A survey on next location prediction techniques, applications, and challenges

Ayele Gobezie Chekol[1*] and Marta Sintayehu Fufa[2]

*Correspondence:
ayele.gobezie@gmail.com
[1] Department of Computer
Science, Wolkite University,
Wolkite, Ethiopia
Full list of author information
is available at the end of the
article

Abstract

Next location prediction has recently gained great attention from researchers due to its importance in different application areas. Recent growth of location-based service applications has vast domain influence such as traffic-flow prediction, weather forecast, and network resource optimization. Nowadays, due to the explosive increasing of positioning and sensor devices, big trajectory data are produced related to human movement. Using this big location-based trajectory data, researchers tend to predict human next location. Research efforts are spent on the put forward overall picture of next location prediction, and number of works has been done so as to realize robust next location prediction systems. However, in-depth study of those state-of-the-art works is required to know well the applications and challenges. Therefore, the aim of this paper is an extensive review on existing different next location prediction approaches. This work offers an extensive overview of location prediction enveloping basic definitions and concepts, data sources, approaches, and applications. In next location prediction, trajectory is represented by a sequence of timestamped geographical locations. It is challenging to analyze and mine trajectory data due to the complex characteristics reflected in human mobility, which is affected by multiple contextual information. Heterogeneous data generated from different sources, users' random movement behavior, and the time sensitivity of trajectory data are some of the challenges. In this manuscript, we have discussed various location prediction approaches, applications, and challenges, and it sheds light on important points regarding future research directions. Furthermore, application and challenges are addressed related to the user's next location prediction. Finally, we draw the overall conclusion of the survey, which is important for the development of robust next location prediction systems.

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

1 Introduction

Location-based service (LBS) has a wide range of applications, including government, emergency services, commercial, and industrial sites [1]. Moreover, breaking news, tracking, shopping, ATM information are examples of location-based services [2]. The wide-spread use of Global Positioning System (GPS) devices, smartphones, Internet of Things (IoTs), and wireless communication technologies are used to track moving objects [3]. Many services, such as social services, advertising recommendations,

traffic scheduling, route planning, and so on, need to predict user locations to improve the quality of information [4, 5]. Location prediction uses users' historical track to train the prediction model and then predicts the next position of the user [6]. Next location prediction usually involves obtaining significant places from the trajectories history and predicting the location with a certain statistical model. The location-based services market such as navigational services, traffic management, and location-based advertisement have grown rapidly in recent years [7]. LBSs are able to predict the activities a user may perform at the next location to visit, due to the needs of effective marketing and efficient system operations. Therefore, robust location prediction techniques are necessary for LBSs targeted at mobile users.

Mobile applications such as Foursquare, where users check-in to broadcast their visits to places, allow us not only to know the geographic coordinates of a user at a given time, but also the exact places they go to [8]. The library, the cinema, and the airport are a few examples among millions of places which are accessible through these services. Knowledge about the places users visit, which goes beyond plain geographic coordinates, can be exploited as an additional dimension to describe human mobility.

Mobile phones leave positioning logs, which specify their localization or cell number, whenever connected with the Global System for Mobile Communication (GSM) network [9]. Likewise, GPS-equipped portable devices can record their latitude–longitude position and transmit their trajectories to a collecting server. The pervasiveness of ubiquitous technologies guarantees that there will be the increasing availability of large amounts of data on individual trajectories, with increasing precision in terms of localization. Knowledge about the positions of mobile objects has led to location-based services and applications, which need to know the approximate location of a mobile user. Due to the unreliable nature of mobile devices and the limitations of the positioning systems, the position of a mobile object is often unknown for a long duration. In such cases, a method to predict the possible future location of a moving object is necessary to anticipate possible services.

Understanding user mobility from sensor data is a central theme in ubiquitous computing [10]. As a significant kind of human behavior, human's transportation mode, such as walking, driving and taking a bus, etc., can endow their mobility with more significance and provide rich context information to the pervasive computing systems.

Next location prediction is one of the significant functions for context-aware systems on a smartphone [11]. The prediction of users' information based on their situation is a function that enables context-aware systems to take proactive and responsive actions. A context-aware system on a smartphone analyzes and recognizes users' situations from sensor logs. Contexts include users' spirit, location, and time, although the definition of a context depends on its application.

Mobility prediction is one of the issues that needs to be explored for mobility management in mobile computing systems [12]. Mobility management in mobile computing environments covers the methods for storing and updating location information of mobile users. Mobility prediction is the prediction of a mobile user's next movement when the mobile user is traveling between the cells of a Personal Communication Systems (PCS) or Global System for Mobile Communications (GSM) network. A user's next location prediction also has a great effect on network resource optimization and user

experience improvement [13]. Human mobility modeling is also a great importance for mobile computing, urban planning, and location-based services [14]. Robust location prediction enables operators to gain access to information that users require, reduce network burden, and optimize network resources [15–18].

Furthermore, the pervasive usage of smartphones and location-based services around the world has contributed to vast and rapid growth in mobility data [19, 20]. The large size of mobility data provides new opportunities for discovering the characteristics of human mobility patterns and making mobility predictions. Generally, mobility prediction is of great importance in a wide range of modern applications, such as personalized recommendation systems, intelligent transportation, urban planning, and mobility management in the fifth-generation (5G) mobile communication system. Therefore, in this paper, an extensive review has been conducted on the next location prediction, which sheds light on future research directions in next location prediction so as to realize the robust location prediction system.

1.1 Methods
The activities to be carried out through the research to accomplish those objectives are as follows.

1.1.1 Literature review
Exhaustive study will be made on the related areas of the research. This will be accomplishing by reading different books, journals, and conference papers which have been done so far with different approaches, so as to have sufficient understanding of the problem. Techniques and approaches appropriate for next location prediction are reviewed.

1.1.1.1 Research questions   There are three important research questions that we need to address in this study.

RQ1 What important features are considered for next location prediction?
RQ2 What technique was applied for the next location prediction?
RQ3 What are the important factors that affect the next location prediction?

1.2 Motivation
The quality of service for the next location prediction affects the user's daily activity. Next location prediction is one of the solutions to provide this type of service. It is essential to provide better system performance in an intelligent transport system. However, the prediction models that have been done so far by different researchers are not adequate to provide a robust next location prediction. A user's next location prediction plays a vital role in location-based services, recommender systems, and network resource optimization. Next location prediction needs comprehensive investigations to enable users to use these plenties of applications.

Various factors have an impact on the performance of the next location prediction. The intelligent transportation system, network resource optimization, and mobility management are applications that need robust next location prediction systems.

1.3 Statement of the problem

Although there is a literature that has been done on the issue of discovering mobile users' frequent patterns in their trajectories, existing studies mostly consider only on the geographic features of user trajectories [9, 21].

Mobile user location prediction has become a hot research topic, but the accuracy of prediction is a challenge, and the prediction models are not optimized. Modeling human mobility needs to extract the movement flow pattern of individuals where the location they have visited. Human mobility exhibits complex sequential transition regularities [22]. In practice, the transitions between two arbitrary locations can be time-dependent and high-order. For instance, the probability of moving from home to office for a commuter is higher in workday mornings but often low in weekend mornings. Meanwhile, the transition may not follow the simple and exact Markov chain assumption, as people may go to different places, like breakfast places, on commuting routes, which leads to high-order and irregular transition patterns. Second, there is often a multi-level periodicity that governs human mobility. This research is a comprehensive survey which is intended to extensively study the next location prediction approaches and identify challenges that sheds light regarding future research directions.

1.4 Objective

1.4.1 General objective

A detailed study on the location prediction approaches.

2 Specific objective

- Identify what features are used by the next location prediction approach.
- Figure out what input data are required for the approach.
- Examine what prediction technique has been applied.
- Distinguish between future opportunities and next location prediction challenges.

3 Literature review

3.1 Next location prediction

There are several location prediction techniques studied so far in disparate research. The general overview of location prediction methods is studied, in this section of the literature review. Location-based services (LBS) are gradually becoming a research hotspot due to the development and widespread use of mobile devices and wireless networks [23]. Next location prediction anticipates a person's movement based on the history of previous stay locations [24]. It is useful for proactive actions taken to assist a person in a constantly changing environment. Individual movements contain a high degree of regularity [25, 26]. Individuals regularly visit a small set of locations and move between locations. The movement regularities can be temporal, periodic, or sequential. Research is quickly identifying the utility of extracting these regularities to predict the future movement of objects, due to the increased availability and adoption of mobile positioning,

computing, and communication technologies. The prediction system applies to broad domain applications, including transport and mobility studies for urban planning, network optimization for mobile communication, and prefetching LBSs.

Collecting the user's current locations and transitions from place-to-place, predicting future destinations, equipping users with location-sensitive information, and handling relevant communication requests are core ingredients of the new generation of service provider applications on mobile devices [27]. Periodic place-to-place transitions are inherent in human movements. Next place predictions are the atomic units in constructing end-to-end user mobility trajectories based on historical trace data.

Trajectories store the location of an object in space at a certain instant of time. There are four categories of trajectory data, such as human mobility, transportation vehicles' mobility, animals' mobility, and natural phenomena' mobility [28]. Trajectory data representing human mobility can help build a better social network [29–31] and travel recommendations [5, 32, 33].

- **Mobility of People**: People have been recording their real-world movements in the form of spatial trajectories, passively and actively for a long time.
- **Active Recording:** For the purpose of memorizing a journey and sharing experiences with friends, travelers log their travel routes with GPS trajectories. Bicyclists and joggers record their behaviors for sports analysis. On Flickr, a series of geotagged photographs can formulate a spatial trajectory as each photograph has a location tag and a timestamp corresponding to where and when the photograph was taken. Likewise, the check-ins of a user in a location-based social network can be regarded as a trajectory when sorted chronologically.
- **Passive Recording:** A user carrying a mobile phone unintentionally generates many spatial trajectories represented by a sequence of cell tower IDs with corresponding transition times. Additionally, transaction records of a credit card also indicate the spatial trajectory of the cardholder, as each transaction contains a time stamp and a merchant ID denoting the location where the transaction occurred.

Human mobility patterns can provide useful information for understanding the impact of human behavioral regularities in urban systems, typically with a focus on traffic prediction, public health, or urban planning [34].

3.1.1 Mobility of transportation vehicles

A large number of GPS-equipped vehicles, such as taxis, buses, vessels, and aircraft, have appeared in our daily lives. For instance, many taxis in major cities are equipped with a GPS sensor that enables them to report time-stamped locations at a certain frequency. Such reports formulate a large number of spatial trajectories that can be used for resource allocation.

3.1.2 Mobility of animals

For years, biologists have been collecting the moving trajectories of animals like tigers and birds, for the purpose of studying animals' migratory traces, behavior, and living situations [35, 36].

3.1.3 Mobility of natural phenomena

Meteorologists, environmentalists, climatologists, and oceanographers are busy collecting the trajectories of some natural phenomena, such as hurricanes, tornados, and ocean currents. These trajectories capture the changing environment and climate, helping scientists deal with natural disasters and protect the natural environment.

3.1.4 Semantic trajectory

Ying et al. proposed integrating semantic information about the places visited by individuals in addition to their location data in order to enhance prediction accuracy about future locations [6]. The proposed approach relies on the notion of semantic trajectories, which represents the mobility of an individual as a sequence of visited places tagged with semantic information. To support the prediction of the next location based on semantic trajectories, the authors have developed a framework called SemanPredict, which is composed of two modules. The offline mining module extracts the semantic trajectories from raw data by first computing the stop points of a trajectory [37], which corresponds to locations in which the user has stayed for more than a certain amount of time. There are numerous opportunities to analyze the movement behavior of moving objects using trajectory data [38–43]. To understand human behavior, it is crucial to discover movement patterns. The extraction of high-level semantics of behavior from which one can infer the underlying purposes or roles of moving objects is a significant challenge in this topic.

3.1.5 Future movement prediction

Xue et al. [44] proposed predicting the destination of a trajectory based on an observed partial sub-trajectory. The space is divided into cells and modeled the transition probability between adjacent cells with the first-order Markov model. Zhao et al. [45] revisited the problem with RNN. Li et al. [46] developed a Bayesian model which is capable of predicting the future movement of a vehicle on the road network. The spatial transition was again modeled with the first-order Markov model. As the Markov model, Wu et al. [47] investigated the possibility of modeling the trajectories with RNN and assumed that the exact destination road segments of trips are known and learned the representations of them to help with route decision because the Markov model requires explicit dependency assumptions and struggles in accounting for the long-term dependency.

3.1.6 Sparse trajectory similarity computation

The low-sampling-rated trajectories bring challenges for similarity computation, as an observed sparse trajectory could have multiple possible underlying routes. To solve this problem, Su et al. [48] proposed to learn the transition patterns among a set of spatial objects from the historical trajectories by using the hidden Markov models; then sparse trajectories are calibrated to these spatial objects to compute similarities. Li et al. [49] addressed this problem with a seq2seq-based model, where they encoded the most probable route information into the trajectory representation.

3.1.7 Route recovery from sparse trajectories

Route recovery is intended to show the most likely route between two road segments that are not adjacent on the road network. Zheng et al. [50] modeled the spatial transition probability between adjacent road segments with a one-order Markov model. Banerjee et al. [51] explored the problem with Gibbs sampling, in which the spatial transition probabilities were also modeled with the Markov model, albeit high-order ones were employed. Wu et al. [52] proposed using inverse reinforcement learning to capture the spatial transition patterns.

Gyozo Gidofalvi et al. proposed When and Where Next: Individual Mobility Prediction [53]. A statistical method explicitly performs these related temporal and spatial prediction tasks in three continuous, sequential phases. In the first phase, the method continuously extracts grid-based stay time statistics from the GPS coordinate stream of the location-aware mobile device of the user. In the second phase, using the grid-based stay time statistics, the method periodically extracts and manages regions that the user frequently visits. Finally, in the third phase, from the stream of region visits, the method continuously estimates parameters for an inhomogeneous continuous-time Markov model and, in a continuous fashion, predicts when the user leaves the current region and where the user will move next.

Understanding human mobility by mining raw GPS logs has been a long-standing subject in academic research [54, 55]. These approaches rely on clustering user visits to extract hot spots. The premier research in adapting the data clustering algorithms for modeling mobility behavior [54] proposes to iteratively extract hot spots of users. A clustering algorithm has been proposed [6], where GPS latitude and longitude coordinates are clustered in the temporal domain to detect the stay points that are used to derive frequently visited regions using a grid-based clustering approach.

3.2 Applications of next location prediction

The following are application areas that location prediction can be applied.

3.2.1 Traffic flow prediction

Positioning technologies are used to track the movement of people and vehicles giving rise to a dazzling array of location-based applications. For example, GPS tracking using positioning devices installed on the vehicles is becoming a preferred method of taxi cab fleet management [56]. Trajectory data can be used to predict traffic congestion so that the vehicle driver can act accordingly to take the next route [57, 58]. Traffic flow management can be done to alleviate congestion in services as Uber sustain because of better traffic flow analysis [59]. In intelligent transport, self-driving vehicles require accurate traffic prediction.

3.2.2 Movement prediction

Researchers have designed data-driven approaches to effectively detect and track moving objects to extract information about the way we live our daily lives. Lv et al. have studied the human living pattern [60]. Fang et al. studied the regular pedestrian trend. Tracking is important in crowded places, and it is beneficial to find a child when abducted or lost. Tracing vehicles can be a useful tool for estimating the wait time [61].

3.2.3 Weather forecast

Climatological forecasting looks at the region over a long period of time rather than just the present [62]. It is employed to examine the conditions of the weather and to perform climate forecasts. The sunny, rainy, windy, and foggy conditions of the climate are predicted.

3.2.4 Early warning system

The warning system is the sequence of the information communication channel, which includes sensors, event identification, and decision support systems [62]. All the systems work synergically to study the signal or condition and report any abnormal disruption that hampers the stability of the environment. Such systems help by proving to warn, giving peoples time to prepare and a mitigation system to alert them to the hazards and reduce the impact.

3.2.5 Anomaly detection

The exploratory growth in mobile devices and communication technology has allowed better suspicious target tracking [63]. Location prediction helps to locate suspicious users who make extreme or abusive comments on the Internet. By prediction, the next destination of the entity can avoid the occurrence of events that may endanger public safety [64].

3.2.6 Resource optimization

If the knowledge about the next movement of the user is generated rather than performing a blind allocation, effective resource allocation can be done. The latency in accessing the resource can be reduced by proper resource disposal for the mobile user and will have higher satisfaction [65]. The mobility prediction scheme is used to optimize the network load balance and the resource allocation scheme to optimize the network load balance based on the users' mobility prediction results and target cell load status analysis [66]. We can arrange an appropriate microcell to reserve resources for the user if we are aware of the user's next target location and the cell's occupied resource situation in the ambient area.

4 Related work

In this section, we discuss research works, particularly related to next location prediction applicable in location-based services in the mobility domain, so as to achieve better quality of service (QoS). The research work that has been done so far on next location prediction using various approaches and gaps is discussed. Finally, the critical factors that affect the next location prediction are discussed.

Context-aware services are pervasive computing paradigms, and next location prediction is one of the context-aware services. Nowadays, due to the increasing importance of location-based services in a wide area of applications, next location prediction is becoming a research topic. The day of the week and time of a day are user contexts, often used to determine the accuracy of prediction of past trip patterns

[67, 68]. The length of stay at the current location and the current user context determine the accuracy of the next location prediction [69, 70].

4.1 Machine learning-based prediction

Amilcar S. J. et al. proposed a semi-supervised approach for the semantic segmentation of trajectories [71]. The first fundamental step in analyzing movement data is trajectory segmentation. It splits trajectories into homogeneous segments based on some criteria. Although trajectory segmentation has been the object of several approaches in the last decade, a proposal based on a semi-supervised remains inexistent. Semi-supervised means that the user manually labels a small set of trajectories with meaningful segments and, from this set, the method infers, in an unsupervised way. The main advantage of pure supervised ones is that it reduces the human effort required to label the number of trajectories. The minimum description length (MDL) principle measures homogeneity inside segments. This work also introduces the Reactive Greedy Randomized Adaptive Search Procedure for Semantic Semi-supervised Trajectory Segmentation (RGRASP-SemTS) algorithm. It segments trajectories by combining a limited user labeling phase with the minimum input parameters and no predefined segmenting criteria. The evaluation tests prove how the approach outperforms state-of-the-art competitors compared to ground truth. However, it needs to improve the overall performance by generating better sets of semantic landmarks instead of just computing averages.

A. Noulas et al. proposed mining user mobility features for next place prediction in location-based services [72]. In this work, by exploring the predictive power offered by different facets of user behavior, the problem of predicting the next venue a mobile user will visit has been studied. First, about 35 million check-ins are analyzed made by about 1 million Foursquare users in over 5 million venues across the globe, spanning five months. Then a set of features that aim to capture the factors that may drive users' movements are proposed. The features exploit information on transitions between places, mobility between venues, and spatio-temporal characteristics of user check-in patterns. Furthermore, the study is extended by combining all individual features into two supervised learning models, based on linear regression and M5 model trees, resulting in higher overall prediction accuracy. It shows that the supervised methodology with multiple features offers high levels of prediction accuracy: M5 model trees can rank in the top fifty venues one in two user check-ins among thousands of candidate items in the prediction list. However, it still needs extra investigation to produce a robust next location prediction model.

MPE: A Mobility Pattern Embedding Model for Predicting Next Locations [73] was proposed by M. Chen et al. A novel mobility pattern embedding model called MPE sheds light on people's mobility patterns in traffic trajectory data from multiple aspects, including sequential, personal, and temporal factors. MPE has two salient features. The first can find various types of information (object, location, and time) to an integrated low-dimensional latent space; the second considers the effect of phantom transitions arising from road networks in traffic trajectory data. This embedding model opens the door to different applications, such as next location prediction and visualization. Experimental results on two real-world datasets show that MPE is effective and outperforms the state-of-the-art methods.

Sung-Bae Cho proposed exploiting machine learning techniques for location recognition and prediction with smartphone logs [74]. Due to the advancement of mobile computing technology and the various sensors built-in in smartphones, context-aware services are becoming in everyday life. Location-based service (LBS), which provides the appropriate service to smartphone users according to their contexts, is becoming more popular, and location is one of the most important contexts. Extracting and recognizing meaningful location information and predicting the user's next destination is crucial for a successful LBS. Many researchers have attempted to predict locations by various methods. But, few of them are considered the working system considering important tasks of LBS on the mobile platform. The next location prediction recognizes user location by combining k-nearest neighbor and decision trees and predicts user destination using hidden Markov models. To show the usefulness of the proposed system, we have conducted thorough experiments on real everyday life datasets collected from 10 people for six months, and we found that the proposed system yielded above 90% of average location prediction accuracy. However, in future work, we will investigate the incremental learning algorithm of the location prediction model for a more practical system to be adaptively learned through real-time data.

Yujie W. et al. proposed unlicensed taxi detection service based on large-scale vehicles mobility data [75]. This work proposed an effective service to incorporate human mobility mechanisms into unlicensed taxis' detection from massive city-wide vehicles. First, to capture the mobility characteristics of unlicensed taxis, 276 spatio-temporal features are extracted. Second, the detection accuracy of three machine learning techniques—support vector machines (SVM), decision tree (DT), and logical regression (LR)—is investigated. The real-world vehicle-license plate recognition dataset in Xiamen, China, contains 336 million passing records for 6.2 million vehicles filmed by 439 devices in August 2016 have been used to test the result. Experimental results show that LR outperforms SVM and DT in prediction accuracy and F-score measurement, while SVM identifies the highest number of unlicensed taxis. However, it is necessary to investigate where and when to seize unlicensed taxis to assist the traffic administrative enforcement department by considering other heterogeneous datasets, such as demographics and points of interest.

4.2 Deep learning-based prediction

Xiaoliang F. et al. proposed a deep learning approach for next location prediction [76]. This research proposed a deep learning-based model to incorporate contextual features into location prediction. First, mining the similarity among candidate locations is performed. Second, they model contextual features among trajectories, including periodical patterns and dynamic trajectory features. Third, both Convolutional Neural Network (CNN) and bidirectional Long-Short-Term Memory (LSTM) networks are adopted to predict each trajectory with contextual information. One hundred ninety-seven million vehicle license plate recognition (VLPR) records in Xiamen, China, are used for experimentation. The results demonstrate that the proposed method outperforms several existing methods. However, the model needs extra enhancement in the learning phase.

Liu et al. proposed a Spatial–temporal Recurrent Neural Networks (ST-RNN), which models local temporal and spatial contexts in each layer for mining mobility patterns

[77]. RNN has extended to propose a novel method called Spatial–temporal Recurrent Neural Networks (ST-RNN). ST-RNN can model local temporal and spatial contexts in each layer with time-specific transition matrices for different time intervals and distance-specific transition matrices for different geographical distances. Experimental results show that the proposed model yields significant improvements over the competitive compared methods on two typical Global Terrorism Database (GTD) and Gowalla datasets.

C. Yang et al. [78] mined both the social networks and mobile trajectories in a neural network, in which they employed RNN to capture the sequential relatedness in mobile trajectories. A novel neural network model jointly models social networks and mobile user trajectories. First, a network embedding method adopted for social networks construction is a networking representation. The key to the model lies in generating mobile user trajectories. Second, four factors are carefully thought about that influence the process to yield mobile users' trajectory data. These are user visit preference, influence of friends, short-term sequential contexts, and long-term sequential contexts. To characterize the last two contexts, RNN and GRU models are employed to capture the sequential relatedness in mobile trajectories at the short-or long-term levels. Finally, the two components are tied by sharing the user network representations. Experimental results on two applications demonstrate the effectiveness of the proposed model. In particular, the improvement over baselines is more significant when either network structure or trajectory data are sparse. However, the proposed model does not consider GPS information, usually attached with a pair of longitude and latitude values. The neural network models should incorporate into GPS information. In addition, the check-in location information can also be with categorical labels.

A. Sassi et. al. proposed Location Embedding and Deep Convolutional Neural Networks for Next Location Prediction [79]. The work focuses on predicting the next location of mobile users by analyzing large datasets of the history of their movements. The work focuses on predicting mobile users' future location by analyzing large datasets of the history of their movements. A classification model is trained with past location sequences to predict future locations. Inspired by the word2vec embedding technique used for the next word prediction, a new method called loc2vec is presented. In loc2vec, every location is encoded as a vector, whereby the more often two locations co-occur in the location sequences, the closer their vectors will be.

Long mobility sequences are classified into several sub-sequences using vector representation and used to form Mobility Subsequence Matrices which run CNN classification which will be used later for the prediction. Extensive experiments are done based on a subset of a large mobility trace database made publicly available through the CRAWDAD project. The results show that loc2vec embedding and CNN-based approach provide improved prediction accuracy compared to state-of-the-art methods. Transfer learning shown on the existing pre-trained CNN model provides better accuracy over CNN models built from scratch on mobility data. It also shows that loc2vec-CNN model enhanced with transfer learning achieves better results.

Chujie W. et. al. proposed Exploring Trajectory Prediction through Machine Learning Methods [80]. The particular focus of this paper is on multi-user multi-step trajectory prediction. A deep learning-based prediction framework has been designed. 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 the future movement trends. Motivated by related works after testifying and analyzing this basic framework on a model-based dataset, they extend it to a region-oriented prediction scheme and propose a multi-user and multi-step trajectory prediction framework which incorporates the Sequence-to-Sequence (Seq2Seq) learning. Experimental results on a realistic dataset demonstrate that the proposed framework has improved generalization ability and reduces the error-accumulation effect for multi-step prediction. However, the work does not consider the semantic context in the trajectory.

M. Chen et al. [81] proposed CEM: Convolutional Embedding Model (CEM) is proposed to predict next locations using trajectory data, via modeling the relative ordering of locations with a one-dimensional convolution. Model (CEM) to predict users' future locations using trajectory data via modeling the relative location ordering with a one-dimensional convolution. CEM is augmented by considering constraints posed by road networks in trajectory data. Learning a double-prototype representation for each location eliminates the incorrect location transition models sequential, personal, and temporal factors that affect human mobility patterns. Thus offers accurate predictions than just accounting for sequential patterns. Experimental results on two real-world trajectory datasets show that CEM is effective and outperforms the state-of-the-art methods.

A. Al-Molegi et al. proposed a novel model called Space Time Features-based Recurrent Neural Network (STF-RNN) for predicting people's next movement based on mobility patterns obtained from GPS devices logs [82]. The internal representation of space and time features is extracted automatically in the proposed model rather than depending on handcraft representation. It enables the model to discover relevant knowledge about people's behavior in an efficient way. Due to the ability of the RNN structure to represent the sequences, it is utilized in the proposed model to keep track of user movement history. A real-life mobility dataset from Geolife projects was used to evaluate the performance of the proposed approach. The model has improved the prediction effectiveness in comparison with the state-of-the-art models.

D. Yao et. al. SERM: A Recurrent Model for Next Location Prediction in Semantic Trajectories [83]. A novel recurrent model for semantics-aware next location prediction is proposed by jointly learning the embeddings of multiple factors (user, location, time, keyword) and the transition parameters of a recurrent neural network. This proposed model can capture different contexts underlying user movements and enable semantics-aware location prediction. The model is evaluated based on two real-life datasets, and the results show the proposed model achieves significant improvements over state-of-the-art methods.

Y. Chen et al. proposed Context-aware Deep Model for Joint Mobility and Time Prediction [84]. In this paper, the authors proposed a novel context-aware deep model called DeepJMT for jointly performing mobility prediction to know where and time prediction to know when. The DeepJMT model consists of three components. First, hierarchical RNN is on a sequential dependency encoder that can capture users' mobility regularities and temporal patterns compared to vanilla RNN-based models. Second, spatial context extractor extracts location semantics, and periodicity context extractor extracts the user's periodicity. Third, co-attention social and temporal context extractors are extract

mobility and temporal evidence from social relationships. Experiments conducted on three real-world datasets show that DeepJMT outperforms the state-of-the-art mobility prediction and time prediction methods. However, it needs extra discovery of different fusion approaches for context information and incorporates other information such as user comments.

Y. Wang et al. proposed Semantic Annotation for Places in LBSN through Graph Embedding [85]. The crucial problem is to find a high-quality representation for each place. It was usually derived directly from observed places' patterns or indirectly from calculated proximity among places or their combination. This paper exploits the combination to represent places but presents a novel semi-supervised learning framework based on graph embedding. The approach is called Predictive Place Embedding (PPE). For place proximity, PPE first learns user embeddings from a user-tag bipartite graph by minimizing supervised loss to preserve the similarity of users visiting analogous places. User similarity has changed into place proximity by optimizing each location embedding as the centroid of the vectors of its check-in users. The underlying idea is that the location can be considered a representative of all visitors. Extensive experiments on real large LBSNs show that PPE outperforms state-of-the-art methods significantly.

J. Lv et al. proposed T-CONV: A Convolutional Neural Network For Multi-scale Taxi Trajectory Prediction [86]. Precise destination prediction of taxi trajectories can benefit many intelligent location-based services such as an accurate ad for passengers. The prediction approaches that treat trajectories as one-dimensional sequences and process them on a single scale fail to capture the diverse two-dimensional patterns of trajectories in different spatial scales. This paper proposes TCONV, models trajectories as two-dimensional images, and adopts multi-layer convolutional neural networks to combine multi-scale trajectory patterns to achieve a precise prediction model. Furthermore, a gradient analysis visualizes the multi-scale spatial patterns captured by T-CONV and extracts the areas with distinct influence on the ultimate prediction. Finally, to explore significant areas deeply for better predictions, multiple local enhancement convolutional fields are integrated. Comprehensive experiments based on trajectory data show that T-CONV can achieve higher accuracy than state-of-the-art methods. In the future, it needs to extend the proposed model, which has two local enhancement areas with fixed size, to the more general one, which has multiple local enhancement areas with tunable size. Furthermore, extend the experiments to validate the model in more real trajectory datasets.

A. de Brébisson et al. proposed Artificial Neural Networks Applied to Taxi Destination Prediction [87]. The task consisted in predicting the destination of a taxi based on the beginning of its trajectory, represented as a variable-length sequence of GPS points, and diverse associated meta-information, such as the departure time, the driver id, and client information. Contrary to most published competitor approaches, we used an almost fully automated approach based on neural networks and ranked first out of 381 teams. The architectures tried to use multi-layer perceptron, bidirectional recurrent neural networks, and models inspired from recently introduced memory networks. Our approach could easily be adapted to other applications in which the goal is to predict the length output from a variable-length sequence. One potential limitation of the proposed clustering-based output layer is that the prediction can only fall in the convex hull of the

clusters. A potential solution would be to learn the clusters as parameters of the network and initialize them either randomly or from the mean-shift clusters. Concerning the memory network, one could consider more sophisticated ways to extract candidates, such as using hand-engineered similarity measure or even the similarity measure learnt by the memory network. In this later case, the learnt similarity should be used to extract only a proportion of the candidates in order to let a chance to candidates with poor similarities be selected. Furthermore, instead of using the dot product to compare prefix and candidate representations, more complex functions could be used such as the concatenation of the representations followed by nonlinear layers.

X. Song proposed DeepMob: Learning Deep Knowledge of Human Emergency Behavior and Mobility from Big and Heterogeneous Data [88]. The frequency and intensity of natural disasters have increased significantly in recent decades. Hence, understanding and predicting human evacuation behavior and mobility play a significant role in planning effective humanitarian relief, disaster management, and long-term societal reconstruction. However, existing models are shallow models, and it is difficult to apply them for the "deep knowledge" of human mobility. Therefore, this study collects big heterogeneous data and built an intelligent system, namely, DeepMob, for understanding and predicting human evacuation behavior and mobility following different types of natural disasters. The component of DeepMob is a deep learning architecture that aims to understand the laws that govern human behavior and mobility following natural disasters from big heterogeneous data. Experimental results and validations demonstrate the efficiency and superior performance of the proposed system and suggest that human mobility following disasters may be predicted and simulated easier than previously thought. In the future, the system can be extended and improved in the following aspects. First, sometimes human evacuation behavior and mobility following natural disasters will be affected by social networking messages like Facebook, Twitter, and Microblog. Therefore, it is necessary to collect social networking data and analyze how social networking messages could influence human mobility following disasters in the future. Second, it is better to use the temporal information of human evacuation behavior. Hence, temporal deep learning approaches such as RNN can be carefully considered and explored in the future.

P. Kothari et. al. proposed Human Trajectory Forecasting in Crowds: A Deep Learning Perspective [89]. In this work, a representation of human social interactions is a prediction for the problem of human trajectory learning. Early works handcrafted this representation based on domain knowledge. However, social interactions in crowded environments are diverse and often subtle. Recently, deep learning methods have outperformed their handcrafted counterparts, as they learned about human–human interactions in a more generic data-driven fashion. This work presents an in-depth analysis of existing deep learning-based methods for modeling social interactions. Novel performance metrics are proposed that evaluate the ability of a model to output socially acceptable trajectories. Experiments on TrajNet + + validate the need for our proposed metrics, and our method outperforms competitive baselines on both real-world and synthetic datasets.

Y. Li proposed Pedestrian Path Forecasting in Crowd: A Deep Spatio-Temporal Perspective [90]. Predicting the walking path of a pedestrian in crowds is a pivotal step

towards understanding user behavior. It is one of the recently emerging tasks in computer vision scarcely addressed to date. The proposed approach is composed of two modules. First, displacement information from pedestrians' walking history is extracted and fed into a convolutional layer to learn the undergoing motion patterns and produce high-level representations. Second, the proposed system learns from the temporal and the spatial components embedded into a single framework via a Long-Short Term Memory-based architecture. The performance of the system is evaluated based on three large benchmark datasets. The result introduces margin size improvements concerning recent works in the literature, both in short- and long-term forecasting scenarios.

W. X. Zhao et al. proposed A Time-Aware Trajectory Embedding Model for Next-Location Recommendation [91]. The proposed approach jointly models multiple kinds of temporal factors in a unified manner based on distributed representation learning. TA-TEM also enhances the sequential context by using a longer context window. Experiments show that TA-TEM outperforms several competitive baselines. However, it needs to explore more advanced deep learning models such as Deep Convolutional Neural Networks for modeling trajectory data.

J. Li et al. proposed a novel approach called trajectory linking via user embedding and trajectory embedding to learn the movement patterns of users and trajectories simultaneously, and use those movement patterns to link trajectories to users [92]. More specifically, the proposed system leverages a graph-based location embedding method to learn the semantics of locations based on categorical and spatial information of locations. Then, a novel dual-objective neural network model is designed to integrate the sequential dependency and temporal regularity of trajectories to learn the movement patterns of users and their trajectories at the same time. A trajectory is then linked to the user who has the most similar movement pattern with it. Moreover, the advantages of the approach are empirically verified on real-world public trajectory datasets with convincing results. However, it needs to investigate more application scenarios with user embeddings such as friend's recommendation and the privacy problem caused by trajectory linking researches.

Karatzoglou et al. proposed A Seq2seq Learning Approach for Modeling Semantic Trajectories and Predicting the Next Location [93]. In this work, the authors investigate whether Attention and LSTM-based Sequence to Sequence (Seq2Seq) learning is used for modeling semantic trajectories and predicting the future location. The approach is evaluated on two real-world datasets, while a standard LSTM neural network, a tree-based framework, and a Markov Chain model serve as baselines. It shows that the Seq2Seq model outperforms both the tree-based and the probabilistic Markov approach. However, no significant benefits in the multi-user compared to the LSTM model. In the single-user modeling, things seemed to be changing for the better for the Seq2Seq learning. In general, they could identify a higher degree of sensitivity to the quantity and the quality of the available training dataset in part of the Seq2Seq method compared to the standard LSTM model. But it needs further investigations to optimize and produce a better outcome during the multi-user case.

Nasrin B. et al. proposed RNN-Based User Trajectory Prediction Using a Preprocessed Dataset [94]. It is essential to ensure a satisfactory level of quality of service for users. To achieve this goal, an intelligent mobility model has been proposed to predict the future

trajectory of the mobile user in mobile networks. The proposed approach has two main parts, such as mobility data preparation and user mobility prediction. The primary focus is on providing a carefully tailored mobility data from raw mobility datasets using line simplification techniques. Next, the accurately prepared data are used for learning user mobility behavior and predicting user future trajectory using recurrent neural networks and its variants. Simulation results show a substantial decrease in execution time from 4616 to 932 s for the best case. The proposed learning approach obtains a loss value of 0.10 using a model based on long short-term memory (LSTM). However, extra investigation is needed so as to realize more robust prediction system.

Shasha T. et al. propose Spatio-temporal Position Prediction Model (SPPM) for Mobile Users Based on model in the mobile edge computing [95]. Firstly, the time series feature extraction method is used to preprocess the historical location data of the mobile user. Next, the model uses the PCA data dimensionality reduction algorithm to process the data and then uses the LSTM model to predict the next spatiotemporal trajectory point of the mobile user. Finally, using 17,621 user trajectory data of Geolife GPS trajectory dataset, the algorithm is tested and verified. The experimental results show that the SPPM model proposed in this paper has higher prediction accuracy and more accurate prediction position.

Jianxin L. et al. propose a multi-context integrated deep neural network model (MCI-DNN) to improve the accuracy of the next location prediction [96]. This model integrates sequence context, input contexts, and user preferences into a cohesive framework. First, authors model sequence context and interaction of different kinds of input contexts jointly by extending the recurrent neural network to capture the semantic pattern of user behaviors from check-in records. After that, they design a feedforward neural network to capture high-level user preferences from check-in data and incorporate that into MCI-DNN. To deal with different kinds of input contexts in the form of multi-field categorical, they adopt embedding representation technology to automatically learn dense feature representations of input contexts. Experimental results on two typical real-world datasets show that the proposed model outperforms the current state-of-the-art approaches by about 57.12% for Foursquare and 76.4% for Gowalla on average regarding F1-score@5.

Prediction of Taxi Destinations Using a Novel Data Embedding Method and Ensemble Learning is proposed by X. Zhang et al. [97]. First, the use of a novel and efficient data embedding method is proposed for time-related feature pre-processing. The key idea behind this is to embed the data into two-dimensional space before feature selection. Second, the use of a novel data-driven ensemble learning approach is proposed for destination prediction. This approach combines the respective superiorities of support vector regression and deep learning at different segments of the whole trajectory. The experiments were conducted on two real-datasets to demonstrate that the proposed ensemble learning model can get superior performance for taxi destination prediction. Comparisons also confirm the effectiveness of the proposed data embedding method in the deep learning model.

Q. Gao et al., Proposed DeepTrip: Adversarially Understanding Human Mobility for Trip Recommendation [98]. This proposed approach is an end-to-end method for better understanding of the underlying human mobility and improved modeling of the

POIs' transitional distribution in human moving patterns. DeepTrip consists of a Trip Encoder to embed a given route into a latent variable with a recurrent neural network (RNN); and a Trip Decoder to reconstruct this route conditioned on an optimized latent space. Simultaneously, an Adversarial Net composed of a generator and critic is defined, which generates a representation for a given query and uses a critic to distinguish the trip representation generated from Trip Encoder and query representation obtained from Adversarial Net. DeepTrip enables regularizing the latent space and generalizing users' complex check-in preference. The efficiency of the proposed model is represented by the experimental evaluations, which show that the proposed approach outperforms the state-of-the-art baselines on various evaluation metrics.

A. Karatzoglou et al. proposed Semantic-Enhanced Learning (SEL) on Artificial Neural Networks Using the Example of Semantic Location Prediction [99]. Semantic location prediction refers to a multi-class prediction task that consists of predicting the future location type to be visited next by users based on their movement history. In this work, letting explicit semantic knowledge flow into a predictive model leads to improved performance regarding training time, accuracy, and robustness. In particular, adding an auxiliary semantic layer to the model is proposed, whose role is to provide it with information about the semantic interrelation of the treated classes, thus creating in this way shortcuts and saving valuable training time while improving its quality at the same time. Several versions of this proposed approach are explored and their functionalities are illustrated in a semantic location prediction scenario using two different real-world datasets.

A. Karatzoglou et al. proposed Matrix Factorization on Semantic Trajectories for Predicting Future Semantic Locations [100]. A novel semantic location prediction approach that provides user-specific predictions based on their past semantic trajectories has been introduced. For this purpose, an item recommendation method called *FPMC* has been adopted and adapted. FPMC relies on a combination of Matrix Factorization and Markov Chains. The algorithm is evaluated against the user-independent standard matrix factorization (MF) and the factorized Markov chains (FMC) and shows that the proposed approach clearly surpasses the performance of the state-of-the-art methods.

W. Liu et al. propose a novel vehicle mobility prediction algorithm to support intelligent vehicle applications [101]. First, a theoretical analysis is given to quantitatively reveal the predictability of vehicle mobility. Based on the knowledge earned from theoretical analysis, a deep recurrent neural network (RNN)-based algorithm called DeepVM is proposed to predict vehicle mobility in a future period of several or tens of minutes. Comprehensive evaluations have been carried out based on real taxi mobility data in Tokyo, Japan. The results have not only proved the correctness of the theoretical analysis, but also validated that the proposed system can significantly improve the quality of vehicle mobility prediction compared with other state-of-the-art algorithms.

Most existing mobility relationship measures are based on pairwise meeting frequency. The more frequently two users meet or co-locate at the same time, the more likely it is that they are friends [102]. However, such frequency-based methods suffer greatly from the data sparsity challenge. Due to data collection limitations and bias in the real-world user check-in data, the observed meeting events between two users might be very few. On the other hand, existing methods focus too much on the interactions

between two users and fail to incorporate the whole social network structure. For example, relationship propagation is not utilized in existing methods. This paper proposes to construct a user graph based on their spatial–temporal interactions and employ a graph embedding technique to learn user representations from a graph. The similarity measure of such representations can be used to describe mobility relationships, and it is especially useful for user pairs with low or even zero meeting frequency. Furthermore, semantic information on meeting events using point-of-interest (POI) categorical information has been introduced. Additionally, when part of the social graph is available as friendship ground truth, such online social network information is encoded through a joint graph embedding. Experiments on two real-world datasets demonstrate the efficiency of the proposed method.

F. Zhou propose a new paradigm for moving pattern mining based on learning trajectory context [103]. The aim of trajectory context learning is the mining of high-level human motion patterns. The proposed method jointly learns hierarchical and sequential patterns of trajectories, beneficial for many downstream tasks needing inference of human trajectories. As demonstrated, trajectory context learning provides valuable insights and promising guidelines for further investigations of the intricacies of motion patterns. As part of the future work, we plan to investigate how to leverage it for modeling the topics of sequential patterns and their use in a wide range of applications, such as POI recommendations and road planning. The method is evaluated on several public datasets and demonstrates that the proposed system improves the performance of sub-tasks compared to state-of-the-art approaches.

H. Sun et al. proposed PeriodicMove, a neural attention model based on a graph neural network for human mobility recovery from lengthy and sparse trajectories [104]. PeriodicMove is a neural attention model based on a graph neural network for human mobility recovery from lengthy and sparse trajectories. First, a directed graph for each trajectory is constructed and captures complex location transition patterns using a graph neural network. A spatial-aware loss function is applied to incorporate spatial proximity into the model optimization to alleviate the data sparsity problem. The evaluation result demonstrates that PeriodicMove yields significant improvements over the competitors on two representative real-life mobility datasets. In addition, by providing high-quality mobility data, our model can benefit different mobility-oriented downstream applications.

5 Challenges of next location prediction

It is challenging to manage, process, and mine trajectory data [105, 106] so as to predict the next location of a certain user. Storing and processing big trajectory data is not an easy task and needs critical data processing algorithms to produce robust location predictions as compared with the state-of-the-art next location prediction approaches. Moreover, apart from the trajectory data processing issue mentioned above, how to handle the heterogeneous trajectory data is another issue. How to optimize parameters and important features representation are other challenges which we found, as well as how to effectively cluster the trajectories that best fit with different users behavior. Temporal information is an important factor that affects the performance of the next location prediction; that is, time can be recorded as a location. Furthermore, heterogeneous data

generated from different sources, users' random movement behavior, and the time sensitivity of trajectory data are some of the challenges of location prediction.

Various temporal cyclic patterns whose distribution can be modeled as a Gaussian mixture distribution affect the user's mobile behavior can therefore be captured more accurately [41]. A user's temporal preferences are correlated with those of their social friends, with a lot of preferences overlapping, and temporal context is complementary to spatial context in improving location prediction performance. Therefore, considering continuous temporal states for modeling cyclic patterns and exploring other types of temporal cyclic patterns is an interesting challenge to improve the next location prediction.

Existing trajectory clustering algorithms group similar trajectories as a whole, thus discovering common trajectories. As a whole, clustering trajectories could miss common *sub*-trajectories [35]. Therefore, discovering common sub-trajectories is very useful in many applications, especially if we have regions of special interest for analysis. Another possible challenge for the next location prediction is parameter insensitivity. It is possible to make the prediction algorithm more insensitive to parameter values. A number of approaches have been developed for this purpose in the context of point data [102].

A Hadoop-based solution is suitable for building a high-performance, cost-efficient, and scalable network traffic monitoring and analysis system [18]. The capability of this system to process large amount of traffic data enables us to reveal a number of network traffic and user behavior phenomena. It can handle massive amounts of traffic data generated from multigigabit network links in real time.

Trajectory data can be generated from sensors, and this generated big data cannot be easily processed. Therefore, Internet of Things (IoT) applications are required to be processed fast. The fog computing paradigm is the most important solution to processing data in which the processing power of devices close to a user (i.e., idle computing power) is harnessed to facilitate storage, networking at the edge, and processing [107]. Fog computing has emerged, where cloud computing is extended to the edge of the network to decrease latency and network congestion.

6 Discussion

In this manuscript, we discussed the literature review on mobility management, especially related to next location prediction approaches and applications. The choice of the mobile user's next location prediction has a great impact on the prediction result. The next location prediction approaches and the challenges are well discussed. A comprehensive study on next location prediction is used to produce a robust system.

Next location prediction is one of the context-aware services, and services according to context, called context-aware services, are pervasive computing paradigms. Nowadays, due to the increasing importance of location-based services in a wide area of applications, next location prediction is becoming a research hot spot. Mobile users' location information is stored and updated by mobility management involves techniques. Mobility prediction is a mobile user's next movement when the mobile user is traveling between the cells of a Personal Communication Systems (PCS) or Global System for Mobile Communications (GSM) network. In many scenarios, such as targeted advertisement and taxi service, mobility prediction is useful to know where is the location and

when a user will arrive next. Trajectory data can be obtained from travel histories of moving things like humans, animals, and vehicles.

As we know in our real life, most of users movement behavior is occasional the trajectory information obtained from this kind of movement patterns leads inaccurate mobility prediction.

7 Conclusion and future work

Next location prediction has recently gained great attention from researchers due to its importance, which can be used in different application areas. Location prediction success can be viewed through widely known location-based services like traffic flow prediction, weather forecasting, movement tracking, network resource optimization, anomaly detection, and early warning systems. Therefore, next location prediction is the paradigm that a lot of relevance has acquired as long as location is the most important user's contextual information.

In this manuscript, we have discussed various location prediction approaches, applications, and challenges, and future research directions are being studied. Trajectory data are of great value to many applications. Due to the complexity of human mobility, it is challenging to analyze and mine trajectory data due to the multiple contextual information.

One of the challenges for next location prediction is knowing how to extract high-level semantic trajectory features. The second challenge we notice is how to discover knowledge to understand different human mobility behaviors, which needs investigation of pattern mining algorithms in trajectory mining. We can also say that the key challenge of traffic prediction lies in how to model complex spatial and temporal dependencies.

In summary, existing next location prediction methods do not fully address the accurate location prediction features in mining mobility patterns. In this paper, we find out the important features that could affect the next location prediction. Furthermore, deep learning solves problems in machining learning as long as it is a neural network architecture with multiple hidden layers. Thus, this paper sheds light on the issues regarding the future research directions for the location prediction systems. This paper discusses existing next location prediction systems and their technical details. Therefore, the paper sheds a little light on the future research directions of next location prediction systems, which can help realize how robust next location prediction systems can be.

Finally, as a future work, confronting heterogeneous trajectory data is a very important and challenging task. Parameter optimization and feature weighting are two other important future challenges that need extra investigation. The impact of social relationships and friendship needs great attention and exploration for further location prediction.

Abbreviations
CEM: Convolutional embedding model; DT: Decision tree; GPS: Global positioning system; GSM: Global system for mobile communications; GTD: Global terrorism database; LBS: Location-based services; LR: Logical regression; LSTM: Long short-term memory; MDL: Minimum description length; PCS: Personal communication systems; RNN: Recurrent neural network; ST-RNN: Spatial temporal recurrent neural networks; SVM: Support vector machines.

Author details
[1]Department of Computer Science, Wolkite University, Wolkite, Ethiopia. [2]Department of Software Engineering, Wolkite University, Wolkite, Ethiopia.

References
1. R. Shokri, Collaborative Location Privacy †, 2011.
2. J. Meyerowitz, R. R. Choudhury, Hiding stars with fireworks : location privacy through camouflage, 2009.
3. P. Rathore, D. Kumar, S. Rajasegarar, M. Palaniswami, J.C. Bezdek, A scalable framework for trajectory prediction. IEEE Trans. Intell. Transp. Syst. **20**(10), 3860–3874 (2019)
4. C. Yu, Y. Liu, D. Yao, H. Jin, F. Lu, H. Chen, Q. Ding, Mining user check-in features for location classification in location-based social networks, in *Proceeding of the IEEE Symposium on Computers and Communication*, vol. 2016–Febru, pp. 385–390, 2016.
5. Y. Zheng, L. Zhang, Z. Ma, X. Xie, W.Y. Ma, Recommending friends and locations based on individual location history. ACM Trans. Web **5**(1), 1–44 (2011)
6. J. Yang, J. Xu, M. Xu, N. Zheng, Y. Chen, Predicting next location using a variable order Markov model, in *Proceedings of the 5th ACM SIGSPATIAL International Workshop on GeoStreaming, IWGS 2014*, pp. 37–42, 2014.
7. J. J. C. Ying, W. C. Lee, T. C. Weng, V. S. Tseng, Semantic trajectory mining for location prediction, in *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pp. 34–43, 2011.
8. D. Liben-Nowell, J. Novak, R. Kumar, P. Raghavan, A. Tomkins, Geographic routing in social networks. Proc. Natl. Acad. Sci. U. S. A. **102**(33), 11623–11628 (2005)
9. A. Monreale, F. Pinelli, R. Trasarti, F. Giannotti, WhereNext: A location predictor on trajectory pattern mining, in *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 637–645, 2009.
10. Y. Zheng, Q. Li, Y. Chen, X. Xie, W. Ma, Understanding mobility based on GPS data, in *Proceedings of the 10th International Conference on Ubiquitous Computing* no. 49, 2008.
11. J. Fukano, A next location prediction method for smartphones using blockmodels, 2013.
12. G. Yavaş, D. Katsaros, Ö. Ulusoy, Y. Manolopoulos, A data mining approach for location prediction in mobile environments. Data Knowl. Eng. **54**(2), 121–146 (2005)
13. Y. Li, L. Lei, M. Yan, Mobile user location prediction based on user classification and markov model, in *2019 International Joint Conference on Information, Media and Engineering (IJCIME), 2019*, pp. 440–444, 2019.
14. G. Wang, Modeling fine-grained human mobility on cellular networks, no. i, pp. 35–37.
15. M. Yan, C.A. Chan, A.F. Gygax, J. Yan, L. Campbell, A. Nirmalathas, C. Leckie, Modeling the total energy consumption of mobile network services and applications. Energies **12**(1), 1–18 (2019)
16. M. Yan, W. Li, C.A. Chan, S. Bian, I. Chih-Lin, A.F. Gygax, PECS: Towards personalized edge caching for future service-centric networks. China Commun. **16**(8), 93–106 (2019)
17. M. Yan, C.A. Chan, W. Li, L. Lei, A.F. Gygax, I. Chih-Lin, Assessing the energy consumption of proactive mobile edge caching in wireless networks. IEEE Access **7**, 104394–104404 (2019)
18. J. Liu, F. Liu, N. Ansari, Monitoring and analyzing big traffic data of a large-scale cellular network with hadoop. IEEE Netw. **28**(4), 32–39 (2014)
19. K. Zhao, S. Tarkoma, S. Liu, H. Vo, Urban human mobility data mining: an overview, in *2016 IEEE International Conference on Big Data*, pp. 1911–1920, 2016.
20. C. Yao, J. Guo, C. Yang, Achieving high throughput with predictive resource allocation, in *2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP).*, pp. 768–772, 2017.
21. E. H. Lu, V. S. Tseng, Mining cluster-based mobile sequential patterns in location-based service environments, pp. 1–10.
22. J. Feng, Y. Li, C. Zhang, F. Sun, F. Meng, A. Guo, D. Jin, DeepMove: Predicting human mobility with attentional recurrent networks, in *Proceedings of the 2018 world wide web conference*, vol. 2, pp. 1459–1468, 2018.
23. J. Qiao, S. Li, S. Lin, Location prediction based on user mobile behavior similarity, in *Proceedings of the International Conference on Parallel Distributed System - ICPADS*, vol. 2017–Decem, pp. 783–786, 2018.
24. J. Petzold, F. Bagci, W. Trumler, T. Ungerer, Comparison of different methods for next location prediction, *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 4128 LNCS, pp. 909–918, 2006.
25. A. Bhattacharya, S. K. Das, LeZi-Update : An information-theoretic framework for personal mobility tracking in PCS networks, pp. 121–135, 2002.
26. C. Song, Z. Qu, N. Blumm, A. L. Barabási, Limits of predictability in human mobility, *Science (80-.).*, 327(5968), 1018–1021, 2010.

27. B. Prabhala and T. La Porta, Next place predictions based on user mobility traces, in *Proceedings of the IEEE INFO-COM*, vol. 2015–Augus, pp. 93–94, 2015.
28. Y. Zheng, Trajectory data mining: an overview. ACM Trans. Intell. Syst. Technol. **6**(3), 1–41 (2015)
29. J. Li, Z. L. Wang, H. Zhao, R. Gravina, G. Fortino, Y. Jiang, K. Tang, A Survey on Recommendations in Location-based Social Networks, in *BodyNets International Conference on Body Area Networks*, vol. V, no. 212, 2017.
30. K. Deng, K. Xie, K. Zheng, X. Zhou, Trajectory indexing and retrieval, *Comput. with Spat. Trajectories*, pp. 35–60, 2011.
31. L.A. Tang, Y. Zheng, J. Yuan, J. Han, A. Leung, W.C. Peng, T. La Porta, A framework of traveling companion discovery on trajectory data streams. ACM Trans. Intell. Syst. Technol. **5**(1), 1–34 (2013)
32. J. Yuan, Y. Zheng, L. Zhang, X. Xie, and G. Sun, Where to find my next passenger?, in *UbiComp'11 – Proceeding of the 2011 ACM Conference Ubiquitous Computing*, pp. 109–118, 2011.
33. Y. Zheng, L. Zhang, X. Xie, W. Y. Ma, Mining interesting locations and travel sequences from GPS trajectories, in *WWW'09 – Proceedings of the 18th International World Wide Web Conferences*, pp. 791–800, 2009.
34. W. Huang, S. Li, X. Liu, Y. Ban, Predicting human mobility with activity changes, no. September 2015.
35. J. Lee and J. Han, Trajectory clustering : a partition-and-group framework.
36. Z. Li, B. Ding, J. Han, R. Kays, P. Nye, Mining periodic behaviors for moving objects, in *Proceedings of the ACM SIGKDD International Conferences on Knowledge Discovery Data Mining*, pp. 1099–1108, 2010.
37. L. O. Alvares, V. Bogorny, B. Kuijpers, B. Moelans, J. Antonio, F. De Macedo, A. T. Palma, Towards semantic trajectory knowledge discovery.
38. C. Renso, M. Baglioni, J.A.F. de Macedo, R. Trasarti, M. Wachowicz, How you move reveals who you are: Understanding human behavior by analyzing trajectory data. Knowl. Inf. Syst. **37**(2), 331–362 (2013)
39. X. Song, Q. Zhang, Y. Sekimoto, R. Shibasaki, Prediction of human emergency behavior and their mobility following large-scale disaster, in *Proceedings of the ACM SIGKDD International Conferences on Knowledge Discovery Data Mining*, pp. 5–14, 2014.
40. S. Ando, E. Suzuki, *Role-behavior analysis from trajectory data by cross-domain learning* (Proc. IEEE Int. Conf. Data Mining, ICDM, 2011), pp. 21–30
41. H. Gao, J. Tang, X. Hu, H. Liu, Modeling temporal effects of human mobile behavior on location-based social networks, in *Proceedings of the 22nd ACM International Conference on Information & Knowledge Management.*, pp. 1673–1678, 2013.
42. S. Liu, Q. Qu, S. Wang, Rationality analytics from trajectories. ACM Trans. Knowl. Discov. Data **10**(1), 1–22 (2015)
43. M.C. González, C.A. Hidalgo, A.L. Barabási, Understanding individual human mobility patterns. Nature **453**(7196), 779–782 (2008)
44. A. Y. Xue, R. Zhang, Y. Zheng, X. Xie, J. Huang, and Z. Xu, Destination prediction by sub-trajectory synthesis and privacy protection against such prediction, in *Proceeding of the International Conference on Data Engineering*, pp. 254–265, 2013.
45. J. Zhao, J. Xu, R. Zhou, P. Zhao, C. Liu, F. Zhu, On prediction of user destination by sub-trajectory understanding: a deep learning based approach, in *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pp. 1413–1422, 2018.
46. A. Ahmed, A. J. Smola, Inferring movement trajectories from GPS Snippets, 2015.
47. Z. Chen, W. Wang, H. Wu, Z. Chen, W. Sun, B. Zheng, W. Wang, Modeling trajectories with recurrent neural networks, 2017.
48. H. Su, K. Zheng, H. Wang, J. Huang, X. Zhou, Calibrating trajectory data for similarity-based analysis, in *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data*, pp. 833–844, 2013.
49. X. Li, K. Zhao, G. Cong, C. S. Jensen, W. Wei, Deep representation learning for trajectory similarity computation, in *Proceedings of the IEEE 34th International Conference on Data Engineering (ICDE) 2018*, pp. 617–628, 2018.
50. K. Zheng, Y. Zheng, X. Xie, X. Zhou, Reducing uncertainty of low-sampling-rate trajectories.
51. P. Banerjee, S. Ranu, S. Raghavan, Inferring uncertain trajectories from partial observations, in *Proceedings of the IEEE International Conference on Data Mining, ICDM*, vol. 2015–Janua, no. January, pp. 30–39, 2014.
52. H. Wu, J. Mao, W. Sun, B. Zheng, H. Zhang, Z. Chen, W. Wang, Probabilistic robust route recovery with spatio-temporal dynamics, in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery Data Mining*, vol. 13–17–Augu, pp. 1915–1924, 2016.
53. G. Gidófalvi, F. Dong, When and where next: Individual Mobility Predic, p. 57, 2012.
54. X. Chen, J. Pang, R. Xue, Constructing and comparing user mobility profiles. ACM Trans. Web **8**(4), 1–25 (2014)
55. V. Kulkarni, A. Moro, B. Garbinato, MobiDict - A Mobility prediction system leveraging realtime location data streams, in *Proceeding of the 7th ACM SIGSPATIAL International Work GeoStreaming, IWGS 2016*, 2016.
56. M. Chen, X. Yu, Y. Liu, Mining moving patterns for predicting next location. Inf. Syst. **54**, 156–168 (2015)
57. P.C. Besse, B. Guillouet, J.M. Loubes, F. Royer, Destination prediction by trajectory distribution-based model. IEEE Trans. Intell. Transp. Syst. **19**(8), 2470–2481 (2018)
58. D. Xia, B. Wang, H. Li, Y. Li, Z. Zhang, A distributed spatial – temporal weighted model on MapReduce for short-term traffic flow forecasting. Neurocomputing **179**, 246–263 (2016)
59. Q. Guo, H.A. Karimi, A methodology with a distributed algorithm for large-scale trajectory distribution prediction. Int. J. Geogr. Inf. Sci. **33**(4), 833–854 (2018)
60. Q. Lv, Y. Qiao, Big data driven hidden markov model based individual mobility prediction at points of interest. IEEE Trans. Veh. Technol. **9545**, 1–12 (2016)
61. X. Fang, X. Li, T. Yu, Z. Guo, T. Ma, *Grey Markov Model Prediction Method for Regular Pedestrian Movement Trend*. Springer, Singapore.
62. V. Koolwal, K.K. Mohbey, A comprehensive survey on trajectory-based location prediction. Iran J. Comput. Sci. **3**(2), 65–91 (2020)
63. M. Wernke, P. Skvortsov, F. Du, K. Rothermel, A classification of location privacy attacks and approaches. Personal and Ubiquitous Comput. **18**(1), 163–175 (2012)
64. K. Michael, R. Clarke, Location privacy under dire threat as TM uberveillance â€™TM stalks the streets. Precedent **108**, 24–29 (2012)

65. E. Naserian, X. Wang, K. Dahal, Z. Wang, Z. Wang, Personalized location prediction for group travellers from spatial–temporal trajectories. Futur. Gener. Comput. Syst. **83**, 278–292 (2018)
66. S. Tian, X. Li, H. Ji, H. Zhang, Mobility prediction scheme for optimized load balance in heterogeneous networks, 2018.
67. C. Manasseh and R. Sengupta, Predicting driver destination using machine learning techniques, *6th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, vol. 94720, pp. 142–147, 2013.
68. M. Symposium, A destination prediction model based on historical data, contextual knowledge and spatial conceptual maps, 2012.
69. H. Gao, J. Tang, H. Liu, Mobile location prediction in spatio-temporal context. Nokia Mob. data Chall. Work. **2**, 1–4 (2012)
70. Y. Zhu, Y. Sun, Y. Wang, Nokia mobile data challenge : predicting semantic place and next place via mobile data, *Mob. Data Chall. by Nokia*, pp. 1–6, 2012.
71. A. Soares, V. Times, C. Renso, S. Matwin, L. A. F. Cabral, A semi-supervised approach for the semantic segmentation of trajectories, in *Proceedings of the IEEE International Conference on. Mobile Data Management*, vol. 2018–June, pp. 145–154, 2018.
72. A. Noulas, S. Scellato, N. Lathia, C. Mascolo, *Mining user mobility features for next place prediction in location-based services* (Proc. IEEE Int. Conf. Data Mining, ICDM, 2012), pp. 1038–1043
73. M. Chen, X. Yu, Y. Liu, MPE: A mobility pattern embedding model for predicting next locations, 2020.
74. S.B. Cho, Exploiting machine learning techniques for location recognition and prediction with smartphone logs. Neurocomputing **176**, 98–106 (2016)
75. Y. Wang, X. Fan, X. Liu, C. Zheng, L. Chen, C. Wang, J. Li, Unlicensed taxis detection service based on large-scale vehicles mobility data, pp. 857–861, 2017.
76. X. Fan, L. Guo, N. Han, Y. Wang, J. Shi, Y. Yuan, A deep learning approach for next location prediction, in *2018 IEEE 22nd International Conference on Computing Support. Cooperative Work Design*, no. Vmm, pp. 69–74, 2018.
77. Q. Liu, S. Wu, L. Wang, T. Tan, Predicting the next location: A recurrent model with spatial and temporal contexts, in *30th AAAI Conference on Artificial Intelligence, AAAI 2016*, pp. 194–200.
78. C. Yang, M. Sun, W.X. Zhao, Z. Liu, E.Y. Chang, A neural network approach to jointly modeling social networks and mobile trajectories. ACM Trans. Inf. Syst. **35**(4), 1–28 (2017)
79. A. Sassi, M. Brahimi, W. Bechkit, A. Bachir, Location embedding and deep convolutional neural networks for next location prediction, in *Proceedings of the 2019 IEEE 44th Local Computing Networks Symposium Emerging Topics Networking, LCN Symp. 2019*, pp. 149–157, 2019.
80. C. Wang, L. Ma, R. Li, T.S. Durrani, H. Zhang, Exploring trajectory prediction through machine learning methods. IEEE Access **7**, 101441–101452 (2019)
81. M. Chen, Y. Zuo, X. Jia, Y. Liu, X. Yu, K. Zheng, CEM: a convolutional embedding model for predicting next locations, in *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–10, 2020.
82. A. Al-Molegi, M. Jabreel, B. Ghaleb, STF-RNN: space time features-based recurrent neural network for predicting people next location. In *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 1–7. IEEE; 2016.
83. D. Yao, C. Zhang, J. Huang, J. Bi, SERM: A recurrent model for next location prediction in semantic trajectories, *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, vol. Part F1318, pp. 2411–2414, 2017.
84. Y. Chen, C. Long, G. Cong, C. Li, Context-aware deep model for joint mobility and time prediction, in *WSDM 2020 Proceedings of the 13th International Conference on Web Search and Data Mining*, pp. 106–113, 2020.
85. Y. Wang, Z. Qin, J. Pang, Y. Zhang, J. Xin, Semantic annotation for places in LBSN through graph embedding, in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, vol. Part F1318, pp. 2343–2346, 2017.
86. J. Lv, Q. Li, Q. Sun, X. Wang, T-CONV: a convolutional neural network for multi-scale taxi trajectory prediction, in *2018 IEEE International Conference on Big Data and Smart Computing (bigcomp), 2018*, pp. 82–89, 2018.
87. A. De Brébisson, É. Simon, A. Auvolat, P. Vincent, Y. Bengio, Artificial neural networks applied to taxi destination prediction. CEUR Workshop Proc. **1526**, 1–12 (2015)
88. X. Song, R. Shibasaki, N.J. Yuan, X. Xie, T. Li, R. Adachi, DeepMob: Learning deep knowledge of human emergency behavior and mobility from big and heterogeneous data. ACM Trans. Inf. Syst. **35**(4), 1–19 (2017)
89. P. Kothari, S. Kreiss, A. Alahi, Human trajectory forecasting in crowds: a deep learning perspective, pp. 1–32.
90. Y. Li, Pedestrian path forecasting in crowd: a deep spatio-temporal perspective, pp. 235–243, 2017.
91. W. X. Zhao, N. Zhou, A. Sun, J. Wen, J. Han, E. Y. Chang, A time-aware trajectory embedding model for next-location recommendation.
92. G. Wang, D. Liao, J. Li, Complete user mobility via user and trajectory embeddings. IEEE Access **6**, 72125–72136 (2018)
93. A. Karatzoglou, A. Jablonski, M. Beigl, A Seq2seq learning approach for modeling semantic trajectories and predicting the next location, in *GIS Proceedings of the ACM International Symposium Advances Geographic Information Systems*, pp. 528–531, 2018.
94. N. Bahra and S. Pierre, RNN-based user trajectory prediction using a preprocessed dataset, 2020.
95. S. Tian, X. Zhang, Y. Zhang, Z. Cao, Spatio-temporal position prediction model for mobile users based on LSTM, pp. 967–970, 2019.
96. J. Liao, T. Liu, M. Liu, J. Wang, Y. Wang, H. Sun, Multi-context integrated deep neural network model for next location prediction. IEEE Access **6**, 21980–21990 (2018)
97. X. Zhang, Z. Zhao, Y. Zheng, J. Li, Prediction of taxi destinations using a novel data embedding method and ensemble learning. IEEE Trans. Intell. Transp. Syst. **21**, 68–79 (2019)
98. Q. Gao, F. Zhou, DeepTrip: adversarially understanding human mobility for trip recommendation, 2019.
99. R. B. Gmbh, M. Beigl, Semantic-enhanced learning (SEL) on artificial neural networks using the example of semantic location prediction, no. Ml, pp. 1–4.
100. S. C. Lamp, R. B. Gmbh, Matrix Factorization on semantic trajectories for predicting future semantic locations, 2017.

101. W.E.I. Liu, Y. Shoji, DeepVM: RNN-based vehicle mobility prediction to support intelligent vehicle applications. IEEE Trans. Ind. Inform. **16**(6), 3997–4006 (2019)
102. M. Ankerst, M. M. Breunig, H. Kriegel, OPTICS: ordering points to identify the clustering structure, pp. 49–60, 1999.
103. F. Zhou, Context-aware variational trajectory encoding and human mobility inference, pp. 3469–3475.
104. H. Sun, F. Zhou, K. Zheng, PeriodicMove : shift-aware human mobility recovery with graph neural network.
105. R.G. Baraniuk, More is less: Signal processing and the data deluge. Science **331**(6018), 717–719 (2011)
106. S. Liu, J. Pu, Q. Luo, H. Qu, L.M. Ni, R. Krishnan, VAIT: A visual analytics system for metropolitan transportation. IEEE Trans. Intell. Transp. Syst. **14**(4), 1586–1596 (2013)
107. A. V. Dastjerdi, H. Gupta, R. N. Calheiros, S. K. Ghosh, Fog computing : principles , architectures , and applications, pp. 1–26.

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