

# Deep Learning for Trajectory Data Management and Mining: A Survey and Beyond

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**Abstract**—Trajectory computing is a pivotal domain encompassing trajectory data management and mining, garnering widespread attention due to its crucial role in various practical applications such as location services, urban traffic, and public safety. Traditional methods, focusing on simplistic spatio-temporal features, face challenges of complex calculations, limited scalability, and inadequate adaptability to real-world complexities. In this paper, we present a comprehensive review of the development and recent advances in deep learning for trajectory computing (DL4Traj). We first define trajectory data and provide a brief overview of widely-used deep learning models. Systematically, we explore deep learning applications in trajectory management (pre-processing, storage, analysis, and visualization) and mining (trajectory-related forecasting, trajectory-related recommendation, trajectory classification, travel time estimation, anomaly detection, and mobility generation). Notably, we encapsulate recent advancements in Large Language Models (LLMs) that hold the potential to augment trajectory computing. Additionally, we summarize application scenarios, public datasets, and toolkits. Finally, we outline current challenges in DL4Traj research and propose future directions. Relevant papers and open-source resources have been collated and are continuously updated at: DL4Traj Repo.

Project Page: [https://github.com/yosshall/Awesome-Trajectory-Computing](https://github.com/yoshall/Awesome-Trajectory-Computing)

**Index Terms**—Trajectory Data Mining, Trajectory Data Management, Deep Learning, Spatio-Temporal Data Mining, Urban Computing



## 1 INTRODUCTION

Since time immemorial, humanity has tirelessly attempted to study the science of mobility, driven by the fundamental laws that emerge from the micro and macro trajectory movements of objects [1]–[4]. The study of trajectories can be traced back as far as the 1960s. Researchers used various marking methods to track the movement trajectories of animals, discovering for the first time that movement behavior patterns possess geographical features and positivity among other patterns [5]. By the end of the 20th century, with the rapid development of Global Positioning System (GPS) and Geographic Information System technologies, it became possible to track spatial movement trajectories with long-term, high precision, and high efficiency. This includes volunteer positioning data, GPS-equipped travel trajectories, mobile terminal positioning, and communication records [6], [7]. These advancements have fueled the rise of trajectory research as a discipline, with wide-ranging applications in areas such as intelligent transportation [8]–[10], public safety [11]–[13], and business services [14]–[16].

However, the effective management and mining of the vast records of highly refined trajectories and quantitative spatio-temporal distribution data poses an urgent challenge

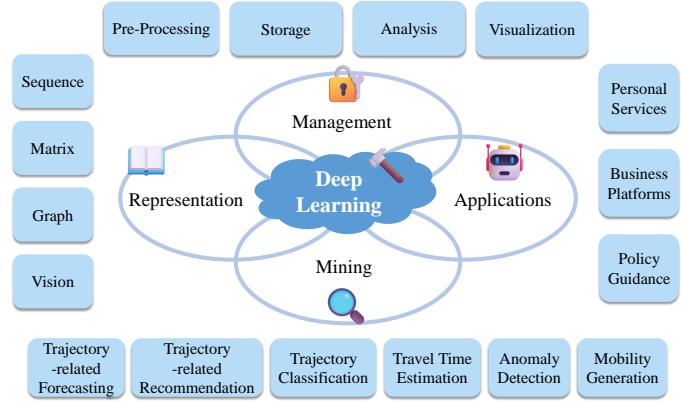


Fig. 1: Trajectory computing overview.

that needs to be addressed. Over the past two decades, many technologies have been proposed for processing, managing, analyzing, and mining trajectory data [31]–[33], leading to the development of a comprehensive framework and theory for trajectory computing. This includes the full process breakdown of trajectory computing analysis, covering trajectory pre-processing, trajectory indexing and retrieval, trajectory pattern mining, uncertainty modeling, and more. These processes are typically loosely coupled, with numerous efficient algorithms developed for different stages. For instance, in trajectory pre-processing, a series of techniques such as map matching and stay point detection have been developed [33]. For trajectory retrieval and indexing, a series of technologies have been developed, including similarity linking, regional querying, semantic querying, etc [23], [34]. Despite these advancements, the following challenges remain: 1) *Lack of uniformity*. Traditional trajectory analysis and processing

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TABLE 1: Comparison between this and other related surveys on data formats (i.e., sequence (S), matrix (M), graph (G), and vision (V)), relevant techniques (i.e., traditional methods (TM), deep learning (DL), and large language model LLM), management tasks (i.e., pre-processing (P), storage (S), analytics (A), and visualization (V)), and mining tasks (i.e., forecasting (F), classification (C), recommendation(R), estimation (E), generation (G), and detection (D)). The number of downstream applications and publicly available datasets are also included. Besides, ✓ indicates content is covered, ✗ indicates that content is not covered, and ~ indicates that content is partially covered.

Survey	Year	Formats				Techniques			Management				Mining					#Applications	#Public Datasets	
		S	M	G	V	TM	DL	LLM	P	S	A	V	F	R	C	E	G	D		
Zheng <i>et al.</i> [17]	2015	✓	✓	✓	✗	✓	✗	✗	✓	✓	✓	✓	✗	✗	✓	✓	✗	✓	6	10
Feng <i>et al.</i> [18]	2016	✓	✗	✓	✗	✓	✗	✗	✓	✓	✓	✓	✗	~	~	~	✗	✗	6	✗
Mazimpaka <i>et al.</i> [19]	2016	✓	✓	✓	✗	✓	✗	✗	✗	✗	~	✗	✓	✓	✓	✗	✗	✓	13	✗
Bian <i>et al.</i> [20]	2018	✓	✓	✗	✓	✓	✓	✓	✗	~	✗	✓	✗	✗	✗	✗	✗	✗	7	✗
Bian <i>et al.</i> [21]	2019	✓	✓	✗	✓	✓	✓	✓	✗	~	✗	✓	✗	✗	✓	✗	✗	✗	7	6
Koolwal <i>et al.</i> [22]	2020	✓	✓	✓	✗	✓	✓	✓	✗	✓	✗	✓	✗	✓	~	~	✗	✗	9	18
Wang <i>et al.</i> [23]	2021	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	✓	✗	~	✓	✓	~	~	13	20
Luca <i>et al.</i> [24]	2021	✓	✓	✓	✗	✓	✓	✓	✗	✗	✗	✗	✓	✓	✗	✗	✓	✗	7	18
Aghababa <i>et al.</i> [25]	2022	✓	✗	✗	✓	✓	✓	✓	✓	✗	✓	✗	✗	✗	✓	✗	✗	✗	6	
Shaygan <i>et al.</i> [26]	2022	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	✓	✗	✓	✗	✓	✓	✓	6	18
Duarte <i>et al.</i> [27]	2023	✓	✗	✗	✗	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	4	
Hu <i>et al.</i> [28]	2023	✓	✓	✓	✗	✓	✓	✓	✗	~	~	✓	✗	✗	✗	✗	✗	✗	4	
Chang <i>et al.</i> [29]	2023	✓	✗	✓	✓	✓	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	5	
Graser <i>et al.</i> [30]	2024	✓	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	~	✓	✓	8	17
<b>This Survey</b>	2024	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	15	38

problems require using different tools, such as rule-based and probabilistic tools, in conjunction with the problem scenario, making the problem modeling process difficult to unify. 2) *Complexity*. Raw trajectory data usually contain complex spatio-temporal heterogeneity and auto-correlation, making it difficult to capture their intrinsic features through feature engineering and simple expert manual rule design. 3) *Adaptability*. Traditional trajectory technologies often face the curse of dimensionality when dealing with massive data, and usually find it hard to adapt to new application scenarios.

In recent years, we have witnessed the rapid rise of deep learning in various fields [35], attributed to its remarkable end-to-end modeling and learning capabilities. More astonishingly, the reach of deep learning technologies has surpassed traditional data types such as images, audio, and text sequences, extending to more general or irregular data in spatial and temporal domains [36]. Among these, trajectory data is the most representative, encompassing multiple dimensions of space, time, and semantics. Therefore, leveraging the formidable power of deep learning, researchers have begun to reshape various key components in the computational framework of trajectory data, including efficient trajectory data management [23], effective trajectory data mining [24], and a variety of novel downstream applications [27] of trajectory data. Specifically, through the rich neural network architectures and learning paradigms, traditional issues are seamlessly transformed into learning tasks. Furthermore, by incorporating expert prior knowledge from fields such as spatial statistics, geometry, and geography, these models can effectively capture complex patterns within spatio-temporal trajectories, fostering the development of various novel applications. In Fig. 1, we provide an overview of deep learning for trajectory data.

**Related Surveys.** Despite the increasing number of studies employing deep learning approaches for various trajectory computing tasks, existing surveys often focus on specific viewpoints within a limited scope, with no survey

comprehensively summarizing the evolution and advancement of deep learning applied to trajectory data. For instance, several studies have individually delved into aspects of trajectory management such as clustering analysis [20], [37], similarity measurement [28], and privacy protection [38]. Likewise, certain research has independently centered on elements of trajectory data mining, including location prediction [22], [39], location recommendation [40], and arrival time estimation [16], [41]. However, their exploration not only limits to specific scenarios but also mentions deep learning techniques only partially. Furthermore, considering that trajectory data is an essential type of spatio-temporal data and the foundation of intelligent traffic analysis, numerous surveys have elucidated the relevant issues and applications of deep learning in spatio-temporal data mining [42]–[44] and intelligent traffic [45], [46], but with limited coverage of trajectory content. Recently, [30] and [24] provided a survey focusing on applying deep learning models in trajectory data mining, but they entirely overlooked the content of trajectory data management. In addition, a series of recent work on foundation models [47] has reshaped the deep learning community, such as large language model (LLMs) [48], [49]. Some studies are currently combining them for trajectory tasks, but there is no relevant review appearing yet. The aforementioned facts underscore the necessity for a comprehensive review. Tab. 1 encapsulates the distinctions between our and other analogous surveys.

**Our Contributions.** To fill the gap in existing literature, this study presents a systematic and up-to-date review of the current state of research on deep learning for trajectory computing. Our contributions are summarized as follows:

- **First Systematic Survey.** To the best of our knowledge, this is the first systematic survey that comprehensively reviews the latest developments of deep learning in the trajectory computing field. We not only offer the broadest research scope in the field but also showcase the most profound advancements, providing readers with a comprehensive

and up-to-date understanding of this topic.

- **Unified and Structured Taxonomy.** We propose a unified and structured taxonomy that categorizes the existing topic of deep learning in trajectory computing into three different parts. In the first part, we delineate forms of trajectory data in detail, covering all forms of trajectories found in different literature. In the second and third parts, we identify the various research tasks common in trajectory management and trajectory mining. In the final part, we present its practical applications and solutions in various fields, emphasizing its functional diversity and practical implications. This structured classification can help readers to fully understand the coherent roadmap of this field.
- **Comprehensive Resource Collection.** In this paper, we have initiated the DL4Traj project, wherein we have curated the most comprehensive collection of trajectory-related datasets and resources to date. We have open-sourced this continuously updated repository aimed at aiding individuals from diverse communities, including researchers, engineers, and urban planners. This repository covers a list of professional papers on deep learning methods and foundation models for trajectory data mining and management. It also integrates multiple types of datasets, including GPS, check-in, simulation, and associated statistical information.
- **Future Directions and Opportunities.** It is worth noting that deep learning has recently entered the era of large foundation models, with LLMs being a representative example. Due to their emerging knowledge intelligence, they have recently begun to sweep the entire research community. Some trajectory mining tasks have also been reshaped by incorporating LLMs. In this paper, we also combine and analyze some recent work in this area. Besides, we also outline several other potential future research directions and offer insights and suggestions that could guide and inspire future directions in the field of trajectory computing.

**Paper Organization.** The rest is organized as follows: Sec. 2 provides the basic definitions, diverse data formats, property analysis of trajectory, and background knowledge of deep learning. In Sec. 3, a taxonomy of deep learning for trajectory computing is presented, which will be detailed in Sec. 4. Sec. 5 encapsulates a multitude of application scenarios and resources. Sec. 6 outlines promising avenues for future research. Finally, we conclude this survey in Sec. 7.

## 2 PRELIMINARY

### 2.1 Definition and Notation

**Definition 1 (Spatio-Temporal Point).** A spatio-temporal point  $p$  is a unique entity in the form of  $(o, t, l, f)$ , where  $o$  represents the access of moving object  $o$  to location  $l$  at timestamp  $t$  under the geographical coordinate system, and comes with an optional record attribute feature  $f$ .

**Definition 2 (Trajectory).** A generalized trajectory  $T$  consists of a series of spatial-temporal point sequences  $(p_1, p_2, \dots, p_n)$  arranged in chronological order, which represents the movement information generated by moving objects in geographical space.

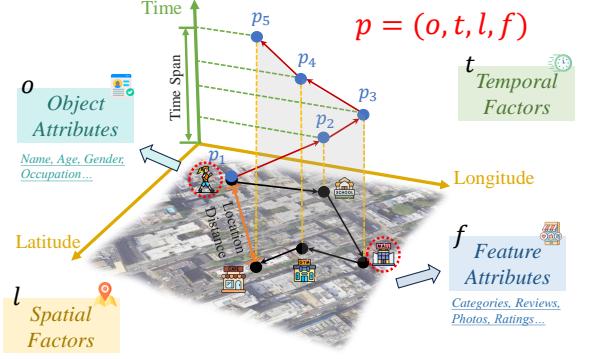


Fig. 2: Illustration of a trajectory.

Based on the fundamental attributes of spatio-temporal points, trajectory can be extended into multiple forms. Firstly, with respect to object attributes, we can categorize them into *Individual Trajectory*, representing quasi-continuous tracking data of individual movements, and *Group Trajectory*, which denote the movements of a group of individuals during the observation period, typically aggregated into edges/nodes, grids, or a set of Points of Interest (POI) in the mobility graph. Secondly, regarding time attributes, we can derive a spectrum of trajectories ranging from *Sparse Trajectory* (e.g., users' check-in data during travel) to *Dense Trajectory* (e.g., movement paths of vehicles equipped with GPS tracking systems) based on the dimension of sampling frequency. Thirdly, regarding location attributes, we can generate trajectories, also known as *Raw Trajectory*, by mapping coordinates to spatial embeddings to discretize the geographic space system. The newly generated sequence of discretized tokens is referred to as *Cell Trajectory*. Further, trajectories composed of tokens with attribute features are termed as *Semantic Trajectory*. The relationship of all the above attributes of trajectories is illustrated in Fig. 2.

### 2.2 Unique Properties of Trajectory Data

Trajectory data exhibits unique characteristics that are pivotal for understanding spatial-temporal movements and predicting urban mobility patterns. The following properties underscore the complexity and richness of trajectory data:

- **Spatio-temporal dependencies.** Trajectory data can be viewed as a series of spatial locations transitioning over time. These sequences reveal high-level patterns that reflect the spatio-temporal transfer modes and travel intentions of each moving objects. Such patterns are crucial for analyzing movement behaviors and forecasting mobility.
- **Personalization.** Trajectory data originates from specific individuals or entities, inherently containing personalized traits. These characteristics shed light on the preferences and mobility habits of the subjects, making it imperative to accurately model these personalized features. Doing so can significantly enhance the precision of various micro-level traffic behavior prediction tasks.
- **Irregularity.** The irregularity of trajectory is primarily due to the limitations of sampling devices or the necessity for data compression. This property means that models often lack sufficient supervisory information during training, for example, lacking the detailed path information between two locations can lead to performance deterioration on

forecasting tasks. Thus, accurately predicting movements in sparse trajectory data presents a substantial challenge.

Each of these properties contributes to the complexity of handling trajectory data, demanding sophisticated modeling techniques to accurately interpret and predict mobility patterns in urban computing contexts.

### 2.3 From Trajectory to Other Formats

The raw trajectory data can be adaptably formatted for various neural network architectures, enhancing its utility in diverse downstream tasks.

**Definition 3 (Matrix).** For a given city, we can divide it into multiple ( $N_1 \times N_2$ ) grids according to the latitude and longitude. Each grid represents a distinct region within the city. As a result, a trajectory can be represented as a continuous sequence of grid identifiers. For the origin, destination, and departure time of trajectories, we can construct the Origin-Destination (OD) matrix  $\mathcal{M} \in \mathbb{R}^{N_1 \times N_2}$  for any time, where each element represents the inflow and outflow in a particular grid.

**Definition 4 (Graph).** A road network for a city can be converted into a directed graph of roads  $\mathcal{G} = (\mathcal{V}, \mathcal{A})$ , where  $\mathcal{V}$  denotes the roads in the network, and  $\mathcal{A}$  represents the connectivity between the road segments. Consequently,  $\mathcal{A}_{ij} = 1$  if and only if road  $i$  and  $j$  can be directly connected. In this setting, the trajectory can be extracted as a sequence of roads based on the road segments that the trajectory passes through.

**Definition 5 (Image).** A raster image, denoted as  $\mathcal{I} \in \mathbb{R}^{H \times W \times C}$ , is composed of pixels arranged in a grid. Each pixel possesses specific semantic and positional information, forming the entire image in a predetermined order. Thus, trajectories can naturally be transformed into raster images. A simple and intuitive approach involves treating the entire map as a binary image, where pixels traversed by the trajectory are set to 1, and those not traversed are set to 0. Effective rasterization primarily considers trajectory shape, speed, and direction, which has been extensively studied in the literature [50], [51].

Trajectories can also be represented in other vision forms, such as converting them into bird's-eye view maps. However, this type of data is more closely related to computer vision and receives less attention in the trajectory data mining and management community. Therefore, we do not include this type of purely visual form here.

### 2.4 Background Knowledge of Deep Learning

Here we introduce basic neural building blocks and advanced learning paradigms for trajectory modeling.

**Learning Building Blocks.** *i)* *Fully Connected Networks (FCs)* [52] consist of a series of layers where all neurons are connected to neurons in the next layer (Fig. 3a). FC typically employs non-linear activation functions to map outputs, allowing them to serve as universal approximators. They are commonly used to model external factors, such as weather conditions or public events. *ii)* *AutoEncoders (AEs)* [53] are neural networks with an encoder and decoder, aiming to minimize the reconstruction error of input

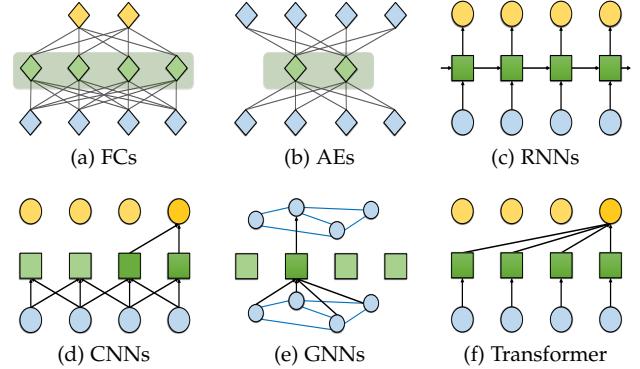


Fig. 3: Deep learning building blocks.

features. The original AE structure often utilizes FC layers for both encoding and decoding (Fig. 3b). AEs are commonly employed to compress and extract general features from road networks and trajectories. *iii)* *Recurrent Neural Networks (RNNs)* [54] effectively handle sequential data, capturing temporal transition patterns in trajectory sequences (Fig. 3c). Comprising an input layer, one or more recurrent hidden layers, and an output layer, RNNs are well-suited for modeling sequential dependencies in trajectory data. Popular variants of RNN include Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. *iv)* *Convolutional Neural Networks (CNNs)* [55] characterized by alternating convolutional and pooling layers (Fig. 3d), are adapted for trajectory computing either by converting trajectory data into raster images or by modifying convolutional kernels and pooling layers to suit trajectory data types. They excel in capturing hierarchical patterns, especially in tasks like traffic flow prediction using OD matrices. *v)* *Graph Neural Networks (GNNs)* [56] perform convolutions on graph-structured data, efficiently learning from node and neighbor information in the graph (Fig. 3e). GNNs are commonly employed to capture spatial dependencies in road network data. *vi)* *Attention Mechanism* [57] assigns varying weights to information at different positions in the input sequence, facilitating more effective capturing of relationships between inputs. *Transformer* [58] models extend attention mechanisms to sequence-to-sequence architectures (Fig. 3f), gaining popularity for their effectiveness.

**Learning Paradigms and Frameworks.** *i)* *Supervised Learning* involves training models on labeled datasets, where input-output pairs are known. It is widely applied in various tasks, such as trajectory prediction, where historical trajectories serve as input, aiming to predict potential future locations. *ii)* *Semi-Supervised Learning* combines both labeled and unlabeled data during training, leveraging information from both types. In situations where labeled trajectory data is limited, it proves beneficial by allowing models to utilize additional unlabeled data to enhance performance. *iii)* *Unsupervised Learning* aims to discover patterns and structures within unlabeled data. *Self-Supervised Learning*, a subset of unsupervised learning, generates supervisory signals from pretext tasks. It is extensively applied in trajectory representation learning, and subsequently applied in diverse downstream tasks. Advanced learning paradigms include *iv)* *Transfer Learning*, which involves leveraging knowledge obtained from one task to improve performance in related

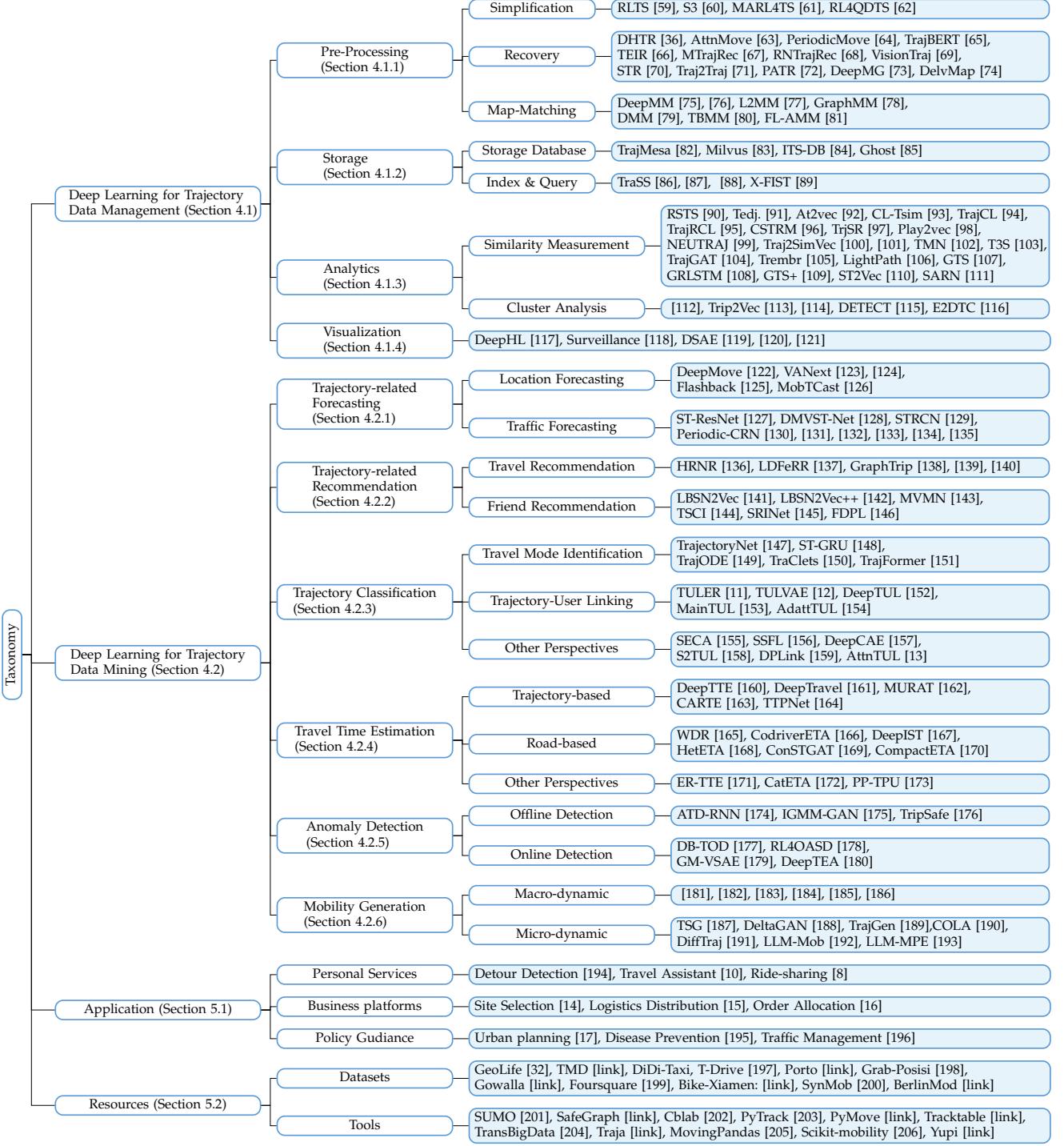


Fig. 4: Taxonomy of this survey with representative works.

tasks. This is particularly useful in knowledge transfer across cities, where fundamental meta-knowledge may differ between cities. *v) Multi-Task Learning* entails training models to simultaneously perform multiple tasks, sharing knowledge across tasks. For instance, in trajectory recovery tasks, simultaneous handling of predicting road segments and predicting movement ratios enhances overall performance. *vi) Deep Reinforcement Learning* involves training models to make sequential decisions through interactions with the environment. It is commonly used for tasks involving trajectory planning and control in dynamic environments, such

as order delivery. *vii) Deep Generative Learning*, including Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Diffusion Models, aims to learn the probability density of observable samples and randomly generate new samples. By limitlessly generating synthetic trajectories, it helps address limitations in scenarios with restricted data. *viii) Federated Learning* enables model training across decentralized devices without exchanging raw data. By collaboratively uploading and training models across distributed devices, it addresses user privacy concerns in trajectory data management and mining tasks.

### 3 OVERVIEW AND CATEGORIZATION

The taxonomy of this survey paper is presented in Figure 4, which is intricately designed to categorize applications and functionalities in trajectory computing with deep learning. This structured approach facilitates a comprehensive understanding of their role in trajectory computing.

- **Deep Learning for Trajectory Data Management.** Trajectory management gears towards conducting various operations on recorded raw trajectory data, encompassing *pre-processing* for data cleansing, efficient data *storage*, high-quality data *analytics*, and clear *visualization*. Deep learning has been seamlessly integrated into each stage to facilitate and advance subsequent mining tasks effortlessly.
- **Deep Learning for Trajectory Data Mining.** Trajectory mining, through the integration of deep learning technologies, offers a comprehensive solution for the six major tasks of discriminative and generative type, namely *trajectory-related forecasting*, *trajectory-related recommendation*, *trajectory classification*, *travel time estimation*, *anomaly detection*, and *mobility generation*. This advancement propels the forefront research and practical applications of trajectory computing.
- **Application & Resources.** Interlinking trajectory management and mining, deep learning has proven effective in generating practical applications across diverse domains such as *personal services*, *business platforms*, and *policy guidance*. Furthermore, a comprehensive exploration of publicly available *datasets* and *tools* has been undertaken.

## 4 DEEP LEARNING FOR TRAJECTORY DATA

### 4.1 Trajectory Data Management

#### 4.1.1 Pre-Processing

Recorded trajectories aim to depict the actual movements of objects. However, inherent inaccuracies arise from sampling devices and environmental uncertainties. Pre-processing refines raw data by simplifying redundant and anomalous points, completing missing ones, and employing map matching for calibration, meeting specific needs.

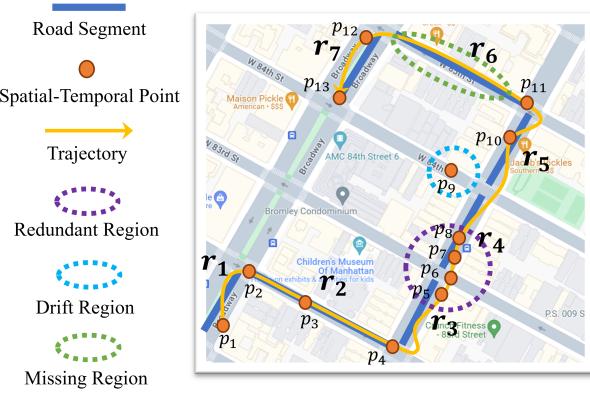


Fig. 5: Pre-Processing example.

**Trajectory Simplification.** In the presence of sensor noise and the inherent characteristics of high-frequency sampling, Fig 5 illustrates the emergence of nearly identical “redundant points” (e.g.,  $p_5 - p_8$ ) and “drift points” (e.g.,  $p_9$ ) within a moving trajectory. To mitigate these issues, *trajectory simplification methods are designed to remove redundant and*

*anomalous points, effectively reducing data without significantly altering the overall information of trajectory.*

Early methods are typically based on human-crafted rules, categorizable into batch mode and online mode based on application range. Batch processing involves access to complete historical trajectory data and aims to balance compression rates and data loss. Notable methods include DP [207] and DPTS [208], which compute the importance value for each point to capture compression errors. In online mode, only access to the buffer’s sensor data is allowed, with methods such as sliding windows [209] and normal opening windowing [210] algorithms used to extract feature points from dynamically changing windows for online compression. Additionally, semantic simplification [211] serves as an alternative, utilizing road networks to facilitate trajectory simplification and reduce spatial redundancy. However, methods with manual rules lack adaptability. To tackle the above limitation, recent studies like RLTS [59] and S3 [60], utilize deep learning to minimize errors between original and simplified trajectories, while constraining the length of the simplified trajectories. RLTS uses reinforcement learning to simplify trajectories by treating the problem as a Markov Decision Process (MDP). It employs reinforcement learning to learn the policy of the MDP for minimizing errors in discarding points. S3 introduces an attention-based sequence to sequence (Seq2Seq) framework with differentiable reconstruction learning for lightweight trajectory simplification under a self-supervised learning paradigm. Additionally, it enhances compression efficiency and effectiveness by incorporating a graph neural network encoder to capture context-aware movement patterns and improve geographical semantic representation of trajectories. Furthermore, MARL4TS [61] extends the goal to minimize simplified trajectory length under bounded error conditions. It’s a multi-agent reinforcement learning approach that divides the process into two MDPs—one for buffer expansion and another for buffer reset—maximizing compression effects with shared rewards between the agents. In addition, RL4QDTS [62] introduces a method termed query accuracy-driven trajectory simplification, employing multi-agent reinforcement learning to collaborate, aiming to address the challenge of large-scale trajectory databases to reduce storage costs and expedite query processing.

**Trajectory Recovery.** Due to issues with recording devices such as communication latency, GPS localization errors, and privacy issues, the collected data usually covers a substantial number of trajectories with low or missing sample rates [23]. Take Fig 5 as an example, the raw trajectory lacks any recorded information within the green dashed region (e.g., driving in areas with missing signal stations), which may hinder its utilization for downstream applications. To this end, *trajectory recovery aims to transform these irregular, low-sampled trajectories into high-sampled ones, effectively supporting mobility computing applications.*

Traditional trajectory recovery [212] treats trajectories as spatial series data, using correlations between adjacent points to fill missing ones. Early methods, like linear [213] and polynomial [214] interpolations, struggled with capturing complex dependencies. Recent deep models improved sparse trajectory completion. Trajectory recovery is categorized into two settings based on the external information. The first,

called free-space trajectory recovery, emphasizes capturing complex transition patterns within trajectory sequences. DHTR [36] first extended the Seq2Seq framework to Sub-Seq2Seq, introducing a deep hybrid model with a Kalman filter for uncertainty reduction. To solve the sparse recovery problem, AttnMove [63] proposes an attention-based model incorporating historical information and periodic patterns, using Bayesian neural networks for uncertainty estimation. PeriodicMove [64] further introduces a GNN-based attention model, which learns complex location transition patterns from directed graphs constructed by trajectories. TrajBERTT [65] and TEIR [66] utilize Transformer to refine the spatio-temporal modeling process, which can be applied to scenarios without explicit geographical coordinates and variable sampling rates.

In the second setting, recovery involves mapping segments or points of interest, utilizing external knowledge like road networks. MTrajRec [67] pioneered multi-task learning in Seq2Seq models for map-constrained trajectory recovery, incorporating modules like constraint masking, attention mechanisms, and attribute enhancement. Furthermore, RNTRajRec [68] introduces a novel spatio-temporal transformer network, GPSFormer, and seamlessly integrates a new road network representation model, GridGNN, for trajectory recovery. Besides, significant semantic and visual information can still be supplemented in practical scenarios. STR [70] addresses this by utilizing a heterogeneous information network encoder to model semantic correlations, while VisionTraj [69] employs a visual and GCN encoder to model the snapshot from road network cameras. Beyond this, Traj2Traj [71] introduces a latent factor module to enhance recovery efficiency, and PATR [72] further incorporates a periodic perception module applied in real logistics platforms.

In addition, another important application of trajectory recovery is the recovery of urban road networks. A representative approach is DeepMG [73], which discovers and extracts the structure of the underlying road network based on a large amount of trajectory data. Furthermore, a number of studies conduct multimodal fusion based on satellite images and trajectory data for enhancing the performance performance of road network recovery [215], [216]. For example, DeepDualMapper [217], DF-DRUNet [218] and DelvMap [74] builds the multimodal fusion architecture based on the deep neural network by incorporating satellite images and GPS trajectory data to provide robust road extraction and recovery.

**Map-Matching**, which converts spatio-temporal points' latitude and longitude sequences into road segment sequences, facilitating downstream intelligent transportation tasks. As illustrated in Fig 5, the original trajectory sequence  $\{p_1, \dots, p_{13}\}$  can be mapped to road segments  $\{r_1, \dots, r_7\}$ .

Most previous studies on map matching evolved from geometric [219] and topological [220] matching to probabilistic statistical [221] algorithms. Among these, the Hidden Markov Models (HMM) exhibit better robustness to noise and sampling rates, as demonstrated in [222]. However, HMM-based methods do not fully capitalize on the vast amounts of trajectory data. DeepMM [75] develops the first deep model with the attention mechanism that accurately map the sparse and noisy trajectory onto the road network. Due to the lack of well-matched trajectory data, a Transformer-based model

with a transfer learning approach [76] is proposed. This method utilizes generated trajectory data to pre-train the model and subsequently fine-tune it with a limited number of labeled data. Furthermore, L2MM [77] suggests high-frequency trajectory augmentation and data distribution augmentation to enhance the model's map matching task generalization. Nonetheless, the above methods ignore the graph nature of map matching. GraphMM [78] incorporates graph neural networks to extract correlations between trajectories and roads, as well as inter-trajectory and trajectory-road correlations. Beyond this, DMM [79], TBMM [80], and FL-AMM [81] extend it to map matching scenarios with wireless sensor data by incorporating technologies such as federated learning and reinforcement learning.

#### 4.1.2 Storage

To cope with the surge in streaming trajectory data, research in trajectory storage, indexing, and querying remains crucial.

**Storage Database.** Traditional trajectory storage systems typically focus on the spatio-temporal point level, and numerous systems have emerged for the storage and query design of trajectory data. The research community has developed a range of specialized management systems [223]–[225] for trajectory data types, while the query types supported by those databases are limited. Simultaneously, the open-source community has expanded existing distributed systems [82] for large trajectory storage by introducing custom data formats such as LineString and GPX [226].

Vector databases, leveraging deep representation learning, have emerged as a popular database type [83]. These databases offer efficient storage, retrieval, and querying capabilities for various data. *Limited research has been conducted on trajectory vector databases [84], [85], with current works primarily focused on advancing trajectory representation learning, aiming to automatically compress raw trajectories into low-dimensional vector spaces.* Given that the quality of trajectory vectors is typically measured by similarity, more detailed work is elaborated in Section 4.1.3.

**Index & Query.** *Trajectory indices are data structures designed to efficiently organize and store trajectories, enabling quick retrieval and analysis.* They play a crucial role in optimizing searching performance of trajectory queries, such as trajectory similarity search, trajectory  $k$ -nearest neighbor query and trajectory similarity join.

Although TraSS [86] recently proposed a novel spatial index XZ for quickly querying trajectories in a key-value database. However, conventional trajectory indices [34], [227], [228] mainly adapt R-trees to organize trajectory points or segments in a hierarchical manner, facilitating trajectory queries by narrowing down search areas. Thus, deep learning has been widely applied to improve this data indices *w.r.t.* query efficiency, *i.e.* learned indices that learn data distribution and access patterns. The existing spatial learned indices [87], [88] mainly focus on low-dimensional data, such as two-dimensional GPS points. X-FIST [89] extends the learned index flood to trajectories, which indexes the minimum bounding rectangles (MBRs) of trajectories. For each data, X-FIST first creates a list of sub-trajectories, and then it builds two Flood indices on the lower left and the upper right vertices of the MBRs of the sub-trajectories, respectively.

TABLE 2: Classification of existing trajectory similarity measures.  $m$  and  $n$  denote the numbers of points in two trajectories, respectively.  $i_m$  and  $i_n$  denote image sizes.  $k_m$  and  $k_n$  denote the numbers of neighbor nodes on the road network graph. Note that, the dimensionality of trajectory embeddings is a small constant and thus it does not affect time complexity results.

Category	Method	Complexity	Robustness	Components
Heuristic	DTW [229]	$O(mn)$	✗	-
	LCSS [230]	$O(mn)$	✓	-
	EDR [231]	$O(mn)$	✓	-
Learning Free Space	Fréchet [232]	$O(mn)$	✗	-
	Hausdorff [233]	$O(mn)$	✗	-
	t2vec [234]	$O(m+n)$	✓	RNNs
	RSTS [90]	$O(m+n)$	✓	RNNs
	At2vec [92]	$O(m+n)$	✓	RNNs
	Play2vec [98]	$O(m+n)$	✓	RNNs
	CL-Tsim [93]	$O(m+n)$	✓	RNNs
	TrjSR [97]	$O(i_m + i_n)$	✓	CNNs
	CSTRM [96]	$O(m^2 + n^2)$	✓	Attention
Learning SL-based	TrajCL [94]	$O(m^2 + n^2)$	✓	Attention
	TrajRCL [95]	$O(m^2 + n^2)$	✓	Attention
	NEUTRAJ [99]	$O(m+n)$	✓	RNNs
	Traj2SimVec [100]	$O(m+n)$	✓	RNNs
	TMN [102]	$O(mn)$	✓	RNNs
Road Network	T3S [103]	$O(m^2 + n^2)$	✓	Attn.+RNNs
	TrajGAT [104]	$O(nk_m + nk_n)$	✓	GNNs
	Trembr [105]	$O(m+n)$	✓	RNNs
	LightPath [106]	$O(m^2 + n^2)$	✓	Attention
	GTS [107]	$O(m+n)$	✗	GNNs+RNNs
Road Network	GTS+ [107]	$O(m+n)$	✗	GNNs+RNNs
	GRLSTM [108]	$O(m+n)$	✗	GNNs+RNNs
	SARN [111]	$O(m+n)$	✗	GNNs+RNNs
	ST2Vec [110]	$O(m^2 + n^2)$	✗	GNNs+RNNs+Attn.

#### 4.1.3 Analytics

Efficient and precise similarity measurement, as well as clustering analysis, are foundational for various mining tasks involving complex and multi-source trajectory data.

**Similarity Measurement.** Trajectory similarity quantifies the similarity of trajectories by a set of distances. Traditional methods, employing heuristic approaches, include point-based DTW [229], LCSS [230], EDR [231] distances, and shape-based Fréchet [232], Hausdorff [233] distance. Recently, studies [90], [92], [234] introduced deep learning to enhance measurement effectiveness and improve computational efficiency. As shown in Figure 6, these methods can be classified according to learning paradigms (Self-Supervised Learning, *a.k.a.* SSL or Supervised Learning, *a.k.a.* SL), and under different metric space (Free Space or Road Network) settings. We combine these two to introduce specific measures for each category, and summarize the differences in Table 2.

○ *Free Space:* Methods in this type measure the similarity of raw trajectories in free space, often converting them into cell trajectories for practical manipulation. They can be categorized into SSL-based and SL-based approaches. SSL-based methods learn robust trajectory representations directly from unlabeled trajectories, eliminating reliance on manually crafted heuristic rules. t2vec [234] is the first deep learning model which adopts SSL by generating similar trajectory training pairs through subsampling. RSTS [90], Tedj [91], and At2vec [92] enhance t2vec from perspectives such as time, multi-granularity, and POI similarity, respectively. These methods are generally considered reconstruction-based approaches. Recently, CL-Tsim [93] introduces a contrastive

method to learn discriminative trajectory representations by creating positive and negative training samples. TrajCL [94] and TrajRCL [95] introduce various trajectory augmentation and contrastive learning methods to jointly capture trajectory similarity from spatial and structural perspectives. Moreover, CSTRM [96] employs a shallow transformer encoder, while TrjSR [97] transforms trajectories into images, both models aim to capture multi-scale similarity. Considering practical scenarios, Play2vec [98] further learns the similarity of motion trajectory datasets and applies it to sports match analysis. SL-based methods can efficiently approximate existing heuristic measurements. NEUTRAJ [99], the pioneer in this category, adapts an RNN model with a spatial attention memory module to learn correlation between spatially proximate trajectories. Traj2SimVec [100] and [101] further improve NEUTRAJ in terms of data pre-processing and training efficiency. After that, TMN [102] proposes an attention-based matching module to directly learn the correlation between points in two trajectories. T3S [103] also combines LSTM with a plain self-attention model to learn trajectory representations in Euclidean and grid spaces. Unlike previous methods, TrajGAT [104] introduces a graph-based self-attention model, representing each trajectory as a graph. It employs a quadtree to partition space into different-sized grid cells, capturing fine-grained dependencies between points.

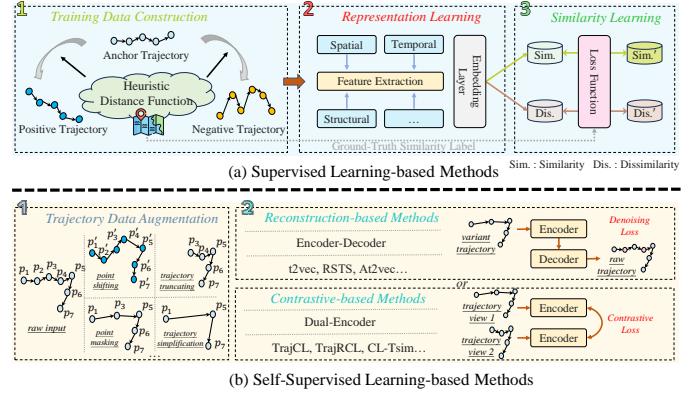


Fig. 6: Different pipeline of trajectory similarity methods.

○ *Road Networks:* Methods in this category aim to measure the similarity between trajectories mapped onto road networks. It is particularly suitable for individuals' or vehicles' trajectories in urban areas. Similarly, those methods can also be categorized by learning paradigms: The SSL-based methods include Trembr [105] and LightPath [106], with RNN and Transformer-based Seq2Seq models, respectively. Constrained by the underlying road network, they encode the intrinsic spatial and temporal properties of trajectories into latent space. LightPath, distinctively, employs knowledge distillation to reduce model size and enhance efficiency. For SL-based methods, GTS [107] is the pioneer that first provides various definitions for trajectory similarity on road networks, then employs GCN and LSTM to learn embeddings for POI sequences in the graph. Building upon this, GRLSTM [108] and GTS+ [109] respectively use knowledge graphs and spatio-temporal LSTM with time gates to jointly capture trajectory and road network attributes from a spatio-temporal similarity perspective. Another study on spatio-temporal similarity on road networks is ST2Vec [110], differing from

GTS+ by integrating spatial and temporal features before inputting them into LSTM. Unlike the aforementioned methods, SARN [111] focuses on learning segment embeddings, proposing a contrastive learning-based graph neural network to capture local and global similarities of road segments.

**Cluster Analysis.** Trajectory clustering groups trajectories into different clusters based on their similarity, aiming to ensure trajectories within the same cluster exhibit a higher degree of similarity to each other. Traditional trajectory clustering methods [235] generally rely on similarity measurement, and the quality of the clustering may vary greatly depending on the choice of measurements. Currently, learning-based

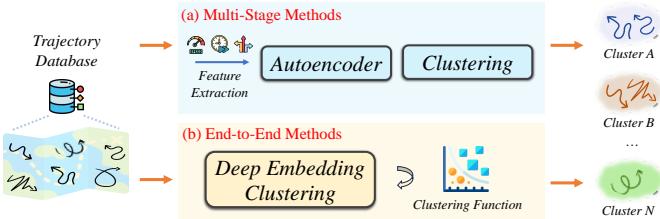


Fig. 7: Different pipeline of cluster analysis methods.

trajectory clustering methods account for the latent features of trajectories and are robust to variations in the spatial and temporal scale. As shown in Figure 7, these methods are typically categorized into multi-stage methods and end-to-end clustering based on their processing workflows.

In general, multi-stage trajectory clustering methods [112], [113] first extract low-dimensional representations for each trajectory, use a sliding-window to extract a set of robust movement features and feed them into an LSTM-based AE to learn fixed-length representations. Subsequently, a traditional clustering algorithm like K-means [236] is employed to generate clusters based on the learned trajectory representations. Trip2Vec [113] extracts three different kinds of trip attributes from trajectories, including time, origins, and destinations. The trip attributes are then inputted into a fully connected AE to generate the representations of trajectories, followed by K-means to form clusters with similar representations. In contrast, end-to-end approaches directly integrate Deep Embedding Clustering (DEC), enhancing trajectory representations and clustering assignments simultaneously. For example, the study [114] applies AE-based t-SNE and DEC for aircraft trajectory clustering. DETECT [115] uses an LSTM-based AE and environmental context to refine embeddings and clustering assignments jointly. E2DTC [116] is an RNN-based AE method. It introduces a triplet loss dedicated to trajectory clustering.

#### 4.1.4 Visualization

To enable real-time visualization and interactive analysis of extensive mobility data, traditional trajectory visualization methods rely on temporal and spatial dimensions of geopoints. Techniques like density maps, heatmaps, and spatio-temporal cubes [237] are used for macroscopic analysis.

However, visualizing large raw trajectories can result in information redundancy, as addressed by deep clustering and simplification methods in Sec 4.1.1 and 4.1.3. Utilizing these methods, researchers can obtain grouped trajectories, allowing for a detailed examination of various trajectory

movement patterns. For instance, [118] presents an interactive system called Surveillance that uses LSTM models and network embedding to detect and visualize urban congestion conditions. Similarly, [120] uses an iterative sampling scheme for OD flows, creating meaningful visual encodings. Deep learning's capability to extract hidden knowledge from data without extensive prior knowledge is also leveraged to assist in individual trajectory visual exploration. [117] introduces DeepHL, employing attention-based neural networks for automatic detection and visualization of meaningful trajectory segments. In DSAE [119], a deep sparse autoencoder extracts hidden features, mapping them to the RGB color space to visualize driving behavior. Later, [121] uses GIS map integration to enhance anomaly visualization. More analyses of visualizations assisted by DNN are discussed in [238].

#### 4.1.5 Recent advances in LLMs for trajectory management

Some literature begins to explore the use of large language models for trajectory management tasks, primarily to improve trajectory recovery and enhancement. One study [239] suggests using generative language models to analyze semantic trajectories and create synthetic semantic trajectory data. Another study [240] shows that using open-source LLMs like LLaMA2 [241] effectively reconstructs flight trajectories, but it faces challenges with longer data sequences due to token length constraints.

**Summary and Discussion:** Deep learning has seamlessly integrated various management tasks, significantly streamlining manual processes and enhancing performance. We further discuss the potential key roles of large language models in the trajectory management domain. Regarding pre-processing, LLMs can intelligently clean data and recover missing semantic information. In terms of storage and retrieval, LLMs can automate query interfaces. For analysis, LLMs can automatically identify behavioral clusters and common patterns. In visualization and interaction, LLMs can provide rich semantic interpretations and enable natural interaction. In summary, we believe that by integrating existing deep learning models, LLMs will bring automated solutions to trajectory management technology and offer more semantic interpretational information.

## 4.2 Trajectory Data Mining

### 4.2.1 Trajectory-related Forecasting

As shown in Figure 8, in trajectory data mining, forecasting tasks aim to accurately predict future movements of individuals (i.e., Location Forecasting) or crowds (Flow Forecasting) based on historical data [24].

**Location Forecasting.** Location forecasting aims to predict individual subsequent locations based on their historical movement data. It involves understanding and modeling the spatial (e.g. location), temporal (e.g. day of week), external (e.g. weather), and personalized (e.g. periodic visits) patterns of individuals. Formally, given the historical movement data of a person, the task predicts the next spatial point or region that the user is most likely to visit. This can be formulated as a classification problem, where the next location is one of several predefined regions, or as a regression problem, predicting the exact geographical coordinates [24]. The challenge of such approaches lies in accurately modeling

the complexity of human movement and the various factors that influence location selection, such as time of day, personal preferences, and social behavior.

Intuitively, the classification model learns from a historical sequence of locations visited by individuals, integrating deep learning methods (FC [242], CNN [243], RNN [125], [244]–[246], ST-RNN [247], [248], Embedding [125], [249], [250], attention mechanisms ([122], [123]), and GNNs [251] to capture transfer probabilities distribution of all possible locations, where the highest probability indicates the most likely next visit. For example, DeepMove [122] is an attentional recurrent neural network-based method. It introduces two attention mechanisms to capture multi-level periodicity and utilizes GRUs to process trajectories for predictions. VANext [123] further enhances DeepMove by employing a variational attention approach that uses variational coding to capture potential features of recent mobility and combines them with recent check-in preferences to predict the location. Flashback [125] is a general RNN architecture designed to address the sparsity issue of user movement trajectories. It uses spatial-temporal context in RNN to search for hidden states with high predictive power for location prediction. Unlike the previously mentioned classification-model-based approaches, the regression-based methods aim to forecast continuous and exact values that represent the next spatial point an individual is likely to visit. For example, Song *et al.* [124] introduce a multi-task deep learning framework using stacked LSTM layers to simultaneously predict future traffic patterns and positions. Considering the influence of multiple types of contexts (temporal, semantic, social, and geographic) on mobile prediction, MobTCast [126] introduces the transformer architecture as a spatial-temporal feature extractor to process both temporal and semantic contexts. Moreover, it introduces an auxiliary prediction task to explore the geographic context and predict the next location.

In addition, numerous studies recently extended location forecasting to two variants: next POI recommendation and predict incomplete paths. The former primarily addresses cold start scenarios and user preference recommendations, while the latter is applied in contexts such as food delivery and logistics, predicting a series of locations based on the worker's current incomplete route tasks, thereby adding complexity to the problem. For a more detailed discussion, refer to [252], [253] and [16], [254], [255].

**Traffic Forecasting.** Traffic forecasting predicts the movement and the density of traffic in a given area over time. This task aims to analyze historical mobility data, congestion patterns, and typical flow trends to predict the number of entities that will congregate in an area at a future time. *Formally, traffic forecasting is typically presented as a time series forecasting problem, where the objective is to predict future flows based on past observations* [256]. The task's complexity arises from the dynamic and unpredictable nature of traffic flow, influenced by factors such as time of day, weather conditions, accidents, and construction [257].

In practice, trajectories are firstly transformed into matrices by the time and the regions belonging to (as presented in Sec. 2.3). Subsequently, forecasts can be made using classical time series models such as Autoregressive Moving Average (ARMA) [258] and Vector Autoregressive (VAR) [259]. However, such straightforward methods have

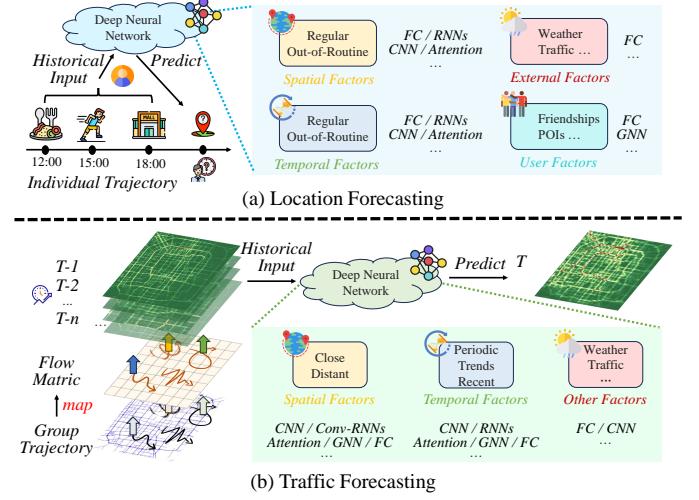


Fig. 8: Forecasting tasks schematic and influencing factors.

difficulty in handling spatial dependencies and a variety of additional features (*e.g.* weather conditions and traffic events), which makes them far from perfect for performance. Since traffic flows are changing in matrix format, it can effectively utilize CNN to obtain their local and global spatio-temporal dependencies. Besides, RNN models such as LSTM can be also used to model the complex temporal dynamics within the data. Thus, deep learning methods can effectively capture patterns in the temporal evolution of crowd flows. ST-ResNet [127] is one of the pioneering efforts to predict traffic flow based on deep neural networks. It utilizes residual CNN units to capture temporal closeness, trends, and periodic patterns. The output of each type of attribute is aggregated with external factors to predict traffic flow. There are a number of follow-up studies. For instance, DMVST-Net studies multi-view spatio-temporal patterns [128]. STRCN combines CNN and LSTM for spatio-temporal modeling and assigns weights to different branches [129]. Periodic-CRN focuses on capturing repeated periodic patterns [130]. Additionally, numerous deep learning-based traffic flow prediction methods have emerged and they can be broadly categorized into ConvLSTM-based methods [131]–[133], multi-task-based methods [134], [135], attention-based methods [196], [260]. In addition, we also observe that the recent studies devoted to using spatio-temporal graphs to model traffic flows [261]–[263], due to the advantages of GNNs.

#### 4.2.2 Trajectory-related Recommendation

As illustrated in Figure 9, *within location-based service systems, the critical tasks of recommendation entail two aspects: travel and friend recommendations. Travel recommendation aims to provide users with suitable routes based on their travel constraints and preferences. Friend recommendation, on the other hand, aims to infer social relationships and recommend potential acquaintances of interest based on users' mobility patterns and behaviors.* By analyzing individual or group historical trajectory data, social connections, and potential needs, the goal is to offer precise recommendations to enhance users' travel experiences and social interactions.

**Travel Recommendation.** *The primary objective of travel recommendation is to generate a series of POI plans for specific*

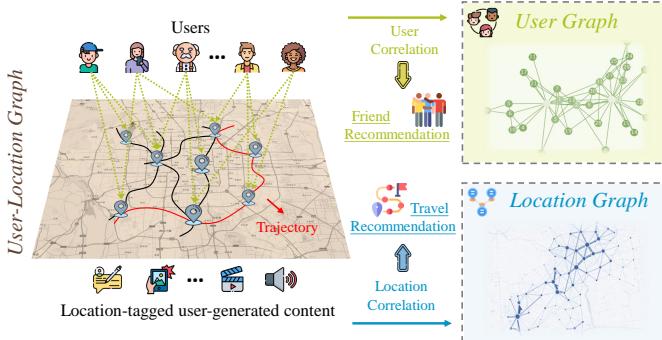


Fig. 9: Recommendation of location-based social networks.

travelers based on their particular constraints, such as duration, origin, and destination points, and the number of attractions to visit. Traditionally, travel recommendation has also been referred to as travel query and planning, aiming to maximize user satisfaction by solving the orientation problem to plan trips. The core idea involves combining POIs and trajectories using heuristic methods. Typically, this categorization includes five methods: search-based, probability-based, biomimetic-based, clustering-based, and constraint-based [264], many of which have roots in the field of robotic pathfinding.

With the proliferation of social media and ubiquitous location-tracking devices providing vast trajectories, researchers have begun employing data-driven approaches for personalized travel recommendations. Early attempts involve hybrid methods, leveraging neural networks to automatically learn the cost function of the A\* search algorithm for route recommendation tasks. For instance, HRNR [136] extends A\* using neural networks, modeling intricate traffic information for swift driving route recommendations. Advancements in deep learning inspire several neural networks for trip recommendations. Sequential-based works [137], [265]–[268] utilize the RNN family to extract features of different POI and introduce maximum diversity constraints to recommend paths with specific scenarios for users. For example, LD-FeRR [137] amalgamates GRU and attention mechanisms to estimate fuel consumption for long-distance driving routes and recommend energy-saving routes for drivers. In contrast, graph-based methods [138], [269], [270] can better capture spatial dependencies. For instance, GraphTrip [138] integrates location-aware information fusion after constructing spatio-temporal graphs and adopts transfer learning to address data sparsity in travel route recommendations. Multi-modal approaches [139], [271] consider integrating text and image information with trajectory data to enhance recommendation outcomes. Zhang *et al.* [139] pioneer the development of a diversified urban route recommendation system by combining Google Street View image data for the first time. Numerous reinforcement learning methods [140], [272] have also been applied to urban route recommendation, wherein mobility options are naturally regarded as actions. For example, Ji *et al.* [140] model the taxi routing problem as a decision-making process and devise an adaptive deep reinforcement learning method.

**Friend Recommendation.** Conducting friend recommendations in location-based social networks (LBSN) contributes to enhancing user experience, stemming from the increased

likelihood of users becoming friends when they frequently check in or visit similar types of locations together [273]. Formally, existing works often present friend recommendation tasks as social relationship inference, where the probability of two users becoming friends is determined based on their historical check-in trajectories and social relationship networks. Some works extend this to top-k friend recommendations.

Early works rely on the co-occurrence frequency of user location visits or the similarity of interests for recommendations. Brown *et al.* [274] demonstrate the correlation between geographic proximity and user social relationships. Subsequently, Chu *et al.* [275] combine user travel locations and stay times, analyzing location similarity among users for friend recommendation. Similarly, Yu *et al.* [276] construct a heterogeneous information network by merging GPS trajectory data and utilize a random walk process to estimate link relevance and recommend geographical friends. With the rapid development of graph neural networks for network representation learning [277]–[279], researchers begin exploring nonlinear representations of mobility and location-based social networks for social relationship inference. LBSN2Vec [141] constructs a hypergraph using various information such as user, time, space, and semantics, proposing a random walk and stay mechanism for automated feature representation used in relationship inference. It is further extended to LBSN2Vec++ [142] by considering the heterogeneity of the hypergraph. Similarly, MVMN [143] proposes a multi-view matching network for friend inference by integrating social, spatial, and temporal factors. Different from above methods, TSCI [144] employs VAE latent variables to estimate friendship trajectory distributions, solving the problem of data sparsity. Considering the noise characteristics of user mobility data, SRINet [145] recently introduces a graph neural network framework to remove noisy edge data for inference performance. FDPL [146], considering pairwise ranking loss function to generate top-k friend recommendations, introduces a deep pairwise learning architecture based on a Bayesian personalized ranking strategy, treating friend recommendation as a ranking task.

#### 4.2.3 Trajectory Classification

Trajectory classification is a crucial task for recognizing and distinguishing various trajectory characteristics. It involves learning latent patterns from historical trajectory (or sub-trajectory) data to identify new trajectories in corresponding categories. The classification categories include transportation modes of moving objects, animal types, vessel types, trajectory owners, etc [280]. Early methods predominantly rely on heuristic approaches. For example, TraClass [281] divides the space into spatial grids and continually reduces the grid cell size until the majority of trajectories within a cell belong to the same class. Subsequently, the study [282] expands the sizes of spatio-temporal grids unevenly based on predefined thresholds. Additionally, studies [283] and [284] extract the features from local and global perspectives, such as the distance and the heading change rate to construct recognition models using classifiers such as support vector machines and random forests. To comprehensively model various sources of information simultaneously, such as time, space, and semantics, the recent deep learning models in trajectory classification tasks typically focus on recognizing transportation

modes of moving objects (Travel Mode Identification, a.k.a. TMI) and linking anonymous trajectories to users (Trajectory User Linking, a.k.a. TUL).

**Travel Mode Identification.** Classifying movement modes based on raw trajectories is a persistent focal point in traditional trajectory classification. The objective is to categorize travel patterns according to the trajectories of moving objects, as these objects may alter their transportation modes during their journeys. For instance, when a student travels from home to school, the transportation modes may involve cycling initially, followed by subway transit, and finally walking. *Formally, given an individual's historical trajectory records, TMI task aims to identify the potential movement modes encompassed in the journey [285].* Therefore, it can be formulated as either a multi-class or multi-label classification task. The primary challenges in such tasks stem from the uncertainty in time intervals between irregular samples and inherent spatio-temporal noise in trajectories.

In pursuit of high-accuracy classification, existing methods have extensively explored modeling techniques employing AE [155], [286], RNN [147]–[149], [287], CNN [150], [288], Attention [151], [289], and GNN [290] models. The prevailing approaches mainly focus on sequence transformation modeling. TrajectoryNet [147] introduces a bidirectional GRU architecture for point-based trajectory classification, enhancing features with segment information and utilizing the Maxout activation for improving prediction accuracy. Besides, the study [287] proposes an end-to-end bidirectional LSTM classifier, improving performance through data normalization and time interval information. Recognizing the limitations of discrete-time updating models like RNNs, ST-GRU [148] introduces a segment-wise convolutional weighting mechanism and uses time interval GRU to better capture spatio-temporal correlations and irregular time intervals in trajectories. Meanwhile, TrajODE [149] proposes a neural ordinary differential equation (ODE) model for continuous temporal dynamics, integrating ODE with latent variables for enhanced robustness. In addition, TraClets [150] transforms trajectories into raster images (as presented in Sec. 2.3), converting the problem into an image classification task, leveraging established CNN techniques. Recent advancements include TrajFormer [151], which effectively adapts the transformer for TMI task, achieving a trade-off between efficiency and accuracy, accompanied by squashing functions and auxiliary supervision.

**Trajectory-User Linking.** Diverging from categorizing trajectories into different movement modes, the trajectory-user linking task has evolved to associate anonymous semantic trajectories with their respective users. This task, owing to its effectiveness in understanding human movement patterns, has proven valuable in facilitating endeavors such as tracking epidemic patients and enabling intelligent business services. *Formally, given an anonymous trajectory, TUL task aims to identify the actual user in the database corresponding to that journey [153].* The primary challenges in such task arise from the difficulty in capturing patterns due to the sparsity of semantic trajectories and the nuanced understanding of hierarchical semantic aspects of human mobility.

TULER [11] is the first study to address the TUL problem. It utilizes an RNN-based model to recognize check-in trajectories and link them to generated users. TULER

TABLE 3: List of the selected papers tackling classification task.

Task	Method	Year	Components	Evaluation	Dataset
TMI	TrajectoryNet [147]	Code 2017	GRU	Accuracy, CE Loss, F1 Score	Geolife
	ST-GRU [148]	2019	GRU	Accuracy	Geolife, SH Taxi, Synthetic
	TrajODE [149]	2021	RNN, ODE	Accuracy	Geolife, Grab-Posisi
	TraClets [150]	Code 2022	CNN, FC	Accuracy	GeoLife, Hurricane, Animals
TUL	TrajFormer [151]	Code 2022	Transformer	Accuracy, FLOPs	Geolife, Grab-Posisi
	TULER [11]	Code 2017	RNNs	Acc@k, Macro-F1	Gowalla, Brightkite
	TULVAE [12]	Code 2018	LSTM, VAEs	Acc@k, Macro-P, Macro-R, Macro-F1	Gowalla, Brightkite, Foursquare
	DeepTUL [152]	Code 2020	RNN Attention	Acc@k, Macro-P, Macro-R, Macro-F1	Foursquare, WLAN
	MainTUL [153]	Code 2022	LSTM Attention	Acc@k, Macro-P, Macro-R, Macro-F1	Foursquare, Weeplaces
AttnTUL [154]	Code 2023	FC, GNN, Attention	Acc@k, Macro-P, Macro-R, Macro-F1	Private Car, Gowalla, Geolife	

takes POI sequences as inputs, employs word embedding for representation, and uses an RNN to capture movement patterns and establish user links. However, RNN models lack a comprehensive understanding of hierarchical semantics in human mobility. Subsequently, TULVAE [12] improves prediction accuracy by introducing variational autoencoders into TUL task. It addresses sparsity issues and learned hierarchical semantics. Despite improvements, it does not take full advantage of rich features and overlooks multi-periodic movement patterns. DeepTUL [152] uses an RNN with attention to mitigate data sparsity, capturing multi-periodic patterns for better accuracy. MainTUL [153] introduces mutual distillation learning with distinct trajectory encoders for short-term and long-term dependencies, improving accuracy. Besides, AdattTUL [154] employs GANs, while SML-TUL [291] uses contrastive learning and considers time and space constraints.

**Other perspectives.** In addition to the approaches mentioned above, various studies explore trajectory classification from alternative angles. SECA [155] proposes a semi-supervised method integrating Conv-AE and a CNN classifier, jointly training on labeled and unlabeled GPS segments. [292] also introduces a semi-supervised algorithm based on proxy labels, while SSFL [156] extends this framework for federated learning. DeepCAE [157] pioneers an unsupervised approach combining pre-trained Conv-AE and clustering for TMI task. For limited data scenarios, [293] suggests wavelet transformations, and [294] incorporates map-matching algorithms. Unlabeled data challenges also arise in TUL task, with S2TUL [158] capturing complex motion relationships of unlabeled data through diverse graphs. DPLink [159] and EgoMUIL [295] addresses TUL for cross-platform heterogeneous data. AttnTUL [13] recently introduces a hierarchical attention network, effectively handling sparse and dense trajectories using GNN.

#### 4.2.4 Travel Time Estimation

*Travel Time Estimation (TTE), also known as Estimated Time of Arrival (ETA), is crucial for the development of location-based services and enhances user experience by enabling efficient trip*

management for commuters and optimizing travel routes for service providers like Google Maps and Didi Chuxing [160]. Traditional methods rely on origin and destination points of trajectory and historical data, but may overlook factors like path choices and road conditions. To address these limitations, modern TTE methods have evolved into two main categories: trajectory-based and road-based, both aiming to integrate various spatio-temporal data for accuracy. We summarize the differences in Table 4.

**Trajectory-based Estimation.** As introduced in Sec. 2.1, trajectories are the sequences of points with geographic locations and timestamps. Trajectory-based TTE methods predict travel time by analyzing these sequences. Wang *et al.* use raw GPS data with an error feedback recurrent convolutional neural network (eRCNN) to estimate travel time and speed, exemplifying direct utilization of GPS sequences [298]. DeepTTE advances this by incorporating geographic information through geo-convolution, enhancing spatial correlation and temporal dependence understanding [160]. Moreover, other studies map trajectories into grids, merging spatio-temporal embeddings with auxiliary data (e.g., traffic condition, weather, departure time) to leverage regional context, employing methods such as multi-task learning, tensor decomposition, and graph neural networks for nuanced spatio-temporal analysis [161]–[164]. However, trajectory-based TTE faces challenges, notably the unrealistic assumption of known future GPS locations and the sensitivity to GPS sampling frequency and accuracy. These limitations highlight the potential of road-based TTE as a more feasible alternative, given its capacity to circumvent these issues by relying less on precise, high-frequency GPS data [165], [172].

**Road-Based Estimation.** Road-based TTE approaches define a trip as a sequence of roads, focusing on modeling their correlations to support diverse route selections and thus overcoming the limitations of trajectory dependence. WDR [165] exemplifies this by employing a regression framework that integrates wide linear models, deep neural networks, and recurrent neural networks to leverage a comprehensive set of travel features for accurate travel time predictions. Subsequent studies include the road network metric learning and personalized driving preferences

TABLE 4: List of the selected papers tackling estimation task.

Task	Method	Year	Components (Focus)	Dataset
Trajectory	DeepTTE [160]	Code 2018	LSTM	Geolife
	DeepTravel [161]	2018	BiLSTM	Porto, Shanghai Taxi
	MURAT [162]	Code 2018	Graph Embedding	NYC-Trip, BJS-Pickup
	TPPNet [151]	Code 2022	RNN, GNN	Beijing Taxi, Shanghai Taxi
Road	WDR [165]	2018	LSTM, FC	DiDi Beijing Porto, Chengdu
	DeepIST [167]	Code 2019	PathCNN	
	ConSTGAT [169]	2020	GAT	Taiyuan, Hefei, HuiZhou
	HetETA [168]	Code 2020	GCN	DiDi Shenyang
	CompactETA [170]	2020	LSTM, FC	Beijing, Suzhou, Shenyang
Others	ER-TTE [171]	2018	En route	Taiyuan, Hefei, HuiZhou
	CatETA [172]	2022	Classification	DiDi [Shenzhen, Chengdu]
	PP-TPU [296]	2021	Uncertainty Privacy	Creteil, San Francisco
	ProbTTE [173]	2023	Classification Uncertainty	DiDi [Beijing, Shanghai]
	DeepTTDE [297]	2023	Travel time distributions	DiDi [Chengdu, Shenzhen]

frameworks, enhancing the sensitivity of the model to road sequences and individual driving behaviors [166], [299]. Fu *et al.* introduce PathCNN, utilizing sub-path images for spatio-temporal analysis, marking a novel approach to route representation [167]. The application of GNNs to model road networks as heterogeneous information graphs or employing spatio-temporal graph attention mechanisms further illustrates the field’s shift towards complex networked representations for dynamic and context-rich TTE predictions [168], [169]. This evolution is enriched by a diversity of graph-based techniques, including attention mechanisms, heterogeneous graphs, and dynamic graph models, showcasing the breadth and depth of current research in road-based TTE solutions [170], [300]–[302].

**Other perspectives:** Beyond the above TTE methods, innovative approaches have emerged to address the TTE problem from novel perspectives. Ye *et al.* and Liu *et al.* consider TTE as a multi-classification challenge, categorizing travel times into different spans based on trip time distribution to mitigate the long-tail effect, offering a novel angle on accuracy improvement [172], [173]. Fang *et al.*’s en route TTE (ER-TTE) method leverages observed and future route behaviors to adaptively refine travel time estimation, illustrating an advanced understanding of spatio-temporal dynamics and user preferences [171], [303]. Besides, research has expanded into specialized areas like uncertainty [296], [304], cross-area [304], and travel time distribution estimation [297], [305], acknowledging the complex variability in real-world TTE scenarios and aiming for more versatile and robust solutions.

#### 4.2.5 Anomaly Detection

*Trajectory anomaly detection aims to identify abnormal movement of objects.* It has a wide range of applications in practice, such as fraud and hazard detection of ride-hailing, traffic congestion detection, and trajectory cleaning. Earlier methods mainly leverage hand-crafted rules to define normal/abnormal trajectories. For example, TRAOD [306] detects outlying sub-trajectories through distance-and-density-based rules. Trajectory anomaly detection methods can be divided into two categories based on application scenarios: offline detection and online detection. Offline methods can only be processed once each full trajectory is provided, while online methods support “on-the-fly” detection on ongoing trajectories being generated. The online methods are more flexible than the offline ones, as they can be also used in an offline manner as well by regarding full trajectories as the ones being generated progressively.

**Offline Detection:** ATD-RNN [174] simply incorporates an RNN model with an FC layer to predict trajectory anomaly in Euclidean space. Unlike ATD-RNN using supervised learning, which may lack sufficient training samples, IGMM-GAN [175] is an unsupervised generative model. It uses a CNN-based bidirectional GAN to learn the characteristics of normal trajectories of which the learned embeddings follow a multi-modal Gaussian distribution, *i.e.* forming multiple clusters. Given a test trajectory, it derives the anomaly score by computing the distance between the test trajectory and each cluster center. TripSafe [176] specializes in ride-hailing trip anomaly detection, considering factors like ordering time and stopping duration. Utilizing two VAEs, it learns

trajectory representation in both Euclidean space and road networks, serving as the backbone for anomaly classification. ATROM [307] utilizes variational Bayesian methods to explore behavioral patterns of trajectories under the guidance of probability measure rules, addressing anomaly trajectory recognition in open-world scenarios.

**Online Detection:** DB-TOD [177] studies online trajectory anomaly detection on road networks. It leverages reinforcement learning to model the transition probability between road segments from historical trajectories, and thereby makes the anomaly detection to be a sequential decision process. RL4OASD [178] is another probabilistic model. In comparison, it refines the process of feature generation and introduces a local reward that aims to emphasize the local continuity of labels. Unlike above methods, GM-VSAE [179] detects trajectory anomalies in Euclidean space. It adapts RNN-based VAE model to learn the probability distribution of trajectories in the latent space. Once the VAE model is trained, it leverages the learned generative model to detect anomalies by computing the likelihood of the test trajectories being generated from Gaussian components and improving online computation efficiency. Building upon this, DeepTEA [180] further takes the temporal dimension into account.

#### 4.2.6 Mobility Generation

Trajectory data faces challenges such as limited public data, privacy issues and authorization issues in practical application scenarios. A viable solution to these obstacles is trajectory generation, which not only adheres to privacy requirements but also supports broader research and application needs by synthesizing realistic trajectory data [24]. As shown in Figure 10, *trajectory generation focuses on creating a generator to mimic complex human or object movement patterns, utilizing deep learning to encapsulate the statistical, spatial, and temporal nuances of actual trajectories, aiming to closely align the generated data with real-world patterns*. Efforts to synthesize realistic trajectory data are split into two main perspectives based on scale: macro-dynamics and micro-dynamics. Macro-dynamics focus on broad mobility patterns, such as population movements within or across cities and regions, emphasizing the modeling of large-scale trends over individual trajectories [24], [308]. In contrast, micro-dynamics concentrate on the detailed mobility patterns of individuals, including specific routes, speeds, and stops. This finer-grained approach is essential for applications requiring high-resolution mobility data, such as personalized location-based services and behavior analysis.

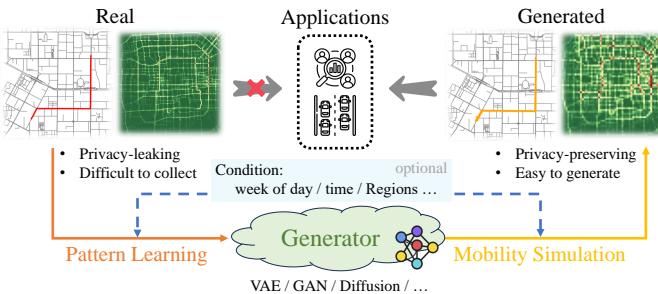


Fig. 10: Macro and micro trajectory generation examples.

**Macro-dynamics.** Macro-level flow generation crafts comprehensive views of mobility patterns, traditionally

relying on statistical models and simulations based on historical data and mobility assumptions [309]. Gravity and radiation models have been instrumental in predicting flows, considering factors like population density and geographic distance [310]. However, these approaches may oversimplify the intricate dynamics of human mobility. The advent of deep learning has transformed flow generation, with neural networks unraveling complex spatial and temporal mobility patterns. FC, CNN, RNN, and GAN have all contributed to more nuanced and dynamic flow representations [182]–[186]. These methods excel in generating adaptable and diverse mobility flows, significantly improving the fidelity and utility of macro-level mobility data. Graph models have also shown promise in enhancing flow generation. Yao *et al.* introduce a spatial interaction GCN model that leverages local spatial networks for improved geographic unit representations [128].

**Micro-dynamics.** At the micro-level, trajectory generation aims to replicate intricate individual movements, capturing the sequence of visited locations, duration of stays, chosen routes, and timing. Early efforts focus on next location prediction as a sequential task, but these are generally constrained by the need for historical trajectory data [122], [311]–[313]. Mehmet *et al.* propose a trajectory mixture model, though it requires extensive data and complex processes for effective generation [314]. The adoption of generative adversarial networks marks a significant shift, with early models like those by Ouyang *et al.* learning from grid-mapped trajectory data to generate realistic paths [315]. Despite improvements, such models face limitations related to the balance between grid size and accuracy [187], [188]. Incorporating reinforcement learning, with generators as agents and discriminators for reward calculation, offers a new perspective on trajectory generation as a series of actions [190], [316]–[319]. Further innovations involve transforming trajectory data into images for generation, though this introduces additional computational complexity [187], [189]. The introduction of denoising diffusion probabilistic models, as demonstrated by DiffTraj [191] and Diff-RNTraj [320], represents a novel class of methods that model generation as particle diffusion motions for detailed path creation.

#### 4.2.7 Recent advances in LLMs for trajectory mining

Compared to management tasks, trajectory data mining has witnessed a plethora of research efforts integrating large language models, primarily focusing on tasks such as forecasting [192], [193], [321], [322], generation [323], [324], and identification [325]. From zero-shot trajectory state recognition using LLMs to hints for language-based mobility prediction, these works have demonstrated remarkable performance in accurately predicting human mobility without the need for specialized training datasets. For instance, LLM-Mob [192] explores prompt engineering incorporating historical stays and context-aware information, achieving precise and interpretable location predictions. UrbanGPT [322] extends this to flow prediction. Furthermore, by integrating LLMs into agent frameworks and spatio-temporal models, a series of trajectory generation methods with semantic and geographical consistency constraints have been introduced, providing solutions for synthesizing sparse and long-tail distributed trajectory data. For example, MobiGeaR [323] transforms the mobility generation problem into a common-

sense reasoning problem, leveraging the chain-of-thought reasoning ability of LLMs.

**Summary and Discussion:** Over the past decade, deep learning models have been widely employed in trajectory data mining tasks and extensively applied in initiatives such as the development of smart cities and intelligent transportation systems. Furthermore, we further discuss the potential key uses of large language models in the trajectory mining domain in the future. For basic mining tasks like forecasting, classification, anomaly detection, and generation, one approach involves fine-tuning the capabilities of unlocked LLMs. Additionally, these tasks may transition to zero-shot execution techniques like language prompting. In decision-making tasks such as travel recommendation, LLMs can serve as the central intelligence agent, working alongside other models to offer personalized decisions.

## 5 APPLICATION AND RESOURCES

### 5.1 Application

Trajectory data management and mining have revolutionary applications in various fields. As shown in Figure 11, we summarize these applications from different groups.

**Personal Services.** Trajectory computing plays a vital role in various aspects of personal outdoor services. Firstly, in the aspect of route detection [9], the analysis of user's driving trajectories enables timely identification and notification of alternative routes or avoidance of traffic congestion, thereby enhancing travel efficiency. Secondly, ride-sharing [8] benefits from the application of trajectory data, as platforms can intelligently match passengers traveling in the same direction, leading to more efficient shared rides, reduced travel costs, and alleviated traffic burdens. Furthermore, personalized recommendation services [251] utilize trajectory data analysis to understand users' preferred locations and behavioral patterns, delivering more tailored recommendations for nearby attractions, restaurants and business areas. Moreover, by combining semantics and multi-modal information, it can further analyze user travel intentions and serve as an intelligent agent [10] to assist users in decision-making.

**Business Platforms.** Trajectory computing significantly influences business operations across various domains, especially for mobility service providers, such as Uber<sup>1</sup>, DiDi<sup>2</sup>, Google Map<sup>3</sup>, Baidu Map<sup>4</sup>, Cainiao<sup>5</sup> and so on. In terms of business site selection [14], the analysis of potential customers' movement trajectories empowers businesses to make informed decisions about optimal operational locations, thereby increasing the likelihood of business success. Additionally, logistics and delivery services benefit from trajectory data, enabling real-time monitoring and rational route planning to enhance delivery efficiency and reduce operational costs [15]. Personalized marketing strategies leverage trajectory data analysis to understand user behavior, implementing more individualized marketing approaches to increase user engagement [326]. Moreover, road condition

prediction and travel order allocation [16], facilitated by real-time analysis, provide businesses with more accurate and efficient services, ultimately elevating overall operational standards.

**Policy Guidance.** Trajectory computing offers valuable insights for policymakers and urban planners. In terms of traffic management, trajectory data analysis allows for the intelligent adjustment of traffic signals [196] and the rational planning of traffic flow [327], thereby improving urban traffic efficiency. Urban planners can utilize trajectory data to provide a more accurate foundation for city planning [17] by understanding the activity trajectories of city residents, facilitating the scientific planning of urban infrastructure and land use. Resource allocation and disease control [195] benefit from trajectory data mining, enabling governments to allocate urban resources more accurately and respond promptly to different regional needs. Real-time monitoring of human movement dynamics assists in the early detection of potential disease spread risks. Finally, in the realm of danger (crime) detection [328], the application of trajectory data aids in identifying abnormal behavior, enhancing urban security and enabling law enforcement agencies to intervene and prevent potential criminal events more effectively.

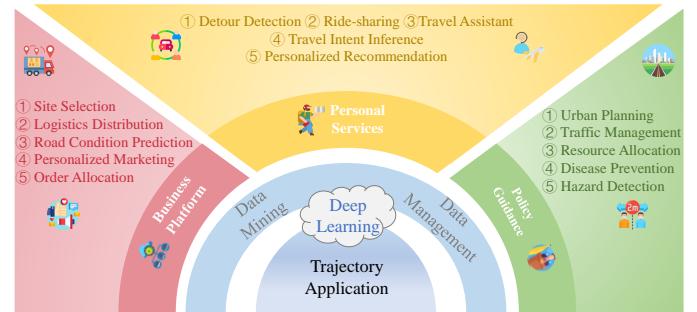


Fig. 11: Trajectory application in various fields.

### 5.2 Resources

Trajectory computing is crucial for understanding human mobility, and significant datasets and tools have been accumulated. We conduct a comprehensive analysis to address the current lack of a detailed survey of available open-source data and tools crucial for fostering transparent research.

**Datasets.** Table 5 lists all known publicly available trajectory datasets, categorized into three groups based on the form of data collection: continuous GPS traces, check-in sequence, and synthetic traces. The table encapsulates pertinent details for each dataset, including its type, main area, duration and statistical information.

**Tools.** For effective analysis and simulation, researchers have various tools at their disposal. SUMO<sup>6</sup> [201], an open-source traffic simulator, provides a comprehensive environment for traffic modeling. SafeGraph<sup>7</sup> offers an academic platform with access to large, anonymous datasets for privacy-preserving analysis. Cblab<sup>8</sup> [202], a toolkit for scalable traffic simulation, consists of CBEEngine, CBData, and CBSenario, enabling efficient simulations and training of traffic policies for large-scale urban scenarios. PyTrack<sup>9</sup> [203]

1. <https://www.uber.com>  
 2. <https://didiglobal.com>  
 3. <https://www.google.com/maps>  
 4. <https://map.baidu.com>  
 5. <https://www.cainiao.com>

6. <https://eclipse.dev/sumo>  
 7. <https://docs.safegraph.com/docs/welcome>  
 8. <https://github.com/caradryanl/CityBrainLab>  
 9. <https://github.com/titoghoze/PyTrack>

TABLE 5: Publicly available trajectory datasets.

Categorization	Type	Dataset Name	Main Area	Duration	Statistics	#Point/Records	#Attributes
Continuous GPS traces	Human	GeoLife [32]: link	Asia	4.5 Years	182 users, 17,621 trajectories, 91% 1~5 s/p sample rate	24.87 million+	7
	Human	TMD: link	Italiana	31 Hours	13 users, 226 trajectories, 0.05 s/p sample rate	–	9
	Human	SHL: link	U.K.	7 Months	3 users, 12 trajectories, 1 s/p sample rate	–	28
	Human	OpenStreetMap: link	Global	From 2005	8.7 million+ trajectories, continuously updating	–	7
	Human	MDC: link	Switzerland	3 Years	185 trajectories, nearly 200 individuals	4,527,539	–
	Taxi	T-Drive [197]: link	Beijing, China	1 Weeks	10357 cars, 177 s/p (Avg.) sample rate	15 million+	4
	Taxi	Porto: link	Porto, Portugal	9 Months	442 cars, 1,710,990 trajectories, 15 s/p sample rate	1,710,990	9
	Taxi	Taxi-Shanghai: link	Shanghai, China	1 Year	4,316 cars, 7.8 million trajectories, 5 s/p sample rate	–	5
	Taxi	DiDi-Chengdu	Chengdu, China	1 Month	3,493,918 trajectories, 3 s/p Avg. sample rate	1.4 billion+	5
	Taxi	DiDi-Xi'an	Xi'an, China	1 Month	2,180,348 trajectories, 3 s/p Avg. sample rate	1 billion+	5
Delivery	Truck	Greek: link	Athens, Greece	–	50 trucks, 1,100 trajectories	112,203	9
	Hurricane	HURDAT: link	Atlantic	151 Years	1,415 trajectories, 6 h/p sample rate	–	5
	Delivery	Grab-Posisi-L [198]	Southeast Asia	1 Months	84K trajectories, 1 s/p sample rate	80 million+	9
	Vehicle	NGSIM: link	USA	45 Minutes	0.1 s/p sample rate, collected through video cameras	–	20+
	Animal	Movebank: link	Global	Decades	8,480 studies, 1,383 taxa, 4,139 data owners	6.1 billion	–
	Vessel	Vessel Traffic: link	USA	9 Years	60s/p, AIS data	–	7+
	Human	Gowalla: link	Global	1.75 Years	196,591 nodes, 950,327 edges	6.44 million+	5
Check-in sequences	Human	Brightkite: link	Global	30 Months	58,228 nodes, 214,078 edges	4,491,143	5
	Human	Foursquare-NY: link	New York, USA	10 Months	38,336 venues, 824 users	227,428	8
	Human	Foursquare-TKY: link	Tokyo, Japan	10 Months	61,858 venues, 1,939 users	573,703	8
	Human	Foursquare-Global: link	Global	18 Months	3,680,126 venues, 266,909 users	33,278,683	15
	Human	Weeplace: link	Global	7.7 Years	971,309 venues, 15,799 users	7,658,368	7
	Human	Yelp: link	Global	15 Years	131,930 venues, 1,987,897 users	6,990,280	20+
	Human	Instagram [329]	New York, USA	5.5 Years	13,187 venues, 78,233 users	2,216,631	–
	Human	GMove [330]	2 cities in USA	20 Days	72K trajectories	1.3 million	–
	Taxi	TLC: link	New York, USA	From 2009	115,990 vehicles	–	10+
	Bicycle	Mobike-Shanghai	Shanghai, China	2 Weeks	390K+ bikes	60 million+	10
Synthetic traces	Bicycle	Bike-Xiamen: link	Xiamen, China	5 Days	50K+ bikes	198,382	6
	Bicycle	Citi Bikes: link	New York, USA	From 2013	68K+ bikes, 2,104 active stations	60K+/month	13
	Delivery	LaDe [15]: link	5 cities in China	6 Months	21,000 users, 10,677,000 trajectories	–	17
	Taxi	SynMob [200]: link	Chengdu, China	1 Month	2,000,000 (unrestricted) trajectories, 3 s/p Avg. sample rate	1 billion+	4
	Vehicle	BerlinMod: link	Berlin, German	28 Days	2,000 vehicles, 292,940 trajectories	56,129,943	–
Other formats of trajectories	Crowd Flow	COVID19USFlows: link	USA	From 2019	220k venues, millions of anonymous users, 100,000 individuals, 85 types of venues, 30-minute intervals, 500-meter grid cells	–	–
	Crowd Flow	MIT-Humob2023: link	Japan	90 Days	1 million users, 20 record/day sample rate	–	–
	Crowd Flow	BousaiCrowd: link	Japan	4 Months	32 × 32 grids, 60 s/p sample rate, 30-minute intervals, 34,000+ taxis	150 million	4
	Traffic Flow	TaxiBJ [127]: link	Beijing, China	17 Months	16 × 8 grids, 60 s/p sample rate, 1-hour intervals, 6,800+ bikes	–	–
	Traffic Flow	BikeNYC [127]: link	New York, USA	6 Months	32 × 32 grids, 600-meter cell length, 30-minute intervals, 17,749 taxis	–	–
	Traffic Flow	TaxiBJ21 [331]: link	Beijing, China	3 Months	–	–	

is a comprehensive tool that allows for the modeling of street networks, conducting topological and spatial analyses, and performing map-matching on GPS trajectories. PyMove<sup>10</sup> can be used for the processing and visualization of trajectories and other spatio-temporal data. TransBigData<sup>11</sup> [204] is a Python package for analyzing transportation big data and offers a systematic method for processing trajectories. Traja<sup>12</sup> is a toolkit for numerically characterizing and analyzing the trajectories of moving animals. MovingPandas<sup>13</sup> [205] provides generalized trajectory data structures and functions for movement data exploration and analysis. Scikit-mobility<sup>14</sup> [206] is a library designed for human mobility analysis, synthetic trajectory generation, and privacy risks assessment. Tracktable<sup>15</sup> is a set of Python and C++ libraries for the processing and analysis of trajectory. YUPI<sup>16</sup> is a set of tools designed for collecting, generating and processing trajectory data.

For detailed information and library access, please visit our official GitHub repository, a central hub for leading

advancements in trajectory computing, featuring research papers, benchmark datasets, and source codes.

## 6 CHALLENGES AND DIRECTIONS

### 6.1 Current Challenges

Examining the core triad of data, models, and algorithms, we delineate the current status and challenges in Figure 12.

**Data.** *i) Standardizing Trajectory Data Management:* Inadequate standardization impedes unified processing and application of trajectory data, necessitating open and standardized management approaches for seamless integration. *ii) Acquiring Multisource Semantic Trajectory Data:* Despite richer data from sources like social media, effective integration remains challenging. Advanced techniques are needed for acquiring and integrating diverse trajectory data to enhance deep learning models' multimodal understanding. *iii) Constructing Comprehensive Trajectory Datasets:* Large-scale, high-quality trajectory datasets are vital for deep learning model training. Balancing diversity and user privacy, along with ensuring spatio-temporal coverage, is crucial for improved model generalization.

**Model.** *i) Modeling Uncertainty in Movement Behavior:* Handling uncertainty in trajectory data, with its sparse, noisy, and long-tailed distribution, requires robust models adaptable to real-world mobility complexities. *ii) Unified*

10. <https://pymove.readthedocs.io/en/latest>

11. <https://transbigdata.readthedocs.io/>

12. <https://github.com/traja-team/traja>

13. <https://github.com/movingpandas/movingpandas>

14. <https://github.com/scikit-mobility/scikit-mobility>

15. <https://github.com/sandialabs/tracktable>

16. <https://github.com/yupidevs/yupi>

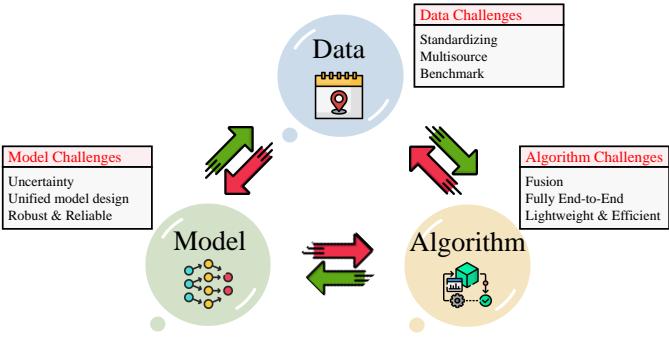


Fig. 12: Current challenges facing the core triad.

**model design:** Specific model architecture hinders the exploration of unified patterns in trajectory data. It is particularly challenging to design unified models for different tasks. *iii) Robust, Reliable, and Stable Trajectory Modeling:* Existing models lack robustness in extreme outliers, especially in practical applications. Ensuring model reliability is imperative.

**Algorithm.** *i) Fusion Algorithms for Multi-source Trajectory Data:* Existing algorithms for multi-source trajectory data can be more efficient. Robust algorithms are essential for global interpretative capabilities in fusing different data types. *ii) Fully End-to-End Algorithm Design:* Complete end-to-end algorithms simplify structures and enhance efficiency, addressing the multi-stage nature of current trajectory models. *iii) Lightweight and Efficient Algorithm Design:* Improving the efficiency of trajectory computing algorithms on resource-constrained edge devices is critical for practical applications.

## 6.2 Future Directions

With the above analysis on deep learning for trajectory, we also summarize potential research directions as follows:

**From Prediction to Planning.** In the application scenarios of trajectory computing, deep learning primarily addresses prediction tasks, given its lagging development. However, simple predictions constitute only the initial step and fall short of the broader objective. We contend that by integrating deep reinforcement learning and multi-agent gaming, trajectory computing progresses from mere prediction to real-time intelligent decision-making. This transformative shift involves not only capturing trajectory patterns but also leveraging real-time data to actively formulate new paradigms in mobility computing, such as traffic optimization [332] and flow control [333]. By integrating deep learning within prediction insights and decision analysis frameworks, researchers contribute to developing more efficient and sustainable urban transportation solutions [334].

**Resolving Distribution Shifts.** Trajectory data is often collected from diverse locations and time periods, leading to significant distribution differences among training and inference [335]. Due to these distribution shifts, a model trained on one dataset may not perform well on other datasets. Despite its importance, this issue is rarely addressed in the design of models for trajectory tasks. Potential research directions worth exploring include continual learning and incremental learning to tackle this problem.

**Multi-Modality Fusion.** Human movement is inevitably associated with various forms of data, such as vision, sensors or text [336]. Furthermore, diverse types of trajectories,

like taxi routes, bike-sharing records, and public transport flow, provide insights into human mobility from different perspectives. Presently, deep learning is advancing towards a multi-modal unified architecture [337], presenting a new opportunity for trajectory computing. Unlike simple concatenation in the past, developing an effective unified framework that integrates diverse modal data for a more comprehensive capture of movement patterns and accurate predictions demands further research attention.

**Foundation Models & Large Language Models.** Current trajectory computing, particularly in mining tasks, often relies on specific data and scenario models, lacking generality and external knowledge. As mentioned earlier, foundational and large language models [47], with their scalable parameters and intelligent compression capabilities, offer an exciting opportunity to enhance trajectory computing. Despite the need for careful cost-benefit analysis, it presents an exciting possibility for unifying trajectory computing tasks. Additionally, leveraging knowledge from LLMs has gained attention. Potential research avenues include, but are not limited to, distilling knowledge from LLMs to assist existing models, fine-tuning or directly leveraging LLMs for current tasks, and treating LLMs as agents for decision [49].

**Interpretability.** Up to now, the majority of deep learning efforts in trajectory computing have concentrated on enhancing task performance through intricate model design. However, there is a notable absence of research into the interpretability of these black-box models, making it unclear which key factors predominantly contribute to improved predictive performance. In recent work, some studies [338], starting from causality and physical laws to guide the design of network architectures, go beyond statistical correlations, leading to more stable and robust predictions. Consequently, constructing interpretable deep learning models for trajectory computing, considering both causality and physics, is a potential and ongoing direction.

**Privacy and Security.** We also need to address privacy and security issues [38], [304] related to trajectory data. Explore techniques to anonymize or protect sensitive information, with potential research lines including incorporating federated learning for privacy protection and leveraging advanced generative models to generate synthetic data.

## 7 CONCLUSION

In this survey, we systematically explore the promising intersection between trajectory computing and deep learning. Our unified framework unveils a structured understanding of deep learning for trajectory computing, dissecting them into deep Learning for trajectory data management and mining. This study offers a concise and organized perspective for researchers and practitioners. Examining existing methods, we provide fresh insights into the core contributions of deep learning to reshape trajectory computing and the field of mobility science. Besides, we summarize application scenarios, resources, providing a roadmap for the future. Our survey addresses challenges, fosters discussions, and suggests new directions.

## ACKNOWLEDGMENT

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