Urban Mobility-Driven Crowdsensing: Recent Advances in Machine Learning Designs and Ubiquitous Applications

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1 Introduction

Urban mobility-driven crowdsensing (UMCS) has been drawing considerable attention in recent years [70, 78]. With the rise of mobile and Internet of Things (IoTs) devices [105, 107], mobile crowdsourcing emerged as a typical form of UMCS extensively due mainly to pervasive proliferation of smartphones [78]. With increasing integration of sensors of various mobility systems, such as taxicabs, ride-sharing vehicles, public transportation platforms, and emerging unmanned aerial vehicle (UAV), the UMCS has been broadened and advanced in the recent decades. Leveraging these prevalent mobile sensing devices and platforms and "crowds as sensors," UMCS enables a myriad of urban applications, as illustrated in Fig. 1.

A UMCS, like a cyber-physical system (CPS), can leverage the distribution of the tasks and mobility of participants in a city and *steers* them toward the sensing tasks via strategizing task allocations and incentive payments quantified based on a certain performance requirement (e.g., signal coverage, data quality). For example, city government can conduct timely noise monitoring by leveraging the human crowds' feedback and smartphone recordings and decides the corresponding measures, such as road network planning and factory management to control the sources and the impacts of the noise. The crowdsensed air quality metrics by mobile devices can serve as an input for a variety of more proactive venting and purification control within a building's heating, ventilation, and air conditioning (HVAC) system or for the city air quality monitoring and environmental response departments to provide

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Fig. 1 Ideas of UMCS, which will enable the environment/data monitoring and data collection through the mobility platforms

timely responses. Furthermore, more adaptive urban traffic control can be realized by harvesting the crowds' Global Positioning System (GPS) location sharing (with individual location privacy preservation).

In summary, the potential of crowds and pervasiveness of mobile devices have made the urban mobility-driven crowdsensing increasingly popular and important. We have witnessed the introduction of various urban and mobile crowdsensing systems and platforms [8], such as Crowdsensing Map [12], Waze [89], and Gigwalk [22, 95]. These recent advances in UMCS platforms have led to the creation of numerous urban and mobile crowdsensing applications.

Note that the success of UMCS hinges on the *interactions* across the UMCS platform (or the platform owner) and the crowdsensing participants (or UMCS users), as well as the urban mobility environments (e.g., transportation network infrastructures, mobility platforms, such as public transportation systems, and built environments). To improve the effectiveness of crowdsensing, numerous researchers have recently investigated how to make use of the interactions of participants' mobility patterns and the crowdsensing platforms as witnessed from various proposals [103, 119]. Furthermore, the prevalence of smartphones, equipped with various radio and environmental sensors, has enabled myriads of interesting mobile applications, of which the crowdsensing has recently become very popular [58, 129].

Driven by the existing efforts, recent progresses, and the remaining technical concerns, this book chapter, as illustrated in Fig. 2, will review the recent advances in response to the following two important aspects within the UMCS designs:

- **Advancing ML Designs for UMCS**: Thanks to urban big data and advances in parallel computing, ML, including deep learning, has been attracting attentions

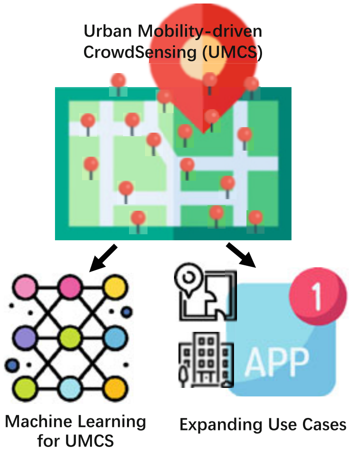

Fig. 2 An overview of the focuses of this book chapter. This chapter focuses on (**a**) the machine learning advances and (**b**) expanding the user cases in the UMCS

from various research and industrial sectors. Traditional urban-scale or large-area crowdsensing is often costly, especially for metropolitan areas or large shopping malls. On the other hand, the distribution of crowdsourcing participants over spatial and temporal spaces is uneven and dynamic, leading to sparse and skewed coverage. In order to reduce the total data collection cost, one may need to devise various deep learning approaches and infer the missing and unexplored signal values by leveraging the spatio-temporal correlations of the signals. Furthermore, the quality of the crowdsourced signals is essential for the UMCS platform. Thus, besides the cost concern, deep learning-based approaches have been taken for estimating and maintaining data quality. In addition, such quality estimation also determines the cycles of crowdsourcing, preventing over- and under-sampling. To overcome the quality issues, thanks to the recent advances in urban big data, various ML approaches, including deep learning, have been proposed and studied. This book chapter will further focus on the recent advances in deep learning approaches for UMCS, with the crowdsourced signal map construction and crowd mobility learning as two typical cases, and illustrate the future directions.

- **Expanding Ubiquitous Use Cases for UMCS**: Crowdsensing, particularly the UMCS paradigm, has emerged as an excellent data source and foundation to address various urban monitoring purposes, enabling a ubiquitous, distributed, collaborative, inexpensive, and accurate manner for a myriad of data collection tasks. Even though there already exist relevant technologies, how to expand further use cases of the UMCS remains to be challenging. To this end, this book chapter, from the scope of smart cities, will re-think about the UMCS from two geo-spatial perspectives, i.e., the indoor and urban (outdoor) UMCS applications, since smart cities are expected to revolutionize our view of the world. With the use cases of indoor crowd detection and urban mobility reconfiguration, we envision the UMCS platforms will achieve a very high level of integration, coordination, and cooperation between crowds and various systems (e.g., mobility-aware CPSs), enabling a greater degree of the ambient intelligence.

The rest of this book chapter is organized as follows. We first provide an overview of UMCS system designs in Sect. 2. We then review the recent advances in machine (deep) learning for UMCS in Sect. 3, followed by the two interesting use cases of emerging ubiquitous UMCS in Sect. 4. We finally conclude this book chapter in Sect. 5.

2 An Overview of Urban Mobility-Driven Crowdsensing

Figure 3 first provides a general overview of the pipeline of a mobility-driven crowdsensing system (UMCS) as follows:

1. **Mobility-Driven Task Publishing**: The UMCS platform publishes M sensing tasks located in different zones of the site of interests (such as cities or the building's indoor environments). Let $\mathcal{M}$ denote the set of these published tasks T_i, i.e.,$\mathcal{M} = \{T_1, \ldots, T_M\}$. Each UMCS is often labeled with its location (e.g., GPS coordinate) or the zone (e.g., if the city map is discretized). Traditionally, each UMCS task should be executed within a time interval (the *effective period* of the task, i.e., with the beginning and the end timestamps), particularly for the spatio-temporarily varying tasks (e.g., air quality monitoring). This part of UMCS often involves the research questions of (a) how to improve the sensing quality and coverage and (b) how to leverage the spatial and temporal correlations of the mobility systems (such as ride-sharing systems) to enhance the UMCS performance.

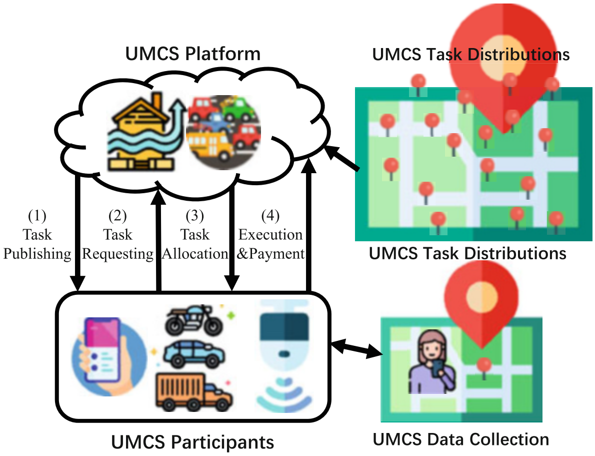

Fig. 3 An overview of the pipeline of urban mobility-driven crowdsensing (UMCS)

2. **Crowdsensing Task Requesting**: We may consider that N mobile users are willing to participate in this UMCS. These UMCS users (or participants) can be human users with their mobile devices (such as smartphones), vehicles, and other related mobile sensors (e.g., cameras, hand-held air quality sensors). Each user may submit her/his location (with certain privacy-preserving mechanism) and available period to request the tasks from the UMCS platform. UMCS platforms often come with task bidding in order to provide effective incentivization, since relocating from one location to another for data collection can be costly (e.g., transportation transit costs, motorized vehicle gasoline consumption, mobile device battery consumption, and other human labor). Each user can also make her/his *bidding* for those tasks based on their preference of the tasks or their own spatial or temporal availability, including the tasks they want to perform and the desired *payments*.
3. **Crowdsensing Task Allocation**: Based on the requests of mobile users, the UMCS platform allocates these UMCS tasks to the N mobile users (say, to maximize the total sensing utility under the limited budget), while considering the potential incentive of users. A UMCS user (participant), based on his or her preference or availability as well as other UMCS platform designs (e.g., the participant's sensing reputations), might be allocated with one or more tasks T_i's or no task. Based on the well-studied game theory framework, different auction-based incentive designs can be further applied in the UMCS task allocation [11]. By considering diverse properties of bidding, the multi-dimensional auction mechanism [87] and the incentive design based on double auction [47] can be further adopted to stimulate both UMCS task requesters and the UMCS participants. Interested readers can refer to these related articles in [78].
4. **Mobility-Driven Crowdsensing Task Execution and Payments**: Upon receiving the task allocation, each UMCS user or participant accomplishes her/his allocated task. One may further consider measuring and updating the reliability of the crowdsourced results based on the participants' UMCS reputations and the uncertainty of user mobility (e.g., spatial and temporal mobility ranges) in the mean time for future task allocation use. After the UMCS participants finish the tasks, they will obtain the sensing payment from the UMCS platform, sometimes called as the *UMCS participant's income*. Once the crowdsourced data are harvested, further data analytics can be conducted with various machine learning and deep learning techniques. In the following section (Sect. 3.1), we will discuss these recent advances in machine learning and deep learning, particularly in the cases of signal map crowdsourcing.

3 Advancing Machine Learning Designs for UMCS

In this section, we will first overview in Sect. 3.1 the machine learning design advances particularly in the case of crowdsensing signal reconstruction, followed by the recent advances in the crowd mobility learning in Sect. 3.2. For each part, we will examine the contributions and importance of deep learning approaches studied.

3.1 Machine Learning Advances in Crowdsensed Signal Reconstruction

Among various UMCS applications, signal map construction has been attracting much attention from both industry and academia due to its importance in the urban and indoor site spectrum monitoring [106, 124, 129], location-based service (LBS) [27, 50, 98], and the wireless network construction [58]. The recent endeavors in the self-driving car development have also stimulated the needs for large-scale urban signal map collection and data construction (e.g., LiDAR signals, camera recordings). For instance, for location-based service deployment [20], the gamification integration with the online learning was proposed in [50] to motivate the users in crowdsourcing Wi-Fi signals.

Despite the prior advances, many of these existing UMCS studies for signal map construction did not consider inference of the potentially missing signals to reduce the overall sensing accuracy and cost. In addition, the gamification designs in their mobility might not necessarily motivate the UMCS participants to fill the missing signals given the complex user mobility. Furthermore, one key challenge lies in how to *jointly* account for the interaction of crowdsourcing payment, coverage, and signal quality, thus achieving better crowdsensing performance. UMCS designs should also carefully consider whether the UMCS design is also amendable to those emerging solutions in the radio frequency (RF) signal map construction to further improve their crowdsourcing quality and deployability [52, 58]. Driven by these needs and gaps, machine learning (including the deep learning techniques) has been considered for the signal map construction. Thanks to the recent advances of big data and parallel computing, the ML techniques have demonstrated their capability of (a) learning the spatio-temporal correlations for missing data inference and (b) capturing the spatio-temporal dynamics of UMCS user mobility [32]. Therefore, one may observe the recently proliferating efforts in studying machine and deep learning approaches for UMCS-based signal map construction.

We first briefly overview the conventional ML approaches for signal map construction. ML-based algorithms have been considered to assist learning dynamic wireless signals in the complicated environments. To capture the inherent spatial correlations between signals, Sun et al. [86] considered the Gaussian process regression (GPR) model to predict the signal map distributions of the received signal strengths based on the limited training data. Some more recent studies consider compressive sensing [17] for the allocation of crowdsourcing tasks [90]. Awareness of cost and density has also been incorporated in [102] and [25], respectively. However, they did not consider the corresponding incentive design to improve performance [105, 106]. Compressive sensing was studied in [68] for air quality monitoring, which, however, did not consider the correlations among sample points to refine the quality. One research direction related to signal map construction is the sparse location estimation. Specifically, the location of a mobile device can be considered as a sparse recovery problem, aiming at recovering from a small number of signal measurements (i.e., a signal map) based on the compressive sensing theory. For instance, Feng et al. [20] proposed a dual-stage location estimator, with a coarse stage classifying which cluster the targe device should belong to, and a fine-grained stage further leverages the compressive sensing to recover the location estimation. These pioneering studies further motivate the usage of compressive sensing in reconstructing the radio map based on partial RSSI measurements during the offline phase [51, 106].

More recent studies have shown that learning the sparsity within the crowdsensed data will help improve the structural designs of UMCS. The work in [29] designed several approaches to jointly address the challenges in signal sparsity, sensing quality, and UMCS user incentivization. In order to reduce the sensing area (cost) needed for task allocation, the work in [29] proposed `BCCS`, i.e., *B*ayesian *C*ompressive *C*rowd*S*ensing) [44], to estimate the unexplored/missing values. At each sensing time step t, the relationship between the i-th sparsely crowdsourced signal sample, z_i^t, and those within the entire signal map of the target site (a city or the indoor environment), $\boldsymbol{s}^t$, is considered as

$$z_i^t = \boldsymbol{\psi}_i \boldsymbol{s}^t + \epsilon_i, \tag{1}$$

where $\boldsymbol{\psi}_i$ is the i-th row (vector) of $(\boldsymbol{\Psi})_{M\times N}$. We let $\boldsymbol{e} = [\epsilon_1, \ldots, \epsilon_M]^T$ be a 1-D vector consisting of M noise elements ϵ_i's. Then, the relationship between the crowdsourced samples and the signal map can be modeled as

$$\left(z^t\right)_{M\times 1} = (\boldsymbol{\Psi})_{M\times N} \left(\boldsymbol{s}^t\right)_{N\times 1} + (\boldsymbol{e})_{M\times 1}, \tag{2}$$

where the projection matrix is formally given by

$$(\boldsymbol{\Psi})_{M\times N} = \begin{bmatrix} \boldsymbol{\psi}_1 \\ \vdots \\ \boldsymbol{\psi}_M \end{bmatrix} = \begin{bmatrix} \psi(1,1) & \ldots & \psi(1,N) \\ \vdots & \ddots & \vdots \\ \psi(M,1) & \ldots & \psi(M,N) \end{bmatrix}. \tag{3}$$

Unlike previous compressive sensing approaches, this approach not only predicts the signals but also further provides a confidence interval for quality estimation through the Bayesian modeling. Thus, the BCS-based approach provides flexibility in signal inference and the subsequent incentive design. Enabled by the BCS framework, the work in [29] estimates the quality of crowdsensing and determines the incentive distribution map at a lower cost with a signal map crowdsensing framework. `BCCS` is designed to iteratively determine signal map, task, and incentive distribution. We further illustrate its process in Fig. 4.

More specifically, the work in `BCCS` provides the following two novel designs:

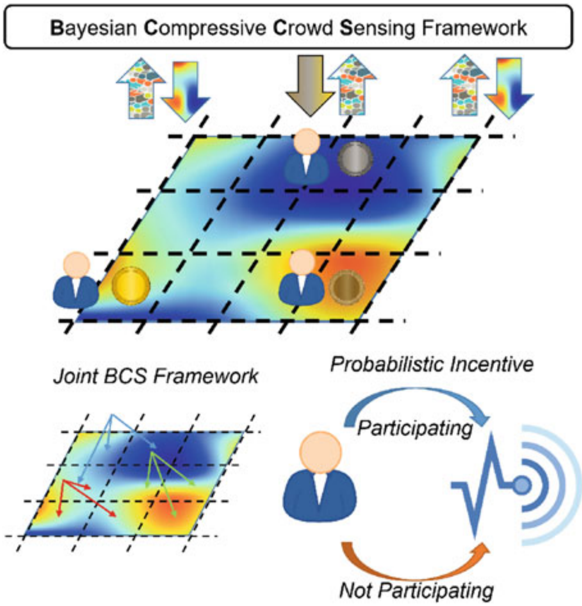

Fig. 4 Ideas of BCCS for the signal map crowdsensing. The framework consists of Bayesian compressive sensing for reconstructing the signal map and the probabilistic inference of participation which will help calculate the payment

(a) *Joint Bayesian Compressive Sensing*: The researchers in [29] have leveraged the latent correlation across different measurement points, i.e., *spatial*, *signal*, and *temporal* dimensions. The BCCS can hence accurately reconstruct from the sparse signals with substantially reduced data collection cost.

(b) *Probabilistic Incentive Design*: BCCS further takes into account the unknown relations between the monetary reward and crowdsensing process. Specifically, BCCS depicts the user participation in a stochastic manner without explicit user cost information and adapts to the participation dynamics with enhanced flexibility.

Extensive experimental evaluation based on urban mesh network and indoor wireless local area network datasets have further validated the effectiveness and applicability of BCCS. Compared to the state-of-the-art approaches in learning- and regression-based approaches, BCCS is shown to significantly reduce the payment and iteration costs, while maintaining higher missing value estimation accuracy.

BCCS is considered a general UMCS framework that can be applied in various emerging crowdsourced signal map construction scenarios [58, 94, 130] beyond utilizing the wireless signals. Another strength is shown in the stochastic modeling. Compared to the existing traditional compressive sensing techniques [25, 77, 90, 91, 102] which provide only a single point estimate, the BCCS framework augments it with a full posterior probability density, showing the confidence level. These error estimates can be further used to improve crowdsensing and steer the sensing cycles, and the approach is experimentally compared with state-of-the-art algorithms [74, 90, 111, 112] in missing value inference, which validated the accuracy and deployment efficiency.

More recent efforts have been focused on the deep learning techniques due to the explosion of urban mobility data. Jung et al. [49] employed an unsupervised signal map calibration approach that includes a hybridized global–local optimization method. Specifically, the global search algorithm builds the initial model without the reference location (i.e., the location point in a signal map) information. Afterward, a local optimization algorithm further estimates locations. To further reduce the data collection costs, methods such as semi-supervised learning techniques with some labeled crowdsourced fingerprints, including manifold-based learning [85, 131] and Gaussian process regression [42, 97], have been proposed. In addition, Sorour et al. [85] locate real-time collected signal values using manifold alignment. The semi-supervised transfer learning method exploits the inherent spatial correlation of wireless values to reduce calibrating load. With some labeled reference locations, the semi-supervised algorithms achieve signal reconstruction accuracy with lower data collection costs. Furthermore, semi-supervised deep learning approaches based on generative adversarial networks (GANs) [13] and convolutional autoencoders [82] can be further considered to enhance the model learnability in complex signal environments.

Driven by these efforts in deep learning model design, Li et al. [59] designed a fine-grained signal map crowdsensing approach using deep spatio-temporal reconstruction networks. This approach leveraged the spatial–temporal residual block and external factor fusion module, where the three-dimensional convolutional layers are considered to learn the signal maps within the time series. A more recent work by Zhao et al. [125] considered reconstructing and updating the signal map in the case of partially measured signal maps through a generative adversarial network (GAN)-based active signal map reconstruction method. The GAN mainly consists of two parts, a generator and a discriminator. The main function of the generator is to generate a fake sample from the input random noise, and the goal of the discriminator is to distinguish the real signal samples from the fake samples generated by the abovementioned generator. This way, the GAN approach can be adopted for the complex signal map crowdsensing given the noisy crowdsourced samples.

A key challenge with the existing deep learning approaches for signal map crowdsensing lies in that the recovered signal map often lacks high-frequency details due to the designs of conventional loss functions (e.g., mean squared error or MSE). Despite the advances in model learnability, the signal map reconstruction accuracy of these deep learning approaches might have a significant drop when the measurement environments get significantly changed. In particular, while crowdsourcing can update the radio map online, how to handle mobile device power consumption, sensor estimation noises, and quality concerns of the harvested data remains to be challenging for developing an effective UMCS system based deep learning, which is worth further exploration for the future studies.

3.2 Machine Learning Advances in Understanding Crowd Mobility Distributions

In addition to signal map construction, machine learning, particularly deep learning, has been widely considered for understanding the mobility patterns of the crowd participants. This is essential to model the distributions of the crowd participants in UMCS, thus enabling more proactive and accurate crowd task allocation, and enhance the performance of the UMCS platform.

With the growing need of handling more complex city systems [127], there have been numerous efforts in urban traffic and mobility analytics, enabled by advent of big mobile data science [101, 114, 121] and Internet of Things (IoTs) [29, 72, 105]. These traffic analytics techniques have been further extended to the UMCS scenarios to support large-scale crowdsensing scenarios that are driven by increasing connectivity and exploding data in ubiquitous computing.

Among these prior efforts, the mobility modeling in smart transportation [45, 93, 99] has recently attracted significant attention [57, 61]. These efforts have investigated the various conventional time series and statistical feature learning analyses for mobility traffic prediction [7, 21]. For instance, instead of considering location-to-location correlations, the authors of [43] studied different feature learning algorithms for prediction. Predicting the aggregated crowd flows at different locations via grouping them into clusters has been explored [10, 43, 57].

Deep learning, thanks to the big data and advancing computing parallelism, has emerged as a more versatile approach toward more promising traffic analytics [93] rather than implementing "shallow" machine learning model structures in the prior studies [60, 88, 120]. For example, the sequence learning approaches, represented by recurrent neural networks (RNNs) and the long-short-term memory (LSTM) techniques [39], have been shown to effectively learn the scalar-based traffic sequence. Convolutional neural network (CNN) has been further explored for traffic monitoring [71], which similarly models the mobility patterns at the neighborhood regions into scalars. In these studies, CNN locally captures, or pools, the spatial dependencies of geo-spatial zones, thanks to its prior success in processing images or photos [55]. Deep residual network [121] and fusion of CNN with LSTM or RNN [71] have been considered to predict aggregated flows for each zone. However, the image-based formulation may not be easily extended to fine-grained prediction of flows at each individual location.

Different from the image-based processing, the advances of geometric signal processing [5] have further enabled the deep graph learning for the non-Euclidean data [100, 104]. Graph data in many real-world applications [41, 100], with variable numbers of both un-ordered nodes and neighbors for each node, make conventional operations like convolutions difficult to apply. To enable graph convolution, various theoretical foundations have been established, including those on spectral graph theory [6], spatial-based aggregation [24], and pooling modules [36]. Despite the differences in notations and approximations, their basic idea all tries to propagate and aggregate the neighbor feature information of nodes in a graph iteratively until convergence.

Though advances have been achieved, the existence of close or distant points of interests (PoIs) and complex zone-to-zone ride correlations have been overlooked by the scalar and region-based learning of RNNs and CNNs. The integration of both still could not fully capture the holistic picture of metropolitan traffic [110] due to their scalar-based nature. A more recent work [31] adopts the capsule networks [79] in a novel spatio-temporal manner. This work proposed `CAPrice` in order to model the crowd mobility patterns for the important UMCS tasks such as ride-sourcing dispatching. `CAPrice` [31] adopts a novel spatio-temporal ride prediction scheme based on deep capsule neural network, which accurately forecasts future demands/supplies via structural and vectorized *capsules*—structured groups of neurons [79].

A capsule neural network [37] can derive both semantic and interpretable representations from input images. Compared with conventional CNNs, the neurons inside a capsule are activated for various physical properties of the input images for better instantiation of the objects of interest [38]. The proposed approach in `CAPrice` takes advantage of this strength in the model and considered formulating the shared taxi or ride-sharing trips into heatmap frames. The neurons in each capsule produce a vector, taking into account essential spatial hierarchies between simple and complex objects in an input image. Considering input mobility distributions. as images, it captures the inherent correlations between pixels (i.e., the city zones) by a novel vectorization structure. A dynamic routing mechanism [79] is then applied in their studies to enhance the prediction accuracy. Compared to scalar-based conventional CNNs, the capsule-based approach has been shown to retrieve more spatial knowledge between locations, leading to better prediction accuracy.

Given the accurate demand/supply predictions, `CAPrice` formulates a joint optimization framework, anticipating prices and subsidies toward incoming ride-requests and thus incentivizing drivers more responsively to customers than previous greedy surge-chasing formulations for the UMCS-based applications. The formulation of *spatial equilibrium* in the UMCS vehicle (re)distribution and long-term ride-request patterns (similar to dynamic pricing [1]) *jointly* optimizes the distributions of incentive-compatible prices and subsidies for the coming rides. This way, `CAPrice` can handle the demand–supply imbalances via more responsive driver distribution flows between zones, realizing a more effective UMCS platform design.

The UMCS applications can leverage the predictive modeling, such as the capsule network, to comprehensively capture the mobility of the participants, such as the inherent pick-up/drop-off relationship among city zones, to provide more informed decisions about the crowdsourcing participants' spatial distributions. Integrated with spatio-temporal ride distributions and external ride factors, existing UMCS applications can benefit from the fusion of the deep mobility learning with the crowd incentivization.

In more recent UMCS studies, the graph convolutional neural network (GCNN) [53] has attracted attention in formatting datasets as networks (e.g., knowledge graphs and social networks). Based on the spectral graph theory [5], the operation of spectral convolutions on graphs [53] can be formally given as the multiplication of an input signal $\mathbf{x} \in \mathbb{R}^N$ with a *graph filter* g_θ in the Fourier domain, i.e.,

$$g_\theta \star \mathbf{x} = \sum_{p=1}^{P} \theta_p \mathbf{E}\mathbf{\Lambda}^p\mathbf{E}^T\mathbf{x} = \sum_{p=1}^{P} \theta_p \mathbf{L}^p\mathbf{x}, \quad (4)$$

where $\mathbf{E}$ represents the matrix consisting of eigenvectors from the graph Laplacian $\mathbf{L}$, i.e.,$\mathbf{L} = \mathbf{I}_N - \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}} = \mathbf{E}\mathbf{\Lambda}\mathbf{E}^T$. Here, $\mathbf{D}$ is the degree matrix, $\mathbf{A}$ is the adjacency matrix, $\mathbf{\Lambda}$ is a diagonal matrix of $\mathbf{L}$'s eigenvalues, $\mathbf{L}^p$ represents its p-th power, and $\mathbf{E}^T\mathbf{x}$ is the graph Fourier transform. In the context of urban mobility learning, one may consider modeling the traffic data as input signal $\mathbf{x}$ for graph learning.

Recently, they have been extended to urban traffic applications, investigating speed prediction for road segments and vehicle flows in [7, 63, 113]. These advances will further gain mobility predictability for the UMCS applications. For instance, `GBikes` in [33] investigates comprehensive spatio-temporal features via mobility network data analytics, aiming to enable more fine-grained traffic prediction model designs. `GBikes` differentiates the correlations of nearby stations and quantifies multiple different levels of temporal correlations. To this end, `GBikes` provides the designs of spatio-temporal *graph attention mechanisms* that can efficiently capture inter-location flows. GCNN therefore does not rely on sophisticated sequence matching via LSTM/RNN [75] and complicated image convolutions.

`GBikes` formalizes the bike station network (stations as nodes and trips as edges) into a *graph* with *attention* upon each station's neighborhood structure. By incorporating spatio-temporal and multi-level features as well as comprehensive external factors, `GBikes` captures the complex bike-flow patterns. Station neighbors with stronger correlations are further identified and discriminated by our attention mechanism, leading to fine-grained correlation modeling and accurate bike-flow prediction. Specifically, in the neighborhood aggregation process, the conventional graph convolution often considers assigning a weight upon two neighboring location nodes based on only their degrees. The graph attention in `GBikes` introduces an additional network structure between neighboring nodes, as illustrated in Fig. 5, and thus more important or correlated neighboring station nodes are assigned with "stronger attentions" and larger weights than others. This way, the

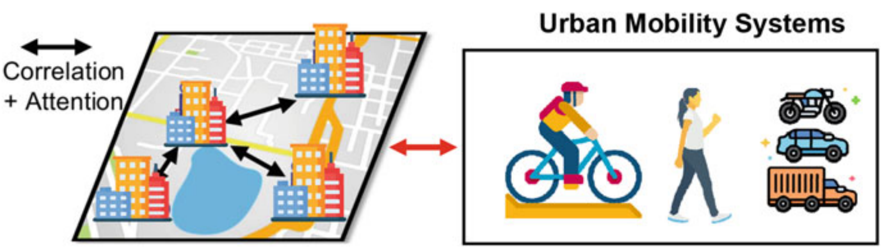

Fig. 5 Illustration of modeling the location networks as a graph for crowd mobility learning

locations that are more correlated spatio-temporally can be further differentiated, yielding better flow prediction.

The researchers in [33] have conducted comprehensive data analytics for bike station networks from multiple metropolitan cities to design and derive data-driven components and parameters. They studied the spatio-temporal factors, such as spatial station-to-station connections, multi-level temporal inflow and outflow trip correlations, points of interest (POIs), and other external factors, and then derived the corresponding component designs for `GBikes`. Extensive data analytics and experimental studies have been conducted on over 1.13×10^7 bike trips from three metropolitan bike sharing systems in New York City, Chicago, and Los Angeles. `GBikes` is shown to outperform state of the arts in terms of prediction accuracy, effectiveness, and robustness given environmental variation. `GBikes` has also demonstrated fine-grained prediction with short time intervals. Such benefits and strengths can further boost the proactiveness of the existing UMCS applications.

In summary, the recent deep learning advances will gain more mobility insights for the emerging UMCS systems on how to account for the uncertainty and dynamics of the UMCS participants (including their transportation modalities) to enhance the performance of UMCS, with important algorithmic implications for future UMCS applications.

4 Expanding Ubiquitous Use Cases for UMCS

After discussing the aforementioned advances in machine/deep learning for UMCS, we further discuss the following emerging new use cases for UMCS. In particular, we will first discuss the interesting use cases of indoor crowd detection and group identification in Sect. 4.1. Afterward, we further present the crowdsourced information fusion for urban mobility system reconfiguration in Sect. 4.2.

4.1 Indoor Crowd Detection and Group Identification

To aid the future UMCS deployment, here we particularly focus on *crowd mobility sensing and learning*, i.e., understanding and capturing the human crowd movement, which is the key enabler for UMCS platforms to determine the crowd distribution, and further enhance the efficiency, effective, coverage, and fairness of task allocation. Accurate crowd detection and group identification can also benefit the city planners and other facility management departments in monitoring the urban events [9], analyzing epidemics [115], and other social recommendation based on location-based services [62]. The recent COVID-19 pandemic has also shed the bright light upon the importance of understanding crowd mobility and distribution for the sake of public health. With the abovementioned social and business values (particularly after the outbreak of COVID-19), the global crowd analytics market was valued at $912.68 million in 2020 and is projected to hit $5.7 billion by 2030. The resulting crowd analytics market has grown at a Compound Annual Growth Rate (CAGR) of 24.3% by 2021 [14], with an estimated future CAGR of more than 20% from 2021 to 2030 [15].

The advent of smart cities accompanied by increasing pervasiveness of Internet of Things (IoTs) provides unprecedented capabilities and opportunities to monitor, model, and comprehend the mobility of urban crowds, benefiting both the smart city planners and residents. With the proliferation of big crowd data, IoTs, and deep learning, myriad of deep mobility modeling approaches have been studied for the ubiquitous and mobile computing applications. Lin et al. [64] investigated a context-aware framework in order to find the long-range spatial features and accounted for various location-based attributes to forecast the crowd flow. Jiang et al. [46] proposed an online crowd mobility system that extracts the deep trend from a momentary and short-term observations to predict the future mobility. Zhang et al. [123] introduced a deep neural network architecture based on residual neural networks [26] to analyze the crowd mobility.

Among the various mobility patterns explored for urban and social sensing, this chapter focuses on finding the individuals in a certain site of interest moving together on similar paths, namely the *crowd flows*. Detecting the existence of crowd flows is key to many emerging UMCS-related applications [18, 76, 81, 83, 122], including event surveillance, urban planning, social analysis, recommendation, and consequent commercial promotions. Crowd status can be obtained from pairing-based [65, 73] and location-based sensing techniques [28]. Trajectory mining for group/community discovery [54] has also been studied. Recently, researchers started associating signal modalities to infer the mobility, social, or demographic patterns of crowds [18, 122]. Kjærgaard et al. [54] considered temporal user clustering with different sensor readings. GruMon [81] detects groups mainly based on users' temporal movement correlation.

Conventional indoor crowd mobility detection and identification studies often require location estimation and subsequent trajectory mining. Despite their success in vehicle networking or macro migration tracking, few of them can be fully deployable in the complex crowded indoor environments, where dedicated infrastructures (say, GPS, CCTV/camera, or wireless probing transceivers) for localizing devices are likely non-existent or provide poor accuracy (due to crowds or other reasons). Beyond these prior coarse-grained estimates, a fine-grained augmentation is needed for more pervasive deployment. In some studies, mutual proximity between users can be obtained from device pairing (say, Bluetooth) but may cause privacy risks, especially when they are discoverable by other parties.

Furthermore, urban crowd flows are highly dynamic due to many opportunistically encountered users. While different signal modalities and their combination have been considered in mobility analytics, few of them considered fine-grained and hybrid signal feature designs for crowd flows and provided spatio-temporally adaptive models for their fast identification. In particular, a *scalable* and *efficient*

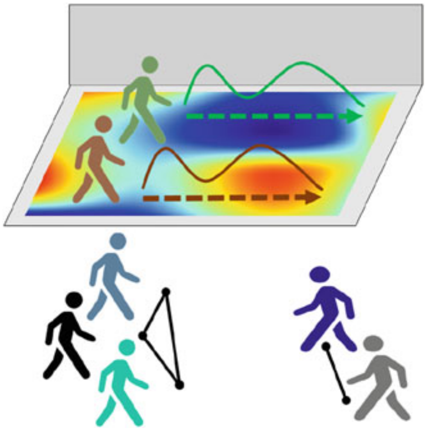

Fig. 6 Illustration of co-flow detection for crowd mobility analytics. By analyzing the similarities of the signals of different users, the proposed work [30] considered a graph-based approach to estimate the crowds. The detected crowd information can be further utilized for UMCS applications

mechanism is required for urban or spacious indoor settings like large malls or airports.

Motivated by ambiance of urban/indoor WLAN infrastructures and geomagnetic anomalies, the researchers in [30] propose `CFid`, a crowd flow identification system via fine-grained spatio-temporal signal fusion, with the following design features. By leveraging the spatial diversity (particularly along a certain walking path), we associate the Wi-Fi and magnetic features measured from individuals' smartphones with their sequential/temporal co-presences or *co-flow*, as illustrated in Fig. 6, without explicitly calibrating, pairing devices, or tracing the locations.

`CFid` advances from the related studies in the following aspects. While most pilot studies focus on single correlation measure in terms of group mobility or signal modalities [48, 81], `CFid` adopts several comprehensive metrics *jointly* on spatio-temporal features to detect crowds more effectively. Furthermore, instead of the computationally-expensive static clustering [3, 40] and supervised learning [54, 81] that requires a priori training, `CFid` adopts the fast graph streaming and clustering framework without extensive model or parameter calibration. Wi-Fi and geomagnetism sensing, due to their ubiquity, have triggered a myriad of mobile apps [40, 80], including location-based service [48, 84] and smartphone sensing [28]. However, few of these studies systematically investigated their *fusion* potential for crowd flow study.

To fill these gaps, the `CFid` approach is built on several novel signal processing and crowd-related feature extraction techniques to unleash their potentials for fast and accurate crowd flow analytics. The resulting crowd detection results can be further fed to UMCS systems to enable more ubiquitous crowdsourcing applications. Specifically, in `CFid`, the closeness or spatio-temporal *similarities* between people in the crowds, who are the device carriers or users, can be efficiently identified by online comparison of fine-grained signal sequences between users, hence enabling fast detection without extensive localization of devices. On the signal patterns derived and fine-grained similarity measures, the proposed work in

`CFid` takes into account the crowd flows as the *graph stream*, where the individuals as vertices or nodes in a graph are dynamically connected via correlations of their signals. The stream of the generated edges can then be fed and processed efficiently. As these signals can be measured from inertial phones and can be easily sanitized and crowdsourced to a central hub or server, `CFid` can mitigate individuals' privacy concerns by regulating pairing or communication with unknown peer devices. By deriving spatio-temporal features from inertially measured smartphone signals (i.e., the Wi-Fi and geomagnetic signals), `CFid` is *amendable* to these studies or applications and can serve as a plug-in to these UMCS applications for their more adaptive and pervasive deployment.

In summary, prior studies, including `CFid`, can provide important use case studies on how to further integrate the indoor social sensing for UMCS applications, and the insights can be further integrated with other indoor UMCS applications such as indoor air quality monitoring and landmark crowdsourcing.

4.2 Urban Mobility Reconfiguration with Crowdsourced Information Fusion

Another important application of UMCS lies in the urban mobility applications, particularly how to leverage the crowdsourced inputs for reconfiguration of the dynamic urban mobility systems. With the advent of smart cities/communities and IoTs, the urban sharing economy, including the bike sharing, has been evolving very rapidly. These applications often originate from the UMCS design principles. In particular, bike sharing service (BSS) has emerged as a popular and revolutionary platform that changes the people's urban life. Bike sharing enables the first-/last-mile urban travel to be more economic, greener and healthier than traditional gasoline-engine-powered vehicle riding. City transportation also benefits from an additional network of bike stations connected by the trips with less hassle of traffic planning.

The emerging UMCS studies and use cases also align with the trends of emerging urban computing applications. Urban computing [127] aims to improve social life quality under the trend of speedy urbanization. With faster computing, smarter IoTs, and more sensing data, many urban transportation problems have been redefined intelligently and efficiently. UMCS should carefully consider integrating the novel cross-domain knowledge fusion technique [126], unleashing the data-driven and crowdsourcing power to reimagine traditional UMCS problems, such as site (re)configuration for emerging smart mobility systems [16, 19, 35, 109].

Thanks to such an expansion, the global bike sharing market is expected to grow at a CAGR of 21% during 2018–2022 [23]. Experiencing the initial deployment successes and receiving positive feedbacks, many BSS providers have begun expanding their bike sharing service networks. Driven by such a growing need, Divvy bicycle sharing program in Chicago, IL is adding 10,500 new bikes and 175 additional stations over the next 3 years from 2019. Meanwhile, Citi Bike in New York City will embrace another 4000 bikes, 13 stations in the busiest areas, and 2500 docks since 2019. On the other hand, there exist BSS network shrinkages (at a micro- or macro-scale) for financial, event, seasonal, or meteorological reasons. Improving the distributions through UMCS designs will also benefit other applications in the recent boom of urban computing and planning, including the site placement of gas stations [116], ambulance points [127], and electric vehicle charging docks [56], which have been investigated to improve their social and business values.

UMCS research provides a new view in expanding the BSS network. One might observe from the existing BSS platforms on crowdsourcing the human suggestions (e.g., station distributions) for expanding and updating the BSS network. We note that such a (re)configuration can be done monthly, seasonally, or annually subject to the urbanization process, profit, cost, and the service provider's own customization. Recent popularity of BSS has triggered many interesting studies, such as mobility and demand prediction [69, 96, 108, 117], station re-balancing [67], lane planning [2], and trip recommendation and station deployment [66, 69].

However, few of state-of-the-art studies have considered optimizing the (re)configuration of existing BSS network with crowdsourced knowledge, which has been overlooked in the important spatial–temporal modeling for real-time bike demand prediction (including dynamic geographical, meteorological, or seasonal factors) [67, 69, 108]. How to fuse long-term batched station usage [92, 128] with aggregated crowdsourced feedbacks, for periodic network (re)configurations, has not been thoroughly studied in these prior works.

In summary, how to reconfigure the BSS network, by integrating the crowdsourced feedback to enhance the performance of the bike sharing stations, remains challenging in the following four perspectives.

- The *first* challenge lies in the *data heterogeneity* of crowdsourced information inputs. Crowdsourced feedbacks often provide local and fragmented suggestions due to each individual's limited geographic scope or personal interest or preference (say, close to their home residence), while BSS network (re)configuration largely relies on global knowledge of user mobility and station-to-station dynamics. How to incorporate the local suggestions or comments together is important and should thus be considered carefully for the related UMCS designs.
- The *second* challenge lies in the *user* side. As all stations are "linked" by users' trips, their *trip tendency* might be discouraged by over-crowded or inadequate BSS network placement and ignorance of popular station–station pairs for users' commute may discourage cyclists, thus lowering bike usage and platform profit.
- The *third* challenges will come from the *platform* side. Since the web crowds are enabled with large freedom to label locations they want, how to address such naturally noisy/biased crowdsourced inputs is challenging which should be considered by a *joint* fusion formulation.
- The *fourth* challenge resides within the *complexity* of BSS reconfiguration. Many external factors may influence the success of (re)configuration [117, 128], including human-built facilities (quality/availability), natural environments (like

topography, season or weather [108]), socio-economic or psychological considerations (say, social norms or habits), and utility (cost and travel time). Though it is very challenging to design a complete model, incorporating historical spatial-temporal usages, large-scale crowdsourced preferences, and refined cost metric would be a good way to accommodate these factors.

Driven by the above challenges, in contrast to recent approaches to BSS deployment [69, 118], the researchers in [34] propose a generic optimization framework that accommodates both network expansion and reduction using data-driven designs and novel semidefinite programming [4]. `CBikes` provides a flexible formulation fusing crowdsourced knowledge with historical usage statistics *jointly* and accounts for mobility interactions of BSS users and the stations, thus adapting much better to complex station correlations. `CBikes` is comprised of four consecutive layers for computing bike station (re)configuration: input, design, core, and action layers.

Specifically, at the *input* layer, the historical and estimated bike usages with respect to each station, the crowdsourced feedback of station expansion/shrinkage suggestions, as well as predefined costs are collected and delivered to a central server hosted by the city planners. These datasets will be preprocessed and then stored into databases. We note that other practical geographic design concerns or constraints, including the number of service bikes and accessible station deployment areas, can be also inputted by the BSS service provider, processed, and stored into its database.

At the *design* layer, `CBikes` forms the joint objective functions and integrates map information and station geographic distances into constraints. The focus of `CBikes` design layer is to develop a generic optimization framework, given the above primary and secondary information.

Then, `CBikes` formulates a joint optimization framework, transforms the input crowdsourced inputs, inter-station trip tendency, and the bike usage as shown in Fig. 7, and solves the joint optimization problem at the *core* layer, optimizing station sites with respect to predefined map grids. Driven by the results of the *action* layer, the service provider may (re)place stations and resize their docks. In case results are not satisfactory, the parameters can be tuned interactively for another optimization trial.

In summary, these prior studies including `CBikes` have developed a novel insight for the emerging UMCS systems on how to reconfigure the UMCS platform by fusing the valuable information from crowdsourced human inputs with other existing mobility data and optimization approaches, with practical data-driven and large-scale mobility use cases for future UMCS applications.

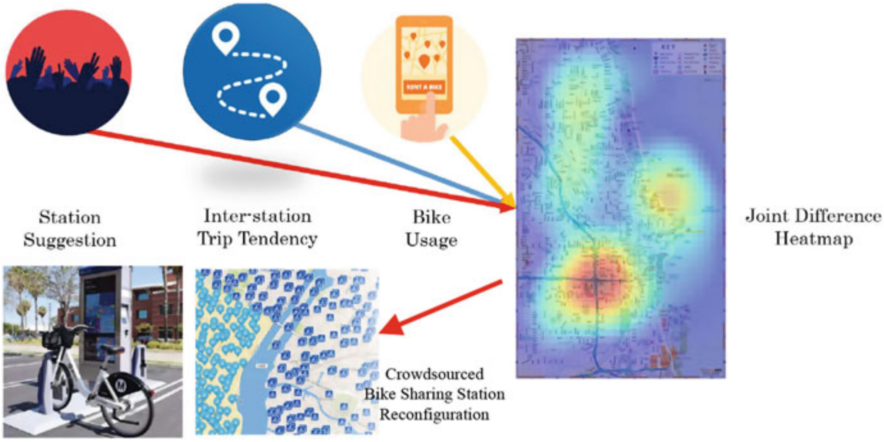

Fig. 7 Illustration of crowdsourced information fusion for BSS reconfiguration. The framework takes in the station suggestions from the crowdsourced inputs, the inter-station trip tendency, and the historical bike usage and generates the joint difference heatmap characterizing the affinity of the BSS network with the urban city map. The resulting station locations can be used to relocate or update the stations

5 Conclusion

In this chapter, we have reviewed the recent advances in the Urban Mobility-driven CrowdSensing (UMCS) that has been widely adopted for various urban and ubiquitous applications, including ubiquitous event monitoring, urban planning, and smart transportation system. In particular, this chapter has examined and analyzed the recent advances and application of UMCS machine learning algorithms and emerging use cases in indoor and urban environments. In particular, we have first overviewed the recent advances of ML techniques and algorithms for crowdsensing signal reconstruction and mobility learning to understand the importance of signal learning and mobility characterization for UMCS.

We have reviewed the emerging applications for UMCS, including the indoor crowd detection and urban mobility system reconfiguration. For each category, we have identified the strengths and weaknesses of the related studies and summarized future research directions, which will serve as a guideline for new researchers and practitioners in this emerging and interesting research field.

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