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Survey of Machine Learning Methods Applied to Urban Mobility

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ABSTRACT To increase the sustainability in urban mobility, it is necessary to optimally combine public and shared vehicles throughout a passenger's trip. In this work, we present a survey on urban mobility based on passengers' data and machine learning methods. We focus on four applications for urban mobility: public datasets, passenger localization, detection of the transport mode and pattern recognition and generation of mobility models. Public datasets lack data of multimodal trips and are in need of guidelines to facilitate the data collection and documentation processes. Passenger localization is predominantly done through fingerprinting in indoor environments; and fingerprinting relies on unsupervised learning to survey access points. The most common mean of transport detected is the bus, followed by walking and biking, while e-scooters are not included within the detected transport modes. The existing works focus on predicting the travel time of the passenger's trajectory and no machine learning method stands out to estimate the travel time. There is still a need for works that analyze how passengers make use of the urban infrastructure, which will support municipalities and transport mode operators in resource planning and service design.

INDEX TERMS Transport modes, public, shared, artificial intelligence, pedestrian, passenger, bus, car, subway, e-scooter, passenger-centric.

I. INTRODUCTION

More than 60% of the world's population will be concentrated in cities by 2030 [1]. There will be a demand on sustainable urban mobility options, which will be achieved through the use of different and optimally combined transport modes within the trip through the city.

The core of new multimodal urban mobility concepts is to combine public transport with other motorized and non-motorized modes as well as with new concepts of vehicle ownership. New multimodal urban mobility concepts involve also the use of smartphones and mobile apps to provide information and access to all transport modes. Some services such as personal mobility assistance involve booking and smart ticketing. Yet there are several challenges to overcome, e.g., accurate passenger localization, lack of information and separate responsibilities.

There is a plethora of applications that aim at overcoming the challenges of urban mobility. 2.5 quintillion bytes of data are generated everyday [2]. Thus, there is potential to address urban mobility challenges through machine learning and artificial intelligence methods. For instance, e-ticketing is a service that enables passengers to use multiple transport modes with a single ticket [3]. One of the key features of this service is that the passenger needs only to pay a monthly, weekly or daily bill that accounts for all the transport modes used. To implement this service, one could use smartphone data and machine learning methods to automatically detect the transport mode and estimate the ticket fare that should be applied.

Urban mobility applications can be broken down into lower level applications, e.g. localization of passengers in urban canyons or the detection of transport mode. The combination of two or more of these applications enables the implementation of higher level ones like e-ticketing.

In this article, we focus on the following aspects of urban mobility applications:

- Collection of public datasets
- Localization of passengers
- Detection of transport modes
- Generation of mobility models

In the literature, there are already different surveys that analyze the state-of-the-art of one specific passenger-centric application, e.g., surveys on localization techniques with

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machine learning [4], surveys on the detection of the transport mode [5] or surveys on mobility models [6], [7]. However, the aforementioned works have two limitations:

- they do not place the passenger at the center of urban mobility applications. Therefore, the existing works do not focus on the crucial role that the passenger plays in urban mobility applications.
- they do not survey urban mobility applications based on both passenger-centric data and machine learning methods. For instance, Zhu *et al.* [7] and Abduljabar *et al.* [8] survey only mobility models based on data from infrastructure-based systems and automated vehicles, respectively. Li *et al.* [4] and Elhoushi *et al.* [5] focus only on localization and detection of the transport mode, respectively.

It is essential to analyze urban mobility applications considering the passenger as their center element. The reason is that passengers are at the heart of all cities and urban mobility applications aim at improving the passenger's experience.

The goal of this article is to survey urban mobility applications based on machine learning methods and passenger-centric data. More specifically, we do have the following objectives:

- survey how the state-of-the-art uses machine learning methods in the four main urban mobility applications listed above, namely, the collection of public datasets, the localization of passengers, the detection of the transport mode and the generation of mobility models, and,
- identify the open challenges that remain to be addressed in order to advance in the development of urban mobility applications based on machine learning methods from passenger-centric data.

The remainder of this article is organised as follows: Section II defines the set of machine learning concepts used throughout the article, Section III surveys the state-of-the-art of public datasets for urban mobility applications, Section IV surveys the state-of-the-art of localization algorithms based on machine learning, Section V surveys the state-of-the-art of algorithms for transport mode detection, Section VI surveys the state-of-the-art of works that carry out pattern recognition and generation of mobility models, and Section VII concludes this work.

II. MACHINE LEARNING CONCEPTS

In this article, we distinguish between machine learning and artificial intelligence. Murphy defines machine learning as "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data or to perform other kinds of decision making under uncertainty" [9]. In contrast, we define artificial intelligence as the area of computer science that aims at creating intelligent machines that work and react like humans [10].

Since we focus on machine learning techniques, we define the concepts that are used in the remainder of this article. A machine learning method comprises a set of parameters that need to be learned, i.e. estimated, based on input data, e.g., sensor data from a smartphone. The output value of a machine learning method can be:

- numerical, e.g., the estimation of a passenger's position. In this case, the machine learning method performs regression.
- categorical, e.g., the estimation of the transport mode. In this case, the machine learning method performs classification.

Machine learning methods can be classified in one of two categories:

- supervised methods are those for which the output value associated to each observation of the input data is known a priori. The known output values are referred to as labels.
- unsupervised methods are those for which the output value associated to each observation of the input data is unknown.

The learning process is depicted in Figure 1. The learning process comprises four main stages:

- Data acquisition is the stage during which the data is collected. In the case of this article, the data sources are the sensors integrated in smartphones and wearable devices.
- Data cleaning & preprocessing is the stage during which the acquired data is cleaned, e.g., by deleting invalid data, and preprocessed, e.g., standardizing categorical data [11]. In this stage, the acquired data is split in a training dataset and a test dataset [12].
- Modelling & learning is the stage during which the parameters of a machine learning method are estimated to fit the training data according to an optimization function [9]. The input to this stage is not only the training dataset, but also constraints specific to each machine learning method, e.g., the number of hidden layers in an artificial neural network [13]. The output of this stage is the set of parameters of the machine learning method.
- Evaluation is the stage during which the performance of the machine learning method is assessed with the test dataset. The output of this stage is a set of performance figures, e.g., the classification accuracy. The estimated performance figures can be used to tune the parameters of the machine learning method in order to optimize the performance figures.

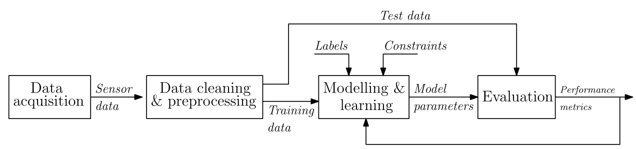

FIGURE 1. Block diagram of the learning process.

III. COLLECTION OF PUBLIC DATASETS

Training and evaluation data are key for the development of machine learning methods. In the case of this article, the data is acquired with smartphones or wearables carried by the passenger. For instance, a transport mode detection algorithm requires data from a smartphone while the passenger is using different transport modes and the corresponding label of the transport mode used at each instant. Another example is positioning in traffic hubs with WiFi signals, which requires signal strength measurements of WiFi signals in the traffic hub of interest and the position of the access points.

Regardless the application, benchmark datasets are an efficient tool to enable the development, evaluation and comparison of machine learning methods. In this section, we review public datasets with passenger-centric data. For the interested reader, there are further application-specific datasets in [14], [15], Kaggle,[1] the Localisation Systems Repository (LSR)[2] [16] or the IndoorLoc repository[3] [17].

We analyze the public datasets regarding three aspects:

1) Sharing platform, see Table 1.
2) Dataset size, sensing technology and environment, see Table 2.
3) Activities, transport modes, ground truth and recording device, see Table 3.

A. SHARING PLATFORM

Table 1 shows that the most popular platform to share data is a dedicated website, e.g., Microsoft in the case of the Geolife GPS Trajectory Dataset. The second most popular platform is data-sharing platforms, like Crawdad,[4] the UCI Machine Learning Repository[5] and Zenodo.[6] The third most popular type of platform in Table 1 is servers.

Each of the aforementioned platforms has advantages and disadvantages. Websites and dedicated servers allow institutions to remain in control of the rights of their datasets and other legal aspects. The disadvantage of these platforms is that they require maintenance.

An advantage of data-sharing platforms is that they are centralized and, with time, they become popular among the community, e.g., the UCI Machine Learning Repository, as *"the place"* where data can be found. Data-sharing platforms could foster the publication of datasets in a standardized and organised manner, e.g., through the publication of data collection and documentation guidelines, which are one of the current challenges in the collection of datasets [15]. The disadvantage of data-sharing platforms is that institutions need to waive the rights on the dataset or accept certain terms

[1]https://www.kaggle.com/ - Last accessed on 03/02/2022
[2]https://lsr.cs.upb.ro/datasets - Last accessed on 03/02/2022
[3]http://indoorloc.uji.es/ - Last accessed on 03/02/2022
[4]https://crawdad.org/about.html - Last accessed on 03/02/2022
[5]https://archive.ics.uci.edu/ml/index.php - Last accessed on 03/02/2022
[6]https://zenodo.org/ - Last accessed on 03/02/2022

TABLE 1. List of passenger-centric datasets, their affiliation and the platform through which these have been published. The following acronyms are used: FTP (file transfer protocol), IPIN (indoor positioning and indoor navigation).

Name	Affiliation	Platform
CamLoc [18], [19]	University Politehnica Bucharest, University of Edinburgh	Google Drive
Geolife GPS trajectory dataset [20]–[23]	Microsoft	Website
Geo-magnetic field and WLAN dataset [24], [25]	Italian National Council of Research	UCI Machine Learning repository
High precision dataset for foot-mounted inertial navigation [26]	German Aerospace Center	Website
Indoor Bluetooth Dataset [27], [28]	Institute of Information Sciencie and Technologies (Italy)	Website
IPIN 2016 Track 3: Smartphone-based (offsite) [29]	University of Alcalá (Spain)	Website
IPIN 2018 Track 3: Smartphone-based (offsite) [30]	IFSTTAR (France)	Website
Pedestrian and bicycle seamless navigation [31], [32]	German Aerospace Center	FTP server
RuDaCoP [33]	Huawei	Website
Sigfox and LoRaWAN [34], [35]	University of Antwerp (Belgium)	Zenodo
Sussex-Huawei locomotion and transportation dataset [36], [37]	University of Sussex, Cyril and Methodius University, Huawei Technologies	Website
The Cambridge/Haggle dataset [38]	Intel Research Cambridge Corporate Laboratory	Crawdad
Transportation mode detection dataset [39], [40]	University of Bologna (Italy)	Website
UJIIndoorLoc dataset [41], [42]	Universitat Jaume I (Spain)	UCI Machine Learning repository
Unaided 3D pocket inertial navigation [43]	German Aerospace Center	FTP server
Wearable-based pedestrian navigation [32], [44]	German Aerospace Center	FTP server
Wi-MEST Dataset [45], [46]	Yeungnam University (Korea)	GitHub
Urban European driving dataset [47]	Institute of Mathematics of the Romanian Academy (Romania)	Google Sites
RISEdb [48]	European Commission Joint Research Center (JRC)	Website
The IDOL Dataset [49]	Carnegie Mellon University	Zenodo
The walking recognition dataset [50]	CiTIUS (Spain)	Website

TABLE 2. List of datasets, their size and the main characteristics of environment. The following acronyms are used: GNSS (global navigation satellite system), GPS (global positioning system), RSSI (received signal strength indicator).

Name	Dataset size	Duration	Sensing technology	Environment	Size	No. of users
CamLoc [18], [19]	1.5 GB	-	Video	Indoor (Room)	$16\,m^2$, $22.5\,m^2$	1
Geolife GPS trajectory dataset [20]–[23]	300 MB	48203 h	GPS	Outdoor (urban)	$1.25 \cdot 10^6$ km	182
Geo-Magnetic field and WLAN dataset [24], [25]	3 kB	2 h	WiFi, geo-magnetic sensor, inertial	Indoor (office building)	$185.12\,m^2$	2
High precision dataset for foot-mounted inertial navigation [26]	98.8 MB	28 min	Inertial, magnetic	Indoor (room)	-	-
Indoor Bluetooth Dataset [27], [28]	13.2 MB	11 h	Bluetooth	Indoor (Office building)	-	11
IPIN 2016 Track 3: Smartphone-based (offsite) [29]	80 MB	-	WiFi, inertial, magnetic, GNSS, smartphone sensors	Indoor (office building)	-	-
IPIN 2018 Track 3: Smartphone-based (offsite) [30]	-	78 MB	WiFi, inertial, magnetic, GNSS, smartphone sensors	Indoor (shopping mall)	-	-
Pedestrian and bicycle seamless navigation [31], [32]	85 MB	-	Inertial, magnetic	Outdoor	12 km	-
RuDaCoP [33]	5.6 GB	56 days	Inertial, magnetic	Indoor (office building)	-	-
Sigfox and LoRaWAN [34], [35]	20 MB	-	Radio	Outdoor (rural, urban)	$1068\,km^2$	20
Sussex-Huawei Locomotion and Transportation Dataset [36], [37]	10 GB	83 h	All smartphone sensors	Outdoor (urban)	-	3
The Cambridge/Haggle dataset [38]	4.4 MB	4 days	Bluetooth	Indoor/outdoor	-	70
Transportation mode detection dataset [39], [40]	190 MB	31 h	Smartphone sensors	Outdoor (urban)	-	13
UJIIndoorLoc dataset [41], [42]	1.4 kB	-	WiFi	Indoor (office building)	$110000\,m^2$	20
Unaided 3D pocket inertial navigation [43]	6.5 MB	10 min	Inertial, magnetic	Indoor (museum)	-	1
Wearable-based pedestrian navigation [32], [44]	385 MB	4 h 51 min	Inertial, magnetic	Indoor	20 km	-
Wi-MEST Dataset [45], [46]	23 MB	-	WiFi	Indoor	$525\,m^2$-$11400\,m^2$	4
Urban European driving dataset [47]	105 GB	21 h	Video, GNSS position	Outdoor	-	-
RISEdb [48]	>110 GB	6 h	Inertial, magnetic, images	Indoor	$1400\,m^2$-$8200\,m^2$	-
The IDOL Dataset [49]	1.2 GB	20 h	Inertial, magnetic	Indoor	-	15
The walking recognition dataset [50]	1.5 GB	-	Inertial, magnetic	Indoor	-	77

TABLE 3. List of datasets and their specific features. IMU stands for inertial measurement unit.

Name	Activities	Multimodal	Ground truth	No. devices	Device(s)	Device location
CamLoc [18], [19]	Walking	-	Ground truth points	3	Cameras	Fixed in a room
Geolife GPS trajectory dataset [20]–[23]	Walking, sports, shopping, sightseeing, dining, hiking	bike, bus, car&taxi, train, airplane, other	Labels of transport mode	1	GPS logger or smartphone	-
Geo-Magnetic field and WLAN dataset [24], [25]	Walking	-	Ground truth points	2	Smartphone, smartwatch	Texting, wrist
High precision dataset for foot- mounted inertial navigation [26]	Walking	-	Position from motion tracking system	1	IMU	Foot
Indoor Bluetooth Dataset [27], [28]	Walking	-	Ground truth points	1	Bluetooth receiver	Handheld
IPIN 2016 Track 3: Smartphone-based (offsite) [29]	Walking	-	Ground truth points	1	Smartphone	Texting
IPIN 2018 Track 3: Smartphone-based (offsite) [30]	Walking	-	Ground truth points	1	Smartphone	Texting
Pedestrian and bicycle seamless navigation [31], [32]	Walking	Biking	GNSS position	1	IMU	Pocket
RuDaCoP [33]	Walking	-	Position from two foot-mounted inertial systems	4	Smartphones	Texting, hip, chest, bag pack
Sigfox and LoRaWAN [34], [35]	-	Car commute	Ground truth points	1	WiFi receiver	-
Sussex-Huawei Locomotion and Transportation Dataset [36], [37]	Still, walking, running	Bike, car, bus, train, subway	Transport mode labels, GNSS position	4	Smartphones	Hand, chest, hip, bag
The Cambridge/Haggle dataset [38]	-	-	-	1	Bluetooth receiver	-
Transportation mode detection dataset [39], [40]	Still, walking	Car, train, bus	Activity labels	1	Smartphone	-
UJIIndoorLoc dataset [41], [42]	Walking	-	Position, building ID	1	Smartphone	Hand-held
Unaided 3D pocket inertial navigation [43]	Walking	-	Same start/end position	1	IMU	Pocket
Wearable-based pedestrian navigation [32], [44]	Walking	-	Ground truth points	4	IMU	Glasses, wrist, pocket, foot
Wi-MEST Dataset [45], [46]	Walking	-	Ground truth points	5	Smartphones	Texting, calling, swinging
Urban European driving dataset [47]	-	Car	GPS position	1	Smartphone	Car mounted
RISEdb [48]	Walking	-	LIDAR position	3	Spherical camera, stereo camera, smartphone	Backpack
The IDOL Dataset [49]	Still, walking, stairs walking	-	Inertial-visual position	1	Smartphone	Handheld platform
The walking recognition dataset [50]	Walking, stairs walking	-	Activity labels	1	Smartphone	Handheld, bag, pocket, phoning

and conditions which may conflict with the interests of the institution that owns the dataset.

B. DATASET SIZE AND ENVIRONMENT

Table 2 lists the dataset size, the amount of data in time, the sensing technology, the environment, the environment size and the number of volunteers who have participated in the tests. The size of the datasets ranges from a few kB to more than [100]GB and depends on different elements. In general, we believe that it is preferable to have:

- long recording times and a large variety of volunteers. The associated challenge is the cost in time and resources.
- efficient data formats to store the data. Larger datasets imply larger sizes, but the choice of one data format over another one can reduce the size of the dataset for a given recording time.
- thorough data documentation. The usability and readability of the measurements in a dataset improves with a thorough documentation, thus increasing the likelihood that the dataset is useful to the community.

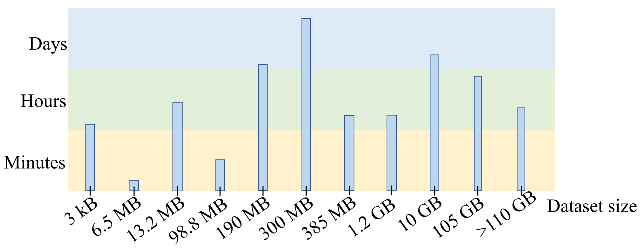

FIGURE 2. Duration of the data in the datasets plotted against the dataset size.

Figure 2 is a qualitative representation of the dataset size and the total duration of the data in minutes or hours. We have only considered the datasets that provide the duration of the tests. First of all, it is key to highlight that 35% of the works do not specify the duration of the data. In some cases, the datasets indicate the duration in days; however, it is not specified if the tests lasted [24]h or only a few hours on each day. The key observation is that the choice of data format influences the size of the dataset. For instance, the Geolife GPS Trajectory Dataset [22], [23] contains [48203]h data stored in [300]MB of files. In contrast, the Sussex-Huawei Locomotion Dataset [36], [51] contains [83]h of data in [10]GB of files. One of the reasons for the disparity between the dataset size and the data duration is that the Sussex-Huawei Locomotion Dataset publishes more data, i.e., all smartphone data, than the Geolife Trajectory Dataset, which only publishes GPS data.

Table 2 shows that all sensing technologies are suitable for indoor use but not for outdoor use. None of the works listed in Table 2 uses WiFi or video technology in outdoor environments, whereas GNSS is used both in outdoors environments and indoor environments through signals of opportunity [29], [30]. The most common indoor environments are office buildings. Thus, there is room for data collection and research in other indoor environments like hospitals, factories or traffic hubs.

71% of the works carry out the experiments indoors. Since passengers transition seamlessly between indoor and outdoor environments, there is a need for datasets with data not only from outdoor environments but also data from indoor-to-outdoor transitions and viceversa.

In Table 2, only 43% of the datasets specify the size of the location and only 62% specify the number of users who have participated in the experiment. This lack of information is an indication of how the collection of datasets in a standardized fashion is still a challenge, not only in the indoor localization community in particular [15] but in the urban mobility community in general.

C. ACTIVITIES, TRANSPORT MODES, GROUND TRUTH AND RECORDING DEVICE

Table 3 details the activities, transport modes, ground truth and devices used in each dataset. The dominant activity is walking, one dataset considers running [36], [37] and one dataset considers leisure activities like shopping and sightseeing [20]–[23].

28% of the datasets consider multimodal transportation. Thus, we can state that it is necessary to invest effort in the collection of multimodal datasets. Only then, machine learning methods can be developed to address the needs of passengers in cities. In fact, the raising popularity of the Sussuex-Huawei Locomotion Dataset [52]–[54] shows that there is a demand for datasets with multimodal transportation data.

A successful urban mobility application has to cope with an unknown smartphone location. An alternative is to develop machine-learning-based methods to predict the smartphone location, as Gjoreski *et al.* suggest [36]. The advantage of datasets like the one in [36] is that the same dataset can be used for different purposes [51], e.g., identifying the carrying mode or developing localization algorithms that are independent of the carrying mode.

The ground truth is a key feature of any dataset and depends on the application. In Table 3, we consider the following types of ground truth:

- Lables, which are tags that identify the activity or the transport mode used by the passenger.
- Ground truth points, which are discrete points with known location and are visited during the trajectory.
- Position, which is a continuous estimation of the volunteer's position computed, e.g., through GNSS or a motion tracking system.

Localization applications frequently use ground truth points [29], [30], [44] whereas classification applications use labels [20]–[23], see Table 3. Designing and collecting the ground truth of a dataset is time consuming, expensive and, in applications like localization, the ground truth needs to satisfy a certain degree of accuracy [15], [55].

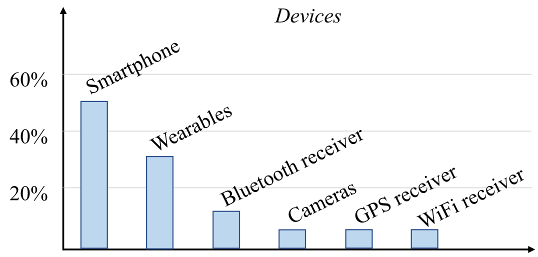

FIGURE 3. **Percentage of the devices used in public datasets.**

95% of the published data sets in Table 3 include ground truth. Labels are the predominant ground truth among the datasets with multimodal transport data [20]–[23], [36], [37], [39], [40]. The reason may be that other types of ground truth are difficult to set up and record when the passenger is not walking. For instance, it is challenging to deploy ground truth points inside public spaces like underground stations and a GNSS-based ground truth is not appropriate inside indoor areas or outdoor urban environments.

The device specified in Table 3 indicates the instrument used to gather data from the sensing technology specified in Table 2. Table 3 shows that some datasets consider more than one device, [18], [24]. There are three main reasons for using multiple devices while collecting a dataset. Firstly, the application itself requires measurements from multiple devices simultaneously [56]. Secondly, the comparison of different systems requires them to be tested under the same conditions [44]. Finally, the data collection requires data variety while maintaining efficiency high and costs low [37].

According to Table 3, the most popular device for data collection is the smartphone. In fact, 62% of the public datasets collect smartphone data, see Figure 3. Wearable devices are the runner-up device in popularity; e.g., inertial measurement units (IMUs) are commonly placed on the foot or the front pocket of the trousers [31], [44].

D. CONCLUSIONS AND OPEN CHALLENGES

Datasets are vital to develop machine learning methods. The choice of platform to publish these datasets conditions the popularity of the dataset and therefore its potential usability.

We have observed that datasets for multimodal transportation consider mostly smartphones as data collection devices. Therefore, these datasets tend not to restrict the carrying mode of the smartphone.

Datasets for urban mobility have open challenges. Among these, we identify the following:

- it is necessary to standardize the methodology for data collection and documentation of multimodal datasets in order to facilitate their usability and understandability.
- it is necessary to invest effort in the collection of datasets with data of outdoor environments, indoor-to-outdoor transitions and viceversa.
- it is necessary to invest on the collection of datasets with multimodal transport modes. At the moment, the predominant transport mode is walking which is not enough to develop machine learning methods in urban mobility.
- it is necessary to develop tools for a standardized collection of ground truth.

We think that researchers and developers could make a better use of tools like conferences and journals to disseminate information on the available datasets. In this way, other researchers and developers could save time by not having to collect datasets and focus on the development of machine learning methods for urban mobility with public datasets. Such a strategy would increase the awareness on public datasets, thus facilitating the analysis of the state-of-the-art, the open challenges and therefore the design of measures to address these challenges.

IV. LOCALIZATION OF PASSENGERS

Urban mobility applications rely on passenger localization, e.g. to implement adaptive trip planning algorithms or to learn how people move around the city, thus enabling an efficient planning of resources.

This section presents our analysis of state-of-the-art works that address localization challenges with machine learning methods. We review two main types of works: localization and detection works. The former refers to works that develop systems or methods that localize a passenger in indoor and outdoor environments and the latter to works that detect environmental features like doors, escalators and elevators. The detection of such environmental features is used to improve the performance of a subsequent passenger localization algorithm.

A. SENSING DEVICES AND THEIR PLACEMENT

Table 4 shows that most of the reviewed works use machine learning for indoor localization and only five of the reviewed works detect environmental features [57]–[60].

Figure 4 shows the percentage of works that use a specific sensing device. Approximately 62% of the reviewed works use a smartphone to localize passengers. This fact reassures that smartphones are currently popular sensing devices to address urban mobility challenges. We see in Table 4 and Figure 4 that some works do not specify the sensing device and that less than 17% of the surveyed works use dedicated devices like wearables, e.g., IMUs, cameras or radio receivers.

In Section III, we mentioned that it is necessary that smartphone-based applications cope with an unknown device location. The column *Arb. plac.* in Table 4 indicates whether a work allows for an arbitrary placement of the device or not. Only two works specify that they support an arbitrary placement of the smartphone [63], [71], which shows that smartphone-based localization is still a challenge. In fact, 54% of the reviewed works do not specify where the device is located.

TABLE 4. List of works that use machine learning for the detection of environmental features (*detection*) or the localization of passengers (*localization*). The next abbreviations are used: arbitrary placement of the device (*Arb. plac.*), device placement (*Dev. place.*), smartwatch (*Smartwa.*).

Application	Area	Device	Arb. plac.	Dev. plac.
Detection [57]	Indoor	IMU	No	Foot
Detection [58]	Indoor	IMU	No	Foot
Detection [59]	Indoor	Smartphone	-	-
Detection [60]	Indoor	-	-	-
Detection [61]	Indoor	Smartphone	No	Handheld
Detection [62]	Indoor	Smartphone	No	Handheld
Localization [63]	Indoor	Smartphone	Yes	-
Localization [64]	Indoor	Channel sounder	-	-
Localization [65]	Indoor	Smartphone	No	Texting
Localization [66]	Indoor	-	-	-
Localization [67]	Indoor	Smartphone	No	Fixed (room)
Localization [68]	Indoor	Testing unit	-	-
Localization [69]	Indoor	Smartphone	-	-
Localization [34]	Indoor	Smartphone	No	Handheld
Localization [70]	Indoor	Smartwa.	No	Wrist
Localization [18]	Indoor	Camera	No	Fixed (room)
Localization [71]	Indoor	Smartphone	Yes	-
Localization [72]	Indoor	Smartphone	-	-
Localization [73]	Outdoor	Smartphone	-	-
Localization [74]	Indoor	Smartphone	-	-
Localization [75]	-	Radio	-	-
Localization [76]	-	Smartphone	No	Pocket
Localization [77]	Indoor, outdoor	Smartphone	No	Handheld
Localization [78]	Indoor	Simulations	-	-

B. MACHINE LEARNING FEATURES

Table 5 summarizes the characteristics of the machine learning methods implemented in the localization works of Table 4. As expected, the works that detect environmental features implement classification methods [57]–[60]. In contrast, the works focused on localization implement regression methods to create a map with specific information [63]–[65], to estimate the passenger's position [18], [34], [70] or to locate unknown transmitters [67]–[69], among other applications.

Table 6 details the characteristics of the machine learning methods that do classification. The main environmental features detected are escalators, elevators [57], [58] and doors [59]. The first two works in Table 4 place the IMU on the passenger's foot because it is the body location closer to the platform that the passenger rides. Therefore, it is easier to identify the platform with a foot-mounted IMU than with an IMU placed further away from the floor.

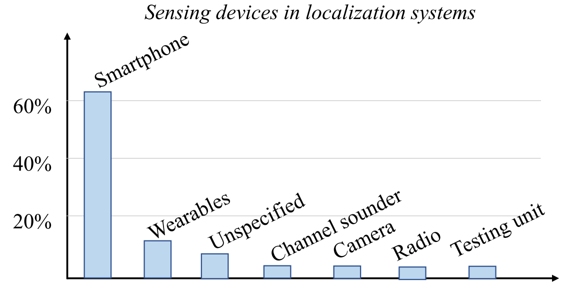

FIGURE 4. Percentage of works that use a sensing device in their localization systems.

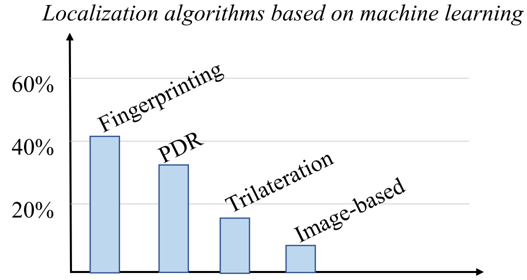

FIGURE 5. Percentage of works that use a machine learning method in their localization systems.

In general, we see from Table 6 that some of the existing classification works do not provide relevant details. For instance, only Lang *et al.* [58] and Jackermeier *et al.* [57] specify how they validate their model, whereas only Lang *et al.* specify their feature selection method.

It is possible to implement localization with classification-based machine learning. For instance, Chriki *et al.* divide the environment in areas of a given size and aim at classifying the area where a passenger is [60].

The input to the machine learning methods in Table 5 are the raw signals or a processed version of the raw signals recorded by the sensors indicated in the column *Sensor*. Figure 5 shows a clear dominance of the use of machine learning in fingerprinting technologies. The reason is that fingerprinting requires learning a map with RSSI values [64], [65] or magnetic signatures [63]. A challenge of radio-based localization is how to survey the existing transmitters and estimate their location. This challenge can be addressed with unsupervised machine learning methods [68], [69].

62% of the works in Table 5 are based on radio technologies like WiFi. One work uses the magnetometer, which indicates that radio-technologies are the dominant ones in nowadays machine-learning-based localization. Nonetheless, these radio-based localization systems are not applicable outdoors.

TABLE 5. List of works focused on localization and the characteristics of their respective machine learning methods. In the column sensor, the term radio has been used if the corresponding work did not specify the radio technology used. The following acronyms and abbreviations are used: pedestrian dead reckoning (PDR), k-NN (k-nearest neightbour), support vector machine (SVM), distance estimation (dist. estim.), transmitter location (trans. loc.), position estimation (pos. estim.), velocity estimation (vel. estim.).

Application	Localization algorithm	Sensor	Machine learning purpose	Machine learning method	Machine learning type
Detection [57]	PDR	IMU, barometer	Classification	Finite state machine	Supervised
Detection [58]	PDR	IMU, barometer	Classification	Naive-based, k-NN, random forest, logistic regression, multi-layer perceptron	Supervised
Detection [59]	PDR	IMU, magnetometer	Classification	Random forest, convolutional neural network	Supervised
Detection [60]	Trilateration	Radio	Classification	Multi-class SVM	Supervised
Detection [61]	PDR	IMU, mangetometer	Classification	Long short-term memory	Supervised
Detection [62]	PDR	IMU, magnetometer, barometer	Classification	SVM, decision tree, deep neural networks	Supervised
Localization [63]	Fingerprinting	IMU, magnetometer, Bluetooth	Regression (create a map)	Zone-based positioning	Supervised
Localization [64]	Fingerprinting	WiFi	Regression (create a map)	Convolutional neural network	Supervised
Localization [65]	Fingerprinting	IMU, radio	Regression (create a map)	Gaussian process	Supervised
Localization [66]	Trilateration	Radio	Regression (dist. estim.)	Neural network	Supervised
Localization [67]	Fingerprinting	WiFi	Regression (trans. loc.)	Hierarchical Bayesian model	Supervised
Localization [68]	Fingerprinting	WiFi	Regression (trans. loc.)	FastGraph	Unsupervised
Localization [69]	Trilateration	WiFi	Regression (trans. loc.)	Optimisation	Unsupervised
Localization [34]	Trilateration	WiFi	Regression (pos. estim.)	Variational autoencoder	Semi-supervised
Localization [70]	Fingerprinting	Magnetometer	Regression (pos. estim.)	Convolutional neural network	Supervised
Localization [18]	Image-based localization	Camera	Regression (pos. estim.)	Deep neural network	Supervised
Localization [71]	PDR	IMU	Regression (pos. estim.)	Recurrent neural network	Supervised
Localization [72]	Fingerprinting	WiFi	Regression (pos. estim.)	Regression, multi-class classifier	Supervised
Localization [73]	Fingerprinting	Radio	Regression (pos. estim.)	k-NN	Supervised
Localization [74]	Fingerprinting	WiFi	Regression (pos. estim.)	SVM, k-NN	Unsupervised
Localization [75]	PDR	Bluetooth	Regression (pos. estim.)	Deep reinforcement learning	Unsupervised
Localization [76]	PDR	IMU	Regression (vel. estim.)	Regression, neural networks, convolutional neural networks	Supervised
Localization [77]	Image-based localization	IMU, camera	Regression (pos. estim.)	Convolutional neural networks	Supervised
Localization [78]	Fingerprinting	Radio	Regression (pos. estim.)	Deep autoencoder	Semi-supervised

C. CONCLUSIONS AND OPEN CHALLENGES

In this section, we identify four main conclusions regarding the use of machine learning methods in passenger localization systems. The first conclusion is already stated in Section III-D: smartphones are the most popular device not only for data collection, but also for developing passenger localization systems.

The second conclusion is that machine learning methods can be successfully used to classify environmental features, e.g., escalators and elevators. The third conclusion is that

TABLE 6. List of localization works that implement classification and the main features of their machine learning methods.

Application	Classes	Feature selection	No. features	Model validation
Detection [57]	Elevator, escalator, no platform	-	12	-
Detection [58]	Elevator, escalator, no platform	Correlation-based feature subset selection, reliefF method	51	k-fold cross validation
Detection [59]	Door, no door	-	-	k-fold cross validation
Detection [60]	Areas in the building	-	-	-
Detection [61]	Corners, escalators, stairs	-	9	-
Detection [62]	Stairs, walking	-	21	k-fold cross validation

machine learning methods for positioning are mostly used in passenger localization systems based on fingerprinting. The reason is the inherent learning component associated to learning a map of radio or magnetic fingerprints.

Finally, the fourth conclusion is that unsupervised machine learning can be used to discover and survey transmitters. Thanks to unsupervised machine learning, one can automate the surveying process and therefore decrease the chances of human errors.

We identify the following open challenges regarding the use of machine learning methods in passenger localization:

- Development of localization algorithms with an arbitrary placement of the smartphone for localization algorithms whose performance depends on the carrying mode, e.g., dead-reckoning algorithms.
- Development of machine learning methods to detect environmental features with radio technologies, e.g., the detection of elevators or doors with radio receivers.
- Development of machine learning methods based on non-radio technologies and machine learning, e.g., magnetic-based fingerprinting valid for both indoor and outdoor environments.
- Validation of the outcome of unsupervised machine learning for the discovery of transmitters.

V. DETECTION OF TRANSPORT MODES

The detection of transport modes can be used to implement urban mobility applications such as e-ticketing or new concepts of the mobility budget service [79].

This section reviews the state-of-the-art works that use machine learning methods to detect the transportation mode used by a passenger. These works have two characteristics in common: they all use a smartphone as sensing device and supervised classification methods.

A. SENSING DEVICES AND THEIR PLACEMENT

Table 7 lists the works that detect the transport mode and focuses on two key aspects of the systems: where the smartphone is placed and the sensing technology. The placement of the smartphone is key to the acceptance of the systems by the passengers. A system will likely be accepted if it works with arbitrary placements of the smartphone.

A total of 67% of the works in Table 7 do not specify the placement of the smartphone. We believe the reason may be one of the following:

- The placement of the smartphone is irrelevant for the system. In this case, the system uses technologies like GNSS [80]–[82]; which enables the system performance to remain almost unaltered regardless the placement of the device.
- The authors skipped this information while elaborating the article. Thus, the lack of information makes it challenging for readers to understand the system performance since not all the required features of the system are provided.

Table 7 specifies two elements regarding the placement of the smartphone. Firstly, column *Arb. plac.* indicates, by *yes*, if the authors specified that their systems work in arbitrary placements of the smartphone. Secondly, some authors restrict the arbitrary placement of the smartphone to the placements listed in column *Smartphone placement.* [52]–[54], [83]. These works restrict the smartphone placement to similar ones; namely the hand, the bagpack, the pocket and the torso.

Table 7 lists the sensing technology or technologies for the detection of the transport mode. Figure 6 shows that there are two dominant technologies: GNSS and inertial sensors.

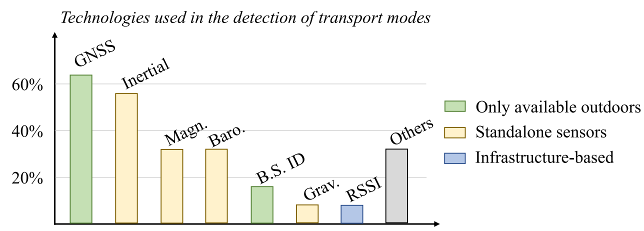

FIGURE 6. Percentage of works that use a technology in their transport mode detection algorithms. The following abbreviations are used: magnetometer (*magn.*), barometer (*baro.*), base station ID (*B.S. ID*) and gravity sensor (*grav.*).

TABLE 7. List of works that classify the transport mode. The next abbreviations and acronyms are used: arbitrary placement (*Arb. plac.*), magnetometer (*magn.*) and barometer (*baro.*), transmission control protocol (TCP).

Cite	Arb. plac.	Smartphone placement	Sensor
[80]	-	-	GNSS
[81]	-	-	GNSS
[82]	yes	-	GNSS
[84]	yes	-	GNSS
[85]	yes	-	IMU
[86]	-	-	IMU, GNSS, magn., gravity, baro.
[87]	yes	-	IMU, GNSS, rotation vector
[52]	yes	hand, pocket, bagpack, torso	IMU, magn., baro.
[53]	yes	hand, pocket, bagpack, torso	IMU, magn., baro.
[88]	-	-	IMU, magn., baro., base station ID
[83]	yes	hand, pocket, bagpack	IMU, GNSS, rotation vector
[54]	yes	hand, pocket, bagpack, torso	Sound
[89]	yes	-	LTE
[90]	-	-	GNSS
[91]	-	-	GNSS, accelerometer
[92]	-	-	GNSS, accelerometer
[93]	yes	hand, pocket, bag, chest, waist, docked	IMU, magnetometer
[94]	yes	pocket, jacket	GNSS, accelerometer

These two technologies are complementary which explains why they are frequently used together. The output of these sensors is used to estimate features that are fed to the machine learning methods that detect the transport mode.

According to Figure 6, magnetometers and barometers are also used in the detection of the transportation mode. One of the reasons is that these sensors are already integrated within most smartphones. Thus, these measurements are available at no additional costs. Magnetometers have potential of aiding the detection of the transport mode as different transport modes may present different magnetic signatures. Likewise, one could assess the barometric pressure measured with a smartphone in different transport modes, as different transport modes may be exposed to different barometric pressure depending on the environment, the altitude, the speed, etc.

It is worth highlighting that GNSS can only be used to detect transport modes that function above ground, e.g., cars or buses. In contrast, technologies like inertial or magnetic sensing are suitable for either outdoor or indoors. Thus, they enable the detection of underground transport modes such as the subway. Another alternative is to use, if available, RSS signatures of free WiFi that the transport operator may have made available to passengers.

B. MACHINE LEARNING FEATURES

Table 8 complements Table 7 and presents the main features of the classification methods that detect the transport mode. In Figure 7, the most popular classification methods to detect the transport mode are random forests followed by neural networks. Decision trees and SVMs are also popular classification methods to detect the transport mode.

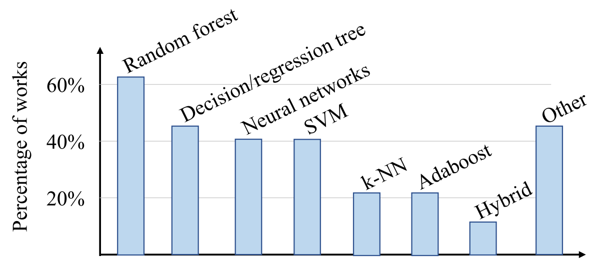

FIGURE 7. Percentage of works that use a machine learning method.

The suitability of one classification method over another one depends on the type of classification problem. In the case of detecting the transportation mode, the classification is more complex the more motorised vehicles are considered. For instance, the differences between a car and a bus are more subtle than between a car and a subway. Therefore, it is more challenging to distinguish travelling by car from travelling by bus than to distinguish travelling by car from travelling by subway.

Figure 8 summarizes the transport modes detected by the works in Table 8. In general, transport modes can be classified in two categories: non-motorised and motorised transport modes. The most common non-motorised transport modes are walking and biking. Running is also considered as a transport mode, but less frequently, provided that running could be considered a fitness activity rather than a transport mode.

Regarding motorised transport modes, we observe that all works detect the bus, and less than 55% of the works include other public transport modes like the subway or the train. Public transport is one of the main commute means in cities, therefore public datasets should include data from other types of mean of transport rather than the bus, e.g. subways, regional trains, trams. [95], [96].

The second most common motorised transport mode in the surveyed works is the car, which can be either a private vehicle or a taxi. We believe this result is an indication that the use of public transport modes in urban areas can still be improved. In fact, recent surveys confirm that private vehicles

TABLE 8. List of works that classify the transport mode and the characteristics of their machine learning methods. The following acronyms are used: CDF (cumulative distribution function).

Cite	Classifier	Classes	No. features	Feature selection
[80]	Random forest, rule-based classifier	Walk, bike, car, subway, bus e-bike	7	-
[81]	Adaboost, gradient boosting decision tree, XGBoost, random forest	Walk, bike,car, subway, bus	7	-
[82]	Multi-layer perceptron	Walk, bike, car, bus, train	54	Principal component analysis
[84]	Bayesian network, naive Bayes, SVM, multi-layer perceptron, decision tree, random forest, random trees, k-means, k-NN, adaboost	Walk, bike, car, bus, run	100	-
[85]	Random forest	Bus	6	-
[86]	Support vector machine	Walk, bike, car, subway, bus, running	-	-
[87]	K-NN, classification and regression tree, SVM, random forest, heterogeneous framework of random forest and support vector machine	Walk, bike, car, bus, run	100	Random forest
[52]	Long-short term memory	Walk, bike, car, bus, train, subway, still, run	-	Convolutional neural network
[53]	Convolutional neural network	Walk,bike, car, bus, train, metro, still, run	-	-
[88]	Long-short term memory	Bus, car, subway, train	169	CDF mapping
[83]	K-NN, SVM, decision tree, bagging, random forest	Walk, bike, car, bus, run	60	Minimum redundancy, maximum relevance
[54]	Convolutional neural network	Walk, bike, car, bus, subway, train, run, still	2	-
[89]	SVM, k-NN, random forest	Walk, bike, bus, train, static	4	-
[90]	Random forest, gradient boosting decision tree, eXtreme gradient boosting, light gradient boosting	Walk, bike, car, bus, subway, train	31	-
[91]	Random forest, SVM, decision tree, multi-layer perceptron, XGBoost	Bus, train, others	10	-
[92]	Decision tree, random forest	Walk, bike, car, bus, train	23	-
[93]	Long short-term memory	Walk, still, run, stairs walking, bike, motorbike, car, subway, train, tram, high speed rail	3240-16200	Autoencoder
[94]	AdaBoost, random forest, SVM	walk, still, bus, tram, train	-	-

remain the main commute choice in multiple countries like the U.S.A., France, Germany, and China. [97].

Figure 9 shows an example of a bike, e-bike and e-scooter and their main motion feature: either pedals or motors or both. Only few works in Table 8 consider transport modes such as e-bikes or motorbikes. E-scooters are becoming increasingly popular, especially with e-scooter sharing services like Lime[7] or Tier.[8] Such a service is attractive for those passengers who need flexibility to move in the city but do not want to cope with the challenges of public transport schedules or parking of private vehicles.

The last column in Table 8 indicates the number of features that each work uses in their respective machine learning methods. Despite the importance that features have, there are

[7]https://www.li.me/electric-scooter

[8]https://www.tier.app/

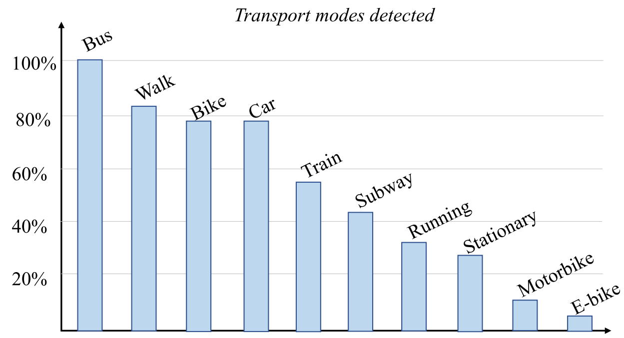

FIGURE 8. Percentage of works that include a specific transport mode in their classification methods.

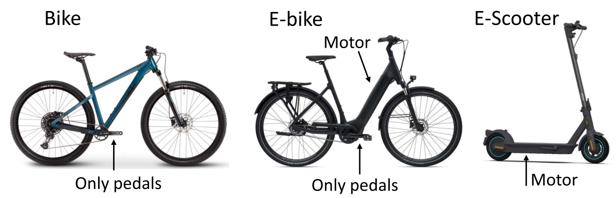

FIGURE 9. From left to right: bike, e-bike and e-scooter. The e-bike has a motor that adds additional push while the biker is pedalling. The e-scooter has a motor and it does not require the biker to pedal.

yet some works that do not provide information on feature design, number of features or feature selection method in their respective articles [52], [53], [86].

We distinguish two types of works regarding the number of features: works which use a low number of features, namely less than 10 features [80], [81], [84], and works which use a high number of features; e.g., [82] with 54 features or [88] with 169 features. Using a low number of features has the advantage that the machine learning method is less computationally complex; however, a low number of features cannot model complex processes. In contrast, a machine learning method with a large number of features can model complex processes and maybe even capture latent patterns not apparent to the human eye, e.g., the differences between travelling by car and travelling by bus. Nevertheless, such a machine learning method will inevitably be computationally demanding, which increases not only the training and the execution time of the machine learning method but also the power consumption of the device running the detection algorithm.

The feature selection method is another piece of information often missed in the articles. In Table 8, only 33% of the articles specify this information. There is a variety of methods that could be used for feature selection [12]. Some of these methods are machine learning methods themselves like random forests or convolutional neural networks.

One of the crucial phases of training machine learning methods is the validation, see Table II. Among the works in Table 8, only 30% of the works specify the evaluation method. In these works, the common method to evaluate the performance of the machine learning method is k-fold cross validation [83], [87], [88].

C. CONCLUSIONS AND OPEN CHALLENGES

The first conclusion of this section is that smartphone-based transport mode detection needs to account for a variable location of the device in order to foster the acceptance among passengers.

The second conclusion of this section is that the two dominant technologies to detect the transport mode are GNSS and inertial sensors either separately or combined. Furthermore, the dominant machine learning methods to detect the transport mode are random forests and neural networks.

The third conclusion of this section is that the bus is the most popular public transport mode in the reviewed works. Future works should consider other transport modes like subways or trains, as they also play an important role in large cities.

The open challenge that we envision regarding the transport mode is the inclusion of e-scooters within the classes of the machine learning method. This transport mode is becoming increasingly popular and future systems will have to be able to detect this transport mode as well.

VI. PATTERN RECOGNITION AND GENERATION OF MOBILITY MODELS

Identifying mobility patterns and generating mobility models is an interesting set of urban mobility applications. Pattern recognition is the analysis of data collected from real-word environments and the subsequent estimation of figures or relevant statistics that quantify the environment from which the data was collected. For instance, a pattern recognition application may target analyzing how passengers make use of a train station at different times during the day. Model generation in urban mobility is the creation of an informative representation of some aspect of the urban mobility environment and can be used to predict features of this aspect. In general, model generation can benefit from the pattern recognition. For instance, a model of the usage of a bike-sharing system may allow to estimate how many bikes will potentially be required at rush hours.

In [8], Abduljabar *et al.* survey the state-of-the-art of urban mobility models generated with machine learning and data from autonomous vehicles. An overview of the process to generate urban mobility models with cellular devices is provided in [6]. The authors review data preprocessing techniques, as well as urban mobility models. The article finalizes with a brief insight into the evaluation of the models. Zhu *et al.* present a survey on urban mobility models with data from infrastructure-based systems [7].

The existing surveys focus on the use of data collected from vehicles or infrastructure, [7], [8]. In the following, we focus on applications that exploit passenger-centric data to either recognize patterns or generate models.

A. MODEL, SENSING DEVICE AND TYPE OF DATA

Table 9 lists the works that aim at recognising patterns and generating mobility models. It provides general details about

TABLE 9. List of works that generate mobility models. Acronyms used: API (application programming interface).

Cite	Focus of the analysis	Device	Data
[98]	Usage of subway stops	Smart-card	Passenger ID, time stamp, stop ID, bus/subway ID, fare type
[99]	Discover locations	Smartphone	Cellular network data
[100]	Trajectory estimation	Smartphone	Twitter data
[101]	Predict travel time	Survey	Gender, age, job, mean of transport, home location, work location
[102]	Predict travel time	Survey	Gender, age, job, mean of transport, home location, work location
[103]	Analyze spatial-temporal distribution of activities	-	Activity type, location and duration, distance from home and from previous activity
[104]	Predict congestion time and duration	Smartphone	Traffic conditions, weather
[105]	Trajectory estimation	Visual tracker	Position estimates
[106]	Identify patterns	Smartphones	Texts, calls, approximate location
[107]	Measure safety perception of public spaces	Survey	Questionnaire information, images
[108]	Model topics and population sentiment on public transport	Twitter API	Twitter data
[109]	Predict weather conditions	Sensors	Temperature, humidity, air pressure
[110]	Predict passenger flow in trains	Ticketing machines	Access, egress, interchange, number of passengers, time of travelling
[111]	Prediction of spatial and temporal impact of planned social events on road traffic	Open street map, event data, proprietary urban information	Event and infrastructure characteristics
[112]	Predict lifetime of urban points of interest	Websites	Map snapshots, taxi rides info
[113]	Predict taxi demand in urban area	Google Maps API, taxi devices	Google maps, taxi trajectories
[114]	Predict number of commuters	Websites	Urban indicators, distance between pairs of cities
[115]	Predict public opinion on dockless bike-sharing systems	Twitter API	Twitter posts

each work, namely the focus of the analysis, the sensing device and the type of data.

The focus of the analysis conditions the type of data required and thus, the sensing device. For instance, ticketing data is required in order to analyze the usage of the public transport infrastructure such as bus or subway stops. This information can be obtained with either smart card data [98] or smartphone apps [116] which are generally released by the public transport operator.

The identification of mobility patterns is done mainly with smarthpone data [106]. This information is useful to transport operators to tailor their services to the need of the passengers. Information such us the start and end stop of a ride, the week day and time of a ride provide useful insights as to how the population use certain transport modes during specific days of the week or times of the day. It is worth highlighting that aspects like traffic congestion can be analysed with passenger-centric data [104], which otherwise would require infrastructure-based data [117], [118].

Surveys have not disappeared as a means to collect passenger data [101], [102]. In fact, they remain a useful tool to provide additional information and context to, for instance, quantitative data such as sensor measurements. In Table 9, surveys are being used to predict the travel time of passengers.

B. MACHINE LEARNING FEATURES

Table 10 lists the key machine learning features of the works in Table 9, namely the machine learning method and the type of machine learning. The only machine learning method that is repeated in different works is the decision tree [99], [100]. The variety of the topics on pattern recognition and model generation leads to the use of a variety of machine learning methods. For instance, similar applications such as predicting the travel time can be addressed with methods like SVM, kNN [101] or a Boltzmann machine [102].

50% of the works in Table 10 implement unsupervised learning. Therefore, 50% of the works have no prior ground truth to evaluate the machine learning method. This result is expected due to the nature of the application at hand, where one cannot expect to have prior information, e.g., regarding how people behave in a train station.

Unsupervised learning is a powerful tool to discover clusters in certain areas of urban mobility. For instance, one could assess with unsupervised learning how gender, age effect the choice of transport mode by analysing data from passengers' smartphones or smart cards [98]. Uncovering this information is useful to adapt mobility options to passenger and even design traffic hubs or cities to match the needs of different population clusters.

C. CONCLUSION AND OPEN CHALLENGES

This section summarizes the three main conclusions regarding pattern recognition and model generation in urban mobility. The first conclusion is that pattern recognition and generation of mobility models for urban mobility is a new topic, which shows potential and we expect it to be explored in more detail in the future.

The second conclusion is that surveys remain a means of extracting additional information which allows to add meaning to quantitative measurements like those of smartphone

TABLE 10. Method and type of machine learning method used in each of the works in Table 9. The following abbreviations and acronym are used: hidden Markov model (HMM).

Cite	Machine learning method	Machine learning type
[98]	Poisson mixture model	Unsupervised
[99]	K-means clustering, decision tree	Supervised, unsupervised
[100]	Decision tree	Supervised
[101]	SVM, k-NN, elasticnet, random forest	Unsupervised
[102]	Mixed-variate restricted Boltzman machine	Unsupervised
[103]	Ada boost	Supervised
[104]	Multi-layered perceptron, linear regression	Supervised, unsupervised
[105]	Growing HMM	Supervised
[106]	Kernel density estimation	Unsupervised
[107]	Logistic regression	Unsupervised
[108]	Latent Dirichlet allocation	Unsupervised
[109]	Long short-term memory, multi-layer perceptron	Supervised
[110]	Artificial neural network	Supervised
[111]	SVM, k-NN, ridge regression	Supervised
[112]	SVM	Supervised
[113]	Long short-term memory	Supervised
[114]	CatBoost, XGBoost, light gradient boosting machine	Supervised
[115]	Naive Bayes, logistic regression, SVM	Unsupervised

sensors. Finally, the third conclusion is on the importance of unsupervised learning to recognise patterns and generate mobility models particularly if no prior knowledge on the training is available.

There are open lines of research in the field of pattern recognition and model generation in urban mobility. The importance of this topic has only grown over the last years and thus, the open challenges in this field are:

- Determining how to respect privacy concerns in the analysis of the usage that passengers make of the urban transport infrastructure,
- Determining how to quantitatively verify the outcome of an unsupervised training,
- Identifying and developing features that quantify how passengers make use of the urban transport infrastructure,
- Developing and evaluating models that represent passenger behaviour and allow to make predictions.
- Identifying patterns and developing mobility models based on data collected from passengers' smartphones.

VII. CONCLUSION

This article reviews the state-of-the-art of how different works use machine learning methods in urban mobility applications. We identify four main applications: data collection for public datasets, localization of passengers, detection of the transport mode and pattern recognition and mobility model generation.

Each section of this work presents the conclusions of each topic, yet we highlight three main conclusions. Firstly, the smartphone is nowadays the most popular device in urban mobility applications. Smartphones provide first-hand insight on passengers' preferences and usage of transport modes. Secondly, public datasets are key for the development of urban mobility applications but are in need of guidelines that aid their design and documentation. In order to address these challenges, municipalities and transport mode operators of public and shared vehicles could work together to generate these guidelines and collect the data. Finally, pattern recognition and model generation are in an early stage. Other applications like passenger localization and transport mode recognition may provide useful inputs to identify mobility patterns and generate models of how passengers use the urban infrastructure and move in cities.

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