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Methods Based on Machine Learning for Precise Trajectory Forecasting

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***Abstract*— Predicting human mobility is crucial for many contemporary applications across various domains, including personalized recommendation systems, fifth-generation (5G) mobile communication systems, and more. In general, different application scenarios have distinct prediction goals. Predicting the whereabouts of mobile users in the near future, from dozens of seconds to a few minutes, is crucial for 5G network applications like resource allocation and mobility management. This is essentially a trajectory prediction problem that needs to be solved in order to prepare ahead of time. In this paper, we first design a basic deep learning-based prediction framework with a focus on multi-user multi-step trajectory prediction. The Long Short-Term Memory (LSTM) network is directly applied as the most critical component to learn user-specific mobility patterns from the user's historical trajectories and predict his/her future movement trends. We expand this fundamental framework to a region-oriented prediction scheme and present a multi-user multi-step trajectory prediction framework by further incorporating Sequence-to-Sequence (Seq2Seq) learning, driven by the associated discoveries after verifying and analyzing this framework on a model-based dataset. Results of experiments on a genuine dataset show that the suggested framework significantly enhances generalization skills and lessens the impact of error accumulation in multi-step prediction.**

***Index terms*—Support vector regression, Fifth-generation, Autoregressive integrated moving average.**

I. INTRODUCTION

Globally, the widespread use of smartphones and location-based services has led to a huge and quick increase in mobility data. The vast amount of mobility data opens up new possibilities for identifying the features of human movement patterns and forecasting mobility. From personalized recommendation systems to intelligent transportation, urban planning, and mobility management in the fifth-generation (5G) mobile communication system, human mobility prediction is practically crucial in many contemporary applications. In general, different application scenarios have distinct prediction goals.

Predicting the whereabouts of mobile users in the near future, from dozens of seconds to a few minutes, is crucial for 5G mobile communications in order to plan for resource allocation and mobility management. In reality, the problem is one of trajectory prediction, where the trajectory is a time series of positions with a predetermined sampling time interval between them.

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Numerous mobility prediction techniques, including frequent patterns mining, Markov-based models, and other machine learning techniques, have been proposed by researchers; however, the majority of these techniques are geared toward discrete location prediction, which is actually a multi-classification problem, and are not appropriate for forecasting trajectories with fixed sampling time intervals. The following are the causes. When the sample time interval is small, locations for trajectories made up of discrete location indexes may remain the same for a number of consecutive time-steps; when the sampling time interval is big, however, locations may change between two adjacent time-steps. As a result, it is difficult for them to accurately depict user movement trends. However, it is challenging to define the discretization granularity of coordinates for trajectories made out of continuous location data. High discretization granularity generally helps to capture trends in user movement. However, under high discretization granularity, the prediction accuracy may decline as the number of candidate locations increases. This work thoroughly examines methods for predicting trajectories made up of continuous coordinates in order to circumvent the aforementioned issues. Traditional regression methods like support vector regression (SVR) and linear regression are viable options because it is essentially a time series regression prediction problem. In addition, another regression approach is autoregressive integrated moving average (ARIMA). It is devoted to processing prediction issues, such traffic and stock prediction, for long-term series made up of numerical data with quantity relationships. However, ARIMA may not be able to handle the trajectory prediction problem since mobility trajectories are typically brief sequences made up of two-dimensional coordinates that represent geographic locations. Fortunately, the Recurrent Neural Network (RNN) has demonstrated its superiority in a number of time series problems within the context of deep learning. These problems are not limited to the natural language processing domain (e.g., machine translation [12], speech recognition [13]), but also include some other domains (e.g., traffic prediction [14], precipitation prediction).

II. LITERATURE SURVEY

Globally, the widespread use of smartphones and location-based services has led to a huge and quick increase in mobility data. The vast amount of mobility data opens up new possibilities for identifying the features of human movement patterns and forecasting mobility. From personalized recommendation systems to intelligent transportation, urban planning, and mobility management in the fifth-generation (5G) mobile communication system, human mobility prediction is practically crucial in many contemporary applications. In general, different application scenarios have distinct prediction goals.

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III. PROPOSED SYSTEM

The overview of our proposed system is shown in the below figure.

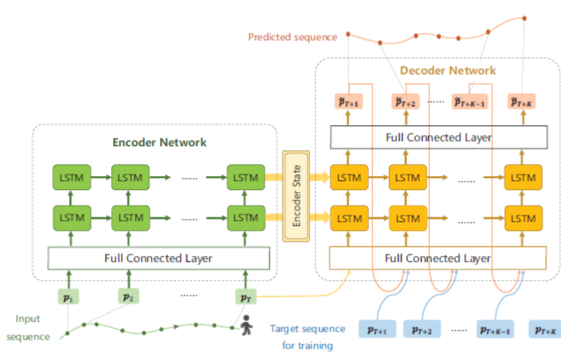

Fig. 1: System Overview

Implementation Modules

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Load Dataset

- This step involves extracting the data from the.csv file and loading the dataset into the software.
- The best features can be extracted from this data through analysis in order to preprocess it.

Preprocess

- A significant number of "NA" values in the provided data set are filtered in Python. Additionally, as the data set is composed of numerical data, we employed robust scaling, which is comparable to normalization but uses the interquartile range, whereas normalization reduces the data to 0 to 1.

Train and Test Model

- The service provider divided the used dataset in this module into 70% train data and 30% test data, respectively. Thirty percent of the data is regarded as test data, which is used to evaluate the model, and seventy percent is regarded as train data, which is used to train the model.

Prediction

- To determine the gender type, the remote enters the online purchasing details in this module. This determines the gender type and assesses the shopping details.

Graph Analysis

- The user can obtain a comprehensive study of the LSTM's performance in predicting trajectory throughout this phase of implementation. The graph analysis takes into account a number of parameters.

Implementation Algorithms

Long Short Term Memory

An artificial recurrent neural network (RNN) architecture used in deep learning is called long short-term memory (LSTM). LSTM features feedback connections, in contrast to conventional feedforward neural networks. It can process whole data sequences (like audio or video) in addition to individual data points (like pictures).

Due to the possibility of unknown-duration lags between significant occurrences in a time series, LSTM networks are ideal for categorizing, analyzing, and forecasting time series data. The vanishing gradient issue that might arise during the training of conventional RNNs was addressed by the development of LSTMs.

IV. RESULTS

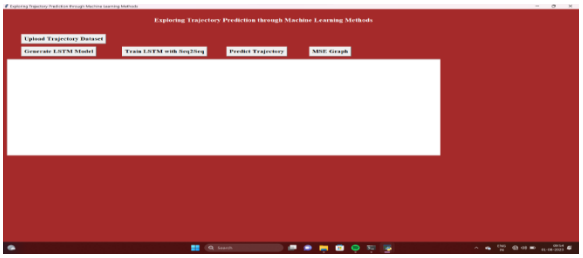

Fig. 2: Opening Page

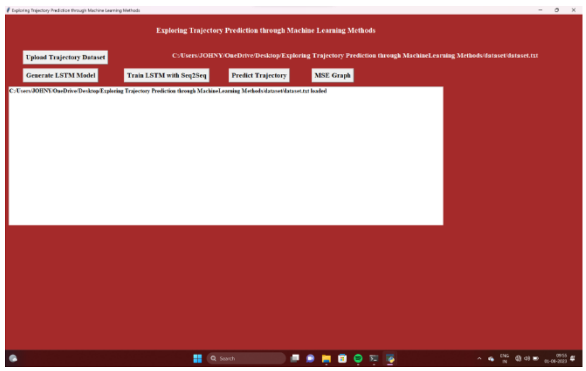

Fig. 3: Load Dataset

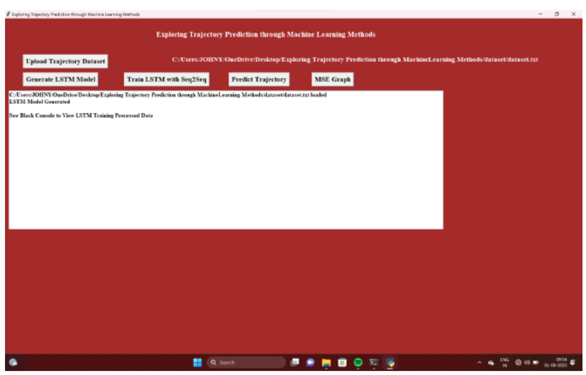

Fig. 4: Generate Model and Train

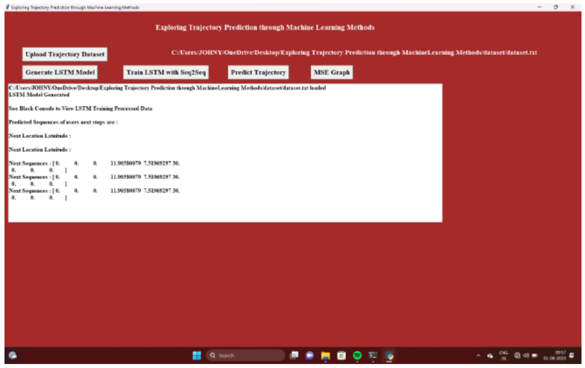

Fig. 5: Predicted Results

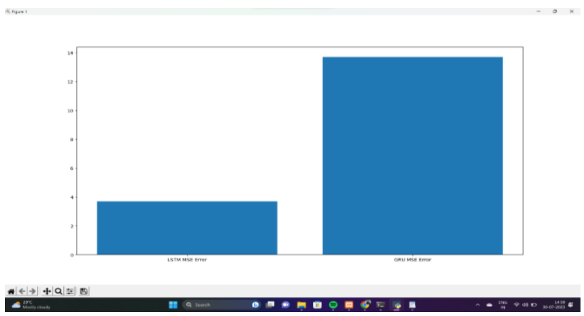

Fig. 6: Loss Graph.

V. CONCLUSION

Intelligent distribution, particularly the FAP's distribution with greater standards, will play a significant role in people's daily lives in the period of smart city building. The intelligent allocation of FAP in smart cities is the focus of this work. We develop a mathematical model to develop distribution routes in a reasonable and scientific manner that balances the relationship between client pleasure and distribution expenses. IQPSO is used for related experiments to confirm the algorithm's stability and efficacy. The findings demonstrate that the relationship between distribution costs and customer happiness may be successfully balanced by the algorithm and the defined model. As a result, it offers a fresh approach to balancing the link between customer pleasure and distribution costs in FAP's intelligent distribution in smart cities. The mathematical model of VRP with multiple supply and demand points will be examined in our upcoming projects. Additionally, we will set up various car models to offer distribution services to clients with various needs.

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