HUMAN TRAJECTORY PREDICTION

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***Abstract* -** Increasing pervasive usage of smart-phones and location based services around the world has contributed to vast and rapid growth in mobility data. The large size of mobility data provides new opportunities for discovering the characteristics of human mobility patterns and making mobility predictions. Practically, human mobility prediction is of great importance in a wide range of modern applications, ranging from personalized recommendation systems to intelligent transportation, urban planning, and mobility management in the fifth-generation (5G) mobile communication system. Generally, the prediction goal varies from different application scenarios.

For the case of 5G mobile communications, it is essential to predict the positions of mobile users in the near future from dozens of seconds to a few minutes so as to prepare for mobility management and resource allocation. It is actually a trajectory prediction problem where the trajectory refers to a time series of positions with a fixed sampling time interval between each other. Although researchers have proposed many mobility prediction methods, such as frequent patterns mining, Markov-based models and other machine learning methods, most of these methods are dedicated to discrete location prediction, which is actually a multi-classification problem, and not suitable for predicting trajectories with fixed sampling time intervals.

***Keywords* -** *Multi-step Prediction, Long-Short Term Memory, Sequence to Sequence, Machine learning, Trajectory Prediction.*

I. INTRODUCTION

Generally, high discretization granularity benefits to reflect user movement trends. However, the prediction accuracy may decrease with increasing number of candidate locations under high discretization granularity. In order to avoid the above problems, we take comprehensive investigation for the approaches to predict trajectories composed of continuous coordinates. Since it is actually a time series regression prediction problem, conventional regression algorithms such as linear regression and support vector regression (SVR) are candidate solutions. Besides, autoregressive integrated moving average (ARIMA) is another regression algorithm. It is dedicated to processing prediction problems for long time series composed of numerical data with quantity relationship, such as stock prediction and traffic prediction. However, the mobility trajectories are usually short sequences composed of two-dimensional coordinates reflecting geographic locations, making ARIMA possibly not competent to the trajectory prediction problem. Fortunately, within the framework of deep learning, the Recurrent Neural Network (RNN) has proved its superiority in various time series problems not only in natural language processing field (i.e. machine translation, speech recognition) but also some other fields (i.e. traffic prediction precipitation prediction). Therefore, as the improved versions of typical RNN, Long Term Short Term Memory (LSTM) and Gate Recurrent Unit (GRU) are promising algorithms for the trajectory.

II. RELATED WORK

With the emergence of smartphones and location-based services, user mobility prediction has become a critical enabler for a wide range of applications, like location-based advertising, early warning systems, and citywide traffic planning. A number of techniques have been proposed to either conduct spatiotemporal mobility prediction or forecast the next-place. However, both produce diverse prediction performance for different users and display poor performance for some users. Here focuses on investigating the effect of living habits on the models of spatiotemporal prediction and next-place prediction, and selects one from these two models for an individual to achieve effective mobility prediction at users' points of interest.

Based on the hidden Markov model (HMM), a spatiotemporal predictor and a next-place predictor are proposed. Living habits are analyzed in terms of entropy, upon which users are clustered into distinct groups. With large-scale factual mobile data captured from a big city, we compare the proposed HMM-based predictors with existing state-of-the-art predictors and apply them to different user groups. The results demonstrate the robust performance of the two proposed mobility predictors, which outperform the state of the art for various user groups.

Many empirical studies of human walks have reported that there exist fundamental statistical features commonly appearing in mobility traces taken in various mobility setting. These include heavy-tail flight and pause-time distributions, heterogeneously bounded mobility areas of individuals and truncated power-law intercontact times. It reports two additional such features, The destinations of people (or we say waypoints) are dispersed in a self-similar manner and people are more likely to choose a destination closer to its current waypoint. These features are known to be influential to the performance of human-assisted mobility networks.

The main contribution of this is to present a mobility model called Self-similar Least-Action Walk (SLAW) that can produce synthetic mobility traces containing all the five statistical features in various mobility settings including user-created virtual ones for which no empirical information is available. Creating synthetic traces for virtual environments is important for the performance evaluation of mobile networks as network designers test their networks in many diverse network settings. A performance study of mobile routing protocols on top of synthetic traces created by SLAW shows that SLAW brings out the unique performance features of various routing protocols.

In order to drive safely and efficiently on public roads, autonomous vehicles will have to understand the intentions of surrounding vehicles, and adapt their own behavior accordingly. If experienced human drivers are generally good at inferring other vehicles' motion up to a few seconds in the future, most current Advanced Driving Assistance Systems (ADAS) are unable to perform such medium-term forecasts, and are usually limited to high-likelihood situations such as emergency braking. In this article, we present a first step towards consistent trajectory prediction by introducing a long short-term memory (LSTM) neural network, which is capable of accurately predicting future longitudinal and lateral trajectories for vehicles on highway.

However, the deployment of smaller cells inevitably leads to more frequent handovers, thus making mobility management more challenging and reducing the capacity gains offered by the dense network deployment. In order to fully reap the gains for mobile users in such a network environment, we propose an intelligent dual connectivity mechanism for mobility management through deep learning-based mobility prediction.

III. PROPOSED WORK

We proposed the significance of trajectory prediction and explore feasible approaches from both the single-user perspective and multi-user perspective. For single-user trajectory prediction, we propose a basic LSTM framework and experimental results on a model-based mobility dataset illustrate the superiority of LSTM to make predictions based on pre-learning of user-specific mobility patterns.

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For multi-user multi-step prediction, we further propose a region oriented prediction scheme and Sequence-to-Sequence (Seq2Seq) framework.

Trajectory prediction has a wide range of applications in 5G networks, such as radio resource pre-allocation caching decision at the wireless edge mobility management and etc. For example, in order to mitigate the negative impact of frequent handovers in dense networks, our previous work in proposes an intelligent dual connectivity mechanism for mobility management based on trajectory prediction, which improves the quality of service of mobile users in the handover process while guaranteeing the network energy efficiency. Moreover, driven by the stringent safety requirement of autonomous driving and advanced driver assistance systems, it is critical to understand the intentions of surrounding vehicles through trajectory prediction. Therefore, trajectory prediction is a problem worth well careful studying.

IV. IMPLEMENTATION

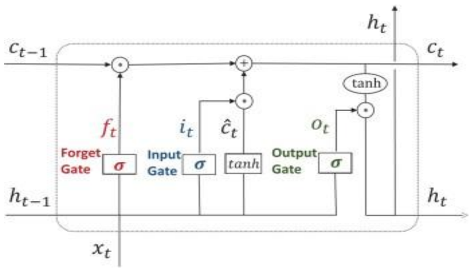


Fig: A typical architecture of the LSTM memory block

The LSTM neural network is com- posed of multiple copies of basic memory blocks and each memory block contains a memory cell and three types of gates (input gate, output gate, and forget gate). The memory cell is the key component of LSTM and responsible for the information transfer at different time-steps. Meanwhile, the three gates, each of which contains a sigmoid layer to optionally pass information, are responsible for protecting and controlling the cell state. As its name implies, the input gate controls which part of the input will be utilized to update the cell state. Similarly, the forget gate controls which part of the old cell state will be thrown away, while the output gate determines which part of the new cell state will be output.

For the memory block at time-step t, we use f_t, i_t, and o_t to represent the forget, input and output gates respectively. Assume that x_t and h_t represent the input and output at the current time-step, $h_{t\ 1}$ is the output at the previous time-step, σ represents the sigmoid activation function, and denotes the Hadamard product and biases of the three gates and the memory cell with subscripts f , i, and o for the forget, input, and output gates respectively, while the subscript c is used for the memory cell. x_t and h_t represent the input and output at time-step t, σ represents the sigmoid activation function.

A. PREDICTION FRAMEWORK DESIGN

In the model-based dataset, different users typically have distinct mobility patterns, making the mobility prediction problem to be user-specific. Therefore, in order to make mobility predictions for a user, the most critical step is to establish a specific mobility model which fully represents the user's mobile pattern from his/her historical trajectories. Fig.5 presents the proposed LSTM-based single-user prediction framework. The prediction process involves three major steps. First, the given trajectory is processed by a fully connected (FC) input layer with 128 neurons so that each two- dimensional coordinate is mapped to a 128-dimensional fea- ture tensor. Then, the processed sequence is sent to the main part of the mobility model, a deep recurrent neural network formed by three stacked LSTM layers each with 128 neurons. Each LSTM layer takes the output of the previous layer as input and feeds its output to the next layer. Finally, an FC output layer with 2 neurons maps the output of the last LSTM layer at each time-step i to a two-dimensional coordinate $p_{i\ 1}$ as the predicted location of the next time-step, and thereby we get the prediction sequence $p\ p_2 p_3$.

. . $p_{T\ 1}$. The training goal is to minimize the distance error between the predicted location and the actual location. Thus, we choose the Mean Square Error (MSE) as the loss function and adopt Backward Propagation Through Time (BPTT) algorithm [34] to update the network parameters. Ultimately, the user's mobility pat- tern is saved in the mobility model as network parameters and the prediction of future trajectory can be completed based on the trained mobility model.

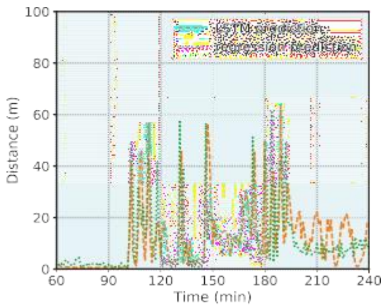
B. MOBILITY PREDICTION RESULTS

In this part, we evaluate the prediction performance of the proposed framework on a user's trajectories from the model- based dataset. The length of each trajectory is 360min at one-minute granularity. In order to fully learn the user's mobile pattern, during the training process, we take the complete trajectory except the last minute (i.e. $p_1p_2 . . . p_{359}$) as input and push the time-series forward one minute as standard output (i.e. $p_2p_3 . . . p_{360}$). During the test process, after one-hour observation, we first make single-step predictions given the user's real position at each time-step. Then, in order to evaluate the prediction performance comprehensively, the case of multi-step prediction where the real position becomes rapidly unavailable is also considered. In this case, we recursively reusing the recent prediction results as input for the following prediction step. For comparison, we also use the conventional linear regression algorithm to fit the user's movements and make predictions.

V. EXPERIMENTS & RESULTS

Multi-user multi-step prediction promises to bring lots of significant merits. Firstly, it allows for more practical near- real-time resource pre-allocation. But it has to deal with the annoying error-accumulation effect. Secondly, the generalization ability of the prediction model across users also makes it feasible to quickly perform trajectory prediction for any user. Thirdly, the computation overhead of training a model for each user separately can be significantly reduced. Therefore, we consider the real-world user movement scenario and propose a multi-user multi-step trajectory prediction framework.

Moreover, the attention mechanism doesn't show obvious superiority over the normal Seq2Seq framework. One possible reason is that unlike machine translation problem where there exists mismatch in the order of words between the input sentence and the output sentence, the trajectory is a time series of positions with an almost left- to-right sequential relationship, especially for the short-term trajectories with fine granularity in our problem. In this case, the global information such as the velocity, direction, and etc., is more important for trajectory prediction.



(c) Error in Single-step Prediction

Fig: Error in Single Step Prediction

The test process of all methods is performed on the Intel Core i5 CPU. Obviously, the Linear Regression shows the highest training efficiency compared with the neural networks, especially those incorporated with the Seq2Seq technique. It is reasonable since a complex model with large number of parameters usually needs more training time to find the optimal solution. Although Seq2Seq framework has relatively larger training time, its test time is much shorter at around 0.27 seconds, which is acceptable for online prediction.

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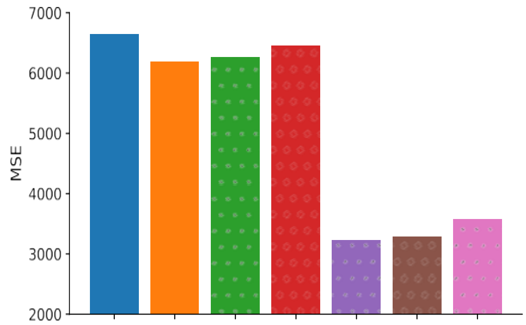

Fig: Comparisons of prediction performance for different methods in terms of MSE

VI. CONCLUSION & FUTURE WORK

We investigate the significance of trajectory pre- diction and explore feasible approaches from both the single- user perspective and multi-user perspective. For single-user trajectory prediction, we propose a basic LSTM framework and experimental results on a model-based

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mobility dataset. Illustrate the superiority of LSTM to make predictions based on pre-learning of user-specific mobility patterns. For multi- user multi-step prediction, we further propose a region- oriented prediction scheme and put forward an LSTM-based Seq2Seq framework.

Our current work does not consider the semantic context in the trajectory like the point of interests because of the limitation of data. For future work, we plan to combine our algorithm with some semantic information to improve the prediction performance.

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