Next Place Prediction Model: a Literature Review

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Abstract. Given the rising attention towards the understanding of people's mobility, this paper focuses on the study of next-place prediction models for mobility demand and path estimation. A systematic literature review was conducted to classify the existing methodologies from a quantitative and qualitative perspective. The findings highlight the availability of several models to study next-place prediction which varies according to the objectives of the study and on the data used, with no specific dominant approach. In conclusion, the study proposes a first attempt of classification, by developing a conceptual framework, that on the one hand explains the relationship between the models' characteristics and on the other hand guides its selection according to the users' needs.

Keywords. Next place prediction, Literature Review, Mobility Model

1. Introduction

People's mobility is a fundamental and common activity for citizens, and it represents an increasingly studied topic given its impacts on society and the growing demand for more integrated mobility policies [1]. Socio-demographic evolution (e.g., urban sprawling) and new mobility means (e.g., shared vehicles) are being observed, and a deeper investigation into this area has been claimed by recent literature [1-2]. Moreover, over the very last few years, particular attention towards mobility policies is given by policymakers, aiming at improving the quality of life and reducing the related carbon footprint (e.g., SDG 11). In this regard, knowledge of people's mobility becomes fundamental to support decision-makers in their response to these challenges. Generally, research in this field investigates, by means of analytical models, how and why people move, identifying the trip characteristics (e.g., origin and destination of trips, frequency and purpose of trips and vehicle used) and understanding users' behaviour aspects. The resulting outcome is typically collected into an O/D matrix, which represents the demand in a specific reference area [2-4]. Mobility models can be divided between short-term ones which focus on predicting mobility patterns within a relatively short time frame, capturing near-future movements, and long-term ones, which operate on a larger time scale capturing long-term trends (e.g., predicting future travel demand) [5,6]. Short-term mobility models rely on intensive use of data that must be as complete as possible in

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terms of spatial and temporal information [5]. With the rise of 'big data', i.e., data characterised by high volumes and speeds of acquisition, variety and veracity, a new panorama opened in short-term mobility studies requiring a deeper investigation. Thanks to them it has been possible to achieve significant benefits thanks to a higher temporal and spatial representativeness of the trips, with some drawbacks that need to be considered such as fragmented knowledge of the path followed and missing behavioural information on the reason for the trip [5-7]. Being able to know the path followed is becoming relevant to understand human mobility and consequently developing possible alternatives. Over the years, to overcome the limitation just mentioned various models able to perform path and short-term prediction have been developed [8-14]. Thanks to these models, it is possible first to identify the path of the users and then to integrate new types of data into mobility studies, generating more accurate and detailed OD matrices from a spatial and temporal perspective [15-17]. Several solutions are proposed in terms of the techniques used and outcomes, with no clear understanding of their application. Schreckenberger et al., [18] work has moved in this direction. A classification of the main models for short-term estimation was performed by means of a literature review. In particular, the study classified the main methodologies used according to the data used (i.e., continuous sampling data) and the time horizon studied (i.e., hour, day, week). The study shows that the models are very data-dependent and have limitations as they are unable to capture changes due to human behaviour. Furthermore, the study focuses on models using continuous data sources (e.g., telephone data), suggesting that the study should also be extended to more sporadic data sources (e.g., social media data).

This study aims to identify and classify existing methodologies used for next-place prediction, overcoming the previous research's boundaries, and classifying them, looking also at possible evolutions and trends over time. A systematic literature search is performed on scientific databases (e.g., Scopus) to collect available publications. Then the papers are screened and reviewed, and the models are classified accordingly.

2. Objectives and Methodologies

2.1. Objectives

To continue the previous discussion, the present study aims to expand the literature on short-term predictive models, overcoming previously identified limitations. This focus is driven by the growing need for policymakers to know how people make their journeys and the continuously evolving data sources and methodologies available to perform these predictions. The objective of this research is twofold: on the one hand to systematically classify the literature to gain a comprehensive view that benefits both academics and practitioners, and on the other hand to identify potential areas for future research.

2.2. Methodology

To meet the objectives set, it was decided to adopt a systematic literature search methodology in line with previous studies in this field. The approach proposed by Mangiaracina et al., [19] was followed, dividing the research activity into four main stages: Literature search – collection and screening of the papers; Classification of the literature – identification of the main characteristics of the papers identified; Analysis of the contents of the selected papers – review of the selected study; Future areas of development – identification of potential areas of investigation.

2.2.1. Literature Search

In the first phase of the literature search, four main sub-step were performed to delimit the context of the research, the unit of analysis, the keywords and their combination and field delimitation to extract only the most relevant publication. As follow a detailed explanation:

- *Context the research:* next place/short-term mobility demand estimation model
- *Unit of analysis:* single scientific paper, both from peer-reviewed journals and grey literature (e.g., conference proceedings). The following choice was performed to source the most updated publications on this topic.
- *Collection of publications:* coherently with previous literature [18], the collection of publications is performed on scientific library databases (i.e., Scopus and Web of Science). The research was conducted by first identifying the main keywords and then synonyms (i.e., “mobility”, “demand”, “estimation”, “prediction”, “trajectory”, “forecast*”, “model*”, “place”) to be combined with logical connectors (e.g., AND/OR). The combination was searched at least in the title, abstract and keywords.
- *Delimitation of the field:* Different boundary criteria were introduced on language, subject area and the publication year (see Figure 1) to exclude areas not linked to transportation systems or outdated publications [5,18,19]. The following approach led to the first identification of 245 papers that were eligible for a title and abstract screening. After the full reading only 39 papers were selected as relevant contributions in the field (See figure 1 for the whole process). The papers were discarded if individual mobility was not central to the discussion.

Once the papers were considered eligible, a data extraction form to collect information on methodology, data gathering method, main purposes, findings, contribution, research limitations, and future research, was developed with the aim to classify and investigate the similarities and differences between studies and to identify future research areas.

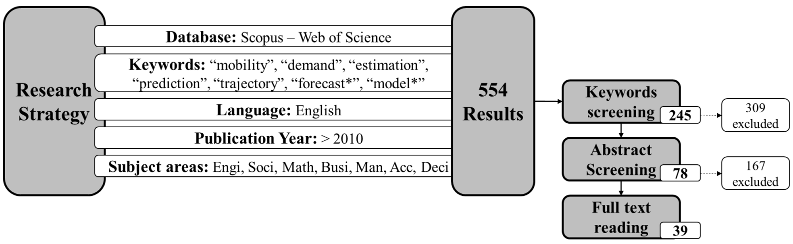

Figure 1. Literature research process (prisma diagram)

In the second phase, the papers were classified according to their characteristics and content to understand the evolution of publications over time and to identify possible areas for further investigation. The 39 papers identified were published in 26 different journals, addressing different publication areas, more in detailed Transportation and Logistics (27%), Modelling (34%), Business and Management (19%) and Social

Sciences (20%). Finally, the papers were also classified based on the affiliation of the first authors to display the geographical spread of the research. It emerged that most of the studies were conducted in China, reflecting the challenges that the country daily faces when dealing with mobility themes [20,21].

3. Literature Analysis – Discussion of Findings

The papers were discussed and reviewed according to the contents and the methodology proposed. To enhance the understanding of the topic and a clearer reading of the discussion, a multi-dimension classification is performed according to five characteristics, i.e., objectives and type of predictions, methods, mobility data sources, secondary data and application that are considered relevant to understand the methodologies.

3.1. Objectives and Predictions

The purposes of the studies can be divided between individual mobility prediction, which captures regularities, and tendencies of individual's mobility behaviours using mobility data, and population mobility prediction, which captures mobility behaviours at a population/group of individual level, capturing aggregated trends. The first predictions are carried out mainly by means of statistic or machine learning techniques according to the data availability [8-13,20-36], while the latter can also exploit data mining techniques or agent-based modelling [6,11,24,37-46]. The identified purposes can be further segmented from a spatial perspective by varying the unit of analysis, resulting in three prediction outcomes per purpose, i.e., trajectory recognition, next location prediction, and next trip prediction. Trajectory recognition refers to the process of identification and classification of patterns and activities within points distributed at different times. The aim is to understand the activities and behaviours of an individual. By doing so, the knowledge can be exploited to understand the next location/trip that an individual may likely follow [14,20,22,25,27-32,34,38,42]. Instead, next location prediction, relying more on statistical analysis, focuses on estimating the most likely destination that a person will visit after the visited one, exploiting historical trajectories and contextual information. By exploiting past behaviours, possible areas where an individual will be in the future can be identified [11,15,23,24,33,37,39,41]. Finally, next trip prediction, similarly to next place prediction, by exploiting historical data, aims to predict the whole trip performed, identifying starting, intermediate and final points [10,12,16,21,35]. The different outcome requires specific models, and data to be collected that will be discussed in the next sections.

3.2. Methods

Most of the papers evaluated considered the various technique to tackle short-term predictions, according to the objectives and the sources considered.

Trajectory-based methods use historical trajectory data of individuals/populations to predict their future destinations. Trajectories consist of a series of location points recorded over time. Various techniques such as Markov Model (MM) and its variants and sequence mining algorithms can be applied to study the probability of occurrence of a series of events (states) to analyse trajectories and extract patterns to predict future places. While employing the model attention should be given to the parameters that are used to determine the state transition, the initial condition setting that may influence the result, and the model assumption on the initial state. In addition, when the input data is sparse the model is not able to provide accurate results [12,35,41]. Instead, machine learning (ML) techniques, both supervised and unsupervised, are commonly used in next-place prediction as they can be trained to identify patterns and relationships. Commonly used algorithms include decision trees, random forests, support vector machines and neural networks. Among them, Long Short-Term Memory (LSTM) and its variants, a specific neural network architecture, is well-suited for modelling sequential data and capturing short and long terms time dependencies [10,13,32]. The models are trained on temporal or spatial features such as time, location, transportation mode, and contextual information. However, ML has some limitations as they require a wide dataset to be tested and trained, with high effort and uncertain output [10,13,28,30]. Similarly, spatial-temporal data mining focuses on extracting patterns and relationships from large-scale spatial-temporal datasets. Techniques such as clustering, frequent pattern mining, and association rule mining are used to discover spatial-temporal patterns in mobility data [26,27,38,41]. Clustering allows the classification of variables based on their features or characteristics (e.g., population density), grouping individual inputs with similar properties into the same category [15,23,27]. Flow-based algorithm [39] is an approach that models complex systems able to represent the interconnected flows between nodes and measures the spatiotemporal variation, predicting the trip. It is suitable to understand mobility flows across city areas, providing valuable insights into the next place prediction problem [15,20,23,24,31]. Probabilistic models utilize probability theory to estimate the likelihood of an individual visiting a particular place next. These models consider various factors such as historical visit frequencies, temporal patterns, and spatial correlations to make predictions. MMs, Bayesian networks (BN), commonly employed [16,22,34,39]. BN capture the dependencies between variables over time, allowing for the representation of dynamic systems and the modelling of complex temporal relationships. However, they require a linearity hypothesis and are not able to capture complex patterns [16,22,25,27,33,34,45].

3.3. Mobility Data Sources

In the following section, the main data sources used for the development of the models have been identified, distinguishing between conventional sources, where the collection methodology is designed specifically for mobility studies (e.g., surveys), and emerging sources, where the methodology is not designed for but allows to collect relevant data and extract meaningful mobility data (e.g., cellular signalling data) [3,4,5]. Among the conventional data sources, Automatic Fare Collection (AFC) are the most used to estimate short-term prediction, thanks to their ability to collect over different time horizon and geographical area detailed information on boarding and in some specific cases alight for public transport services [10,17]. Given the partial information collected, the models using these types of data tend to address next-location prediction mainly by means of probabilistic models [10,16,28]. The AFC data, despite its availability, suffers from underrepresentation as only trips on public transport are detected [2,5,17]. On the other hand, emerging data sources are becoming the most used and studied data types for several reasons as they are an extremely persuasive, information-rich and easy-to-collect type of data [20,27]; secondly, they are data with a lot of noise and low accuracy, which requires supporting modelling [32,38,41]. From the overview, the data source could be categorized into three groups: users' devices, GPS, and social media interaction. Users' devices include phone signalling, Bluetooth, and Wi-fi data sources [11,29,20,33,34]. These data usually do not provide an exact location or full trajectory of the users and rely on the device being used or active [11,22,42]. Network data helps to improve and determine matrices to understand and identify travel patterns [22,31]. Inputs extracted from users' devices allow to accurately distinguish when the user is travelling and when is stationary [20,27,45]. However, these methodologies have some limitations as the data depend on the infrastructure collecting the signal and the privacy legislation [4,25,34,38]. Instead, Global Positioning System (GPS) are able to provide high-resolution mobility information, with higher spatial accuracy [26,33]. In addition, thanks to its presence on mobile phones is becoming a persuasive and reliable source of data. However, [39], the GPS data is not able to provide personal users' information and remains difficult to be collected in a systematic way [39,46]. Finally, Multi-media includes contextual information from social media platforms, web search engines, and online check-in systems [11,12,40,44]. These methods allow to collect spatiotemporal data and provide behavioural information on the users [36]. Check-in data could provide real user trajectory in which spatiotemporal influencing factors like the travel distance and time interval between successive check-ins need to be considered [30]. Social media with geo-tagged and timestamp data [15,32] could measure the evolution of mobility in a region at multiple spatial scales [14]. These data are non-recurrent and difficult to exploit systematically.

3.4. Secondary Data

The models, in addition to the previously discussed mobility data, may require additional information for the development of variables and assumptions to ensure the right functioning of the model.

Among them the most used are socio-demographic and socioeconomics which are observable characteristics representing demographic and economic information concerning the population considered while performing the study. The most used variables refer to age, gender, income, and population density. These data are instrumental to understanding and clustering users' behaviours, determining different patterns [11,14,24,30]. Contextual variables instead refer to observable elements that can affect travel patterns, commuting behaviours, and mobility choices and are not linked to socio-economic or socio-demographics. For example, the time period in which the trip is performed (e.g., day of the week, season), weather conditions, and events [15,16,28,37]. Finally, infrastructure information refers to information about the physical environment, such as maps, road networks, transportation infrastructure (e.g., railways stations, vehicle locations), landmarks, points of interest, and device locations that may impact travel behaviours [21,27,31,38].

3.5. Application

The studies have been grouped into three main categories of applications that aim to provide evidence on how these models can be used to support decision-makers. Among them, two are related to the planning and improvement of the local transport service (service and infrastructure planning), while the other one is related to space planning (space planning). The application of models to understand the infrastructure and the service allows to evaluate user journeys within public transit. For these studies, no principal model emerged to be applied as it is relevant to understand both the user's entire route and the possible next point [12,14,17,32,37,43]. With the support of these models, the public decision-maker can understand whether to implement infrastructural changes [16,21,27,43], i.e., adding a stop/station, creating a new line, or modifying the service [17,20,32,35], i.e., varying the number of trips during the day. Instead, the use of models to understand how urban/rural spaces are used, allows the identification of new possible 'attraction' points and/or areas of increased frequentation, whether due to commuting or tourism [10,15,26]. For the former, mainly telephone data are used, for the latter, social media ones. With the support of these models, the public decision-maker may be able to plan measures to improve territorial planning [18,29,36,42].

4. Findings and Conclusions

The classification of models carried out allowed the identification of the main characteristics of each methodology used to study short-term mobility predictions.

Figure 2 plays the dual role of data visualization, displaying the relationships between each identified classification axis and a framework to support the model selection in a given scenario. Circle size represents the total number of articles belonging to the categorisation, while the thickness of the lines represents which way the articles contribute between the different axes (the greater the thickness, the greater the number of articles). The number of articles related to the population mobility prediction study is indicated in brackets to highlight the difference compared to the individual mobility prediction studies. The models are designed to predict the movement of users (Prediction). These studies are mainly carried out at the individual level, but some studies are carried out at the population level (Objectives). Over the years, three distinct modelling approaches of either statistical, machine learning or trajectory studies nature have emerged to investigate the topic (Methods). To define the models, mobility data are required, and these can be collected using different sources (Data and Secondary data). The output of the model is thus able to generate a forecast that can be used by public decision-makers (or authorities) to define new mobility solutions, by proposing modification of the present service or infrastructure (Application).

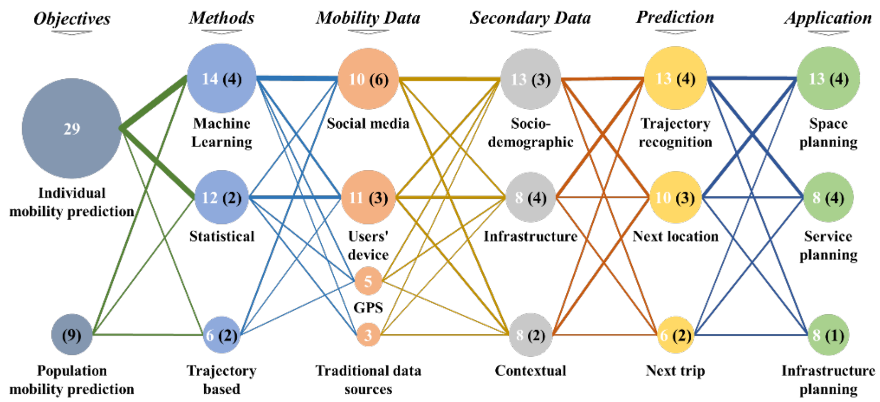

Figure 2. Visual representation of research results. Inside each circle the number of contributions for each topic, with a distinction between studies on individual mobility prediction (white number) and population mobility prediction (black number in bracket).

Given the increasing attention towards mobility and in particular on short-term models to support it, this study aims to propose an up-to-date literature review on these topics. A total of 39 articles from different journals, published between 2010 and 2023, were considered. Previous reviews identified on these topics were limited in both time (i.e., the one identified is from 2018) and topic (i.e., only continuous data sources were considered).

The analysis and classification of the literature made it possible to identify the main types of models approach. The decisive role of new data source options emerges and how they are playing a vital role in the development of the models themselves [5,6,12,20,28].

In addition, this study identifies some criticalities that previous studies have not adequately addressed, rising the attention on them. Firstly, the literature focuses mainly on the development of models, with limited emphasis on the implications of these in the practitioners' decision-making process, creating a gap between research and deployment. Integrating this aspect to a greater extent would enable the added value of these models to be understood. Secondly, the current models struggle to keep up with ongoing mobility developments, mainly due to the difficulty in collecting mobility data. Furthermore, occasional events, such as tourism, remain difficult to be fully grasped. Through continuous and less restricted data collection, it would be possible to overcome this limitation.

The following study provides both a contribution for academics and practitioners. For the former, it proposes a classification of the current solutions used to study the problem of the next place location, while for the latter, it attempts to propose a framework capable of supporting practitioners in choosing a model based on the objectives and the available data, giving visibility to all the possible options.

Finally, a possible limitation of this study should be identified. Despite the research methods being as much inclusive as possible, some studies may have been unintentionally omitted. Despite that, this review can provide a clear representation of the actual body of research on next-place prediction models.

References

[1] Reul, J., Grube, T., & Stolten, D. (2021). Urban transportation at an inflection point: An analysis of potential influencing factors. Transportation Research. Part D, Transport and Environment, 92(102733), 102733. https://doi.org/10.1016/j.trd.2021.102733

[2] Pelletier, M.-P., Trépanier, M., & Morency, C. (2011). Smart card data use in public transit: A literature review. *Transportation Research. Part C, Emerging Technologies*, *19*(4), 557–568. https://doi.org/10.1016/j.trc.2010.12.003

[3] Waller, S. T., Chand, S., Zlojutro, A., Nair, D., Niu, C., Wang, J., Zhang, X., & Dixit, V. V. (2021). Rapidex: A novel tool to estimate origin–destination trips using pervasive traffic data. *Sustainability*, *13*(20), 11171. https://doi.org/10.3390/su132011171

[4] Harrison G, Grant-Muller SM, Hodgson FC. New and emerging data forms in transportation planning and policy: Opportunities and challenges for "Track and Trace" data. Transp Res Part C Emerg Technol [Internet]. 2020;117(102672):102672. Available from: http://dx.doi.org/10.1016/j.trc.2020.102672

[5] Barbosa, H., Barthelemy, M., Ghoshal, G., James, C. R., Lenormand, M., Louail, T., Menezes, R., Ramasco, J. J., Simini, F., & Tomasini, M. (2018). Human mobility: Models and applications. Physics Reports, 734, 1–74. https://doi.org/10.1016/j.physrep.2018.01.001

[6] Davies, V. A. (2000). Evaluating mobility models within an ad hoc network. 2000-2009-Mines Theses & Dissertations.

[7] Song, C., Koren, T., Wang, P., & Barabási, A. (2010). Modelling the scaling properties of human mobility. Nature Physics, 6(10), 818–823. https://doi.org/10.1038/nphys1760

[8] Wang A, Zhang A, Chan EHW, Shi W, Zhou X, Liu Z. A review of Human Mobility research based on big data and its implication for smart city development. ISPRS Int J Geoinf [Internet]. 2020;10(1):13. Available from: http://dx.doi.org/10.3390/ijgi10010013
[9] Kamel Basmenj S, Li S. A review of urban human mobility research based on crowd-sourced data and space-time and semantic analysis. ISPRS - Int Arch Photogramm Remote Sens Spat Inf Sci [Internet]. 2022;XLIII-B4-2022:247–52. Available from: http://dx.doi.org/10.5194/isprs-archives-xliii-b4-2022-247-2022
[10] Chi H, Wang B, Ge Q, Huo G. Knowledge graph-based enhanced Transformer for metro individual travel destination prediction. J Adv Transp [Internet]. 2022; 2022:1–9. Available from: http://dx.doi.org/10.1155/2022/8030690
[11] Sun J, Kim J. Joint prediction of next location and travel time from urban vehicle trajectories using long short-term memory neural networks. Transp Res Part C Emerg Technol [Internet]. 2021;128(103114):103114. Available from: http://dx.doi.org/10.1016/j.trc.2021.103114
[12] Hadachi A, Pourmoradnasseri M, Khoshkhah K. Unveiling large-scale commuting patterns based on mobile phone cellular network data. J Transp Geogr [Internet]. 2020;89(102871):102871. Available from: http://dx.doi.org/10.1016/j.jtrangeo.2020.102871
[13] Errounda FZ, Liu Y. A mobility forecasting framework with vertical federated learning. In: 2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC). IEEE; 2022.
[14] Terroso-Saenz F, Muñoz A, Arcas F, Curado M. An analysis of twitter as a relevant human mobility proxy: A comparative approach in spain during the COVID-19 pandemic: A comparative approach in spain during the COVID-19 pandemic. Geoinformatica [Internet]. 2022;26(4):677–706. Available from: http://dx.doi.org/10.1007/s10707-021-00460-z
[15] Comito C. NexT: A framework for next-place prediction on location based social networks. Knowl Based Syst [Internet]. 2020;204(106205):106205. Available from: http://dx.doi.org/10.1016/j.knosys.2020.106205
[16] Zhao Z, Koutsopoulos HN, Zhao J. Individual mobility prediction using transit smart card data. Transp Res Part C Emerg Technol [Internet]. 2018;89:19–34. Available from: http://dx.doi.org/10.1016/j.trc.2018.01.022
[17] Crocco F, Forciniti C, Mongelli DWE. A management system of territorial planning and mobility: a case study. Procedia Soc Behav Sci [Internet]. 2011;20:100–9. Available from: http://dx.doi.org/10.1016/j.sbspro.2011.08.015
[18] Schreckenberger C, Beckmann S, Bartelt C. Next place prediction: A systematic literature review. In: Proceedings of the 2nd ACM SIGSPATIAL Workshop on Prediction of Human Mobility. New York, NY, USA: ACM; 2018.
[19] Mangiaracina, R., Perego, A., Seghezzi, A., & Tumino, A. (2019). Innovative solutions to increase last-mile delivery efficiency in B2C e-commerce: a literature review. *International Journal of Physical Distribution & Logistics Management*, *49*(9), 901–920. https://doi.org/10.1108/ijpdlm-02-2019-0048
[20] Xiong Q, Liu Y, Xie P, Wang Y, Liu Y. Revealing correlation patterns of individual location activity motifs between workdays and day-offs using massive mobile phone data. Comput Environ Urban Syst [Internet]. 2021;89(101682):101682. Available from: http://dx.doi.org/10.1016/j.compenvurbsys.2021.101682
[21] Xu Y, Zou D, Park S, Li Q, Zhou S, Li X. Understanding the movement predictability of international travelers using a nationwide mobile phone dataset collected in South Korea. Comput Environ Urban Syst [Internet]. 2022;92(101753):101753. Available from: http://dx.doi.org/10.1016/j.compenvurbsys.2021.101753
[22] Uras M, Cossu R, Ferrara E, Liotta A, Atzori L. PmA: A real-world system for people mobility monitoring and analysis based on Wi-Fi probes. J Clean Prod [Internet]. 2020;270(122084):122084. Available from: http://dx.doi.org/10.1016/j.jclepro.2020.122084
[23] Jiang H, Yang F, Su W, Yao Z, Dai Z. Activity location recognition from mobile phone data using improved HAC and Bi-LSTM. IET Intell Transp Syst [Internet]. 2022;16(10):1364–79. Available from: http://dx.doi.org/10.1049/itr2.12211
[24] Li X, Hu R, Wang Z. Next-point-of-interest recommendation based on joint mining of regularity and randomness. Knowl Based Syst [Internet]. 2022;258(110052):110052. Available from: http://dx.doi.org/10.1016/j.knosys.2022.110052
[25] Su R, Dodge S, Goulias KG. Understanding the impact of temporal scale on human movement analytics. J Geogr Syst [Internet]. 2022;24(3):353–88. Available from: http://dx.doi.org/10.1007/s10109-021-00370-6
[26] Solomon A, Livne A, Katz G, Shapira B, Rokach L. Analyzing movement predictability using human attributes and behavioral patterns. Comput Environ Urban Syst [Internet]. 2021;87(101596):101596. Available from: http://dx.doi.org/10.1016/j.compenvurbsys.2021.101596

[27] Bonnetain L, Furno A, El Faouzi N-E, Fiore M, Stanica R, Smoreda Z, et al. TRANSIT: Fine-grained human mobility trajectory inference at scale with mobile network signaling data. Transp Res Part C Emerg Technol [Internet]. 2021;130(103257):103257. Available from: http://dx.doi.org/10.1016/j.trc.2021.103257
[28] Yu C, Li H, Xu X, Liu J, Miao J, Wang Y, et al. Data-driven approach for passenger mobility pattern recognition using spatiotemporal embedding. J Adv Transp [Internet]. 2021;2021:1–21. Available from: http://dx.doi.org/10.1155/2021/5574093
[29] Dyrmishi S, Hadachi A. Mobile positioning and trajectory reconstruction based on mobile phone network data: A tentative using particle filter. In: 2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). IEEE; 2021.
[30] Zhou F, Dai Y, Gao Q, Wang P, Zhong T. Self-supervised human mobility learning for next location prediction and trajectory classification. Knowl Based Syst [Internet]. 2021;228(107214):107214. Available from: http://dx.doi.org/10.1016/j.knosys.2021.107214
[31] Li L, Chen X, Li Q, Tan X, Chen J, Wang D, et al. Contextualizing human dynamics: Understanding the semantics of movement trajectories with Wi-Fi data. Travel Behav Soc [Internet]. 2021;25:183–92. Available from: http://dx.doi.org/10.1016/j.tbs.2021.07.005
[32] Comito C. Mining human mobility from social media to support urban computing applications. In: 2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS). IEEE; 2019.
[33] Shams B, Haratizadeh S. GraphLoc: a graph based approach for automatic detection of significant locations from GPS trajectory data. J Spat Sci [Internet]. 2018;63(1):115–34. Available from: http://dx.doi.org/10.1080/14498596.2017.1327374
[34] Dash M, Koo KK, Gomes JB, Krishnaswamy SP, Rugeles D, Shi-Nash A. Next place prediction by understanding mobility patterns. In: 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops). IEEE; 2015.
[35] Huang W, Li S, Liu X, Ban Y. Predicting human mobility with activity changes. Geogr Inf Syst [Internet]. 2015;29(9):1569–87. Available from: http://dx.doi.org/10.1080/13658816.2015.1033421
[36] Feng F, Zhang J, Liu C, Li W, Jiang Q. Short-term railway passenger demand forecast using improved Wasserstein generative adversarial nets and web search terms. IET Intell Transp Syst [Internet]. 2021;15(3):432–45. Available from: http://dx.doi.org/10.1049/itr2.12036
[37] Comito C. Exploiting Twitter for next-place prediction. In: 2017 International Conference on Information Society (i-Society). IEEE; 2017.
[38] Luo X, Yuan Y, Li Z, Zhu M, Xu Y, Chang L, et al. FBVA: A flow-based visual analytics approach for citywide crowd mobility. IEEE Trans Comput Soc Syst [Internet]. 2019;6(2):277–88. Available from: http://dx.doi.org/10.1109/tcss.2018.2877149
[39] Schreckenberger C, Bartelt C, Stuckenschmidt H. Enhancing a crowd-based delivery network with mobility predictions. In: Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Prediction of Human Mobility. New York, NY, USA: ACM; 2019.
[40] Petrasova A, Hipp JA, Mitasova H. Visualization of pedestrian density dynamics using data extracted from public webcams. ISPRS Int J Geoinf [Internet]. 2019;8(12):559. Available from: http://dx.doi.org/10.3390/ijgi8120559
[41] Xia T, Shen J, Yu X. Predicting human mobility using Sina Weibo check-in data. In: 2018 International Conference on Audio, Language and Image Processing (ICALIP). IEEE; 2018.
[42] Traunmueller MW, Johnson N, Malik A, Kontokosta CE. Digital footprints: Using WiFi probe and locational data to analyze human mobility trajectories in cities. Comput Environ Urban Syst [Internet]. 2018;72:4–12. Available from: http://dx.doi.org/10.1016/j.compenvurbsys.2018.07.006
[43] Chen G, Viana AC, Fiore M. Takeaways in large-scale human mobility data mining : (invited paper). In: 2018 IEEE International Symposium on Local and Metropolitan Area Networks (LANMAN). IEEE; 2018.
[44] Moyo T, Musakwa W. Exploring the potential of crowd sourced data to map commuter points of interest: A case study of Johannesburg. ISPRS - Int Arch Photogramm Remote Sens Spat Inf Sci [Internet]. 2019;XLII-2/W13:1587–92. Available from: http://dx.doi.org/10.5194/isprs-archives-xlii-2-w13-1587-2019
[45] Fekih M, Bonnetain L, Furno A, Bonnel P, Smoreda Z, Galland S, et al. Potential of cellular signaling data for time-of-day estimation and spatial classification of travel demand: a large-scale comparative study with travel survey and land use data. Transp Lett [Internet]. 2022;14(7):787–805. Available from: http://dx.doi.org/10.1080/19427867.2021.1945854
[46] Huang H, Gartner G. Current trends and challenges in location-based services. ISPRS Int J Geoinf [Internet]. 2018;7(6):199. Available from: http://dx.doi.org/10.3390/ijgi7060199