

Exploring Trajectory Prediction through Deep Learning Techniques

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Abstract

The prediction of an individual's next location has emerged as a crucial area of research, driven by its far-reaching implications for various applications. The proliferation of location-based services has led to a significant impact on diverse domains, including traffic flow prediction, weather forecasting, and network resource optimization. The rapid growth of positioning and sensor devices has resulted in the generation of vast amounts of trajectory data related to human movement. By leveraging these large-scale location-based trajectory data, researchers are now focused on developing models that can accurately predict an individual's next location. Considerable research attention has been devoted to developing a comprehensive understanding of next location prediction, resulting in the development of numerous robust systems. However, a thorough examination of these state-of-the-art works is necessary to gain a deeper understanding of their applications and challenges. This paper aims to provide a comprehensive review of existing next location prediction approaches, offering a detailed overview of the field, including fundamental definitions and concepts, data sources, methodologies, and applications. In the context of next location prediction, a trajectory is typically represented as a

sequence of time-stamped geographic locations, which serves as a crucial input for predictive models. Analyzing and mining trajectory data poses significant challenges due to the intricate patterns inherent in human mobility, which is influenced by a multitude of contextual factors. The complexities of trajectory data, including its heterogeneity, the randomness of user movement, and its time-sensitive nature, further exacerbate these challenges. This manuscript provides a comprehensive overview of various location prediction approaches, applications, and challenges, highlighting key areas that require further exploration in future research. Additionally, it delves into the applications and challenges associated with predicting a user's next location. Ultimately, this survey culminates in a conclusive summary, which is essential for the development of robust and reliable next location prediction systems.

Keywords: Next location prediction, Semantic trajectory, Machine learning, Deep learning

1. Introduction

The widespread adoption of smartphones and location-based services globally has led to a significant and swift expansion in mobility data. This extensive dataset offers new opportunities to uncover human mobility patterns and forecast movements. Human mobility prediction plays a crucial

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role in various modern applications, including personalized recommendation systems, intelligent transportation, urban planning, and mobility management in fifth-generation (5G) mobile communication systems. [1], [2].

Typically, the objectives for predictions differ across various application scenarios. In the context of 5G mobile communications, it is crucial to forecast the locations of mobile users within a short time frame, ranging from several seconds to a few minutes, to facilitate effective mobility management and resource allocation [2].

This is a trajectory prediction problem, where the term "trajectory" denotes a sequence of positions recorded at consistent time intervals. Numerous methods for predicting mobility have been suggested by researchers, including the mining of frequent patterns. [3], [4],

Markov-based models and other machine learning techniques primarily focus on discrete location prediction, treating it as a multi-classification problem. This approach is not suitable for predicting trajectories with fixed sampling time intervals for several reasons.

For trajectories made up of discrete location points, if the sampling interval is short, the locations might remain unchanged for several time-steps, whereas with a larger sampling interval, there could be abrupt changes between steps. This makes it difficult to accurately capture user movement trends. Conversely, trajectories based on continuous location coordinates present challenges in determining the appropriate level of granularity for discretization. Typically, finer granularity improves the reflection of user movement patterns.

However, prediction accuracy can decline as the number of candidate locations increases with finer discretization granularity. To address these issues, this paper thoroughly investigates methods for predicting trajectories using continuous coordinates. Given that this is a time series regression prediction problem, traditional regression algorithms like linear regression and support vector regression (SVR) are viable solutions. Additionally, the autoregressive integrated moving average (ARIMA) model is specifically designed for long-term time series forecasting, making it suitable for applications such as stock market and traffic flow predictions.

2. Literature Survey

This paper begins by examining trajectory data mining techniques, including both statistical and deep learning approaches. It then explores the trajectory prediction challenges across various research domains. Finally, it reviews key advancements related to deep generative models.

2.1 Trajectory Data Mining

Trajectory data contain huge amount of information about moving objects, encouraging many studies and a variety of downstream applications such as constructing location-based social networks, predicting traffic dynamics and planning urban services [3]. Next we discuss statistical and deep learning models in trajectory data mining based on different mining tasks. As trajectory prediction is the primary focus of the this thesis, we discuss it in more detail in the next section.

2.1.1 Statistical Models

Pattern Mining: In tradition, there are several basic mining tasks that have been

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explored within this area. Pattern mining of trajectory data is an important domain that includes clustering, frequent sequence mining [20], periodic pattern mining [21] and moving together pattern mining [22]. Specifically, clustering is to divide trajectory data in different clusters based on the movement properties. A general clustering approach is to represent each trajectory with a feature vector, and then, measure the similarity between trajectories by calculating the distance between their feature vectors [23, 24]. Lee et al. [25] propose a partition-and-group-based framework for clustering trajectories. Trajectories are divided into multiple line segments and similar line segments are grouped together into a cluster. Yan et al. [26] present a model that is hybrid of spatiotemporal and semantic information of trajectories. The model encapsulates both the geometry and semantics of mobility data, which can be used in trajectory clustering. Li et al. [27] propose a road-network-based clustering algorithm. Instead of clustering the moving objects, road segments are clustered based on the density of common traffic they share. Similarly, Han et al. [28] introduce NEAT, a method designed for efficiently clustering spatial trajectories of mobile object son road networks. This model considers three key aspects: the physical constraints of the road network, the network proximity and the traffic flows among consecutive road segments, to effectively group trajectories into spatial clusters. Pechlivanoglou and Papagelis [29] present an one-pass sweep-line algorithm over the trajectories (SLOT) that can eff ectively compute the node importance of moving objects in a trajectory network. Sawas, Abuolaim, Afifi and Papagelis [30] propose a novel versatile method, time W groups , for efficient discovery of pedestrian groups dynamics, including various definitions of group gathering and dispersion. Classifi cation.

Classifi cation is another classical spatiotemporal data mining task.

Zheng et al. [31] apply a decision tree-based inference model to classify different transportation modes based on GPS data. Bolbol et al. [32] use SVMs for transportation mode classifi cation. Another sub-domain of classifi cation is trajectory outlier or anomaly detection, which involves the detection of significantly anomalous observations compare to the majority of the datasets. One of the approaches are to partition trajectories into a set of sub-trajectories and then detect the outlying sub-trajectories by applying a distance function or clustering approach. For example, Lee et al. [33] propose a Partition-and-Detect framework. The model includes a two-level trajectory partitioning strategy for the partition phase, which improves quality and efficiency. Additionally, for the detection phase, they introduce a method that use both distance-based and density-based approaches.

2.1.2 Deep Learning-based Models

Investigates the distribution of the trajectory data mining problems addressed by deep learning. Over 70 percent studies are predictive learning, and others are inference and anomaly detection, and so on. Next, we discuss deep learning models based on different tasks. Graph-based Prediction Models. In some cases, graphs are constructed from trajectory data. For example, in road network-scale traffic prediction, the transportation network can be naturally modeled as a graph, making it suitable to apply graph-based deep learning models. Chai et al. [35] propose a multi-graph convolutional neural network (CNN) model to predict bike flow. More specifically, the authors generate multiple

graphs that reflect heterogeneous inter-station relationship between bike stations. These graphs are then fused and convolutional layers are used to predict station-level future bike flow. Li et al.[36] present a model called the Diffusion Convolutional Recurrent Neural Network (DCRNN) for traffic forecasting. In their paper traffic flow on a transportation network is viewed as information that propagates through a graph, and the model employs bidirectional random walks to capture spatial dependencies among graph nodes and an encoder-decoder architecture with scheduled sampling to capture temporal dependencies. Zhang et al.[37] propose Traffic GAN, an adversarial learning framework to predict traffic flow. To capture the spatial and temporal correlations among roads in a road network, CNN and LSTM are embedded in the framework.

Estimation and Inference: There have been a lot of studies about estimation and inference, which mainly focus on the problem of estimating travel time, trip purpose and travel mode from the mobility trajectory data. Accurately estimating the duration of a trip based on its origin and destination locations and departure time is essential in numerous real-world applications. To tackle this problem, Li et al.[38] present a deep multi-task representation learning model that estimates the arrival time of a trip. The model utilizes the underlying road network and spatiotemporal knowledge to generate trip representations that retain various trip properties. Fu et al.[39] develop Compact ETA, a novel ETA learning system that can provide accurate online travel time inference. Their approach leverages a spatiotemporal weighted road network graph and applies a graph attention network to encode high-order spatial and temporal dependencies into trip representations. In addition, they encode the sequential information of the travel route using

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positional encoding. Martin et al. [40] study the problem of inferring the purpose of a user's visit to a specific location using trajectory data. To address this issue, they propose a Graph Convolutional Neural Network (GCN) for inferring activity types from GPS trajectory data generated by personal smartphones. The mobility graphs of a user, which are fed into GCNs, are generated based on all their activity areas and the edges are constructed based on trajectory data. Zhu et al.[41] propose a Semi-supervised Federated Learning (SSFL) framework that includes a novel identification module called Convolutional Neural Network-Gated Recurrent Unit, which can accurately infer travel modes from GPS trajectories. In addition, the authors design a pseudo-labeling method that allows to set pseudo-labels on their local unlabeled datasets using a small public dataset on the server. Alix and Papagelis [42] present a reinforcement learning method PathletRL for constructing a small set of basic building blocks that can represent a wide range of trajectories. This dictionary can be useful in various tasks and applications, such as trajectory compression, travel time estimation, route planning, and so on.

Anomaly Detection.: The other important task for trajectory data is anomaly detection or outlier detection, which aims to identify the rare observations that differ remarkably from the majority of the data. Chen et al.[43] collect huge amount of traffic accident data and users' GPS records to study the influence of human mobility on traffic accident risk. They propose a deep model of Stack denoise Autoencoder to learn hierarchical feature representations of human mobility, which can be utilized to predict traffic accident risk level. Denget al.[44] propose a generative adversarial network that leverages graph convolutional

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gated recurrent unit (GCGRU) to help the generator and discriminator learn the spatiotemporal features of traffic dynamics and traffic anomalies respectively. After adversarial training, both the generator and discriminator can act as separate detectors. The generator learns to model normal traffic patterns, while the discriminator provides detection criteria based on spatiotemporal features.

2.3 Deep Generative Models

Generative models are a class of machine learning models designed to learn and mimic the underlying data distribution of a given dataset (see Bond-Taylor et al. [67] for a comprehensive survey). The fundamental idea behind generative models is to capture the statistical patterns and relationships present in the data so that the model can generate new samples that look and feel like the real data. They have shown remarkable results in creating realistic data samples, and they have been used for various creative and practical applications including image synthesis, text generation, music composition, and more. There are several types of generative models, but some of the most prominent ones include Generative Adversarial Networks (GANs) [68], Variational Autoencoder (VAEs) [69], Autoregressive Models [70], Flow-based Models [71], and Transformers [17]. In our research, we propose the use of generative models for addressing the trajectory prediction problem. We specifically employ a transformer-based architecture such as GPT (Generative Pre-trained Transformer) [72]. To the best of our knowledge, this is the first attempt to employ deep generative models to the (non vision-based) trajectory prediction problem.

3. Problem statement

Human mobility prediction is of great importance in a wide range of modern applications in different fields such as personalized recommendation systems, the fifth-generation (5G) mobile communication systems, and so on. Generally, the prediction goal varies from different application scenarios. For the applications of 5G network including resource allocation and mobility management, 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 make preparation in advance, which is actually a trajectory prediction problem.

In this research, we focus on the trajectory prediction problem, which refers to the task of predicting the future path or trajectory of an object (or individual) based on its current state and historical data. Efficient methods for trajectory prediction are highly desirable in various domains and applications, including transportation systems, human mobility studies, autonomous vehicles, robotics, and more.

4. Objectives

In this Research Work, some of the challenges related to SA are considered with a focus on classification of reviews or opinions in a best possible way. The main objective of this research work can be outlined as:

1. To collect the dataset, the dataset must contain real life trajectory movement dataset which consist of user's movement latitude, longitude and users id and each user has 10 locations.
2. To train the dataset using machine learning algorithms. (LSTM and Seq2Seq).

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3. To Generate LSTM Model' for the initialization of LSTM algorithm or to generate model with number of features given in dataset.
4. Upload of dataset with initialize LSTM and Seq2Seq Encoder and Decoder object.
5. To apply LSTM and Seq2Seq model is train and so it can predict user's location. After finding the location it will appear which as users current latitude, longitude and user_id to predict next sequences.

5. Proposed Methodology

The flow of methodology in the research work on trajectory prediction through machine learning methods can be outlined as follows:

Dataset Acquisition: Obtain two types of datasets: a model-based dataset generated using mobility models like SLAW and SMOOTH, and a realistic GPS trajectory dataset from the Geolife project.

Data Preprocessing: Clean and preprocess the datasets by selecting relevant location records, converting coordinates, and filtering noise points to ensure data quality.

Algorithm Selection: Choose Long Short-Term Memory (LSTM) and Gate Recurrent Unit (GRU) as promising algorithms for trajectory prediction based on their capabilities

Model Development: Develop an LSTM-based single-user prediction framework to learn user-specific mobility patterns and predict future movements. Extend the framework to a region-oriented prediction scheme and propose a multi-user multi-step trajectory prediction framework using Seq2Seq learning.

Experimental Setup: Design experiments to evaluate the performance of the prediction frameworks on both the model-based and realistic datasets.

Performance Evaluation: Assess the accuracy, generalization ability, and error-accumulation effects of the prediction models through empirical experiments.

Results Analysis: Analyze the experimental results to understand the strengths and limitations of the proposed trajectory prediction framework. Discuss the implications of the findings, including the effectiveness of the multi-user multi-step prediction framework and potential areas for improvement.

By following this methodology flow, the research aims to advance the understanding and application of machine learning techniques for predicting human mobility patterns with a focus on multi-user multi-step trajectory prediction.

Conclusion

The conclusion drawn from the survey on trajectory prediction through machine learning methods can be summarized as follows:

Significance of Human Mobility Prediction:

Human mobility prediction plays a crucial role in various modern applications, ranging from personalized recommendation systems to 5G mobile communication networks.

Methodological Advancements:

The survey highlights the utilization of machine learning algorithms, such as Long Short-Term Memory (LSTM) and Gate

Recurrent Unit (GRU), for trajectory prediction.

The research introduces a region-oriented prediction scheme and a multi-user multi-step trajectory prediction framework using Seq2Seq learning, showcasing advancements in prediction accuracy and generalization ability.

Dataset Utilization:

The survey leverages both model-based and realistic GPS trajectory datasets to evaluate the performance of the prediction frameworks.

Experimental Findings:

Empirical experiments demonstrate the effectiveness of the proposed prediction frameworks in mitigating error accumulation and improving prediction accuracy for multi-user trajectory prediction.

Future Research Directions:

The survey identifies the need to incorporate semantic information, such as points of interest, to enhance prediction performance in future research endeavors.

There is a potential for further research in combining the proposed algorithms with semantic context and exploring their applicability in diverse scenarios.

Overall Impact

The survey underscores the importance of accurate trajectory prediction in resource allocation, mobility management, and other applications, showcasing the advancements made through machine learning methods.

the survey on trajectory prediction through machine learning methods demonstrates the advancements in predicting human mobility patterns, with a focus on multi-user multi-

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step trajectory prediction. The findings contribute to the field of trajectory prediction and pave the way for future research in enhancing prediction performance and applicability in various real-world scenarios.

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