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SURVEY PAPER

Analyzing large-scale human mobility data: a survey of machine learning methods and applications

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Abstract Human mobility patterns reflect many aspects of life, from the global spread of infectious diseases to urban planning and daily commute patterns. In recent years, the prevalence of positioning methods and technologies, such as the global positioning system, cellular radio tower geo-positioning, and WiFi positioning systems, has driven efforts to collect human mobility data and to mine patterns of interest within these data in order to promote the development of location-based services and applications. The efforts to mine significant patterns within large-scale, high-dimensional mobility data have solicited use of advanced analysis techniques, usually based on machine learning methods, and therefore, in this paper, we survey and assess different approaches and models that analyze and learn human mobility patterns using mainly machine learning methods. We categorize these approaches and models in a taxonomy based on their positioning characteristics, the scale of analysis, the properties of the modeling approach, and the class of applications they can serve. We find that these applications can be categorized into three classes: user modeling, place modeling, and trajectory modeling, each class with its characteristics. Finally, we analyze the short-term trends and future challenges of human mobility analysis.

Keywords Human mobility patterns · Mobile phones · Machine learning · Data mining

1 Introduction

According to a 2016 worldwide Pew report, around 90% of people have a mobile phone, and between 45 and 80% have a smartphone [71]. In recent years, we have witnessed a mobile computing revolution—mobile technology is now more connected, sophisticated,

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location-based, personal, and powerful than ever. Positioning technologies that serve mobile phones such as the cellular antenna, global navigation satellite systems (such as the Global Positioning System—GPS), and the WiFi positioning system (WPS) provide increasingly accurate and continuous geographic positions of mobile devices [56]. It is now dramatically easier to track the location of a huge number of mobile devices, leading to a wealth of information about the mobility of humans, vehicles, devices, and practically anything that can be fitted with a mobile computing device. The availability and scale of mobility data are expected to grow exponentially, as more and more physical objects will be connected to the Internet of Things (IoT).

Large-scale location information poses a considerable opportunity for commercial, governmental, and academic applications that analyze and act upon people's locations and movements. However, this opportunity requires researchers and developers to overcome various challenges that stem from the scale, complexity, and sensitivity of the mobility data. This opportunity is also apparent in cutting-edge research and development. Mobility data have been used to answer questions such as how people travel between cities [73] and what the patterns are of their daily commute [37, 80], as well as to predict socioeconomic trends [33], find relationships in online social networks [21], identify people's weight and health status [65], discover employment patterns [28], and follow the spread of infectious diseases [5, 93]. Mobility data were also found to represent human behavior in catastrophic events, e.g., the 2010 Haiti earthquake [9, 57] or the 2011 Japan earthquake [31]. Models of mobility were used in designing public transportation systems [11], in taxicab allocation [43], and in performing crowd-sourcing tasks [76]. In addition, the analysis of mobility patterns leads to a growing field of commercial applications by mobile communication service providers such as Telefonica[1] and Verizon,[2] as well as by several companies that have already started to provide location-based services analyzing mobile phone location traces. Mobile phone location traces are created through ongoing positioning of the mobile phone, whether stationary or moving. Advances in mobile positioning including cellular antenna base station geographic positioning, WiFi antenna triangulation, and global navigation satellite positioning systems (such as GPS) contribute to the increasing number of locatable phones.

Recent advances in machine learning (ML) and modeling provide a vast set of tools that can analyze mobility data, but choosing the right tool for a given task remains confusing. There are dozens of different ML (and non-ML) methods associated with mobility patterns, and while most of them aim at modeling people's movements, they make different assumptions on how a location is defined and sensed, and how it should be analyzed. Usually, these methods are also tailored to the application and are modified accordingly, and therefore lose their transferability. As a result, applying the methods developed in one research work to another is challenging. For example, a mobility model that is focused on the positioning of users inside a room may be inapplicable to model daily commutes of users between cities. However, knowledge from one domain may often be useful in another domain. Different positioning technologies, such as those described above, can produce traces that can be analyzed by similar models. That is, knowledge extracted using one mobile location tracking method may be very effective in another. For example, the method suggested by Sohn et al. [79] is used by Reddy et al. [74], even though the former uses call detail record data, while the latter utilizes combined data from the GPS chip and the accelerometer. Finding common ground between relevant research studies is a crucial, but challenging task, as the research communities working on mobility analysis are quite often diverse, ranging in domains from

1 https://www.telefonica.com/en/.

2 https://www.verizonwireless.com/featured/precision/.

physics [37, 81], to geography [70], ubiquitous computing [67], and machine learning [39]. Because human mobility analysis is inherently interdisciplinary, interpreting and bridging these works is essential for advancing both the theoretical and practical aspects of an analysis.

In this survey, we extend previous reviews of methods and approaches for the analysis of mobility patterns that are based on various types of location trace data, such as those collected from cellular cell tower positioning records, global navigation satellite positioning systems, WiFi positioning, and other methods that can produce a large set of geographic locations. We describe and categorize these methods and approaches by considering both the model and semantics of the location data, rather than only the way the data were collected and produced, and extend previous surveys that mainly focused on specific applications or specific data sources. Previous surveys focused on specific applications that make use of mobile phone sensing, including location tracking, to facilitate urban operations [40] and urban computing [102, 103], or on anticipatory mobile computing [68]. Others [60] focused their review on trajectory modeling, but overlooked some user modeling applications that portray longitudinal patterns of mobility of individuals or places, or analyzed specific location data sources such as GPS traces [54] or GPS taxicab traces [17], but ignored data sources such as call detail records (CDRs). Another survey [84] focused on anomaly detection in spatiotemporal data streams as a means to model urban traffic.

In this survey, we take a wider approach to human mobility analysis, reviewing papers from multiple disciplines and applications, which are based on various location data sources, including cellular antenna positioning, GPS, WiFi, and other beacon-positioning technologies. We argue that papers from distanced domains to mobility analysis can also be useful for this analysis, as the underlying methods may be similar, regardless of the data source or the application domain. Due to the interdisciplinary nature of research in this field, we categorize the approaches according to a general set of application classes: user modeling, place modeling, and trajectory modeling. We analyze these applications according to their positioning technology and the resolution level and properties of the data, as well as the modeling methods that are used to extract knowledge from such data.

Section 2 of this survey gives a background of human mobility patterns and their analysis. In Sect. 3, we categorize mobility pattern analysis methods in a taxonomy we suggest according to: (1) three classes of applications which are served by the methods that are used for user, place, and trajectory modeling; (2) the modeling approach; and (3) the tracking properties of the mobility patterns. In Sect. 4, we thoroughly explore the three application classes. Finally, in Sect. 5, we analyze future challenges and opportunities for large-scale pattern mining of human location traces.

2 Background: human mobility patterns

The first efforts to learn human mobility patterns were associated with classic social sciences. Since the nineteenth century, sociologists in what are called time-use or time-budget studies have been measuring the time people spend doing different activities throughout the day [85]. Transportation forecasting was one of the first research fields that made use of mobility analysis, and mobility patterns have been studied since the late 1950s [24]. The first analytical models implemented pre-calculated probability distributions of possible travel destinations mainly based on land use and demographics. In the field of Industrial Engineering, activity-based models and mobility analysis have been implemented in work studies trying to minimize movements of workers, products, and inventories, if such are found to be unnecessary in terms of their added value [7]. Starting in the 1990s, this approach was gradually enriched by activity-based models, e.g., computerized models that use agent-based simulations, where the agents are modeled and driven by specific human activity such as work, leisure, and shopping [43]. Until recent years, most mobility data used in empirical geographic-oriented domains, such as transportation, epidemiology, engineering, and urban ecology, were gathered from user reports: travel diaries, recall interviews, and surveys. With the markdown in cellular base tower geographic positioning, GPS, and WiFi positioning technologies, more studies have been conducted using automatic location recordings [12].

The availability of massive human location tracking datasets was enabled by mobile technologies, such as big-data technologies in mobile telecommunication networks and large-scale deployment of GPS technologies. Large-scale studies analyzed mobility patterns by using statistical models that captured some general properties of these observed patterns. Gonzalez et al. [37] showed, based on analyzing 100,000 mobile phone traces, that the travel distances of people follow a power–law distribution. Similar patterns were found by analyzing travel paths of banknotes [13]. The number of diverse patterns was found to be rather limited, providing an encouraging foundation for predicting and analyzing mobility [80].

Another emerging area of social science studies of human mobility relies on complex network theory and statistical and information theory tools. These studies, sometimes termed as Computational Social Science, focus on analyzing social relations and aggregating mobility patterns from masses of individuals' data. For example, in a series of papers, Eagle and Pentland [25, 26], and Eagle et al. [27] studied human social structure using mobility data that were collected from mobile phones. Aggregating geographic locations for pattern extraction purposes has proven to be useful in predicting interactions between people and in modeling the spread of infectious diseases in humans [5], as well as the spread of mobile phone viruses [91].

Location tracking and location-based services are being used in a growing number of commercial applications. These applications are provided by mobile carriers, such as Telefonica (see Footnote 1) and T-Systems,[3] a host of startup companies, such as Airsage,[4] StreetLightData,[5] and TrendIt,[6] and by established companies, such as ArcGIS.[7] The applications provided by these companies use large-scale location data to analyze the commercial prospects of a business by evaluating the mobility of those customers who visit that business. In retail industry that suffers from a significant decrease in shoppers to brick-and-mortar stores due to e-commerce competition, new mobility and customer tracking solutions are provided. In particular, companies such as Euclid Analytics,[8] ShopperTrack,[9] and RetailNext[10] analyze the mobility of shoppers into stores and in the store in order to optimize the location of products and improve the customer experience. Other services are aimed at individuals by providing value for personal use, including applications that personalize search results (e.g., Google local search[11]), help users avoid traffic jams (e.g., Waze[12] and Google Maps[13]),

[3] https://www.t-systems.com/de/en/solutions/cloud/solutions/outdoor-analytics/traffic-analysis-75652.

[4] http://www.airsage.com/.

[5] http://www.streetlightdata.com/.

[6] http://www.trendit.net/.

[7] http://www.esri.com/software/arcgis.

[8] http://euclidanalytics.com/.

[9] http://www.shoppertrak.eu/.

[10] http://retailnext.net/en/home/.

[11] http://searchengineland.com/new-google-local-search-display-230525.

[12] https://www.waze.com/en-GB/.

[13] https://www.google.co.il/maps?source=tldso.

Table 1 Categorization of mobility pattern analysis methods according to the application served by the method, the modeling approach, and the tracking properties

Application class	Modeling approach	Tracking properties
1. User modeling	1. Non-ML models	1. Tracked object
2. Place modeling	2. ML supervised learning	2. Tracking method
3. Trajectory modeling	3. ML unsupervised learning	3. Data scope

and find personalized venues (e.g., Yelp[14] and Urbanspoon[15]). Other applications provide social utility for groups of individuals, such as checking into venues (e.g., Foursquare[16] and Facebook Places[17]), transportation sharing (e.g., Uber[18] and Lyft[19]), and location sharing (Apple's FindMyFriends[20]).

3 Taxonomy of mobility pattern analysis methods

To survey methods of mobility pattern analysis, we propose a threefold taxonomy that ties together the mobility data, modeling approach, and application classes. Our categorization emphasizes the class of applications that are driven by the modeling approach used, with specific focus on the properties of the location tracking data. The categorization was developed in an iterative process, in which we analyzed the data prerequisites for each application class, the data preparation processes it requires, the algorithms it uses, and the possible outputs and usage of the underlying algorithms. Table 1 describes three aspects of the taxonomy, starting with the classes of possible applications (Sect. 3.1), through the modeling approaches (Sect. 3.2), and up to the tracking properties (Sect. 3.3).

The research works, which are included in this survey and are categorized according to Table 1, were selected according to their relevancy to mobility analysis, their prominence (evident by the number of relevant citations), as well as our view on their potential influence on the field of location tracking analysis. The first inclusion criterion requires the work to use coordinate-based location data. In a small number of cases (e.g., Monreale et al. [61], Eagle et al. [27]), we also included approaches that were based on accelerometer data, but only if the location data were the main source of information for modeling the mobility patterns. The second inclusion criterion was that the work revolved around tracking of humans (or good proxies for humans such as vehicles). We excluded approaches that tracked animals, natural phenomena, or shared public transit systems (such as trains and fixed bus lines). Finally, we included only papers that are influential, a property we measured according to the number of citations in Google Scholar, and according to a qualitative analysis of the impact of the work. As it is difficult to assess the influence of new papers, we also surveyed contemporary ones that we believe are noteworthy and promising.

14 https://www.yelp.com/sf?home=1.

15 https://itunes.apple.com/il/app/urbanspoon-restaurant-food/id284708449?mt=8.

16 https://foursquare.com/.

17 https://www.facebook.com/places/.

18 https://www.uber.com/.

19 https://www.lyft.com/.

20 https://itunes.apple.com/il/app/find-my-friends/id466122094?mt=8.

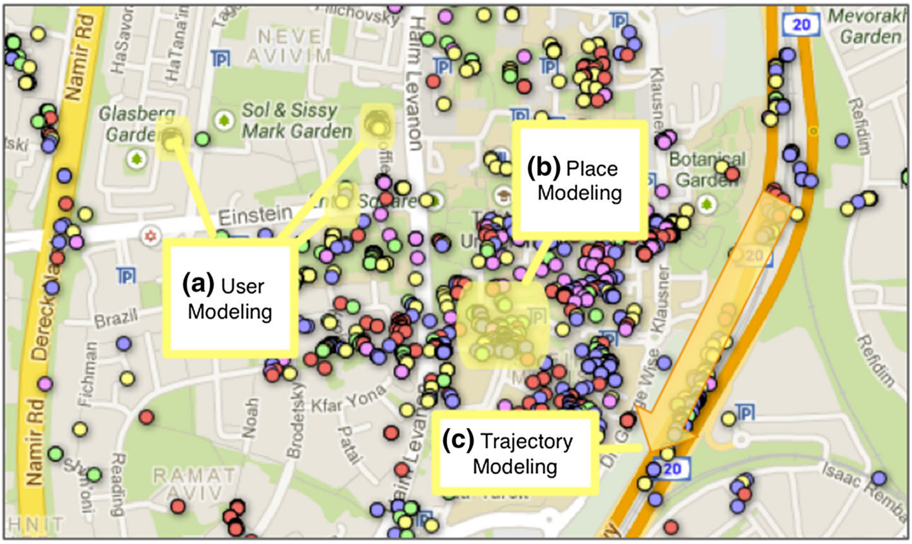

Fig. 1 Visualization of the three application classes: (*a*) user modeling where the object of analysis is a single user (represented by circles of the same color), (*b*) place modeling where the object is a geographic area (visited by different users; each is represented by a circle of its own color), (*c*) trajectory modeling where the object is a set of spatial–temporal points by the same user (represented by a yellow arrow). The map was generated using Google Maps

3.1 Application class

Mobility pattern analysis methods are used in the context of a particular application, providing a service that is based on data about a particular entity that is being tracked and modeled. We have grouped applications by classes, aiming at representing domains of functions that can be accomplished by each application while using particular datasets. Through an iterative process, we classify the studies in three main categories according to the aim of the model that is used by the application: user modeling, place modeling, and trajectory modeling. Figure 1 exemplifies the three application classes focusing on modeling the (a) human user, (b) places the user moves through, and (c) trajectories of the user movements.

User modeling applications analyze the mobility of a single user (or object) for extended periods of time (Fig. 1a). In such applications, the model can predict where a particular user will be at different times of the day. For example, in homeland security applications, targeted users can be modeled by the distribution of their geographic locations over time in order to trigger an alarm if an abnormal situation occurs.

Place modeling applications analyze the characteristics of a geographic location or a set of locations. For example, in Fig. 1b, the model can predict the number of incoming and outgoing people in a place (say a large store), profile its traffic, and classify the type of place according to the mobility patterns of people around it.

Trajectory modeling applications analyze a set of spatial–temporal points that reflect a trajectory, defined as a movement pattern through a set of locations of a single object or a set of objects and time. In contrast to user modeling, in trajectory modeling, the identities of the moving objects are not necessarily a factor in the analysis; thus, for example, all the moving objects along the modeled trajectory can be analyzed aggregately. In contrast to place modeling, the entity in trajectory modeling is a route between geographic locations,

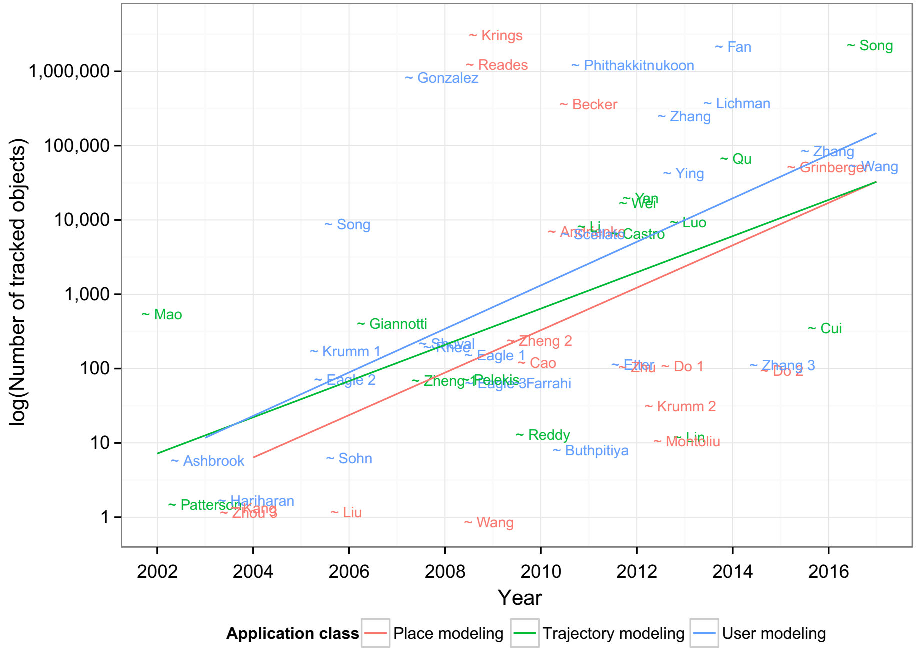

Fig. 2 Research papers plotted by their year of publication, numbers of tracked objects (on a base 10 logarithmic scale), and their application classes. Papers are noted by the name of the first author and are numbered if there is more than a single work by the same author. Lines represent trends (based on linear regression) for each application class

rather than a single location. For example, Fig. 1c visualizes a trajectory that may be used in modeling road segments or road networks by an application that predicts traffic conditions.

A dimension by which applications differ from each other is the level of the aggregated analysis. For example, some applications model a single object (e.g., a user), whereas others model a multitude of objects. An example of the latter is community modeling, in which a group of users is modeled according to their location data. In our survey, we distinguish between these two types of applications. Note that in Sect. 4, we elaborate on user, place, and trajectory modeling.

Figure 2 visualizes the relation between the application classes and the number of tracked objects. The largest datasets with regard to this number are used in user and place modeling, whereas middle-sized datasets, e.g., of taxicab and truck fleets, are used in trajectory modeling. One possible explanation is that many of the datasets are based on transactional data, such as CDRs, which have low location and time resolutions and, therefore, are not detailed enough for trajectory modeling. Finally, while the research papers we analyze are only a representative sample, we see that the size of datasets is increasingly (logarithmically) growing with time in all the application classes.

3.2 Modeling approach

The second aspect according to our taxonomy is of the modeling approach that is used in mobility pattern analysis. Different modeling approaches use different methods, which differ by their expressiveness, type of the used algorithm, and their predictability. Since the majority of the methods are based on machine learning, we classify the approaches into machine learning methods, which apply either supervised or unsupervised learning, and non-machine learning methods.

Table 2 organizes the papers according to the modeling approach, analysis method, and application class. The differentiation among non-machine learning methods is based on the general approach of the model toward describing mobility data, whether it is in a generalized or statistical manner. We call the first type of models "generalized" since they represent the entire mobility information by a compact set of formulas or rules that fit the data, or by a "gross" statistical description of mobility properties, such as the daily travelled distance or the entropy measure of the random walks, rather than providing a detailed granular description of individuals, places, or trajectories. Generalized models rely on a description of mobility patterns using universal models or laws, for example, the gravity law in Balcan et al. [5], continuous-time random walk in Song et al. [81], and Levi walks in Kagan and Ben-Gal [41, 42], or using a set of rules [63, 77] or a social network [27]. Non-generalized (statistical) models may represent objects (e.g., moving objects, such as people, devices, or vehicles) by using structural schemes that specifically detail mobility information about the objects. These detailed models can characterize or predict the mobility of the object, e.g., a single individual, place, or trajectory using statistical models, e.g., regression [79] or Markovian models [59].

Machine learning methods can be categorized in a traditional manner to supervised and unsupervised learning, each of which provides a different descriptive and predictive ability to model mobility patterns. In the supervised learning approach, the algorithm learns a set of tagged (labeled) data instances during the training phase in order to map the instances to their labels. Such mapping can then be used to predict new untagged instances. In unsupervised learning, labeled instances are not available, and the model is used to group together instances that share the same common behavior (related to their mobility patterns in this case) and to find similarities and dissimilarities in the data.

Supervised methods are common in user and place modeling, as these provide good opportunities for obtaining labeled datasets of known users and known places, respectively. Labeled data can be collected automatically (e.g., Monreale et al. [61]) through a semi-manual process that includes some external ground truth, for example, in user modeling [48] or in place modeling by relying on the geographic properties of the places [23]. The most common supervised modeling tasks are classification if the target variable is discrete (ordinal or categorical), and regression if the target variable is continuous. Classification can be used, for example, to find if a user (or a location) belongs to a known class of users (or places). Based on the classes, the class of mobility patterns of a new user (or that describing a new place) can be predicted. Possible classification applications focused on users can include location-based services, insurance plan optimization based on telematics profiles, and link analysis among a group of users. Regression models can be used, for example, to predict the exact (numerical) location (say latitude and longitude) of a user or to estimate the expected mileage travelled per month for a specific user or within a specific mall. For both classification and regression methods, the output of the supervised model can be a class-conditional probability, where, e.g., in a classification problem, a user (or place) is associated with some probability to belong to one class or more. In such cases, a supervised model, such as a decision tree (e.g., CART, C4.5, J48, and CHAID), can estimate this class-conditional probability. Other supervised models used to analyze mobility patterns are Bayesian classifiers, n-grams, random forest [44], and discriminant analysis functions, such as support vector machines (SVMs) and neural nets [34, 71], and recently also deep learning [102, 103].

Table 2 Methods of three approaches used in user, place, and trajectory modeling

Approach	Method	User modeling	Place modeling	Trajectory modeling
Non-machine learning models	Generalized (non-statistical) models (e.g., nonlinear time series analysis, gravity model, rule-based, survey-based)	Phithakkitnukoon et al. [70], Scellato et al. [77], Balcan et al. [5], Sohn et al. [79], Song et al. [80], Kagan and Ben-Gal [41, 42], Eagle et al. [27], Espin-Noboa et al. [29], Fan et al. [31]	Krings et al. [45], Zheng et al. [101], Montoliu et al. [63], Souto and Liebig [84]	Giannotti et al. [35], Qu et al. [72], Cui et al. [22]
	Statistical models (e.g., regression, Markov models, and kernel density estimation)	Buthpitiya et al. [14], Eagle and Pentland [25], Zhang and Chow [100], Lichman and Smyth [53], Zhang et al. [99], Zhang et al. [98]	Zhu et al. [104], Song et al. [82], Tong et al. [87]	Mao et al. [59], Yan et al. [95]
Supervised learning	Support vector machine	Sohn et al. [79], Li et al. [52], Wang and Prabhala [90]	Zhu et al. [104]	Lee et al. [50]
	Neural networks	Etter et al. [30], Song et al. [83]		Zheng et al. [102], Zheng et al. [103], Song et al. [83]
	Decision trees and random forests	Monreale et al. [61], Krumm and Horvitz [48], Etter et al. [30], Khoroshevsky and Lerner [44]	Zhu et al. [104], Do and Gatica-Perez [23], Krumm and Rouhana [49]	Patterson et al. [67], Reddy et al. [74], Zheng et al. [102, 103]
	Other supervised learning models	Krumm and Horvitz [48], Etter et al. [30]	Zhu et al. [104]	Zheng et al. [102, 103]
Unsupervised learning and latent variable models	Clustering methods (e.g., K-means, hierarchical, and spectral)	Ashbrook and Starner [4], Shoval et al. [78], Andrienko et al. [2], Ying et al. [96]	Ashbrook and Starner [4], Cao et al. [16], Reades et al. [73], Wang et al. [91], Rösler and Liebig [75], Souto and Liebig [84]	Nanni and Pedreschi [64], Lee et al. [51], Pelekis et al. [69], Wei et al. [92], Lin et al. [55], Andrienko et al. [1], Zheng et al. [102, 103]
	Topic models (e.g., latent Dirichlet allocation—LDA)	Hariharan and Toyama [38], Farrahi and Gatica-Perez [32], Wang et al. [89], Ben-Zion and Lerner [10]	Liu et al. [56]	

Among the unsupervised machine learning methods, the most popular are clustering methods that are especially used in trajectory modeling. One reason for their popularity might be the fact that these methods do not require any specialized ground truth or a priori knowledge, which is usually difficult to obtain with mobility data and is needed in supervised learning. Furthermore, the spatial–temporal properties of location tracks provide a natural distance metric (often Euclidean although some information–theoretical measures can be used) that lends itself easily to clustering. Clustering can be used, for example, to find how objects (users) are similar to each other with respect to their spatial–temporal trajectories, or trajectories of the same user are similar to each other [44]. Possible clustering applications can include carpooling services based on common trajectories (e.g., Uber), profiling of users for transportation and route planning, and collaborative filtering and other association rules techniques to find which locations are often associated by their trajectories (e.g., how popular is Central Park for people who visit the Statue of Liberty and Times Square) [71]. Other unsupervised modeling can be exploited by latent variable models to learn human behavior and lifestyle [10].

Due to the large dimensionality of the mobility data, various dimensionality reduction and feature selection techniques (such as principle component analysis) can be applied to find which dimensions can best describe an object's trajectory preferences or be used in a specific application. Finally, causal modeling (e.g., Bayesian networks) can be used to find the (possibly hidden) reason why some observed objects follow certain trajectories at certain times.

3.3 Tracking properties

All the studies we surveyed analyze datasets of human location traces. However, these datasets differ according to some tracking properties, such as the type of tracked object, trace time resolution, and resolution and accuracy of the location positioning technology. These properties affect the types of modeling methods that have to be selected and their performances, and the classes of applications that can use the location data. Moreover, the type of tracked objects may dictate the purpose of the analysis. For example, datasets that are used to investigate the mobility of taxicabs [17, 52, 59] can be used to better understand urban traffic, but can hardly be used to investigate social relations, whereas a dataset that holds tracks of individual people [21, 27] can be used for social network analysis.

We consider the resolution of mobility patterns according to two aspects: time resolution (frequency of sampling) and location resolution (the spatial accuracy of the location traces). At one end of the scale, there are analysis methods that rely on (almost) continuous representation or frequent location sampling using dedicated sensors, in which location is tracked every several minutes [14]. At the other end of the scale, CDRs [3] provide sparse temporal records because they are often generated only when a communication event occurs,[21] rendering cell phone users often "location invisible" at all other times [8]. Location resolution in which location traces are recorded is another facet of the tracking method. GPS traces have an accuracy of several meters, whereas CDRs provide traces that are coarse in space because they express locations at the granularity of a cell tower sector, giving an uncertainty approximately one square mile or even higher in less populated areas. Thus, a dataset of location traces collected with a dedicated GPS device will have higher location and time resolutions than a dataset of CDRs collected by mobile service providers. Dedicated GPS trackers provide

[21] There are other paging policies that use time and spatial-based approaches for location management, e.g., as in Krishnamachari et al. [46] and Xiao et al. [94].

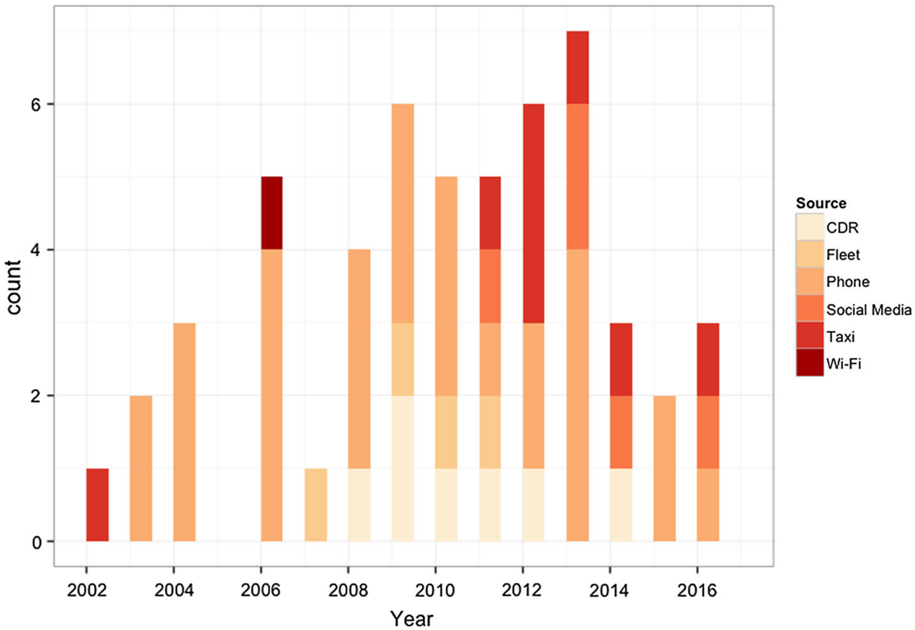

Fig. 3 Number of papers according to year and the source of the dataset

accurate and continuous tracking, whereas use of CDRs provides non-continuous, event-driven tracking, which is relatively inaccurate.

In many cases, there is a trade-off between the resolution and the scope of a dataset holding information about tracked objects. For example, CDRs can include information about millions of people, whereas dedicated GPS devices mostly use smaller samples. Moreover, the mobile operators that collect the location data are often exposed only to the CDR-based locations and not to the GPS-based ones because of privacy restrictions. Thus, a CDR dataset cannot be used to accurately analyze small-scale movements, while in most cases, a GPS dataset cannot provide solid statistical profiles of an entire large population of users. The tracked objects in the surveyed studies were mostly people or vehicles. People were tracked with CDR data [8, 37], dedicated GPS devices [4, 48], and lately GPS-equipped smartphones [31, 55]. Vehicle tracking was carried out using GPS tracking of fleets of taxicabs [52, 59] or trucks [35]. The largest datasets were CDR datasets, and the largest of which includes 1.6 million users [31].

Figure 3 provides an overview of the use of different data sources in the papers that we survey. We see a gradual change in the type of dataset sources used by the works. While most early methods from the 2000’s were using small datasets based mostly on phone sensing using dedicated hardware or software, other methods from that era were based on data derived from car fleets and WiFi networks. The prevalence of tracking and positioning systems, especially in taxicab systems, gives rise to datasets, large in volume and duration. Papers that analyze taxicab datasets make a considerable part of recent works, providing many technical achievements, mainly in trajectory and traffic analysis. However, they have some drawbacks. First, taxicab datasets are unlabeled and do not contain information about the types of places, characteristics of drivers and so on. Also, in most taxicab datasets, the identity of the driver or the cab is not recorded (for privacy reasons), making the datasets mainly relevant to trajectory analysis. Location data from social media sources, especially from Twitter, Foursquare, and Gowalla, are another popular data source in recent years. Social media datasets contain rich information, such as the venue type or the tweet information. At the same time, as location traces are triggered by the user's actions, such as a check-in a venue or publishing a geo-located tweet, they lack continuity and are arbitrary in nature. Therefore, they are mainly used for place analysis.

4 Application classes of human mobility patterns

In Sect. 3.1, we introduced a taxonomy of three application classes that we suggest a researcher/practitioner consider when analyzing mobility patterns. In the following subsections, we detail the three application classes, highlighting how various approaches tackle the challenges involved in managing and modeling location data.

4.1 User modeling

Implementing analysis methods on users' location data enables various types of analysis on individuals' mobility patterns. For example, user modeling can enable prediction of a user location, foreseeing the place in which the specific user will be situated in a particular time period of the day, based on historical patterns. User modeling can also be used to categorize and cluster locations and other properties of individual users, as well as to predict the mobility of users or clusters of users. Predicting future mobility of a user can be tremendously beneficial in numerous applications such as recommendation systems, forecasting the dynamics of crowds, traffic control, and location-based advertising.

User modeling applications can be categorized according to their purpose, working mechanism, and expressiveness. Abstract models (such as the distance-based model seen in Fig. 4a) describe a straightforward numerical property of mobility such as the daily distance travelled by a user [37, 80]. We call these models abstract, as they do not aim to provide a detailed descriptive or predictive model of a single object, but of a general model that represents the behavior of a population of objects. In contrast, Fig. 4b depicts detailed geographic models, which provide a geographic location pattern for a single object, e.g., when the object moves between specific locations [4, 30]. Figure 4c depicts semantic models, which describe

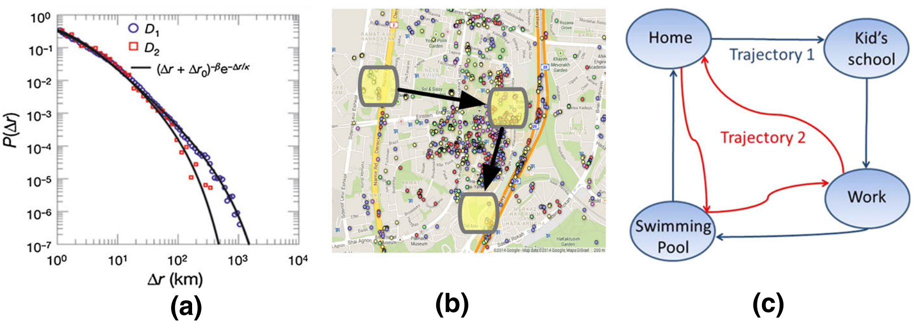

Fig. 4 Three levels of user modeling by **a** abstract model (e.g., representing the user's travel distance), **b** geographic model (e.g., representing locations visited by the user), **c** semantic model (e.g., representing the semantic meaning of places the user has visited) (from [37])

a mobility pattern of an object using common and meaningful categories of locations that have semantic meaning for a place or activity, e.g., “home,” “work,” and “shopping” [32].

The vast majority of a user’s location predictions are based on modeling a location pattern for a single user using machine learning or other statistical models. To accomplish a location prediction task, Sohn et al. [79] used two-step logistic regression; the first step predicts whether the user is stationary or not, and the second step whether that user is walking or driving if they were initially predicted as not stationary. In next place prediction, the location of an object in the near future is predicted according to data on its current location as well as on historical locations. Etter et al. [30] and Wang and Prabhala [90] proposed a user-specific predictor that learns from the user mobility history and predicts, based on the current context, the next location the user will visit. Such prediction may be based on different machine learning techniques, e.g., Bayesian methods [48], neural networks [30], and random forest [44]. Gonzalez et al. [37] demonstrated how Levy flight clustering could be used to predict the user’s next location. Farrahi and Gatica-Perez [32] used topic models to predict the user’s next location with data that contain location, motion, and Bluetooth signals.

Probabilistic models were suggested for recognizing daily activities such as walking, driving, and working. These models were also used to build activity maps, i.e., maps that classify places according to the type of activity they represent such as work places, homes, and restaurants. Ekman et al. [28] faced the diversity of daily activities by modeling them using several sub-models, representing work, home, and travel routines separately, and then joining them in a unified framework. Fan et al. [31] used tensor factorization to model and classify routines of over 1.6 million people and to model how these routines change during catastrophic events, such as in the Great East Japan Earthquake of 2011.

Combining semantic information and geographic locations to create a semantic trajectory for modeling mobility can result in more robust models than if using either of these alone. A semantic trajectory[22] consists of a sequence of locations labeled with semantic tags (called semantic locations) that capture the meaning of the places passed by a user. These semantic tags imply the activities being carried out along the trajectory. Consider Fig. 3c, where trajectories go through a number of locations with semantic tags, such as “home,” “school,” or “work.” The figure exemplifies how semantic trajectories can be useful for mobility modeling and prediction. For example, let us assume that the two trajectories visualized in Fig. 3c are prevalent in the user’s routine. If the user leaves home and drops the kids at school on the way to work (Trajectory 1), then a mobility model can predict with high probability that the user will stop at the swimming pool on the way back from work. However, if the user goes swimming on the way to work, then the model can assume that Trajectory 2 holds, and it can predict that the user would not stop at the swimming pool on the way back from work. An example for a semantic model is the SemanPredict framework that combines geographic and semantic information, showing promising results in location prediction using a small sample [96]. Another example is the mobile application Waze that starts to enrich its navigation capability by asking the user questions at certain hours that are related to semantic tags, for example, asking users in the morning: “Are you driving to work?”

Scaling mobility pattern analysis from a single user to multiple users is still an open question when considering the models and usage. There are several ways to aggregate information about users, for example, in a geographic place (e.g., people living in a single house or in the same city), having similar travel patterns (e.g., people who visit nightclubs on certain evenings), or relying on online social networks (e.g., Waze that enables users to share their

[22] Note the difference to trajectory modeling (Sect. 4.3), in which moving objects along a route are analyzed together.

location and paths with friends). There are some initial studies showing the promise in aggregated mobility modeling. For example, Cho et al. [20] showed that a person's social network can be used to better identify their mobility patterns. Humans experience a combination of periodic movement, which is geographically limited, and seemingly random jumps that seem to be well correlated with their social network activities. Cho et al. improved existing mobility models by taking into account the information the social network structure holds on an individual's mobility and showed that social relationships can explain about 10–30% of human movements, while a periodic behavior explains 50–70% of this movement. Monreale et al. [61] offered a location prediction technology called WhereNext; instead of using only the history of movements of an individual user as the basis for prediction, they proposed to use the movements of all users in a certain area to refine the user-based prediction. The basic assumption is that people often follow the crowd, i.e., individuals tend to follow common paths both in nature as well as at commercial sites. Thus, if enough data exist to model a typical behavior of groups of individuals, such information can be used to predict the future movement of each individual in the group.

4.2 Place modeling

Methods addressing place modeling can be divided into several categories, based on the way spatial environments are defined and organized. Traditional studies of place modeling rely on specialized spatial databases that describe the underlying world map (using vector graphics representation) and define the topology and relations among different vector objects (points, lines, polygons). Typically, place modeling represents a location in its physical form using geographic coordinates or other local coordinate systems, enabling what is usually called spatial data mining (SDM) [66]. SDM is mostly used in domains such as climatology, earth science, public health, and demographic analysis in which human mobility traces augment geographic models, providing insights into how humans use the space.

Figure 5 exemplifies possible levels of place modeling. In individual place modeling (Fig. 5a), the analysis process uses location traces to identify the places users stay in [4]. The definition of a place in most research relates to a specific location or a polygon that the user remained for a meaningful period of time. In the second level of modeling (Fig. 5b), a place is modeled statistically based on visitation patterns of users in this place [15]. Semantic place modeling (Fig. 5c) analyzes the semantic properties of places, such as "residential" or "commercial" [104]. Finally, activity-based place modeling (Fig. 5d) provides semantic annotation that individuals give to a place they visit according to their activity in this place, such as "studying" or "shopping" [49].

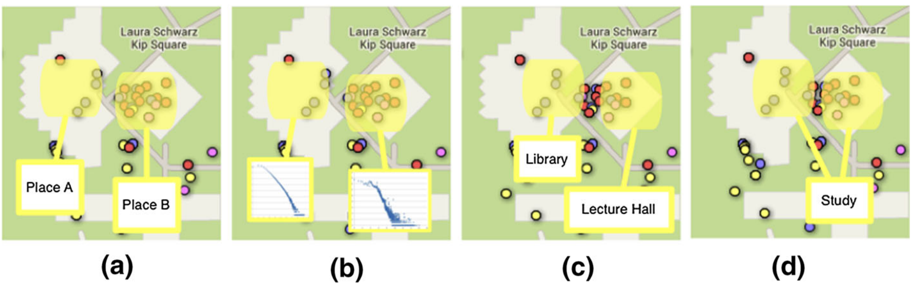

Fig. 5 Levels of place modeling **a** of an individual, **b** statistical, **c** semantic, **d** based on activity

The first level of individual place modeling requires abstraction of the physical location data. Without abstraction, the continuous, high precision location data do not allow a simple extraction of mobility patterns. Some high-level analysis relies on straightforward geographic definitions, such as of countries, states, cities, and neighborhoods. For example, Krings et al. [45] provided a statistical analysis of the relationships between cities, modeling people's movement between cities using a gravity function. A more detailed abstraction is often the partitioning of the geographic space into (uniquely) labeled segments so the location of waypoints falling within a segment can be replaced with the segment label [63]. While partitioning is an abstraction, it retains the essential spatial attributes (as well as shortcomings) of the physical locations. For example, two waypoints that are very far apart will generally be assigned different labels even if both fit the same semantic label (e.g., two restaurants).

In statistical place modeling, information about people's visits to a particular place is accumulated and analyzed using statistical tools such as regression and distribution plots. Reades et al. [73] divided Rome into even-sized areas of 250,000 square meters and described each area according to distinct patterns of visitation. While the method portrays the dynamic of a city through a large-scale data analysis, the fact that the analysis was done for an arbitrary division of the urban environment limits the type of knowledge that can be derived from such analysis. In contrast, studies such as Krishnamachari et al. [46] and Xiao et al. [94] investigated how knowledge about human mobility can be used to divide urban areas into meaningful sub-areas, finding that dividing areas into even sizes (polygons of cells) is less effective than dynamic area allocation based on users' mobility. Other studies focused on finding significant places from mobility analysis using clustering methods [1, 38].

Semantic place modeling provides a higher level of abstraction and, like semantics in other fields, abstracts different geographic granularities of a place. For example, several waypoints located in a classroom on a university campus might be labeled "Room No. 438," "Engineering Building," or "University Campus." These labels represent different categorizations of places according to some predefined semantics. Yan et al. [95] suggest using hidden Markov models to infer the semantic labels of a place, where the hidden states represent the categories of those places. Zhu et al. [104] used several methods, e.g., L1-norm logistic regression, SVM, gradient boosted trees, and random forest to attach semantic labels to places.

Finally, place modeling can be based on user activity that is carried out in a certain place. Then, two persons in the same place, say a class, a teacher and a student, will label this place differently, e.g. "Work" and "School," respectively [49]. Zaslavsky et al. [97] present a framework that gathers data from many sensors, including low-level wearable sensors, to label activities in different granularities.

4.3 Trajectory modeling

Analyzing trajectories is a key to understanding many of the questions related to transportation and human mobility. Trajectory is an abstraction of a route, i.e., a set of spatial–temporal points that reflect movement through a set of locations. Unlike user modeling, in trajectory modeling the identity of the moving object is not a factor in the analysis, and all the moving objects are often analyzed in an aggregated manner. Also, user modeling is concerned with analyzing long-term traces, whereas trajectory modeling is concerned with a single drive. Unlike place modeling, trajectory modeling analyzes a travel path, rather than a place. As paths are defined by movements and are not necessarily fixed in space, the models used to analyze paths are different than those that model places.

We can distinguish between context-free methods that make no assumptions about geography and context-dependent methods that rely on existing geographic knowledge (such as known road networks). Context-free methods rely on the internal properties of trajectories. For example, Zheng et al. [102, 103] suggested predicting the transportation method along a given trajectory based purely on positioning information and using either of a set of machine learning methods, e.g., decision trees, dynamic Bayesian nets, and a conditional random field. Lin et al. [55] proposed an unsupervised method based on a Kolmogorov–Smirnov test for analyzing the transportation method. Recognizing whether two or more objects share a trajectory is the first and foremost aggregated trajectory modeling task, for example, for deciding whether two drivers are driving on the same route. Several studies suggested methods for clustering trajectories by measuring a similarity function over them [35, 44, 51, 64, 69], yet the question of which metric to use to measure similarity or distance between trajectories is still open and often depends on the specific application itself. Other studies tried to model certain properties of the trajectory; the most popular application in this domain is traffic forecasting. Castro et al. [18] provided a method for predicting traffic conditions in a road network and determining the capacity of road segments. Qu et al. [72] analyzed the value of a trajectory from an economic perspective, suggesting cost-effective driving routes to taxi drivers.

Context-dependent methods are used in situations in which the structure of the trajectories is already known, and the model aims at learning the properties of the trajectories. Lee et al. [50] used SVM to classify trajectories on road networks. Mao et al. [59] used weighted Markov models to predict the driving directions of cars in an urban environment. Wei et al. [92] suggested a method for finding the top-k most frequent paths in a large trajectory database, whereas Luo et al. [58] proposed a method that boosts the performance of finding the most frequent path. Giannotti et al. [35] mined similar sequences of movements from users' trajectories, showing how a compact representation of massive trajectory data can be used to find regions of interest and typical travel times of moving objects. Li et al. [52] modeled taxicab strategies (i.e., "wait" or "search") based on cellular data and feature selection using SVM with a loss function regularized by the L1-norm. Buthpitiya et al. [14] showed how an unsupervised n-gram method can be used to recognize anomalies in mobility patterns, which is a useful feature in areas such as elderly care, health monitoring, and homeland security.

5 Future challenges and conclusions

In this section, we point to several challenges we discovered in surveying the literature of mobility pattern analysis.

5.1 Standardized and succinct mobility models

When reviewing the literature of mobility analysis, we could not find an emergent model that can be used for standardizing location trace storage or analysis processes. The ability to carry out scalable and useful mobility data mining relies on having standardized models that can be used to store the meaningful features of mobility in a compact way. First, the models should be useful in many scenarios. For example, temporal models are used in many place prediction tasks, as well as in routine modeling tasks. At the same time, temporal models can be stored in a fraction of the space required for complete location traces. As the volume of mobility data continues to grow at an increasing rate (Fig. 2) and, thus, becomes a challenge for fine-grained analysis, reducing the size of the representative models is essential for building commercial tools for analyzing mobility data. We advocate that the domain could benefit from a standard format to manage mobility analysis in Hadoop or in other big-data infrastructures.

5.2 End user applications

Most of the industrial applications that currently rely on big mobility data are geared toward providing large and small businesses and organizations with statistical data. For example, Telefonica Dynamic Insights[1] and Verizon's Precision Market Insights[2] use mobility data to provide aggregated consumer statistics to businesses. However, there are relatively only a small number of applications that use big mobility data to fuel end user applications. End user applications are becoming increasingly important for computing and mobile computing in particular and, therefore, pose an ongoing opportunity for big mobility data. For example, many context-aware applications, such as location-based search or location-based advertising, can use large-scale mobility data to provide richer and more meaningful context. Nowadays, using large-scale data in end user applications is limited mainly to traffic and navigation applications (e.g., Google Maps and Waze). Therefore, a major challenge to large-scale mobility analysis is to find more killer applications that can provide tangible value to end users.

5.3 Data labeling

A major challenge for future research is the ability to draw and learn meaningful models from mobility datasets. As Fig. 2 exemplifies, large datasets are becoming more widespread, but that does not mean that the datasets are more useful. As researchers increasingly rely on existing datasets rather than collecting their information independently, their ability to collect related information diminishes. Indeed, data sources based on taxicabs and social media are limited in their ability to produce meaningful insights. There are many ways to work around this challenge. One is to promote efforts to collect large-scale semantically enriched information, such as in the Nokia dataset [30]. Other ways include bootstrapping information from multiple data sources to create a more varied mixture of data sources [83].

5.4 Privacy threats

Collecting, storing, and analyzing location traces have significant privacy implications. Several approaches demonstrated the high potential for re-identification and de-anonymization of location data [36, 62]. In many countries, such as in the European Union, there is an active legislation that limits the duration and purposes of using telecommunication data, including location traces. Other countries, such as the USA, do not have a general regulatory framework for data protection and privacy, but some aspects of telecommunication data are specifically regulated. A survey on privacy concerns related to location sharing has shown that users are worried of certain uses of their location data [88] or exposing specific locations [86]. A large number of privacy enhancing technologies and methods have been suggested for location data [3], e.g., methods to enhance anonymity, obfuscate spatial and temporal data [6], hide raw location data from the requesting application, and allow users to manage how to share their location data [47].

Mobility pattern analysis offers both risks and opportunities for privacy. The ability to produce a detailed model about a person's routine, lifestyle, and social network from large-scale mobility data can lead to new threats to privacy. These threats go beyond the knowledge of a person's location. On the other hand, data mining by machine learning is by definition a knowledge aggregation process, which can lead to development of new privacy enhancing technologies. For instance, replacing raw location data with semantic places can lead to better privacy protection and stronger anonymity. Thus, privacy poses several questions to mobility data analysis: Can privacy threats be understood and quantified from mobility data mining? How can we build tools that empower users to manage their mobility privacy? And how can mobility analysis be used as a tool to enhance privacy?

5.5 Conclusions

In this work, we reviewed more than 100 papers that analyze location traces to learn human mobility patterns. Due to a huge increase in the volume of work on mobility pattern analysis, as well as an increase in diversification of applications and methods, we acknowledge the need to provide better ways to understand this emerging field. The challenge of mining significant patterns within this large-scale, high-dimensional mobility data led us to focus our survey on machine learning methods, which excel in such challenges. We examined common categorization approaches in the field, often executed according to the properties of the location traces, together with analysis methods and models, and various potential applications for such analyses. Our taxonomy reveals three major classes of applications: user modeling, place modeling, and trajectory modeling. While it is impossible to find a clear-cut distinction between these classes, analyzing studies through our taxonomy can help researchers and practitioners to better find and understand mobility modeling technologies and evaluation studies. Finally, we also discussed several important challenges that are critical for future advancement of this new and fascinating research field.

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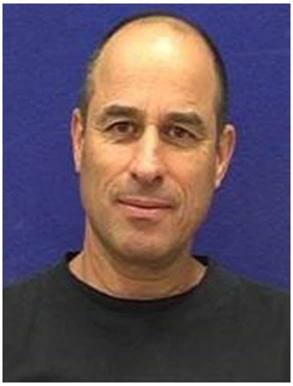

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