents and this problem is analyzed by Bengio et al in detail. Hoch Reiter et al proposed Long Short-Term Memory RNNs in order to deal with long term dependencies in the data by splitting the transferred activation into two-components.

2.3 Long Short-Term Memory RNN

Long shorter-term memory (LSTM) overcomes RNN's problem of gradient disappearance. LSTM's closed structure splits short-term and long-term dependence, allowing the model to handle longer entry data sequences better. LSTM also has cells, and has four gates that cover different operations in each cell: (1) Forget Gate; (3) Input Gate; The historical information that is learned is transferred in cellular state and changed by other gates during this process. Some operations offer learning effects and forgetfulness in the doors. The upper input-output is called long term memory (LTM) and represented as C_t´1 and C_t. The lower input-output is called short term memory (STM) and represented as $h_{t\ 1}$, h_t in the formulas. In the next sections, the operations in the gates of an LSTM cell are discussed.

III. RESULT:

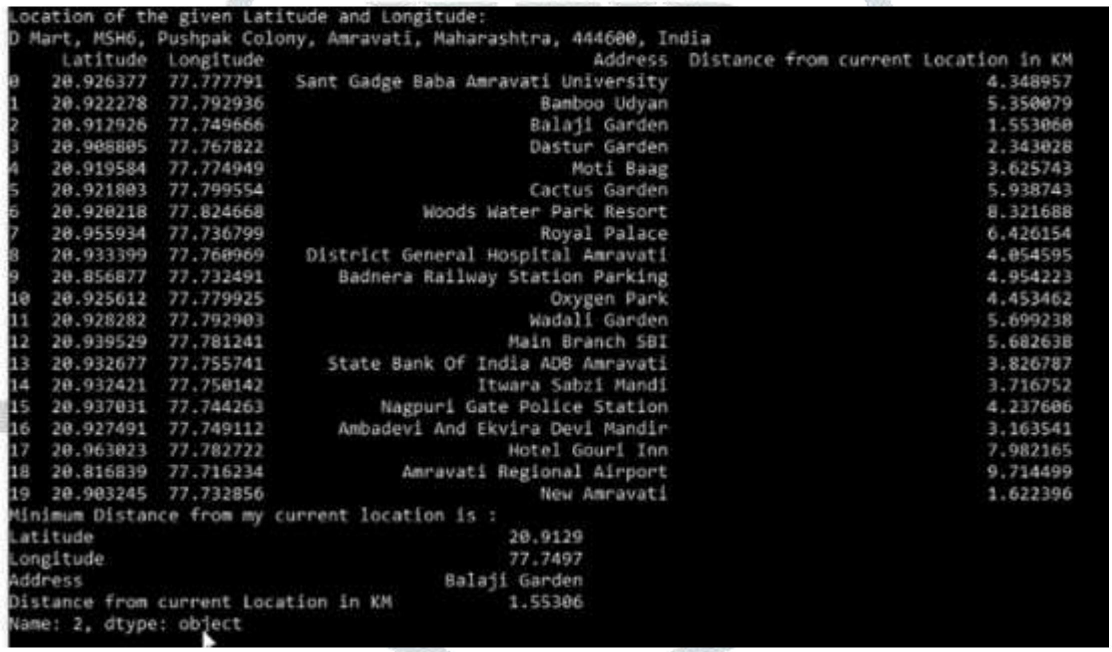
3.1 Current Location Near to Balaji Garden



```
if __name__=='__main__':
    myLocation = (20.899066291504354, 77.7478200615003)
    geolocator = Nominatim(user_agent="googlemap")

    path = "gpsDataSet.txt"

    lat = myLocation[0]
    long = myLocation[1]
    print("Current Location: ")
    print("Latitude: ",lat )
    print("Longitude: ", long)

    location = geolocator.reverse(myLocation)
    print("\nLocation of the given Latitude and Longitude:")
    print(location.address)
    DataExtract(path, myLocation)
```

Fig. 3 Placing Latitude and Longitude in program

Above figure shows where we needed the vehicle from nearest town the latitude and longitud of our current location



Location of the given Latitude and Longitude:
D Mart, MSH6, Pushpak Colony, Amravati, Maharashtra, 444600, India

	Latitude	Longitude	Address	Distance from current Location in KM
0	20.926377	77.777791	Sant Gadge Baba Amravati University	4.348957
1	20.922278	77.792936	Bamboo Udyan	5.350079
2	20.912926	77.749666	Balaji Garden	1.553060
3	20.908805	77.767822	Dastur Garden	2.343028
4	20.919584	77.774949	Moti Baag	3.625743
5	20.921803	77.799554	Cactus Garden	5.938743
6	20.920218	77.824668	Woods Water Park Resort	8.321688
7	20.955934	77.736799	Royal Palace	6.426154
8	20.933399	77.760969	District General Hospital Amravati	4.054595
9	20.856877	77.732491	Badnera Railway Station Parking	4.954223
10	20.925612	77.779925	Oxygen Park	4.453462
11	20.928282	77.792903	Wadali Garden	5.699238
12	20.939529	77.781241	Main Branch SBI	5.682638
13	20.932677	77.755741	State Bank Of India ADB Amravati	3.826787
14	20.932421	77.750142	Itwara Sabzi Mandi	3.716752
15	20.937031	77.744263	Nagpuri Gate Police Station	4.237606
16	20.927491	77.749112	Ambadevi And Ekvira Devi Mandir	3.163541
17	20.963023	77.782722	Hotel Gouri Inn	7.982165
18	20.816839	77.716234	Amravati Regional Airport	9.714499
19	20.903245	77.732856	New Amravati	1.622396

Minimum Distance from my current location is :

Latitude	20.9129
Longitude	77.7497
Address	Balaji Garden
Distance from current Location in KM	1.55306

Name: 2, dtype: object

Fig. 4 Nearest position according to above latitude and longitude

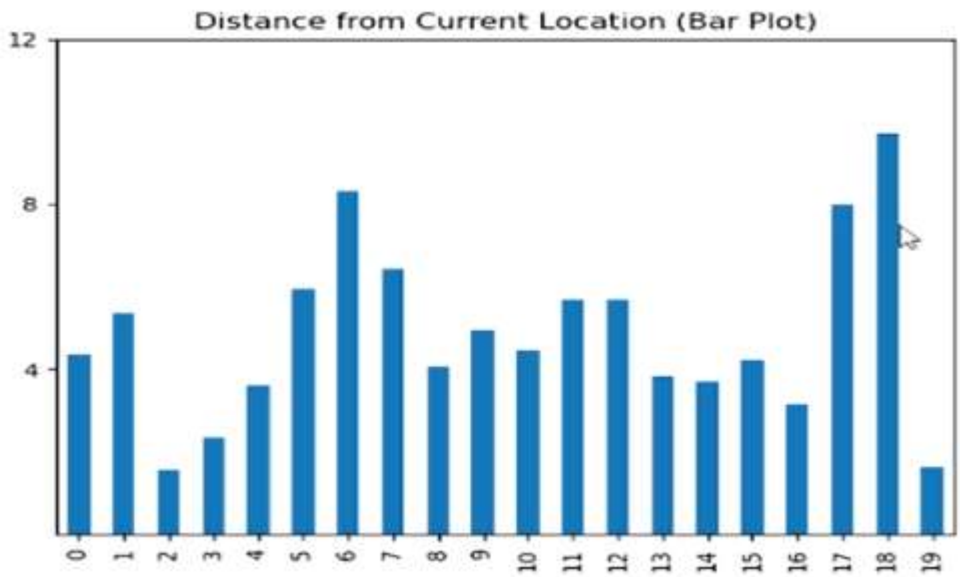
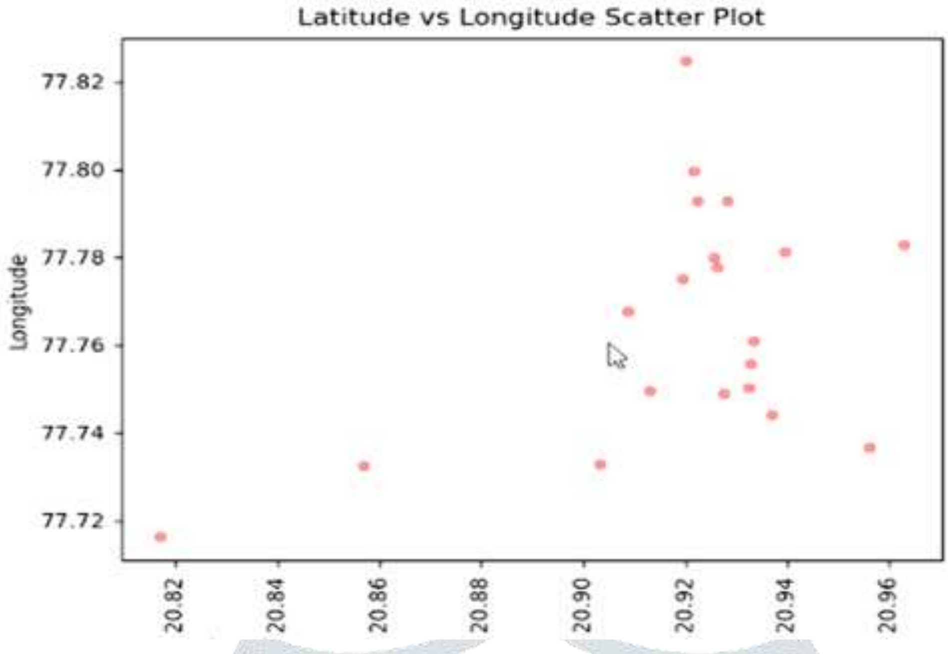


Fig. 5 Graph of Distance from Current Location



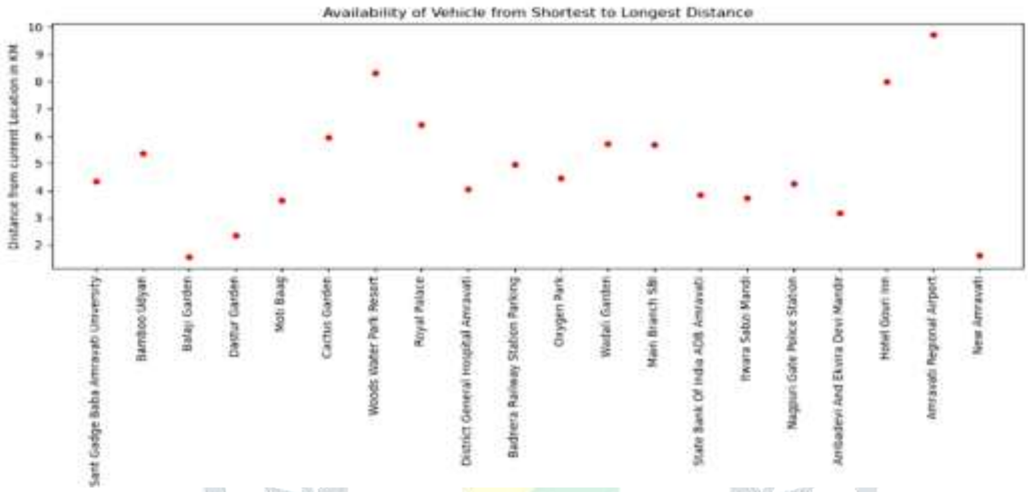


Fig. 6 Latitude Vs Longitude Plot

IV. CONCLUSION

This paper proposes an algorithm known as DeepVM to support intelligent vehicle applications, a thorough learning mobility prediction. The theoretical analysis shows first that a long trajectory of the vehicle helps reduce uncertainty regarding future mobility of vehicles. DeepVM uses a deep recurrent neural network to prevent car mobility, based on knowledge gained from theoretical analysis. Comprehensive assessments have shown that DeepVM can greatly improve the quality of vehicle mobility projections, mainly due to its ability to process a much longer vehicle trajectory compared to other high-tech algorithms.

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