Predicting Next Useful Location with Context-Awareness: The State-of-the-Art

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Predicting the future location of mobile objects reinforces location-aware services with proactive intelligence and helps businesses and decision-makers with better planning and near real-time scheduling in different applications such as traffic congestion control, location-aware advertisements and monitoring public health and well-being. Recent developments in smartphone and location sensors technology and the prevalence of using location-based social networks alongside the improvements in AI and machine learning techniques provide an excellent opportunity to exploit massive amounts of historical and real-time contextual information to recognise mobility patterns and achieve more accurate and intelligent predictions. This unique survey provides a comprehensive overview of the next useful location prediction problem with context-awareness and the related studies. First, we explain the concepts of context and context-awareness and define the next location prediction problem. Then we analyse more than 30 studies in this field concerning the prediction method, the challenges addressed, the datasets and metrics used for training and evaluating the model and the types of context incorporated. Finally, we discuss the advantages and disadvantages of different approaches, focusing on the usefulness of the predicted location and identifying the open challenges and future work on this subject.

CCS Concepts: • **Information systems** → **Spatial-temporal systems**;

Additional Key Words and Phrases: Location prediction, Context-awareness, Location-awareness, Mobility prediction

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1 Introduction

The prediction of mobility patterns holds significant importance across a spectrum of applications, ranging from urban planning and intelligent transportation systems to resource management in personalised medical services, tailored recommendation systems and mobile communications. Anticipating mobility trends equips decision-makers with the tools to address challenges like traffic congestion by formulating realistic transportation plans and efficient scheduling strategies. Online ride-hailing and ride-sharing platforms rely heavily on precise mobility predictions to gauge travel demands, enabling more streamlined resource planning. Additionally, these predictions facilitate the identification of users with similar destinations, enhancing match-making, optimising scheduling strategies and ultimately reducing operational costs and energy consumption.

The advent of ubiquitous computing, coupled with advancements in **Internet of Things (IoT)**, sensor advancements and the extensive use of cellular networks, smartphones and GPS gadgets, has generated vast repositories of mobility data collected from diverse sources. Simultaneously, the rapid growth of social networks such as X (formerly known as Twitter), Facebook and Foursquare has given rise to spatiotemporal mobility data enriched with contextual information such as text, images, videos, user activity, preferences and sentiments. The presence of abundant mobility data, coupled with the capabilities of AI and **Machine Learning (ML)** methods, offers an unparalleled chance for researchers to tackle the task of predicting mobility. This involves harnessing diverse contextual information from various sources to construct robust models, leading to enhanced predictive accuracy.

In the realm of mobility prediction, an essential and valuable aspect is the anticipation of an individual's upcoming locations or destinations. This form of prediction finds applicability across diverse domains, including public health monitoring [2, 4, 41], traffic congestion management [46], location-sensitive advertising enhancement and link prediction within social network platforms [52, 72]. Forecasting an individual's forthcoming location(s) is inherently challenging, as it necessitates capturing their habitual spatiotemporal mobility patterns, discerning their intention to explore new venues at different times and identifying potential new places they may consider visiting. While individuals often adhere to regular movement patterns, an element of randomness in their mobility behaviour complicates precise prediction of their whereabouts [48]. Moreover, the integration of contextual information that influences human decisions regarding destination selection remains an ongoing challenge. Researchers have endeavoured to harness various types of contextual information in the prediction process, including spatial context (e.g., historical trajectories), temporal context (e.g., day of the week, hour of the day, both for past visits and predictions), social ties (e.g., information related to individuals in social relationships), user profiles (e.g., preferences, occupation, schedule) and environmental context (e.g., spatial maps, details of visited and unvisited venues in the vicinity).

Numerous survey papers have comprehensively reviewed studies centred around mobility [1, 6, 16, 32, 53, 56, 57, 70]. However, two characteristics are common across these reviews. First, the majority of these reviews emphasise the methodologies employed for capturing mobility patterns or select studies based on their methodologies. For example, [32] and [6] focus on studies employing **Deep Learning (DL)**-based approaches for human mobility analysis. Second, a prevailing tendency among these surveys is to treat the task of predicting the next location as synonymous with trajectory prediction, thereby implying a primary reliance on spatiotemporal context—specifically location and time. While spatiotemporal context is indeed pivotal for forecasting future locations, the potential contributions of other contextual factors to model efficacy should not be overlooked. In contrast, our survey stands out in several key ways:

(1) *Emphasis on Context-Awareness*. To the best of our knowledge, our survey is the first study to highlight the critical role of context-awareness in next location prediction. We systematically categorise and analyse various types of contextual information, including individual, location, time, activity and relational contexts. This emphasis on diverse contextual factors provides a more nuanced understanding of the prediction task. Xu et al. [57] include social context but do not comprehensively cover other types of context. Similarly, Luca et al. [32], Wang et al. [53] and Chen et al. [6] primarily focus on methodologies without delving deeply into context types beyond spatiotemporal context.
(2) *Targeting the Specific Task of Next Location Prediction*. Unlike other surveys that target broader areas such as human mobility or trajectory mining, our survey specifically targets the task of next location prediction. The review by [1] covers human mobility models and applications, and [16] and [6] provide an overview of trajectory data mining techniques where the latter targets the DL applications in this domain. This specificity in targeting a particular task by the current survey allows for a more focused and detailed analysis of the methods and challenges unique to predicting the next location.
(3) *Comprehensive Categorisation of Methods*. We classify the next location prediction methods into five main categories: evidence-based, probabilistic and distribution-based, **Deep Neural Networks (DNNs)**-based, pattern-based, Markov model-based and Hybrid methods. Each category is thoroughly discussed in terms of its characteristics, research progress and ability to incorporate different types of contextual information. Other surveys like [1] and [56] provide overviews of methods but do not offer such detailed categorisation and analysis regarding their ability to incorporate various contextual types. The works by [32, 53] and [6] focus specifically on DL methods, lacking a comprehensive categorisation of diverse methodologies.
(4) *Detailed Dataset Analysis*. Our survey offers a detailed examination of datasets used for training and evaluating next location prediction methods, categorising them into GPS traces, social network data and **Call Detail Records (CDRs)**. We analyse the strengths and weaknesses of these datasets, providing a clearer understanding of the data landscape in this field. The studies by [16] and [70] provide general overviews of datasets but do not delve into detailed analysis and categorisation. Xu et al. [57] focus on geo-social networking data but do not cover other types of datasets comprehensively.
(5) *Extensive Review of Recent Studies*. We review 34 recent studies that focus on the next location prediction task, describing their advantages and disadvantages from the perspective of context-awareness and prediction performance. This extensive review offers a richer understanding of the state-of-the-art compared to other surveys. The reviews by [6, 32] and [53] provide extensive reviews but focus more narrowly on specific methodologies such as DL. The works by [56] and [1] offer broader overviews but do not emphasise context-awareness and the integration of diverse contextual information.
(6) *Identification of Open Challenges and Future Directions*. Our survey highlights several open challenges and points out possible future research directions, providing a roadmap for future studies from the context-awareness point of view. This forward-looking perspective is crucial for guiding ongoing research efforts. Other surveys, such as [70] and [1], provide historical

perspectives and foundational techniques but do not emphasise future research directions as explicitly. The work in [32] and [53] discusses future directions but within a narrower scope focused on DL.

(7) *Experimental Performance Summary*. While other surveys, like [56], provide summaries of experimental performance for different context types and prediction methods, they primarily focus on spatial-temporal context. Our survey extends this by integrating various context types and summarising their impact on prediction accuracy. For example, incorporating activity context can improve prediction accuracy by up to 6%, and relational context explains a significant portion of human movement, which other surveys often overlook. Besides that, despite the challenges in comparing the experimental performance of different methods in the domain of next location prediction, we tried to extract as much information as possible to compare the performance of different models in this domain. This couldn't be achieved by studies like [6, 32] and [53] in which the focus was on a single category of methods.

In conclusion, our survey's novelty lies in its comprehensive focus on context-awareness, detailed categorisation of methods and datasets, extensive review of recent studies, forward-looking identification of future research challenges and its specific focus on the task of next location prediction. These contributions significantly advance the understanding of next location prediction which can provide valuable insights and resources for researchers in the field.

The remainder of this article is organised as follows: In Section 2, we lay the foundational concepts of context and context-awareness, clarify the next location prediction problem and present the notion of context-aware next location prediction, as well as providing the background and the related work to this study. Additionally, we explore the array of context sources that furnish invaluable insights and enrich the predictive task. Section 3 categorises the research studies conducted in this field based on their prediction method and analyses them from different perspectives, such as context-awareness and context types incorporated into the prediction task. In Section 4, we introduce different datasets commonly used by the studies in this field for training and evaluating the models and discuss the evaluation metrics used by them in order to assess the performance of the model.[1] Section 5 discusses the advantages and disadvantages of the studies analysed in the previous section. In Section 6, we present the open challenges and the future research directions, and finally, we conclude this survey in Section 7.

2 Background and Related Work

2.1 Context and Context-Awareness

Context constitutes a fundamental attribute within contemporary IoT-enabled systems. Over recent decades, numerous scholars have endeavoured to conceptually and operationally delineate context [3, 12, 25]. The concept of context-awareness is credited to Schilit and Theimer [45]. In essence, context-awareness encompasses software that 'adapts according to its location of use, the collection of nearby people and objects as well as changes to those objects overtime'. This trait characterises software's responsiveness to its environment. Dey's interpretation [12], which defines context as 'any information that can be used to characterise the situation of an entity' has gathered widespread acceptance. Put differently, any data generated or consumed by a system is an intrinsic part of its contextual makeup. Simply stated, a system can be considered context-aware if it leverages contextual insights to enhance its performance, efficiency, effectiveness and overall utility.

Context exhibits varying levels of abstraction. For instance, consider temperature inference based on raw data from a thermometer in binary format, denoted in centigrade/fahrenheit units

[1] In this article, the performance of a models refers specifically to the accuracy of the model in predicting the next location.

(e.g., 24°C/75.2°F), and the subsequent categorisation of weather warmth (e.g., hot/warm/cool/cold) stemming from these data. Both instances embody context, albeit at distinct abstraction tiers. However, the level of abstraction in context integrated into operations, such as prediction, can wield an impact on performance. Sigg [47] introduces an alternative, computation-centric stance, classifying the degree of abstraction in context based on the extent of preprocessing applied to raw data. While this approach introduces reasoned differentiation, it fails to delineate between high-level context and the notion of situation. Padovitz et al. [40] present a three-tier hierarchy of abstraction levels termed the Context-Situation pyramid, aimed at addressing this limitation. As per their delineation, the most rudimentary data form is 'sensory-originated data', employed, perhaps in conjunction with computation, to construct a contextual notion. In this schema, 'context' assumes the role of information employed within a model to simulate real-world scenarios. On a higher plane, 'situation' emerges as a meta-level concept, inferred through contextual analysis.

Within this survey, for the purpose of distinguishing between context-aware and non-context-aware methodologies, we adhere to the delineations and classifications presented by Padovitz et al. [40] and Sigg [47]. Our criterion for regarding information as context necessitates its preliminary processing and partial or complete comprehensibility by humans. To clarify, consider instances such as 37.811760,144.964821 or 37°48'42.3"S 144°57'53.4"E; these represent raw sensory-originated data. In contrast, designations like 'McDonald's' encapsulate context, while descriptors such as 'eating' or 'working' delineate the situation. Consequently, we adopt the view that a model qualifies as context-aware if it assimilates contextual elements into its operational framework.

2.2 Context-Aware Next Location Prediction

This subsection will explore the key aspects of the next location prediction problem, contrasting it with next **Points of Interest (POI)** recommendation. It will discuss the importance of context-awareness in approaching this problem and the unique benefits it brings.

2.2.1 Next Location Prediction Problem. Next location prediction involves foreseeing[2] the subsequent location (stay point) that an individual or object will reach, based on their historical mobility and environmental data and any related real-time contextual information. In other words, the goal is to utilise patterns and trends from past movements to forecast where the entity will be at a specific point in the future. In a formal sense, let u represent a user, T_u their trajectory and $PL_t \in T_u$ their present location. The primary objective is to predict u's next destination PL_{t+1}. This challenge can be approached through two distinct paradigms: (i) as a multi-class classification task, wherein the number of classes corresponds to the various locations, aiming to predict the next possible venue to be visited (PL_{t+1}); (ii) as a regression task, projecting $PL_{t+1} = (x_{t+1}, y_{t+1})$, whereby x_{t+1} and y_{t+1} denote the geographical coordinates of the next location [30].

2.2.2 Next Location Prediction versus Next POI Recommendation. Recommending POIs constitutes a pivotal facet of **Location-Based Social Networks (LBSNs)**. This task aims to recommend POIs that the user may be interested in visiting in the future. Many studies have addressed this problem, with one of the primary and popular approaches being collaborative filtering and its variants [66]. While the general task of POI recommendation may not directly correlate with next location prediction, there are significant overlaps between the two. Both tasks require modelling regularity in user behaviour, where periodic patterns are essential for prediction, as demonstrated in studies like [10], which learns spatial-temporal periodic interests for next POI recommendation.

A variant of POI recommendation endeavours to forecast the subsequent (sequential/successive) POI that an individual is poised to visit [68, 69]. This variant aligns closely with next location

[2]In this article, the terms foreseeing, forecasting, and predicting have been used interchangeably.

prediction by focusing on users' mobility patterns, often incorporating elements of both regularity and exploration. While next POI recommendation models predominantly emphasise users' interests, next location prediction delves into users' intentions, considering the contextual and spatiotemporal data to forecast the exact location or stay point.

Next location prediction focuses on forecasting the exact future location (or stay point) a user will visit, based on their historical trajectories and current contextual data. This task can be framed as a classification problem, where the aim is to identify the next location from a predefined set of possible locations, or as a regression problem, where the goal is to predict the geographical coordinates of the next destination. The core of next location prediction problem lies in understanding and modelling user movement patterns over time, considering both regular and exploratory behaviours. While the focus of this survey is on methodologies specific to next location prediction, the inclusion of relevant insights from next POI recommendation studies where methodologies align ensures a more comprehensive perspective. By narrowing our survey to next location prediction, we provide a specialised contribution while leveraging overlaps with POI recommendation studies to enhance the depth and breadth of the review.

2.2.3 Importance of Context-Aware Next Location Prediction. Many attempts were made to address the mobility, specifically, the next location prediction problem [8, 14, 18, 30, 38, 65]. However, most of the techniques proposed by the studies are based on the historical movement of a user/object, trying to extract the behaviour and movement patterns to predict possible future locations. These methods usually have a training phase to extract regular movement patterns to predict future locations. While human mobility patterns typically adhere to regular spatial-temporal rhythms [48]—particularly evident in urban settings, where individuals predominantly navigate around their dwellings and workplaces—there exist instances of infrequent visits to specific locales (e.g., shopping centres, museums, friends' residences) and even sporadic deviations from established routines. Besides that, people occasionally change their routines and try to visit and explore new venues (e.g., a restaurant recommended by a LBSN) or meet some friends in a bar chosen by them. Hence, human mobility is evidently steered by more than mere regularity, exhibiting significant uncertainty influenced by lateral unpredictability. This inherent randomness and uncertainty limit the predictability of mobility. However, it is still not impossible to overcome this uncertainty if the information and context for tackling this issue are chosen carefully.

This lateral randomness brings us to the exigency of context-aware mobility prediction, where not only a user's movement patterns should be extracted from the historical behaviour but, more importantly, the information characterising the situation of the user, his/her environment and any other entity in interaction with him/her should be exploited to predict his/her possible future location. For example, a meeting scheduled in a user's diary, which will take place in a couple of hours in a restaurant, is valuable information in predicting his/her future whereabouts, while neglecting it may lead to a false prediction. Considering sunny weather on the weekend can help predict the user will probably go to a beach where not taking the weather into account may not result in the same outcome. Furthermore, consider the case of a college student whose movement patterns harmonise with class locations throughout an entire semester. As the subsequent semester starts, the student's schedule may experience a complete upheaval. Herein, a model founded solely on historical movement trends might necessitate the entirety of the semester to assimilate this new information accurately. Conversely, a context-aware model that integrates the student's university semester schedule is poised to yield enhanced precision in predictions.

2.3 Context Categories

Although the definitions of context presented in Section 2.1 give us an intuition about the concept of context, situation and context-awareness, for operational use of context, such definitions can be

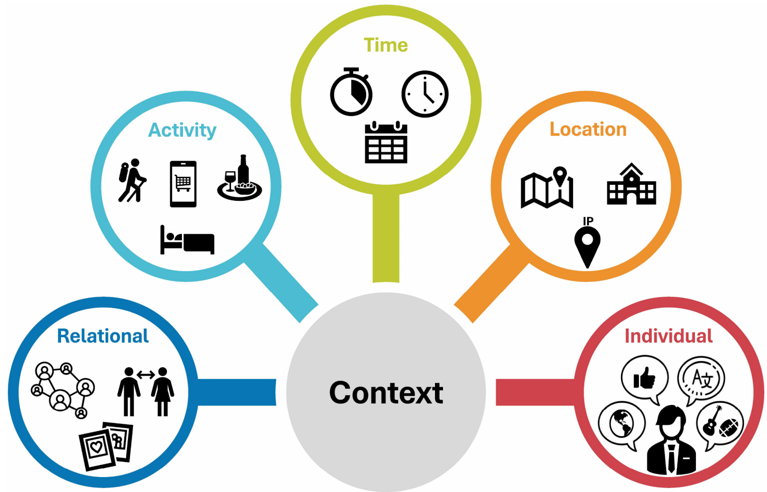


Fig. 1. Context categories.

general and incomplete, leading to weak practical usefulness. In a bid to introduce a more actionable delineation of context, Zimmermann et al. [73] provide an operational framework wherein context is classified into five general categories: individual, location, time, activity and relational. We use this categorical schema summarised below, to identify the contextual information incorporated to the next location prediction task (Figure 1).

— *Individual Context*. Individual context refers to detailed information about entities, including their state and behaviour within a system. For example, this can include a tree's age and species (natural entity), a person's language preferences on a smartphone (human entity), a laptop's screen size and RAM (artificial entity) or a sports team's shared strategies and skills (group entity). This context varies based on the entity's role, nature and interaction with its environment.
— *Location Context*. Involves the spatial arrangement of physical objects, devices and human mobility. It includes absolute locations (exact positions) and relative locations (positions relative to other entities). Quantitative models use coordinates like GPS for precise positioning, while qualitative models describe locations in terms of buildings, rooms and streets, enhancing human spatial cognition by introducing various granularity levels.
— *Time Context*. Involves the temporal aspects of an entity's environment, including current time, time zones, intervals, day of week and recurring events. It helps in modelling behaviour, predicting future contexts and managing historical context for analysis.
— *Activity Context*. Refers to an entity's current and future activities, including its goals, tasks and actions (e.g., shopping, dining and sleeping). It defines what the entity aims to achieve and how, such as a user's goal to complete a report or a device's role in executing tasks.
— *Relational Context*. Captures the connections an entity has with other entities, such as people, objects, devices or information. It includes social relations (e.g., friends, colleagues), functional relations (e.g., using a tool or interacting with a device) and compositional relations (e.g., parts of a machine or components of a system). These relationships define the entity's environment and roles and can change dynamically based on spatial, temporal or contextual factors.

3 Next Location Prediction Methods

This section delves into an in-depth discussion and categorisation of the various research endeavours centred around the next location prediction task. The analyses encompass their context-awareness levels, employed methodologies and integrated context types. From a comprehensive pool of closely correlated research papers, 34 pertinent studies were chosen and analysed with respect to the aforementioned facets.

In the quest for these studies, an exhaustive bibliographic exploration was undertaken across IEEE, ACM, ScienceDirect and Springer. This selection was based on the quality and pertinence of the publications in relation to the subject. Employing a purposeful search string ('location prediction' OR 'next place prediction' OR 'destination prediction' OR 'location'), some filters were applied to the paper selection process:

(1) *Publication Date*. The papers were confined to those published within the temporal span ranging from 2012 to 2022. A couple of exceptions were admitted due to their importance in the domain.
(2) *Publication Type and Citations*. Papers that were presented in workshops, symposiums or cited less than 100 times were not considered. This rule included recent papers that gained attention.
(3) *Relevance*. We carefully reviewed the abstracts of each paper to determine their relevance to the context, resulting in a final selection of 34 articles. It's worth noting that surveys related to next location prediction were not included in this group.

As a summary, Table 1 provides an overview of the selected papers concerning challenges they addressed, methods exploited, datasets used for training/evaluation, evaluation metrics and the context types they incorporated in their model.

To enhance the understanding of the workflows employed by the different methodologies discussed in this section, Figure 2 provides a consolidated flowchart. The flowchart illustrates the key steps—input, preprocessing, processing/modelling, prediction and output—across various method categories, including evidence-based, probabilistic, pattern-based, Markov-based, DNNs, graph-based and **Large Language Model (LLM)**-based approaches. This visual representation facilitates a clearer comparison of the underlying processes and distinctions between these methods.

3.1 Evidence-Based Methods

A significant theoretical approach called the theory of belief functions, also known as evidence theory or **Dempster–Shafer Theory (DST)**, provides a flexible framework for handling uncertainty. This theory has connections to other frameworks like probability, possibility and imprecise probability theories [22]. DST has gained attention for its effective approach in addressing challenges related to combining different pieces of evidence to make decisions in situations with high uncertainty. One key advantage of this theory is its ability to model the refinement of hypotheses through accumulating evidence, while explicitly representing uncertainty due to lack of knowledge or reservations in judgement. The theory is based on two main principles: assigning belief degrees to hypotheses and using Dempster's rule to combine these degrees from different bodies of evidence. The core of Dempster's rule lies in its ability to support consistent evidence while handling conflicting information.

Illustratively, Samaan and Karmouch [44] introduced a predictive framework based on DST. This innovative effort marked the initial steps to tackle the next location prediction challenge by incorporating context. The framework orchestrates the integration and reasoning of contextual information, including real-world maps, user profiles, preferences, tasks and schedules. Leveraging

Table 1. Summary of Next Location Prediction Papers (Ordered Chronologically)

Authors	Year	Challenges Addressed	Model	Method	Datasets	Metrics	Context Types					
							Loc.	Time	Rel.	Act.	Ind.	Other
Samaan and Karmouch [44]	2005	Cold start—randomness of human mobility	-[a]	Evidence theory-based	Self-collected GPS data—questionnaires	Accuracy	✓	✓		✓	✓	Spatial maps containing semantic information
Monreale et al. [38]	2009	Cold start—data sparsity—Accuracy	WhereNext	Pattern-based	GeoPKDD	Coverage—Accuracy	✓	✓				
Cho et al. [8]	2011	Examine the influence of social routines on patterns of human mobility, as well as the impact of social connections, such as friends whom individuals travel to meet	PMM and Periodic & Social Mobility Model (PSMM)	Distribution-based	Gowalla—Brightkite—CDR	Accuracy—MAE	✓	✓	✓			
Ying et al. [65]	2011	Adding extra context to prediction (e.g., activity) by using semantic labels of locations instead of using coordinates or label-less clusters	SemanPredict	Pattern-based	MIT reality dataset	Precision—Recall—F-measure	✓	✓				
Do and Gatica-Perez [13]	2012	Finding relevant contextual features—integrating general and personal prediction models to be used in 'cold start' situations	-[a]	Probabilistic-based	Self-collected GPS data	Accuracy	✓	✓				
Xue et al. [58]	2012	Data sparsity—privacy—computational performance	Sub-Trajectory Synthesis (SubSyn)	Markov-based	T-drive	Coverage—MAE	✓	✓				
Noulas et al. [39]	2012	Feature selection and extraction	-[a]	-[b]	Foursquare	APR—Accuracy	✓	✓	✓			Contextual information related to historical visits and temporal context
Gao et al. [20]	2012	Investigate the effect of social-historical ties on users' check-in behaviour	SHM	Probabilistic-based	Foursquare	Accuracy	✓	✓	✓			

(Continued)

Table 1. Continued

Authors	Year	Challenges Addressed	Model	Method	Datasets	Metrics	Context Types					
							Loc.	Time	Rel.	Act.	Ind.	Other
Gambs et al. [18]	2012	Incorporate more than one previous state of the user into the Markov model in order to increase prediction accuracy	n-MMC	Markov-based	Self-collected GPS data—Geolife	Accuracy	✓	✓				Motion speed
Gao et al. [19]	2013	Analyse the effect of temporal layer of source of context in LBSNs	Social-historical + temporal model (SHM + T)	Probabilistic-based	Foursquare—Brightkite	Accuracy	✓	✓	✓			
Ying et al. [64]	2013	Incorporate the geographic/temporal/semantic triggered intentions in prediction—incorporate similarity between user GTS pattern trees into prediction	Geographic-Temporal-Semantic-based Location Prediction (GTS-LP)	Pattern-based	EveryTrail—Bikely	Accuracy—Coverage—F-measure	✓	✓				Stay time in each venue and transition time between them
Preoţiuc-Pietro and Cohn [43]	2013	Show the importance of temporal patterns in mobility prediction	-[a]	-[b]	Foursquare	Accuracy	✓	✓		✓		
Lian et al. [28]	2015	Data sparsity—predict exploration probability to incorporate location recommendation into prediction task	Collaborative Exploration and Periodically Returning Model (CEPR)	Markov-based	Gowalla—Jiepang	Accuracy	✓	✓	✓			User, spatial and temporal context extracted from historical check-ins (e.g., user and location entropy)
Wang et al. [55]	2015	Randomness (incorporate both regularity and conformity)—data sparsity—heterogeneous data	RCH	Hybrid method	Sina Weibo—Taxis and Buses GPS	acc@K—APR	✓	✓				
Liu et al. [30]	2016	Capture the impact of elements in the most recent history—continuous time interval and geographical distance problem which causes data sparsity problem in transition matrices	Spatial Temporal Recurrent Neural Networks (ST-RNN)	Neural Networks	Global Terrorism—Gowalla	recall@ [1,5,10]—F1-score@ [1,5,10]—MAP— AUC	✓	✓				

(Continued)

Table 1. Continued

Authors	Year	Challenges Addressed	Model	Method	Datasets	Metrics	Context Types					
							Loc.	Time	Rel.	Act.	Ind.	Other
Lv et al. [33]	2017	Randomness— Integrate users' lifestyle patterns into the prediction process	HMM-ST & HMM-NEXT	Markov-based	CDR	Accuracy	✓	✓				User's mobility habits (day postman/family person /party person/hard person)
Yao et al. [62]	2017	Incorporate semantic trajectories texts containing information for location prediction instead of classic GPS trajectories	Semantic-Enriched Recurrent Model (SERM)	Neural Networks	Foursquare—X	acc@ [1,5,10,20]—MAE	✓	✓		✓		
Feng et al. [14]	2018	The intricate sequential transition patterns observed with time-dependent and high-order characteristics—the multi-level periodic nature of human mobility—the diversity and scarcity of the gathered trajectory data	DeepMove	Neural Networks	Foursquare—CDR	Accuracy	✓	✓				
Kong and Wu [26]	2018	Data sparsity	HST-LSTM	Neural Networks	Baidu	acc@ [1,5,10,20]—MRR	✓	✓				
Yang et al. [60]	2019	Automate feature learning using graph embedding	LBSN2Vec	Graph Embedding	Foursquare	acc@10	✓	✓	✓	✓		
Feng et al. [15]	2020	Privacy—tradeoff between privacy preserving and performance/accuracy	Privacy-preserving Mobility prediction framework via Federated learning (PMF)	Neural Networks	Foursquare—X—Self-collected GPS data	acc@ [1,3,5]	✓	✓				
Chen et al. [7]	2020	Data sparsity—joint modelling of location and time prediction	DeepJMT for joint mobility and time prediction	Neural Networks	Foursquare	acc@ [5,10,20]	✓	✓	✓			
Yang et al. [61]	2020	Data sparsity—low coverage	DestPD	Markov-based	Taxis GPS	Coverage—MAE	✓	✓				

(Continued)

Table 1. Continued

Authors	Year	Challenges Addressed	Model	Method	Datasets	Metrics	Context Types					
							Loc.	Time	Rel.	Act.	Ind.	Other
Comito [9]	2020	Integrating individual and collective mobility into prediction task—incorporate temporal context into prediction	NexT	Pattern-based	Foursquare—X	Coverage—acc@ [1,10,20]—Overall performance	✓	✓				User and venue-related context from frequent patterns of the geo-tagged tweets (e.g., identify night and weekend locations)
Yang et al. [59]	2020	Data sparsity	Flashback	Neural Networks	Foursquare—Gowalla	acc@ [1,5,10]—Mean Reciprocal Rank (MRR)	✓	✓				Spatial and temporal distance between each check-in
Mo et al. [37]	2021	Extraction of latent activity patterns to infer travel purpose—predict stay time simultaneously	Input-output hidden Markov model (IOHMM)	Markov-based	Public transit smart card	Accuracy	✓	✓		✓		
Cui et al. [10]	2021	Capturing periodic interests in user behaviour—Integrating long-term and short-term interests effectively—Enhancing representation learning for spatiotemporal periodicity	Spatial-Temporal Periodic Interest Learning (ST-PIL)	Neural Networks	NYC and TKY datasets	Acc@[1,5,10]—MRR@[5,10]	✓	✓		✓		
Sun et al. [50]	2022	Incorporate semantic features into prediction—cold start—data sparsity	ST-LSTM	Neural Networks	Foursquare	acc@ [1,5,10,50] — Recall	✓	✓		✓		
Long et al. [31]	2022	Feature selection and extraction—data sparsity	Regularity and Preference-based Deep neural network (DeepRP)	Neural Networks	Vehicles GPS data	acc@ [1,5,10]—F1-Score—MRR	✓	✓				Visit frequency

(Continued)

Table 1. Continued

Authors	Year	Challenges Addressed	Model	Method	Datasets	Metrics	Context Types					
							Loc.	Time	Rel.	Act.	Ind.	Other
Chen et al. [5]	2022	Incorporate travel time context into prediction	TTDM	Graph Embedding/Probabilistic	Vehicles GPS data— Taxi trajectory data	acc@ [1,2,3,4,5]	✓	✓				
Liu et al. [29]	2023	Capture temporal dependencies and location topology information using a Graph NN model	GNN-based long- and short-term preference model (GLSP)	Neural Networks	Foursquare	acc@ [1,5,10]	✓	✓				
Yao et al. [63]	2023	Combine location and spatiotemporal information to extract the semantics of human mobility	Geographical Embedding and Multilayer Attention—Bidirectional Long Short-Term Memory (GEMA-BiLSTM)	Neural Networks	Shenzhen CDR	MAE-RMSE—Accuracy	✓	✓				Semantic info of stay places (e.g., home/work)
Hong et al. [23]	2023	Learn transition patterns from historical location visits, their visit times and activity duration, as well as their surrounding land use functions	Multi-Head Self-Attentional (MHSA) neural network	Neural Networks	Foursquare—GC Dataset [36]	acc@ [1,5,10]	✓	✓				Visit duration and stay point semantics
Wang et al. [54]	2023	applying LLM models in the mobility prediction task	LLM-Mob	LLMs	Geolife—Foursquare	acc@ [1,5,10] —F1-score	✓	✓		✓		Visit duration

[a]No name is assigned to the proposed model.
[b]No model is proposed.

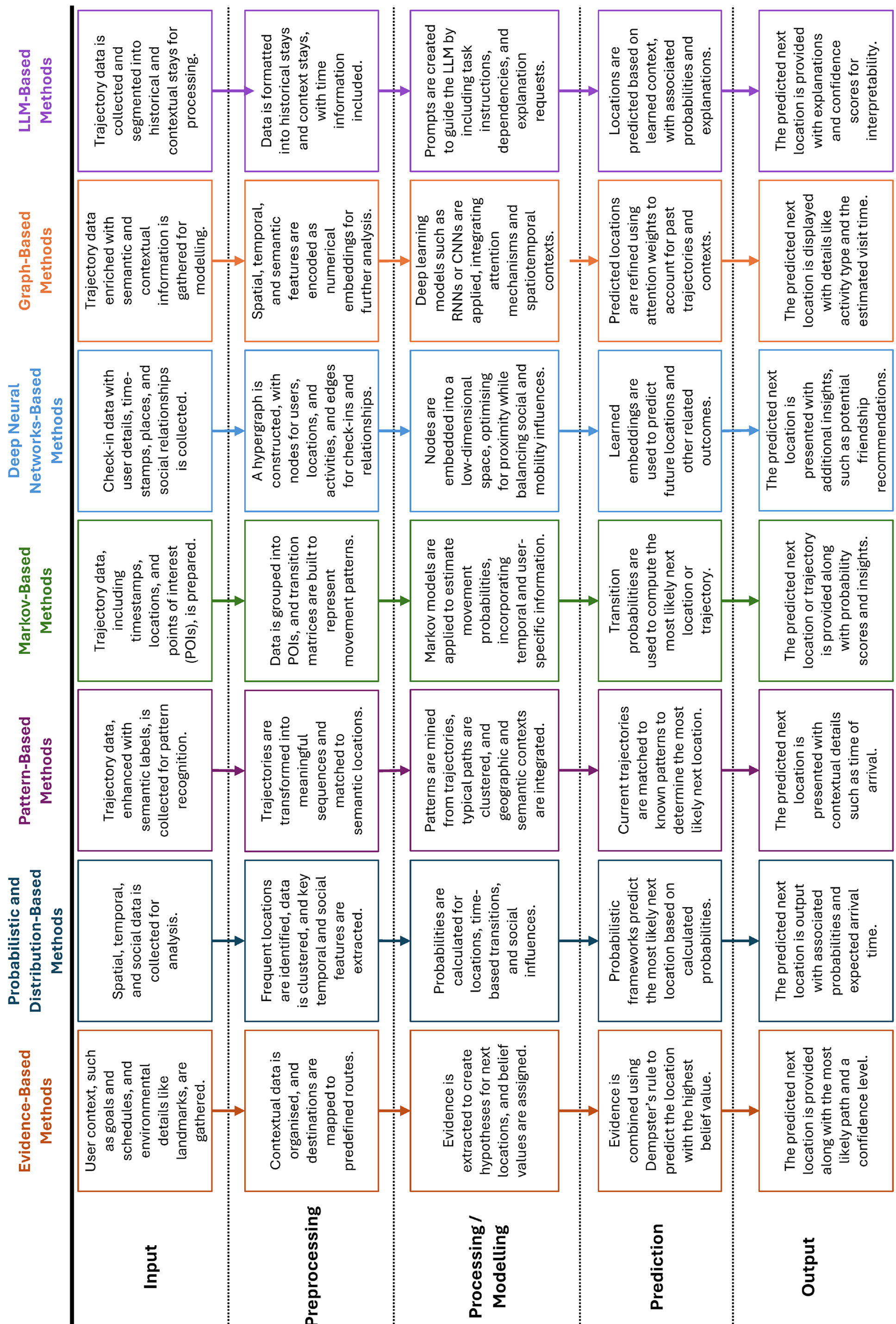


Fig. 2. General workflow of different methods for next location prediction.

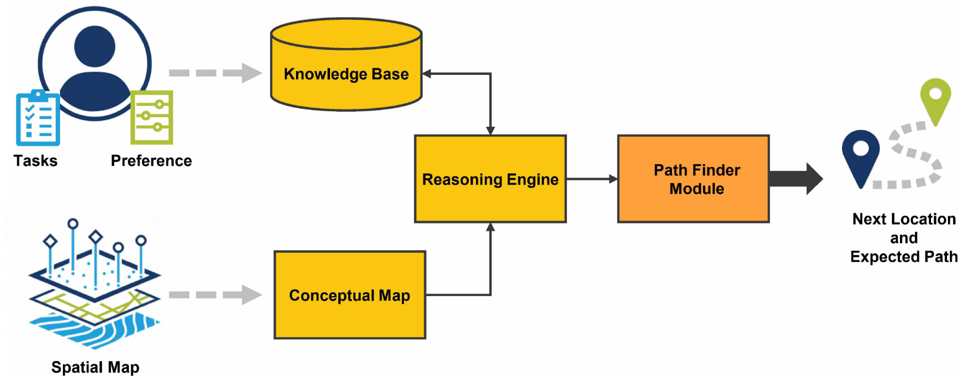


Fig. 3. Structure of the evidence theory-based prediction framework proposed by [44].

DST, the model aims to understand the user's behavioural patterns in relation to their decisions about upcoming locations. This approach enables the model to adapt to new scenarios and enhance its effectiveness by combining contextual hints, allowing it to predict the user's mobility trajectory and future destination with substantial confidence (Figure 3).

3.2 Probabilistic and Distribution-Based Methods

Methods that fall into the probabilistic and distribution-based group usually model human mobility using two approaches. First approach is modelling mobility patterns using distributions of location and time (e.g., Gaussian or Gaussian mixture models). Second approach is computing the plausibility of a user arriving at a location using probabilistic models (e.g., Bayes' theorem) [8, 13, 19, 20].

Cho et al. [8] explored how individuals travel and connect with others in social networks. They investigated how our daily habits and friendships impact the way we go from one place to another. Through studying data about people's movements, they discovered some fascinating trends in our behaviour. They found that short trips tend to follow a consistent pattern in specific locations and times, regardless of our friends. However, when we travel longer distances, our social relationships become more significant. Surprisingly, our social connections can explain about 10–30% of how we move, while regular behaviours in certain places account for around 50–70% of the patterns in how we move around.

The authors introduce a model called the **Periodic Mobility Model (PMM)**, which is a comprehensive framework consisting of two main elements: the places a person regularly visits and the shifts between these places over time. This model effectively captures the complex patterns of how someone moves between different locations using a model that considers the specific patterns for each day. The central idea of the PMM is how it represents places in a detailed way. It achieves this by using a combination of Gaussian models centred around two key places: 'home' and 'work'. To explain further, the authors create a probability distribution that describes the person's state ($P[c_u(t)]$) by using a specific type of Gaussian distribution that is based on time:

$$N_{(H/W)}(t) = \frac{P_{c(H/W)}}{\sqrt{2\pi\sigma^2_{(H/W)}}} exp\left[-\left(\frac{\pi}{12}\right)^2 \frac{(t-\tau_{(H/W)})^2}{2\sigma^2_{(H/W)}}\right]. \quad (1)$$

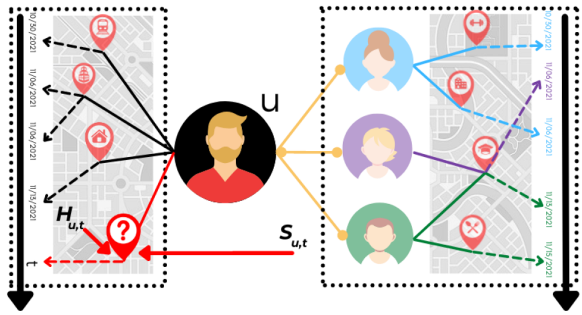


Fig. 4. Contextual information involved in modelling user u's mobility behaviour [19].

Subsequently, the probability of the user's state $c_u(t)$ being either 'home' or 'work' is determined by the ratio of the Gaussian models, leading to the following expression:

$$P[c_u(t) = (H \text{ or } W)] = \frac{N_{H/W}(t)}{N_{H/W}(t) + N_{W/H}(t)}. \tag{2}$$

Upon establishing the user's state at a given time, the authors proceed to compute the likelihood of the user's next location, which hinges upon the amalgamation of the 'home' and 'work' distributions. This computation is framed as follows:

$$P[x(t) = x] = P[x_u(t) = x | c_u(t) = H] \cdot P[c_u(t) = H] + P[x_u(t) = x | c_u(t) = W] \cdot P[c_u(t) = W]. \tag{3}$$

Here, $\tau_{(H/W)}$ signifies the average time of day when a user typically assumes the 'home' or 'work' state, $\sigma_{(H/W)}$ corresponds to the variance associated with the time of day for these respective states and $P_{c(H/W)}$ represents the time-independent probability linked to the generation of any given check-in within the 'home' or 'work' state.

This study can be categorised as partially context-aware, as it harnesses low-level contextual information to facilitate the prediction of the subsequent location. These context-rich elements encompass the day of the week, the hour of the day, the semantic implications of the GPS traces (such as 'home' and 'work') and the presence of interpersonal affiliations (such as friendship) among users.

Similarly, Gao et al. [19] adopt a probabilistic and distribution-based methodology for addressing this task. They assume that LBSN data comprise three distinct layers of information: a social layer, a geographical layer and a temporal layer. Their investigation hones in on the temporal layer, delving into the ramifications of temporal dynamics and cyclic patterns within human mobility. Illustrated in Figure 4, this research discerns the configuration of contextual spatiotemporal and social information designed to model the behaviour of user u. Here, $H_{u,t}$ and $S_{u,t}$ signify the observed historical check-in actions of user u and their friends, respectively, leading up to time t.

Various temporal indications linked to cyclic patterns can be inferred from t, signifying a user's check-in state, encompassing factors like the hour of the day, day of the week, month of the year and more. Given the corresponding observations of $H_{u,t}$ and $S_{u,t}$, along with the temporal context represented by $r(t)$, the probability distribution over user u's check-in locations at time t is defined in Equation (4), where c_u denotes the user's current location and l represents an arbitrary location.

This probability distribution is disassembled into spatial and temporal components by applying Bayes theorem (Equation (4)). The spatial component is computed using the **Social-Historical Model (SHM)** proposed by Gao et al. [20], which models mobility behaviour using the Pitman-Yor Process. The Pitman-Yor Process is a stochastic process, with its sample path forming a probability distribution.

$$P(c_u = l | r(t), H_{u,t}, s_{u,t}) \propto P(r(t) | c_u = l, H_{u,t}, s_{u,t}) P(c_u = l | H_{u,t}, s_{u,t}). \tag{4}$$

The second component, the temporal component, is formulated as a probability function that encapsulates the combined effects of personal preferences from $H_{u,t}$ and social influences from $S_{u,t}$.

$$P(r(t) | c_u = l, H_{u,t}, s_{u,t}) \propto \alpha P(r(t) | c_u = l, H_{u,t}) + (1 - \alpha) P(r(t) | c_u = l, S_{u,t}) = \tag{5}$$

$$\alpha P(r(t) | c_u = l, H_{u,t}) + (1 - \alpha) \frac{\sum_{u_i \in F(u)} sim(u, u_i) P(r(t) | c_u = l, H_{u,t})}{\sum_{u_i \in F(u)} sim(u, u_i)},$$

where α is a parameter governing the contribution of personal preferences and social influence, $F(u)$ represents the group of user u's social friends and $sim(u, u_i)$ stands for the cosine similarity between the visited locations of u and u_i.

3.3 DNNs-Based Methods

DNNs have become a pivotal tool in next location prediction, addressing the inherent complexities of spatiotemporal data. These models are capable of capturing non-linear relationships, sequential dependencies and contextual variations, offering significant improvements over traditional methods. By leveraging spatiotemporal features, semantic embeddings and contextual information, DNNs tackle challenges such as data sparsity, dynamic user behaviour and intricate dependency modelling. Furthermore, advancements in architectures such as attention mechanisms, **Graph Neural Networks (GNNs)** and privacy-preserving frameworks have extended their scalability and utility.

Recently, DL models such as **Recurrent Neural Networks (RNNs)** and **Convolutional Neural Networks (CNNs)** have been applied to a range of spatiotemporal problems, including traffic flow prediction [34, 42], traffic congestion prediction [35], on-demand services [51] and successive POI recommendation [24]. The task of next location prediction, as a significant sub-task within spatiotemporal problems, has also been addressed using DNNs by various studies [7, 14, 15, 26, 30, 59, 62]. These models have demonstrated remarkable performance due to their inherent capabilities of automatic feature representation, selection learning and function approximation. Nonetheless, these models are not without limitations. They often require substantial amounts of training data and exhibit lower interpretability compared to traditional ML approaches.

3.3.1 RNNs. RNNs are widely used in next location prediction due to their ability to model sequential dependencies. Liu et al. [30] proposed an RNN model that incorporates time-specific and distance-specific transitional matrices to account for recent mobility history and geographical variations. Similarly, Yang et al. [59] enhanced RNNs by introducing a flashback mechanism, allowing the model to revisit critical historical mobility data. This approach effectively addresses data sparsity and improves predictive performance for user trajectories.

3.3.2 Attention Mechanisms. Attention mechanisms enhance RNN-based models by dynamically focusing on critical trajectory points. Feng et al. [14] developed *DeepMove*, which combines RNNs with an attention mechanism to model both short- and long-term dependencies in sparse trajectory data. Hong et al. [23] extended this approach with a multi-head self-attention mechanism, enabling the model to attend simultaneously to spatial and temporal dimensions. This significantly improves context-awareness in mobility prediction.

3.3.3 GNNs. GNNs have emerged as a powerful approach for modelling relational and structural information in mobility data. Liu et al. [29] introduced a GNN-based model that captures both long-term user preferences and short-term behaviours. By structuring mobility data as a graph, the model effectively learns complex relationships between users, locations and temporal patterns.

3.3.4 Hierarchical Models. Hierarchical models address the multi-scale nature of mobility patterns by capturing dependencies at different temporal and spatial resolutions. Kong and Wu [26] proposed *HST-LSTM*, a hierarchical spatial-temporal LSTM model that integrates fine-grained spatial-temporal patterns. This structured approach enables robust understanding of both immediate and long-term mobility behaviours.

3.3.5 Semantic Embedding and Context Modelling. Embedding semantic information into DL models enriches predictions by incorporating additional layers of meaning. Yao et al. [62] developed the *SERM* model, which combines semantic trajectory embeddings with spatiotemporal contexts. Similarly, Long et al. [31] leveraged user travel preferences and behavioural regularities as semantic features, enabling personalised and accurate predictions.

3.3.6 Privacy-Aware Frameworks. Given the sensitive nature of mobility data, privacy-preserving frameworks have gained prominence in this domain. Feng et al. [15] proposed *PMF*, a federated learning framework that ensures data privacy while maintaining predictive accuracy. This method addresses data sensitivity concerns in large-scale mobility applications, balancing privacy with robust performance.

3.3.7 Context-Aware DL. Contextual information has proven crucial for improving prediction accuracy and addressing challenges such as data sparsity and the cold-start problem. Sun et al. [49] incorporated semantic time-series and behavioural similarity to fill gaps in sparse datasets. By introducing virtual friendships based on behavioural patterns, the authors addressed the cold-start issue and improved model performance for LBSNs.

Despite these advancements, DL models face significant challenges, including their high data requirements, computational complexity and limited interpretability. Future research could focus on integrating DNNs with interpretable frameworks, such as neuro-symbolic reasoning or reinforcement learning, to enhance scalability and transparency. Privacy-preserving techniques and hybrid models that combine DNNs with traditional approaches also hold promise for advancing next location prediction.

3.4 Pattern-Based Methods

An effective approach for addressing the next location prediction challenge involves utilising a subset of data and pattern mining techniques, commonly known as trajectory mining. This method involves mining users' trajectories, which consist of sequences of locations and corresponding timestamps, to identify frequent sequential patterns that can be leveraged for predicting future locations.

A pioneering study in this category is undertaken by Monreale et al. [38]. This study focuses on extracting frequent movement patterns, termed T-patterns, utilising a trajectory pattern mining algorithm. These T-patterns are then aggregated to construct a prefix tree referred to as the T-pattern tree. In this tree, nodes represent regions that are frequently visited, while edges symbolise travel between these regions along with associated typical travel times. Common prefixes among T-patterns translate into shared paths within this tree. Ultimately, the T-pattern tree serves as the basis for predicting the future location of a moving entity. Notably, since this approach employs all trajectories irrespective of individual users, it implicitly addresses challenges associated with the cold start problem and data sparsity.

Ying et al. [65] also harness raw spatiotemporal data, i.e., trajectories, for predicting subsequent locations. However, In terms of context-awareness, this study introduces semantic significance to clusters of locations (referred to as stay points) through the utilisation of geographic semantic information databases and reverse geocoding. Their proposed location prediction framework, known as SemanPredict, strives to uncover semantic trajectory patterns of individuals and categorise users based on their mobility behaviour, leveraging maximal semantic trajectory pattern similarity between different users. The final step involves using frequent semantic trajectory patterns from similar users to predict a user's upcoming stay point. As this framework solely considers the sequence of semantic stay points, temporal context does not play a central role in their proposed method.

3.5 Markov Model-Based Methods

Markov chains, also known as Markov processes, are stochastic processes that describe a sequence of potential events while assuming the Markov property [17]. These chains are frequently employed to model a user's location history by considering the transition probabilities between different locations. This approach assumes that the prediction of a user's next location relies on their current or recent locations. Markov-based models offer a popular means of capturing mobility patterns and forecasting the subsequent state.

Gambs et al. [18] propose a two-phase model for predicting the next location. The first phase involves extracting low-level context from raw spatiotemporal data to cluster trajectory data into meaningful stay places, such as 'home', 'work' and 'unknown'. This low-level contextual information encompasses semantic labels of the clusters, travel time between points, staying duration at a location and speed for filtering on-the-move points. The second phase employs an n-Mobility Markov Chain, where states correspond not only to individual POIs but also encompass sequences of the two preceding visited POIs.

Another attempt to address the next location prediction challenge is pursued by Lv et al. [33]. This study introduces a framework grounded in Markov chains. Their innovative contribution lies in devising distinct models for various mobility behaviours, tailored to individual users' living habits. The process begins with the extraction of POIs from trajectories via a clustering algorithm. Subsequently, these identified POIs are used to transform point-based trajectories into travel sequences. In the end, users are sorted into four categories, namely 'Day Postman', 'Family Person', 'Party Person' and 'Hard Postman', based on the entropy in their travel behaviour.

Enhanced Markov models are introduced for prediction purposes. The first model, termed **HMM-Based Spatiotemporal Prediction (HMM-ST)**, forecasts a user's location at a specific future time. The second model, known as **HMM-Based Next-Place Prediction (HMM-NEXT)**, predicts a user's subsequent location upon leaving their current place. By comparing the performance of these models across user categories, the study suggests incorporating users' living habits to enhance model performance and flexibly applying mobility predictors based on individual models. The proposed structure of this model is illustrated in Figure 5, where Stages 1–5 correspond to the previously outlined procedures.

3.6 Hybrid Methods

Hybrid methods for mobility prediction leverage diverse techniques to model different aspects of the problem. Wang et al. [55] adopt a hybrid approach by integrating regularity and conformity aspects of human mobility into a unified model. This study introduces the **Regularity, Conformity, Heterogeneous (RCH)** hybrid predictive model, which combines both the regularity (characterising the consistent nature of human mobility) and conformity (reflecting how people's movements are influenced by others) aspects of human mobility. Regularity is modelled using the gravity model,

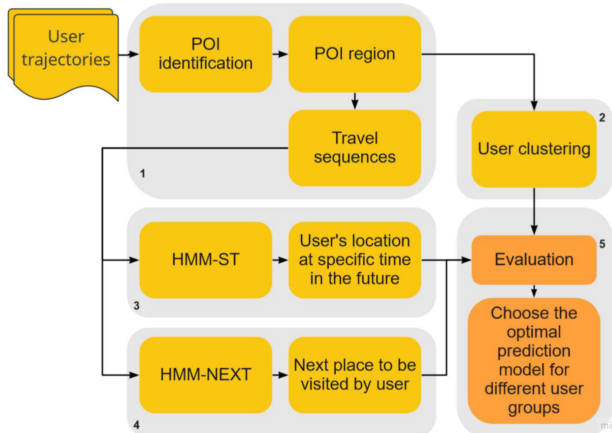


Fig. 5. Structure of the prediction framework proposed by [33].

while conformity is addressed using collaborative filtering. To boost predictive accuracy, the model acquires location profiles from diverse mobility datasets using a gravity model.

For predicting a user u_i's visit to venue v_j, two key components are considered: regularity ($R_{ij}^{(r)}(t)$) and conformity ($R_{ij}^{(c)}(t)$). The regularity term is defined by integrating the visiting frequency of a grid cell and the transition probability between different grid cells, influenced by the gravity model. The conformity term is modelled based on the social conformity theory, considering users' similarities in terms of backgrounds, interests and social status. The hybrid model effectively combines these components to predict users' mobility patterns and locations.

3.7 Other Methods

Out of the 34 research papers reviewed in this survey, only three studies [5, 54, 60] could not be categorised into the primary methodologies discussed previously. These three papers employ unique approaches, specifically graph embedding methods and LLMs, for addressing the next location prediction task. This section provides an overview of these methods and a summary of each paper.

3.7.1 Graph Embedding Methods. Graph embedding methods transform spatial-temporal data into continuous vector spaces that preserve the structural and semantic relationships within the data. In the context of next location prediction, locations are represented as nodes in a graph, and transitions between these locations are represented as edges, often weighted by factors like travel time or transition frequency. The embedding process maps these nodes into a low-dimensional vector space, allowing ML models to effectively capture and predict mobility patterns.

Yang et al. [60] present a hyper-graph embedding approach called LBSN2Vec, specifically designed for LBSNs. The authors highlight the intrinsic complexity of LBSN data, which forms a hyper-graph consisting of user-user edges (friendships) and user-time-POI-semantic hyper-edges (check-ins). To address this complexity, they introduce a random-walk-with-stay scheme to jointly sample friendships and check-ins from the hyper-graph. This method preserves n-wise node proximity by optimising the proximity of nodes within each hyper-edge.

LBSN2Vec integrates social and mobility data, balancing their impact with a tunable parameter. The approach is evaluated using a large-scale LBSN dataset, showing significant improvements in both friendship and location prediction tasks. The results demonstrate an average improvement of

25.32% in location prediction. The study reveals the asymmetric impact of social and mobility data, suggesting that social data has a stronger influence on friendship prediction, while mobility data are more crucial for location prediction.

Chen et al. [5] build upon the concept of graph embedding by introducing the **Travel Time Difference Model (TTDM)**, which integrates travel time analysis with graph embedding techniques. They construct a weighted location transfer graph from historical vehicle trajectory data, where nodes represent locations and edges denote transitions weighted by travel time. TTDM calculates the shortest travel times between all location pairs, providing a robust representation of travel dynamics.

This model is combined with a **Sequential and Temporal Predictor (STP)** to form a comprehensive joint model. TTDM captures global travel time differences, while STP focuses on local sequential transitions and temporal patterns. Extensive experiments on real-world datasets demonstrate that the joint model significantly outperforms baseline methods, highlighting the effectiveness of incorporating graph embedding and travel time differences in next location prediction.

The primary difference between [60] and [5] lies in the types of graphs and embedding techniques used. Yang et al. [60] focus on hyper-graph embedding to capture the multi-faceted nature of LBSN data, incorporating user-user edges and user-time-POI-semantic hyper-edges. Their approach balances the influence of social and mobility data for both friendship and location prediction.

In contrast, Chen et al. [5] use a traditional graph structure but enhance it with travel time analysis through the TTDM. Their model integrates global travel time information with local sequential transitions, emphasising the importance of accurate travel time differences in predicting the next location.

3.7.2 LLMs. LLMs have revolutionised various fields by leveraging their advanced capabilities in understanding and generating human-like text based on context. In the domain of next location prediction, LLMs can be employed to capture complex temporal and contextual dependencies in trajectory data, utilising their powerful sequence modelling abilities to provide accurate predictions.

Wang et al. [54] explore the potential of LLMs for human mobility prediction by introducing LLM-Mob, a novel framework that leverages the language understanding and reasoning capabilities of LLMs. The authors propose organising mobility data into historical stays and context stays to capture long-term and short-term dependencies in human movement. This data formatting enables time-aware prediction by incorporating the time information of the prediction target.

To enhance the predictive performance, the authors design context-inclusive prompts that guide LLMs in understanding and reasoning about the mobility data. These prompts help the model consider both historical activity patterns and recent contextual information, enabling accurate and interpretable predictions.

Extensive experiments on two public human mobility datasets demonstrate that LLM-Mob significantly outperforms state-of-the-art models in predictive performance. The results highlight the untapped potential of LLMs in advancing human mobility prediction techniques, offering a paradigm shift from domain-specific DNNs to a general-purpose LLM-based approach. The study also emphasises the importance of effective data formatting and prompt engineering in leveraging LLMs for tasks beyond their traditional use cases.

4 Available Data Sources and Evaluation Metrics

Developing effective models for predicting the subsequent location of individuals or devices necessitates the use of appropriate datasets containing valuable information for both model training and evaluation. This section will provide an overview of the datasets frequently employed by various research studies, encompassing sources like GPS trajectory records, LBSN check-ins and detailed call records. These datasets play a crucial role in training and assessing next location prediction models. Subsequently, the following subsection will delve into the evaluation metrics commonly employed to gauge the performance and accuracy of such prediction methods.

4.1 Related Datasets for Next Location Prediction Task

Over the past few decades, advancements in technology and the IoT have facilitated the accumulation of substantial mobility data. These data are obtained either passively through embedded devices like GPS in vehicles or actively shared by users on various platforms, such as LBSN check-ins and geo-tagged tweets [56]. This paradigm shift has enabled researchers to tackle the challenge of predicting next locations. However, the public unavailability of some of these datasets makes it difficult to reproduce results. To address this, Wu et al. [56, 70] have compiled a comprehensive set of human mobility datasets, and Luca et al. [32] have curated a valuable repository (note that not all datasets are suitable for individual-level next location prediction due to some being group-level datasets like crowd flow data). In this section, we will categorise and summarise datasets explicitly employed by researchers in the field of next location prediction. A detailed overview of these datasets, including their types, sizes, usage scenarios and key features, is provided in Table 2 to enhance clarity and facilitate comparisons.

4.1.1 GPS Traces. A typical GPS trace consists of tuples $(u, t, lat, long)$, where u represents the user's ID, t is the timestamp and lat and $long$ denote the latitude and longitude of a specific location, respectively. This type of data often requires preprocessing to mitigate noise and handle missing information. As GPS data are considered raw, preprocessing is essential to extract contextual details such as semantic labels of locations and temporal context (e.g., day of the week, hour of the day). This conversion from raw GPS data to a format compatible with context-aware models facilitates subsequent analysis. GPS traces are frequently captured at predefined intervals by embedded positioning devices, making this data collection passive in nature. Noteworthy GPS traces datasets commonly employed for next location prediction tasks include:

GeoLife Dataset. The GeoLife dataset was assembled as part of the Microsoft Research Asia GeoLife project [71]. Over a span of 3 years (from April 2007 to August 2012), 182 users contributed to this dataset. It encompasses 17,621 trajectories, covering a cumulative distance of approximately 1.2 million kilometres and a total duration exceeding 48,000 hours. Diverse GPS loggers and GPS-equipped phones were employed to capture these trajectories at varying sampling rates. Notably, 91% of the trajectories were recorded using dense sampling strategies, such as intervals of 1–5 seconds or distances of 5–10 metres between consecutive points. This dataset comprehensively documents a wide spectrum of users' outdoor movements, encompassing daily routines like commuting to work or returning home, as well as recreational and sporting activities like shopping, sightseeing, dining, hiking and cycling.

T-Drive Dataset. The T-drive dataset originates from the T-drive project [67], offering a real-world and extensive collection of taxi trajectory data. This dataset encompasses a remarkable 580,000 taxi trajectories recorded within the city of Beijing. The trajectories collectively span a distance of 5 million kilometres and encompass a staggering 20 million GPS data points.

GeoPKDD Dataset. The GeoPKDD dataset is a compilation of trajectory data derived from cars fitted with GPS receivers, operating within the city of Milan over a span of 1 week. This dataset was curated as part of the GeoPKDD project [21], and it presents a comprehensive overview of vehicular movement patterns and trajectories within the urban context.

4.1.2 LBSNs Data. Social media posts shared by users can either include or omit geographical information about their locations. Platforms like Facebook and X, for instance, may contain posts

Table 2. Summary of Datasets for Next Location Prediction

Category	Dataset	Type	Size	Usage Scenarios	Key Features
CDRs	Varies by provider	Mobile Network Data	Depends on the telecommunication provider; dataset sizes vary widely based on the number of users, events and duration covered	Analysing user mobility patterns, network optimisation	Records communication events (e.g., calls, texts) with timestamps and tower locations; useful for large-scale population studies
GPS Traces	GeoLife	GPS Trajectories	17,621 trajectories; 1.2M km	Daily routines, recreational activities	Dense sampling (1–5 seconds or 5–10 metres); diverse movement patterns
	T-drive	Taxi Trajectories	580,000 trajectories; 20M GPS points	Urban taxi operations	Real-world, large-scale taxi data; focuses on urban transportation dynamics
	GeoPKDD	Vehicular Trajectories	1-week data from Milan	Vehicular movement patterns in urban areas	Urban traffic analysis; car-based trajectory data
LBSNs	Foursquare	LBSN Check-ins	33,278,683 check-ins by 266,909 users across 3,680,126 venues in 415 cities over 18 months	Social and geographical behaviour analysis	Long-term, global-scale check-in data; includes semantic labels; diverse user activity patterns
	Gowalla	LBSN Check-ins	196,591 users, 950,327 social connections and 6,442,890 check-ins from February 2009 to October 2010	User mobility and social interaction analysis	Combines spatiotemporal data with social network information; includes precise timestamps and geolocation coordinates for each check-in
	AllTrails (Every-Trail)	Trip-sharing and Social Networking	Data size depends on the selected activities and trips, which can be customised through web crawling	Personal travel planning, tourist navigation	Includes GPS logs, photos and labelled activities; focuses on trips with stay points (e.g., sightseeing, walking)
	Brightkite	LBSN Check-ins	58,228 users, 214,078 social connections and 4,491,143 check-ins from April 2008 to October 2010	Social mobility patterns, check-in behaviour	Combines spatiotemporal data with social network information; includes precise timestamps and geolocation coordinates for each check-in
	X	Geo-tagged Tweets	1.1 million geo-tagged tweets from Los Angeles collected from August 2014 to November 2014	Sentiment analysis, sparse trajectory analysis and event detection	Includes anonymised user IDs, GPS coordinates, timestamps and messages; sparse as location services are infrequently used

with geographic details such as POI names or latitude/longitude coordinates. Conversely, platforms like Foursquare and Gowalla necessitate users to explicitly specify their locations in each shared post, leading to what is termed as geo-tagged social media posts. A geo-tagged post on social media refers to any content, be it text, photos or videos, shared by a user. This content is associated with geographical information indicating the user's location. Depending on the platform, this location information might manifest as venue identifiers, categories or geographical coordinates, along with a timestamp denoting the time of the post. Such a specialised form of social media, wherein all posts are required to be geo-tagged, is commonly referred to as LBSNs. The general term used for user-shared content on LBSNs is 'check-ins'.

While data gathered from these LBSNs significantly contributes to the task of predicting the next location, other social networks also possess substantial amounts of geo-tagged content. The value of these data is further augmented by the spatiotemporal context present in the posts, which can include text, photos and videos. Another notable aspect of social network data is the presence of friendship links between users. As previously mentioned, researchers have extensively explored how these social connections and relationships can impact human mobility and its predictability [8, 55]. However, this type of data is not without limitations. Given that social media posts are typically shared voluntarily by users, they fall under the category of actively recorded data. Users' locations are only recorded when they actively post something or check-in at a location, which gives rise to the issue of data sparsity. To facilitate research, most social networks offer APIs for data retrieval, albeit often subject to restrictions such as a limit on the number of downloadable posts or queries per day. Commonly employed social network datasets for next location prediction tasks encompass platforms like Foursquare [60], X, Gowalla [8], Brightkite [8], Jiepang (a Chinese LBSN) and AllTrails (formerly known as EveryTrail).

4.1.3 CDR. A CDR refers to a data record generated by a telephone exchange or similar telecommunications equipment. It serves to document the specifics of a communication event, encompassing calls and other telecommunication transactions such as text messages and data usage, that traverse through the said facility or device. These records play a pivotal role in various aspects, including billing and operational management. Telecom service providers maintain these data for diverse purposes.

In the context of CDRs, each user's connection to a **Radio Base Station (RBS)**, responsible for covering a designated geographical area, assumes significance. Consequently, each CDR encapsulates pertinent details such as the identities of the involved users in the communication, the corresponding RBS assignment during the transaction, the timestamp of the communication event and supplementary information. However, a notable drawback associated with this data type is the inherent data sparsity. User location information is only logged when users engage in telecommunication interactions, contributing to a scarcity of location data.

Another limitation pertains to the manner in which user locations are recorded within CDRs. As highlighted earlier, these records often log the ID or location of the RBS that facilitated the user's network connection, rather than the precise user location. This practice compromises the accuracy of the provided location information. Given the sensitive nature of the personal information contained within CDRs, they are generally not accessible to the public. In certain cases, access may be granted for research purposes, contingent upon approval. Nonetheless, this restricted availability hampers the reproducibility of results derived from using CDR data for training and evaluation purposes.

4.2 Next Location Prediction Evaluation Metrics

The next location prediction problem is approached by the analysed studies through two primary methods. The first method involves predicting the precise geographical coordinates of a user's next location. Here, the problem is framed as a regression task, with the target variables being the future longitude and latitude coordinates. Evaluating the performance of models in this scenario entails employing distance metrics.

Conversely, the second method treats the problem as a classification task, aiming to predict the subsequent place, venue or POI that the subject will visit. This approach is inherently more context-aware compared to the former, as it incorporates semantic attributes of the locations, venue categories and the user's activities during their time at those locations.

Another subset of methods adopts a different approach by dividing the spatial map into grids of uniform size. The objective is to predict the specific grid cell where a user or device will be situated next. While this method falls under the classification-based approach, it shares similarities with regression-based techniques from the context-awareness perspective.

4.2.1 Distance Metrics. For approaches treating the next location prediction problem as a regression task, the objective is to forecast the precise future location of the subject. The evaluation of these models is centred around the discrepancy between the predicted geographical location and the actual location [8, 61].

Distance metrics play a crucial role in this evaluation. Typically, the distance between two points can be quantified using either the Euclidean distance or the haversine distance, which calculates the angular separation between two points on the surface of a sphere. The haversine distance between two points $p_1(\phi_1, \lambda_1)$ and $p_2(\lambda_2, \lambda_2)$ is computed using Equation (6).

$$distance_h = 2R\ arcsin(\sqrt{sin^2(\frac{\phi_2 - \phi_1}{2}) + cos\phi_1.cos\phi_2.sin^2(\frac{\lambda_2 - \lambda_2}{2})}). \tag{6}$$

Here, ϕ and λ represent the latitude and longitude of a point, respectively. After calculating the distance error for each prediction query, performance metrics like **Mean Average Error (MAE)**, MSE or **Root Mean Squared Error (RMSE)** are employed to indicate the model's average error (Equations (7), (8) and (9)). However, it's important to note that comparing this metric across different users might introduce bias, as users with larger gyration radius tend to have higher average errors. To address this, the MAE can be normalised by dividing the average error of each user by their corresponding average gyration radius.

$$MAE = \frac{1}{|Q|} \sum_{i=1}^{Q} Distance(True, Prediction) \tag{7}$$

$$MSE = \frac{1}{|Q|} \sum_{i=1}^{Q} Distance^2(True, Prediction) \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{Q}\ Distance^2(True, Prediction)}{|Q|}}. \tag{9}$$

4.2.2 Classification and Ranking Metrics. For approaches treating the next location prediction as a classification problem, the focus is on predicting the discrete venue or place the subject will visit next, or ranking the most probable venues. Several metrics are commonly used to evaluate these methods, each shedding light on different aspects of model performance [30, 31].

Precision/Accuracy. Precision, also referred to as accuracy in some studies, reflects the model's precision. It is calculated as the ratio of correct predictions to all predictions made (Equation (10)) [5, 37].

$$accuracy/precision = \frac{correct\ predictions}{predictions\ done} = \frac{p^+}{p^+ + p^-}. \tag{10}$$

Here, p^+ and p^- represent the number of correct and incorrect predictions. A variant of accuracy, known as acc@K, is used. In this case, a prediction is considered correct if the actual next location (ground truth) appears within the top-X predicted places.

Coverage and Recall. Coverage, or prediction rate, is employed by both regression- and classification-based models to showcase the model's prediction ability. It's the proportion of prediction queries for which the model delivered a result (true or false) out of the total requested queries ($|R|$)

(Equation (11)) [38, 58, 61].

$$coverage = \frac{predictions\ done}{predictions\ requested} = \frac{p^+ + p^-}{|R|}. \tag{11}$$

Recall offers a comprehensive view of precision and coverage, calculated by dividing the number of correct predictions by the total number of predictions requested (Equation (12)).

$$recall = \frac{correct\ predictions}{predictions\ requested} = \frac{p^+}{|R|}. \tag{12}$$

Similar to accuracy, recall can be applied as recall@K to alleviate result stringency.

F-Measure. The F-measure, also known as F-score or overall performance, combines precision and recall. It's the harmonic mean of these two metrics (Equation (13)) [8, 30, 31, 64]. The F-measure assesses a classifier's ability to predict accurately (correctly classifying instances) and robustly (not missing a significant number of instances). A high-precision, low-recall classifier is highly accurate but misses hard-to-classify instances. Conversely, a high-recall, low-precision classifier provides a prediction for every query but has mostly incorrect predictions. Some studies calculate F-measure@K using acc@K and recall@K (Equation (14)).

$$F - measure = 2 \,.\, \frac{precision \,.\, recall}{precision + recall} \tag{13}$$

$$F - measure@K = 2 \,.\, \frac{acc@K \,.\, recall@K}{acc@K + recall@K}. \tag{14}$$

Mean Reciprocal Rank (MRR). The MRR measures processes that provide lists of possible responses to questions, ordered by how likely they are to be correct. When we look at the order of correct answers, the rank is given as a fraction: 1 for the first place, $\frac{1}{2}$ for the second place, $\frac{1}{3}$ for the third place and so on [5, 26, 59]. The average of these fractions for a group of questions Q gives us the MRR. This measure is stricter than accuracy and acc@K because it considers both how well the correct answer is ranked and its actual rank.

$$MRR = \frac{1}{|Q|} \sum_{i=1}^{Q} \frac{1}{rank_i}. \tag{15}$$

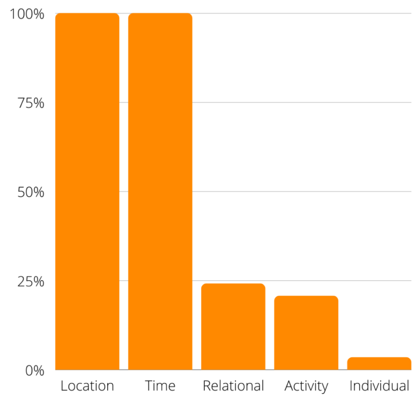
Average Percentile Rank (APR). The APR is found by calculating the average of **Percentile Rank (PR)** scores for all user check-in predictions [39, 55]. It shows the average position of the correct answer in the list of ranked answers (Equation (16)). A PR score of 1 means the predicted place is ranked first, and the score decreases linearly to 0 as the correct place's rank goes down (N is the total number of possible places).

$$APR = \frac{1}{|Q|} \sum_{i=1}^{Q} \frac{N - rank_i + 1}{N}. \tag{16}$$

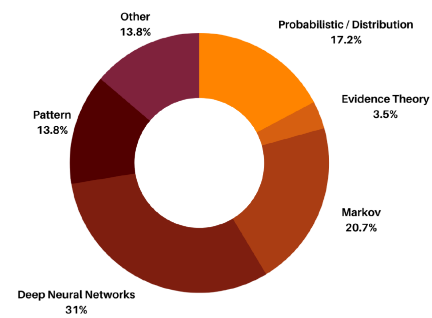
5 Critical Discussion of Strengths and Weaknesses of Existing Approaches

In this section, we summarise and discuss the findings of this survey. Figure 6(a) demonstrates the proportion of papers that used each type of context. According to this chart, all the papers we analysed incorporate spatiotemporal context for predicting the next location. Less than 25% of the studies used activity and relational context. Individual context (containing information about the entity's profile containing his schedule, tasks, habits, etc.) was used by only one study.

A comprehensive study on the effectiveness of incorporating various types of context in next location prediction is notably absent from current literature. While existing studies primarily utilise



(a) Proportion of papers that incorporated different context categories for next location prediction



(b) Proportion of different methods exploited for next location prediction

Fig. 6. Summary of contextual information and methods used for addressing the next location problem.

location and time contexts to address this task, the potential benefits of incorporating activity, relational and individual context types remain underexplored.

Nevertheless, some studies have begun to investigate these overlooked types of contextual information, demonstrating promising results in enhancing next location prediction. Despite the general lack of studies specifically aimed at examining the effectiveness of integrating different context types into this problem, insights can be gleaned from several notable findings. For instance, approximately 25% of surveyed studies included activity context in their experiments, yet only two reported performance metrics with and without this context [43, 62]. According to [43], incorporating a user's last activity improves prediction accuracy by 3%, while [62] found that semantic information about user activities can increase accuracy by 6%.

Regarding relational context, five studies provide compelling evidence of its effectiveness in predicting next locations [7, 8, 19, 20, 39]. For example, [8] suggests that social relationships can explain between 10% and 30% of human movement, with periodic behaviour accounting for 50–70%. Noulas et al. [39] explore the impact of Global Mobility data (aggregated data from all users) on predicting individual mobility patterns, finding that it explains an average of 15% of such patterns. Gao et al. [19, 20] highlight the role of social-historical ties in LBSNs, showing that friends tend to share more check-ins than strangers, leading to an 8% performance improvement on average when incorporating social correlations. Furthermore, [7] demonstrate that omitting temporal, spatial and social context extractors from their models decreases prediction accuracy, with social context contributing approximately 2% to overall accuracy.

Individual context remains largely overlooked in studies of human mobility prediction. As illustrated in Table 1 and Figure 6(a), only [44] integrates individual context such as user tasks, schedule and interests into their analysis. However, gathering individual context poses significant challenges including data collection logistics and privacy concerns. Unlike spatiotemporal data easily collected via smartphones or GPS devices, personal details like appointments or health status require sensitive handling to avoid privacy breaches and misuse. However, to achieve more accurate predictions and services to the users, some privacy concerns may have to be relaxed.

In conclusion, while there is insufficient evidence on the comprehensive effectiveness of different context types in next location prediction, several studies demonstrate promising results for various context types. Future research should delve deeper into these areas to better understand their impact and potential for enhancing predictive models.

Regarding prediction methods exploited for the next location prediction task, there are some pros and cons to each method category. Figure 6(b) demonstrates the exploitation ratio of different prediction methods by the papers we analysed in the previous section. Nearly 30% of the articles exploited DL-based approaches to tackle the next location prediction task, followed by Markov-based, probabilistic/distribution-based and pattern-based methods by 20, 17 and 14%, respectively.

Comparing the experimental performance of different methods in the domain of next location prediction faces two significant challenges. The first challenge is that studies proposing innovative methods within each category explained in the previous section typically compare their proposed method's performance with baseline and naive methods[3] or with other models within the same category [7, 19, 20, 28, 31, 33, 37]. Even when methods from other categories are included, results are often compared with a baseline or simple method from another category. The second challenge is that different studies use different datasets and metrics to evaluate their proposed methods. Furthermore, even when the same datasets are used, each study applies its own tailored data cleansing and filtering methods, making cross-study comparison difficult. However, in the following discussion, we will explore the advantages and drawbacks of each method and compare their performance where possible, referencing studies that provide experimental comparisons.

The work by Saman and Karmouch [44] is the only study applying an evidence theory-based method to the 'next location prediction' problem. The significance of this study lies in its incorporation of individual context into the prediction problem. However, the model's performance was not compared with any other methods nor has it been evaluated by any subsequent studies.

Distribution and probabilistic-based approaches rely on the temporal aspect of movements and predict the probability of each location to be visited next, based on the temporal occurrence of visits in the past [8]. These techniques model mobility behaviour by considering location, time and other variables as independent variables. Although probabilistic theories such as Bayes' theorem provide foundations to accumulate evidence from existing context and ignore it in case of missing evidence, the independency assumption between different variables limits their prediction ability.

Markov model-based methods using the Markov property (the future location of an entity depends only on its current or last several locations) cannot capture the long-term dependency of regular movements and only consider the short-term history in predicting the next location. These models do not utilise the temporal context fully and only use it to extract the sequence of transitions between different locations. Markov model-based approaches share these two disadvantages with pattern-based methods.

Traditional ML approaches demand substantial efforts in feature engineering, a complex and time-intensive procedure reliant on domain expertise. Furthermore, this process may inadvertently overlook valuable features. In contrast, DL-based methods have demonstrated encouraging performance across various domains, including spatiotemporal challenges. Leveraging their distinctive capacity for automatic feature selection and extraction, coupled with their adeptness at discerning intricate patterns and approximating complex functions, DL methods can proficiently grasp the spatial, temporal, social and geographic aspects of human mobility. This is achieved through the utilisation of CNNs for spatial context, RNNs for temporal context and attention mechanisms for capturing long-term dependencies.

However, a considerable amount of data is required to enable a DL-based model to extract appropriate features and successfully capture complex patterns. The lack of enough data for training the model brings down their performance extensively, which is their main drawback compared to their rivals. It also requires expert knowledge for designing the proper network architecture

[3]e.g., the most frequent location method, which predicts the next location as the most frequently visited venue by a user at the time of prediction.

and tuning hyper-parameters. Another drawback to these models is that they are less interpretable than the traditional ML approaches.

In seeking insights into the experimental performance of different methods in this domain, we identified a few studies which have compared their proposed models with methods from different categories [14, 26, 30, 37, 59, 62, 63]. With the exception of [30], all these studies propose neural network-based models (mostly RNNs). This is to be expected, as NN-based models are part of the most recent research, which necessitates comparing new models with previously established ones to validate their performance. Nearly all the baseline methods used in these studies are Markov-based models, which are typically outperformed by the proposed NN-based methods. For example, [26] compares their proposed model's performance with two Markov-based methods, resulting in an average 8% improvement in accuracy.

Additionally, [31, 59] provide comprehensive performance comparisons between their proposed models and various types of NN-based models. For instance, [59] compares their results with three Markov-based methods and several RNN variations using the Gowalla and Foursquare datasets. They outperform Markov-based models by an average of 4% on the Gowalla dataset and 15% on the Foursquare dataset. They also demonstrate that their model surpasses simple RNNs and tailored RNNs for location prediction (e.g., [14]) by 2% and 3% on the Gowalla dataset and by 7% and 1% on the Foursquare dataset. Another study that compared their model's performance with Markov-based methods and other NNs is [63]. The findings demonstrate that their model achieves a next location prediction accuracy of 87.63%. When compared to other NN-based methods and Markov models, the accuracy is improved by 2.28% and 17.64%, respectively.

As we will discuss it further in the future works section, obtaining valuable insights into the performance comparison of different method categories requires examining the performance of state-of-the-art methods from each category on the same datasets using consistent evaluation metrics.

6 Open Challenges and Future Work

This section will discuss the open challenges and possible future work in the next location prediction domain.

6.1 Data Collection

One of the challenges that future research on this subject faces is data collection and acquisition. As explained before, most methods are dependent on data for their training and evaluation phases. Researchers rely on existing datasets such as GPS traces, CDRs and LBSN check-in datasets; however, the contextual information provided by these datasets is limited, making it difficult to extract meaningful insights and semantics. Although data collected from LBSNs contains location, time, activity and relational context, this data source suffers from the lack of useful individual context and data sparsity problems. Unlike GPS traces and CDR data, which are collected regularly, LBSN posts are shared actively by the users (voluntarily). There may be workarounds to this challenge. One solution is trying to collect large-scale semantically enriched information [27]. Another solution is fusing contextual information from multiple data sources and accumulating existing evidence that helps achieve a better prediction [44, 55].

6.2 Randomness and Prediction Accuracy

Although mobility behaviour follows some patterns and humans usually commute based on regular patterns, there is inherent randomness in it to a certain level. According to the findings of [48] the maximum predictability of human mobility can reach up to 93% if all the regularities and patterns are adequately captured, and the remaining 7% follows a random, stochastic and unpredictable pattern.

Cho et al. [8] show that periodic mobility behaviour of the users explains 50–70% of all human movement while social relations can explain 10–30% of it. As another exploration into human mobility, Cuttone et al. [11] report that for each user, on average, only 5–10% of the places are visited more than once, and they visit 70% of the venues only once and 20–25% of the destinations are new places. All these findings point to the importance of studying the exploring attitude of human mobility behaviour alongside mining regularity patterns. One solution to tackle this challenge is predicting a user's intention to explore before attempting to find his/her future location based on his/her movement pattern. This issue can be addressed by combining the problem of movement pattern mining which tries to capture the regularities in movement behaviour, with the problem of the (next/sequential) POI recommendation, which focuses on finding the new venues that probably the user will be interested in visiting.

6.3 Privacy Preservation

The analysis of mobility behaviour offers both opportunities and privacy risks to users. Existing methods addressing the next location prediction challenge require access to diverse contextual information linked to users to achieve accurate predictions. This information encompasses location, time, social relationships, activities and personal data collected from GPS devices, smartphones and social media platforms. Consequently, ensuring privacy preservation becomes of paramount importance for individuals utilising these services [15, 58]. Such information could empower malicious entities to deduce users' mobility patterns, discern their residential and workplace locations and construct detailed models of their routine movements and social networks. These privacy threats extend beyond mere knowledge of an individual's whereabouts. With the digitisation of vehicles gaining momentum, the susceptibility to cyberattacks has increased, elevating the significance of privacy preservation. Unauthorised access to users' personal information, particularly their location and daily routines, amplifies the potential for malicious actors and heightens the risk of successful cyberattacks.

6.4 Cold Start and Data Sparsity

Various studies addressed the problem of cold start; however, some aspects of this problem remain unsolved. The cold start issue arises when there is no or few historical data for a user. In this case, the standard approach is to match the user's current trajectory's pattern (since it may be the only spatiotemporal information in hand) with similar other users may give us intuition about predicting the user's next destination. Individual contextual information can play a crucial role in tackling the cold start problem. This type of context refers to the information about the entity itself and is independent of time and location, so it changes with less frequency. Incorporating this context into the prediction task can help recognise the user's personality, which may lead to a better guess about their movement patterns. As a future direction to address this issue, rule-based methods can also be considered.

The data sparsity problem concerns the situation where the spatiotemporal data is not dense enough to illustrate the whole movement patterns of the users. The sparsity depends on the source of data used for training and inference. As discussed in Section 4.1, GPS trajectory sources are sufficiently dense, but noise filtering, extracting semantics and meaningful concepts from this type of data remains a challenging task. On the other hand, LBSN data are semantically rich; however, since they are recorded voluntarily by the users, this data source suffers from the data sparsity problem the most. CDR data sources also lack adequate denseness because they only contain records of telecommunication transactions. Also, the location data in these datasets are not accurate enough to enable semantics extraction since they log the locations of RBSs instead of the users. Overall, the GPS trajectory data seems to be the best data source for this task. However, semantic information should be extracted to obtain contextual information about the places and achieve context-aware predictions.

6.5 Future Work

In the rapidly evolving field of next location prediction, several promising research directions warrant further exploration to enhance the accuracy and applicability of predictive models. Below, we outline key areas for future investigation:

6.5.1 Incorporation of Multi-Modal Contextual Data. Future research should focus on integrating a broader range of contextual data, including environmental, social and user-specific factors, to improve prediction accuracy. For instance, combining data from weather reports, social media activity and personal schedules could provide a more holistic understanding of user mobility patterns. This multi-modal approach could help in capturing the diverse influences on individual movement decisions, leading to more precise predictions.

6.5.2 Advanced ML Techniques. Exploring advanced ML techniques, such as reinforcement learning and transfer learning, offers significant potential for improving next location prediction models. Reinforcement learning can adaptively learn user preferences and mobility patterns in real-time, while transfer learning can leverage knowledge from related tasks or domains to enhance model performance, especially in scenarios with limited training data.

6.5.3 Privacy-Preserving Prediction Models. As the use of personal data becomes increasingly scrutinised, developing privacy-preserving prediction models is crucial. Techniques such as federated learning and differential privacy should be investigated to ensure that predictive models can operate effectively without compromising user privacy. These methods allow for the aggregation and analysis of mobility data in a secure manner, fostering user trust and compliance with data protection regulations.

6.5.4 Real-Time Prediction and Adaptability. Future models should aim for real-time prediction capabilities to provide immediate and actionable insights. This involves developing algorithms that can process and analyse data on-the-fly, adjusting predictions dynamically as new information becomes available. Enhancing the adaptability of prediction models to changing user behaviour and environmental conditions is essential for maintaining accuracy over time.

6.5.5 Cross-Domain Applications. Expanding the application of next location prediction beyond traditional domains such as transportation and urban planning could reveal new opportunities and challenges. For example, applying these models in healthcare to predict patient movements within hospital environments or in retail to anticipate customer flows can offer valuable insights and improve operational efficiency in various sectors.

6.5.6 Evaluation Metrics and Benchmarking. Developing standardised evaluation metrics and benchmarking datasets is vital for assessing the performance of next location prediction models. Establishing common benchmarks will facilitate the comparison of different approaches and promote the development of more robust and generalisable models. Future research should focus on creating comprehensive and publicly available datasets that reflect diverse real-world scenarios.

6.5.7 Incorporating Uncertainty and Probabilistic Models. Addressing the inherent uncertainty in human mobility is another critical area for future work. Probabilistic models and methods that explicitly account for uncertainty can provide more realistic and reliable predictions. Exploring techniques such as Bayesian inference and stochastic processes will help in quantifying and managing the uncertainty associated with next location predictions.

By pursuing these directions, future research can build on the current state-of-the-art to develop more accurate, reliable and versatile next location prediction models, ultimately enhancing their practical utility across various applications.

7 Conclusion

This article presents a comprehensive overview of recent advances in addressing the next useful location prediction problem by examining the context-awareness aspect. Thirty-four studies in this field are analysed and categorised based on their methods, the contextual information incorporated, the challenges addressed and the datasets used. These method categories consist of evidence theory-based, neural networks-based, pattern mining-based, distribution, probabilistic-based and hybrid methods. An operational definition of contextual information comprising individual, location, time, activity and relational context is considered to examine these studies from the context-awareness perspective. We discuss the strengths and weaknesses of the existing methods focusing on their ability to employ different context categories. To the best of our knowledge, our survey is the first study to highlight the critical role of context-awareness in next location prediction. Finally, we presented some of the open problems and pointed out the future research directions for this field.

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