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# SURVEY OF FEDERATED LEARNING MODELS FOR SPATIAL-TEMPORAL MOBILITY APPLICATIONS

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## ABSTRACT

Federated learning involves training statistical models over edge devices such as mobile phones such that the training data is kept local. Federated Learning (FL) can serve as an ideal candidate for training spatial temporal models that rely on heterogeneous and potentially massive numbers of participants while preserving the privacy of highly sensitive location data. However, there are unique challenges involved with transitioning existing spatial temporal models to decentralized learning. In this survey paper, we review the existing literature that has proposed FL-based models for predicting human mobility, traffic prediction, community detection, location-based recommendation systems, and other spatial-temporal tasks. We describe the metrics and datasets these works have been using and create a baseline of these approaches in comparison to the centralized settings. Finally, we discuss the challenges of applying spatial-temporal models in a decentralized setting and by highlighting the gaps in the literature we provide a road map and opportunities for the research community.

**Keywords** Federated Learning, Spatial-Temporal Mobility, Privacy-preserving Learning, Flow prediction, Point-of-Interest recommendation

## 1 Introduction

Spatial temporal mobility data collected by location-based services (LBS) [42] and other means such as Call Data Records (CDR), WiFi hotspots, smart watches, cars, etc. is very useful from a socio-economical perspective as it is at the heart of many useful applications (e.g., navigation, geo-located search, geo-located games) and it allows answering numerous societal research questions [51]. For example, Call Data Records have been successfully used to provide real-time traffic anomaly as well as event detection [90, 92], and a variety of mobility datasets have been used in shaping policies for urban communities [31] or epidemic management in the public health domain [80, 79]. From an individual-level perspective, users can benefit from personalized recommendations when they are encouraged to share their location data with third parties [22].

While there is no doubt about the usefulness of location-based applications, privacy concerns regarding the collection and sharing of individuals' mobility traces or aggregated flow of movements have prevented the data from being utilized to their full potential [87, 9, 53]. Indeed, various studies have shown that numerous threats are open if location data falls into the hands of inappropriate parties. These threats include re-identification [68], the inference of sensitive information about users [53, 94](e.g., their home and work locations, religious beliefs, political interests or sexual

Table 1: Federated learning definitions.

Variable	Description
$G^t$	global model at round $t$ .
$n$	total number of participants.
$m$	subset of participants selected for a single round.
$\eta$	global learning rate.
$L$	locally trained model.
$\mathcal{D}$	local data.
$E$	number of epochs for local training.
$lr$	local learning rate.
$S$	clipping bound.
$\sigma$	amount of added noise.

orientation). In some extreme cases, sharing geo-located data may even endanger users' physical integrity (e.g., the identification of protesters in dictatorial regimes or during wars<sup>1</sup>) or their belongings (e.g., robbery<sup>2</sup>).

To address privacy challenges, a variety of solutions are being investigated, among which Federated Learning (FL) [73] is increasingly considered a promising approach. FL relies on clients (be it users' smartphones or edge devices) to train a machine learning model on their local training data and share the model weights with a central server (called the FL server) that aggregates the received clients' contributions. As such, FL empowers clients by allowing them to benefit from a globally trained model while keeping their private data on their premises.

In the context of geo-located services, FL has recently started to draw attention as an alternative to centralized machine learning-based approaches.

In this survey, we study 20 existing spatial temporal models that have been adapted to the FL paradigm and discuss their strengths and limitations. In reviewing these recent works, we give a concise but concrete description of each approach along with a comparison of the baseline datasets. We then conclude this paper with open challenges and a roadmap that we envision for the research community to explore in the coming years. The remainder of this paper is structured as follows. First, we present a background on FL in Section 2. Then, we present a set of spatial temporal applications under study in Section 3 and detail the used FL approaches for these applications in Section 4. Finally, we discuss open research challenges in Section 5 and conclude the paper in Section 6.

## 2 Federated Learning

*Federated Learning (FL)* is a paradigm to perform distributed machine learning at the edge [11, 46, 72, 52]. In FL, models are trained in a decentralized fashion without the need to collect and process user data centrally. The central service provider distributes a shared ML model to multiple users for training on local data, and then aggregates the resulting models into a single, more powerful model, using *Federated Averaging* [72].

More particularly, an FL framework randomly selects a subset of  $m$  participants from the total participants  $n$  and sends them the current joint model  $G^t$  in each round  $t$ . Choosing  $m$  involves a trade-off between the communication cost and the convergence speed. Each selected participant updates this model to a new local model  $L_i^{t+1}$  by training on their private data and sends the difference  $L_i^{t+1} - G^t$  back (see notation in Table 1). Communication overhead can be reduced by applying a random mask to the model weights [52]. The central server then aggregates the received updates [83] to create the new joint model:

$$G^{t+1} = G^t + \frac{\eta}{m} \sum_{i=1}^m (L_i^{t+1} - G^t) \quad (1)$$

Federated Learning can be categorized into two settings: Cross-device and cross-silo. In cross-device applications of FL, clients represent individual users' devices, whereas, in cross-silo settings, the clients involved in training are entities that want to avoid sharing their data (e.g., cellular operators). Figure 1 presents an overview of the schema for cross-silo federated learning. There are various challenges in FL that the research community has been studying in the

<sup>1</sup><https://www.independent.co.uk/news/ukraine-ap-russia-gps-kyiv-b2093310.html>

<sup>2</sup><https://pleaserobme.com>

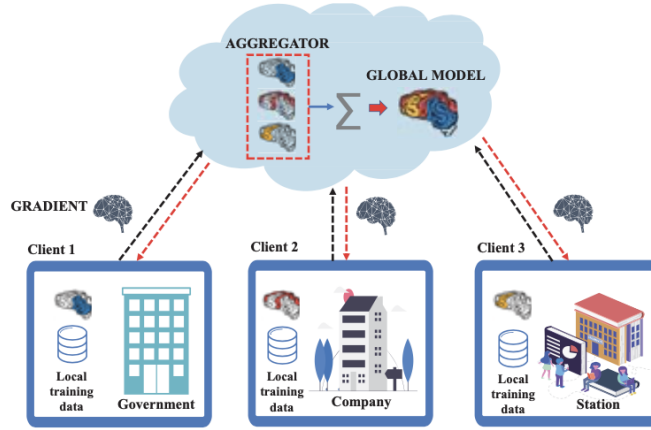


Figure 1: Figure taken from [66] shows an example of cross-silo federated learning where each client is an organization with access to their own datasets only, and the federated server is in charge of orchestrating training across the clients.

past years (see [47] for full reference). The two main challenges impacting FL models are generally regarding **data heterogeneity** and **model heterogeneity**.

- Data heterogeneity refers to the scenario where clients' data are not identically and independently distributed (iid) which could lead to domain shift problems making learning a generalizable representation a difficult task. In data heterogeneity  $P_i(X|Y) \neq P_j(X|Y)$ , that is there exists domain shift amongst conditional distribution of  $P(X|Y)$  across participants even if the labels are clients have a distinctive feature  $X$  for same classes.
- Model heterogeneity, on the other hand refers to the personalization that is required for the global model to perform accurately for each client. Understanding what level of generalization can be learned globally and what layers of the models need to be personalized locally is an active area of research.

As we will discuss in the next sections, the human trajectory of FL has been shown to be extremely unique [20], which has caused a skew in the distribution of the data and an increased need for personalization and model heterogeneity. Other challenges within FL include the protection of user data and model parameters through methods such as differential privacy [74], Trusted Execution Environments [77], or encryption [12, 39].

## 2.1 Frameworks

In recent years, several Federated Learning frameworks, including TensorFlow Federated [89], Flower [10], PySyft [115], and Fate [63], have emerged to offer scalable and flexible solutions for privacy-preserving machine learning in distributed environments. These frameworks differ in their approaches to privacy and security, with TensorFlow Federated and PySyft using both differential privacy (DP) and secure multi-party computation (SMPC), Fate relying on homomorphic encryption (HE), and PaddleFL [4] extending DP and SMPC with secret sharing. Another key difference is deployment support, with only some frameworks extending the single-host standard setting with a multi-host deployment. Flower offers a language-agnostic (e.g., torch, Tensorflow) and scalable solution for both vertical and horizontal FL. However, most of these federated learning frameworks face challenges such as communication and computation efficiency, device heterogeneity, and data quality, with bench-marking being a notable challenge for spatial mobility applications. While most frameworks are bench-marked for computer vision and NLP tasks, FedScale [54] stands out as the only framework that includes starting pack mobility datasets. More specifically, it provides a taxi trajectory prediction task on TaxiPorto [75]. It also includes the Waymo Motion Dataset, which contains object trajectories and corresponding 3D maps for 103,354 scenes and is used in autonomous driving use cases. It is also worth noting that FederatedScope [96] provides benchmarks for graph learning, which might be relevant for GNN-based approaches toward flow prediction tasks. Table 2 offers a holistic view of these key differences. For a full comparison across the described FL frameworks refer to [61], while peer-to-peer FL frameworks have been extensively compared in [7].

Table 2: Available functionalities and bench-marking across different FL frameworks.

Name	OS	Deployment	Privacy tools	Scenario	Benchmarking
Tensorflow Federated (TFF)	Linux MacOS	Single	DP SMPC	Simulation	Computer Vision NLP
Pysift & Pygrid	Windows Linux MacOS Mobile	Single Multi	DP SMPC	Simulation Real	Computer Vision
FATE	Linux MacOS	Single Multi	HE	Simulation Real	Computer Vision
Flower	Linux Mobile	Single Multi	DP	Simulation	Computer Vision
PaddleFL	Linux Mobile	Single Multi	DP SMPC Secret Sharing	Simulation Real	Computer Vision NLP Recommendation
FederatedScope	Windows Linux MacOS Mobile	Single Multi	DP SMPC	Simulation Real	Computer Vision NLP Recommendation <b>Graph Learning</b>
LEAF	Linux MacOS	Single Multi	/	Simulation	Computer Vision NLP
FedML	Linux MacOS Mobile	Single Multi	SMPC	Simulation Real	Computer Vision NLP
FedScale	Linux MacOS	Single Multi	DP SMPC	Simulation Real	Computer Vision NLP Recommendation <b>Mobility Prediction</b> RL

### 3 Applications

**Mobility Prediction** Mobility prediction can be defined as algorithms and techniques to estimate the future locations of users. Predicting the next location of users can help with a range of applications including networking (e.g., handover management), pandemic management (e.g., contact tracing), etc. This type of prediction is performed on individual users’ traces where the historical trend of the user’s visited locations can help in predicting the likelihood of their next location.

**Transportation** With the rising availability of transportation data collected from various sensors like road cameras, GPS probes, and IoT devices, there is an enormous opportunity for city planners to leverage these types of data to facilitate various tasks such as traffic flow prediction. Different from *trajectory* data that records a sequence of locations and time in each trip, crowd flow data only have the start and end locations of a trip, and how many people flow in and out of a particular region can be counted. Indeed, traffic flow prediction using spatial-temporal data has been one of the main focuses of the research community (See comprehensive survey [44]). In the context of transportation, this problem is often considered as forecasting which is to predict traffic speed or traffic flow of regions or road segments based on historical aggregated mobility data.

**Community Detection** Community detection is an important aspect of urban planning as it allows researchers and planners to identify patterns and trends in human movement. By identifying groups of individuals or locations that are highly connected, researchers and planners can gain insight into how people move through a city, which can inform the design of transportation systems and urban spaces. Additionally, community detection can help identify areas of a city that are at risk of overcrowding or under-utilization, allowing for proactive measures to be taken to address these issues. The underlying enabler of identifying urban communities [35, 31] is spatial temporal data that presents the amount of time spent in different parts of the city. Researchers have shown that human mobility exhibits a strong degree of non-linearity [19] and models that rely on non-linear clustering algorithms, such as the one proposed by Ferreira et al. [30], to detect urban communities have been shown to outperform traditional approaches such as Principal

Component Analysis (PCA), and Model-Based Clustering (MBC) and DB-SCAN techniques on a variety of centralized geospatial traces.

**Location Based Social Networks** LBSNs such as Foursquare and Flickr are social networks that use GPS features to locate the users and let the users broadcast their locations and other content from their mobile devices. LBSNs do not merely mean that the locations are added to the user-generated content (UGC) in social networks so that people can share their location information but also reshape the social structure among individual users that are connected by both their locations in the physical world and their location-tagged social media content in the virtual world. LBSNs contain a large number of user check-in data which consists of the instant locations of each user. Such social networks could also be thought of as the underlying application of Location-based recommendation systems.

## 4 Approaches

In this section we summarize federated learning spatial-temporal approaches in three main categories of i) trajectory predictive approaches which focus on the next-point prediction of user's trajectories, ii) flow-based approaches, and iii) clustering approaches. For each approach, we discuss the architecture of the model, the dataset used for evaluation, and FL strategies. Table 3 provides an overview of these works.

Table 3: CD denotes Cross-Device approaches and CS for cross-silo

Model	Year	Approach	Dataset	Federated Strategy
<b>Trajectory Predictive Approaches</b>				
Fan et al. [25]	2019	Transfer-learning	Private Mobile Phone Traces	CD
PMF [27]	2020		Foursquare [99], DenseGPS [26], CD, Attack-resilient Twitter [105]	
STSAN [56]	2020	ST Attention Layer	Foursquare[99], Twitter [106] Yelp [65]	CD Adaptive Model Fusion
Ezequiel et al.[24]	2022	GRU-Spatial and Flashback	Foursquare [99], Gowalla [17]	CD
STLPF [93]	2022	AutoEncoder with Global/Local attention	Foursquare[99]	CD
<b>Flow Predictive Approaches</b>				
FedGRU [62]	2020	GRU	PeMS [15]	CS, FedAvg
FedTSE [102]	2022	Reinforcement Learning	England Freeway Dataset[21]	CS, FedAvg
FedSTN [101]	2022	GNN	Taxi-NYC [1], Taxi-BJ [43]	CS, Vertical FL
CNFGNN [76]	2021	GNN	PeMS-BAY [58], METR-LA [43]	CS
CTFL [107]	2022	GNN	PeMSD4, PeMSD7	Clustered FL, CS
MVFF [23]	2022	GRU+GNN	Yelp [65], NY-Bike [2]	Vertical FL, CS
<b>Community Detection Approaches</b>				
F-DEC [70]	2021	Deep Embedded Clustering	GeoLife [114]	CD, FedAvg
<b>Other</b>				
EDEN [49]	2021	Privacy Optimization		CD
PREFER [37]	2021	Location Rec Sys		CD
PEPPER [6]	2022	Location Rec Sys		CD, Gossip Learning
MTSSFL [108]	2021	Transport Mode Inference		CD
Fed-DA [104]	2021	Network Traffic		CS
Fed-NTP [86]	2022	Network Traffic		CS

### 4.1 Trajectory Predictive Approaches

Given a user's trajectory, these approaches aim at predicting the user's next position. In a centralized setting where the training data containing all users' trajectories are available, RNN-based approaches including LSTM and GRU can be

broadly applied in dealing with trajectories and predictive tasks [59, 26, 33, 60]. As this type of data (i.e., trajectory) is highly privacy sensitive, one of the challenges that the research community has been focusing on has been on creating models that can be tuned for privacy and utility, namely, PUTs (Privacy-Utility Tradeoff). Models such as [103, 82, 22] leverage the centralized training data to enhance the privacy level of the traces by reducing user’s re-identification and at the same time optimizing for the utility of the predictions (i.e., higher accuracy of next point predictions).

#### 4.1.1 Metrics

Trajectory prediction models are commonly benchmarked on a handful of available datasets using  $Acc@K$  metric which is computed as an average of how many times the correct location was within the top-k predicted places (sorted by the model’s output weights). For example, for an  $Acc@5$  metric, the target (or actual output) is compared against a vector of the top-5 most probable locations output by the model. If the target is an element of the top-5 vector, the prediction is correct (or true positive). Papers commonly report on Average Percentile Rank (APR) which is the average Percentile Rank for the prediction of a location.

#### 4.1.2 Datasets

The following mobility datasets are used to evaluate the trajectory predictive approaches in the research community:

**Foursquare [99]:** It comprises two sub-datasets, Tokyo and New York data. The Tokyo dataset contains 0.5 million check-ins in Tokyo while the New York one contains over 0.2 million, both collected over a span of about 10 months (from 12 April 2012 to 16 February 2013). Each check-in includes an anonymized user ID, timestamp, and location information, e.g., GPS coordinates and semantic meaning (represented by fine-grained venue categories).

**Twitter [106]:** It contains around 1.1 million geo-tagged tweets from Los Angeles. These tweets are collected from 1 August 2014 to 30 November 2014. Every geo-tagged tweet consists of four parts, e.g., an anonymized user ID, location information (GPS coordinates), timestamp, and the message published by the user. Compared with the other two platforms, Twitter data is very sparse when location service is not a frequently-used function for Twitter users.

**Gowalla [17]:** It consists of two parts: a check-in dataset and a friendship network dataset. The check-in dataset contains over 6.4 million check-ins contributed by more than 196,000 users, collected over the period of February 2009 to October 2010. Similarly to Foursquare, each check-in includes an anonymized user ID, latitude and longitude coordinates, a timestamp, and a location ID. As for the friendship network dataset, it contains information about social relationships between users, represented by over 95,000 undirected edges.

**Brightkite [17]:** This dataset is similar to Gowalla in that it includes check-in data and a friendship network. However, this dataset is significantly sparser, as check-ins were deliberately shared by users, leading to a sparser dataset. Quantitatively, the dataset includes nearly 4.5 million check-ins and 58,228 users, collected between April 2008 and October 2010.

**Weeplaces [110]:** This dataset has been sourced from Weeplaces, a website that provides visual representations of users’ check-in activities on location-based social networks (LBSNs). The platform has been integrated with other location-based social networking services, such as Facebook Places, Foursquare, and Gowalla, through APIs. This dataset contains 7,658,368 check-ins from 15,799 users, as well as their friends present on Weeplaces.

**GeoLife [114]:** It is a GPS trajectory dataset that was collected from 182 users over a span of five years (from April 2007 to August 2012). This dataset comprises 18,670 trajectories, each represented by a sequence of time-stamped points containing latitude, longitude, and altitude information. These trajectories capture a diverse range of users’ outdoor movements, including routine activities (e.g., going home), as well as leisure activities (e.g., shopping, hiking, and cycling). Recently, 69 out of the 182 users have labeled their trajectories with transportation modes, such as driving, taking a bus, riding a bike, and walking. The labels for transportation mode are stored in a separate file for each user’s folder.

**Priva’Mov [8]:** It comprises data collected from multifarious sensors, including WIFI, GPS, and Cellular, and contains around 286.7 million records, where each record is a timestamped trajectory point containing latitude, longitude, userID. It was collected from 100 users over a period of 15 months and primarily focuses on urban mobility around Lyon city of France.

Finally, **DenseGPS [26]:** It is a dataset that includes private data from a major mobile application provider in China with 5000 users with one-month dense location records. This dataset is not available for the research community to use.

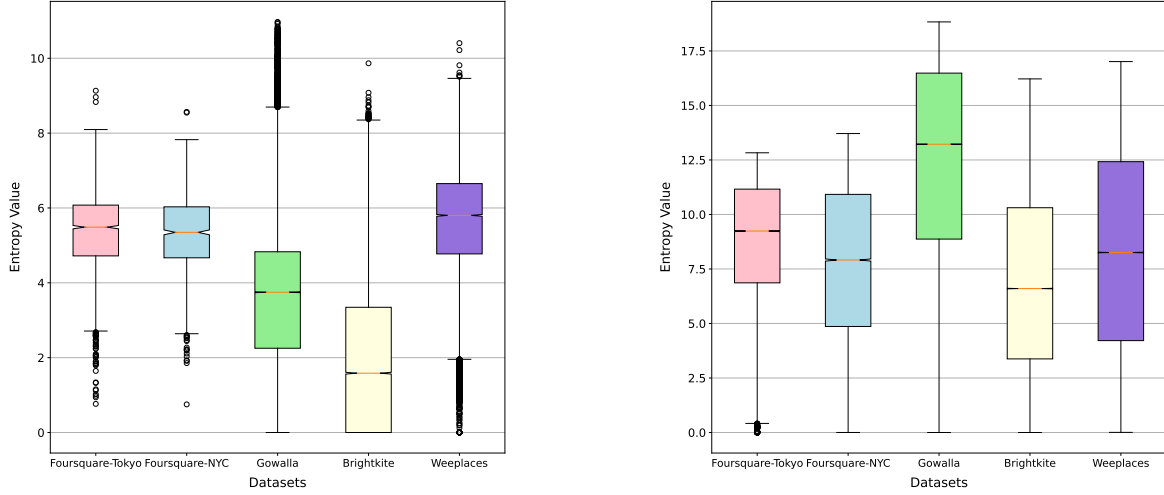
(a) Horizontal entropy  $H_u$  across different check-in datasets.(b) Vertical entropy  $H_l$  across different check-in datasets.

Figure 2: Entropy Experiments.

Table 4: Global Statistics across check-in datasets.

	$N_u$	$N_l$	$N_c$	$\tilde{N}_u$	$\tilde{N}_l$
Foursquare-Tokyo	2293	61858	573703	3.43	92.44
Foursquare-NYC	1083	38333	227428	2.37	84.05
Gowalla	107092	1280969	6442892	3.11	37.18
Brightkite	50686	772780	4491080	1.39	21.16
Weeplaces	15799	971308	7658368	2.72	166.64

#### 4.1.3 Data sparsity and heterogeneity in trajectory prediction tasks

Mobility literature defines the highest potential accuracy of predictability of any individual, termed as “maximum predictability” ( $\Pi_{max}$ ) [67]. Maximum predictability is defined by the entropy of information of a person’s trajectory (frequency, sequence of location visits, etc.). We adopt this measure to compute the non-iid property of the mobility traces. We use Shannon’s Entropy  $H(x)$  to get a sense of both the sparsity and non-iidness of several check-in datasets. In this process, we adjust the metric proposed by [84] to extend the individual entropy of users (i.e., horizontal) with an individual entropy of point-of-interests (i.e., vertical). We argue that having these two dimensions for the entropy is necessary to draw conclusions w.r.t to sparsity and heterogeneity. To quantify this relationship, we first measure the horizontal entropy in the following manner:

$$H_u(x) = - \sum_{i=1}^n P_u(x_i) \log_2[P_u(x_i)] \quad (2)$$

Where  $n$  is the number of POIs and is the size of the probability vector.  $P_u(x_i)$  is the probability of an individual user  $u$  visiting location  $x_i$  considering exclusively spatial pattern.

We compute the vertical entropy as follows:

$$H_l(x) = - \sum_{u \in U} P_u(l) \log_2[P_u(l)] \quad (3)$$

Where  $U$  is the set of all users.  $P(x)$  is the probability of user  $u$  visiting location  $l$ .

In Figure 2, a comparison of entropy levels is shown for different check-in datasets. Meanwhile, Table 4 provides a summary of more conventional statistics about these datasets. More specifically,  $N_u$  denotes the number of users,  $N_l$  denotes the number of POIs,  $N_c$  denotes the number of check-ins,  $\bar{N}_u$  denotes the average number of users that visited each point of interest and  $\bar{N}_l$  denotes the average number of POIs visited by each user. Figure 2 seems to indicate that Brightkite has the least entropy, as expected. In fact, Subfigure 2a even shows that a significant proportion of Brightkite users have zero entropy, indicating that some users have only one check-in. This correlates with the high sparsity levels of the dataset (refer to Table 4). This downward trend is also evident when viewed through the lens of vertical entropy, although it may be less pronounced. Considering these observations, we see this dataset as an appropriate option to tackle the sparsity problem in distributed learning on mobility data. Conversely, Weeplaces exhibits two important trends: Firstly, there is a considerably higher level of horizontal entropy compared to what is seen on Brightkite, without a corresponding increase in vertical entropy. This suggests that in general users are more active and less predictable, but have not explored a much wider spectrum of points-of-interest. Secondly, Figure 2a exhibits a significant number of user outliers, particularly those with low entropy, indicating the presence of a short tail. These observations, correlated with the results of the table 4, which shows a high  $N_l$  and a quite low  $N_u$ , indicate low heterogeneity levels within this dataset. Oppositely, Gowalla exhibits more horizontal entropy, which indicates that users are more active globally while also having a higher vertical entropy, indicating that users have substantially less in common than in WeePlaces. These two observations suggest a more heterogeneous, yet less sparse dataset. This makes Gowalla a perfect candidate for works tackling heterogeneity. However, the presence of a significant proportion of highly mobile outlier users should also be noted. Finally, Foursquare datasets show good entropy levels on both axes, making them an excellent choice for sanity tests.

#### 4.1.4 Federated Trajectory Predictive Approaches

The challenges of trajectory predictive approaches in decentralized learning are different. Firstly, the unique properties of people’s mobility [20] lead to a non-iid distribution of the data amongst clients. Second and as a result of the first challenge, creating a global model for predicting the next location of users that works equally well for all the users becomes an extremely challenging task. That is one must decide to what extent should clients adopt the global model and when to opt-in for a purely personalized model. In this section we review the existing works in this domain, review how they account for the mentioned challenge, and compare their performances in Table 5 against centralized predictive approaches namely ST-RNN [60], MCARNN [59], DeepMove [26], and VANext [33].

Table 5: Baselines for next location prediction models

	Foursquare NY		Foursquare Tokyo	
	Acc@1 (ACC@5)	APR	Acc@1 (ACC@5)	APR
Centralized Baselines				
ST-RNN [60]	0.2633	0.9431	0.2567	0.9536
MCARNN [59]	0.3167	0.9595	0.2770	0.9532
DeepMOVE [26]	0.3010	0.9221	0.2668	0.9257
VaNext [33]	0.3627	0.9792	0.3436	0.9735
Federated Approaches				
STSAN [57]	0.4297	0.9902	0.3906	0.9847
STLPF [93]	0.4067	0.9893	0.3887	0.9856
PMF [27]	NA	NA	0.2130	NA
Ezequiel [24]	0.1133	NA	NA	NA

**Fan et al.** [25] proposed a decentralized attention-based personalized human mobility prediction. They apply a *few-shot* learning human mobility predictor that makes personalized predictions based on a few records for each user using an attention-based model. Furthermore, they take advantage of pre-training strategies where the predictor is trained on another smaller mobility dataset to accelerate the FL training on devices. However, even with the pre-training and attention-based strategy, the model requires over 1000 rounds of data communication rounds and is not sufficiently robust for the irregular nature of the human movement.

**STSAN [56]** Li et al. in 2020 proposed a cross-silo personalized next point prediction model named STSAN (Spatial-Temporal Self-Attention Network) which integrates *AMF* (Adaptive Model Fusion Federated Learning) for offering a mixture of a local and global model. The spatial attention layer allows for capturing the user’s preference for geographic location, and temporal attention captures the user’s temporal activity preference. To overcome the non-iid challenge, the AMF function enables the algorithm to learn specific personalization at each aggregation step on the FL server. The approach is evaluated on Foursquare, Twitter, and Yelp datasets. Table 3 reports its performance on the Foursquare



dataset against centralized prediction approaches and shows the superior performance of 99% APR and 6% increase in Acc1 compared to VANet [33].

**PMF [27]** Feng et al. proposed PMF, a privacy-preserving mobility prediction framework that uses FL to train general mobility models in a privacy-aware manner. In PMF, every participating device trains locally a representation of the global (centralized) model by using only the locally available dataset at each device. The framework also accounts for attack cases in the mobility prediction task and uses a group optimization algorithm on mobile devices to tackle these attacks. In the group optimization procedure, the whole model is divided into the risky group trained with protected data and the secure group trained with normal data. Furthermore, an efficient aggregation strategy based on robust convergence and an effective polling schema for fair client selection in the centralized server. The results of this model on DenseGPS and Twitter dataset show similar top-1 performance to DeepMove [26] but on Foursquare Tokyo it performs poorer than centralized baselines and other FL approaches.

**STLPP [93]** Wang et al. proposed a spatial-temporal location prediction framework (STLPP) where the next point prediction algorithm is trained based on a self-attention layer that enables information to be learned between long sequences in both local and global models. Furthermore, as part of the framework, the authors propose an approach that enables clients to cooperatively train their models in the absence of a global model. Their evaluation shows marginal improvement in the accuracy of next point prediction (APR) on the Foursquare dataset when compared to the centralized approaches, and their approach performs similarly to STSAN [56] (See Table 5).

**Ezequiel et al. [24]** develop two implementations of GRU-Spatial and Flashback on FL for predicting the next location in human mobility. To the best of our knowledge, they are currently the only work that has worked on baselining these different approaches in an FL framework, namely Flower [10] and measuring the computational complexity of the model. They evaluate their model on Foursquare NY and Gowalla datasets.

## 4.2 Flow Prediction Approaches

Accurate Traffic Flow Prediction is an extremely useful to mitigate traffic congestion and as a result, air pollution, travel time, and driving experience. Approaches in predicting the traffic patterns range from classical approaches to time-series analysis (such as ARIMA) to more advanced models such as those based on Recurrent Neural Networks and Graph Neural Networks. For a comprehensive survey of deep learning models for traffic predictions in centralized settings refer to [44]. Given that this type of data in real world could be collected by various entities and organizations, Cross Silo Federated Learning is a promising paradigm for ensuring that the records are not shared outside of each organization. Flow prediction approaches require slightly different settings in FL than trajectory prediction. Unlike individual predictive approaches where each client is assumed to correspond to an individual with their mobility traces as the non-iid data, in flow predictive approaches, the clients are often considered to be entities or organizations that are maintaining their flow data private. When different organizations use data collected by sensors to predict traffic flow, the collected data often cannot not be shared due to regulatory reasons. This *cross-silo* configuration of FL reduces some of non-iid problems but imposes challenges regarding vertical FL.

Current works in Federated Traffic Flow Prediction can be grouped into two groups of grid-based (such as recurrent neural networks, etc.) and graph-based approaches. We first review the metrics and datasets used for these tasks and then review the current literature.

### 4.2.1 Metrics

The forecasting performance for traffic flow predictions is commonly measured as a mean absolute error (MAE), mean square error (MSE), root MSE (RMSE), and mean absolute percentage error (MAPE).

### 4.2.2 Datasets

For flow predictive approaches the following datasets are widely used to benchmark the comparison of various algorithms.

- **Taxi Datasets:** The following datasets contain taxi in-out flow data collected via GPS, which include pick-up time, drop-off time, and trip distance.
  - **TaxiBJ [111]** contains data collected in Beijing from four time intervals: 2013/7/1 to 2013/10/30, 2014/3/1 to 2014/6/30, 2015/3/1 to 2015/6/30, and 2015/11/1 to 2016/4/10. The data was collected at 30-minute

intervals and include trajectories of over 34,000 taxis. It additionally contains meteorology data such as weather conditions, temperature, and wind speed.

- **TaxiNYC [1]** contains data collected in New York City, which was collected between 2016/4/1 and 2016/6/30 and contains over 35 million records. A more extensive version of this dataset, collected from 2009 to 2022, is also available.
- **TaxiPorto [75]** comprises a full year (from 2013/7/1 to 2014/6/30) of trajectories for all the 442 taxis running in the city of Porto, Portugal. It also contains information on the type of taxi call: central-based, stand-based, and demanded on a random street.
- **T-Drive [113]** contains GPS traces collected in Beijing, China. The dataset was collected over a period of three years from 2008 to 2011, and it consists of over 10,000 taxi drivers' GPS trajectories. The dataset contains a total of 1.07 billion GPS points, covering approximately 150 million kilometers. That being said, the sample released by Microsoft is over a span of one week only, containing around 15 million GPS points and covering a total distance of trajectories that reaches 9 million kilometers.
- **METR-LA [43]:** is Los Angeles traffic collected using 207 sensors mounted around highways, and 1515 edges from 2012/3/1 to 2012/6/30.
- **PeMS** is a traffic flow dataset collected from California Transportation Agencies Performance Measurement System (PeMS).
  - **PeMS-BAY [58]:** It contains 325 nodes (traffic sensors) and 2369 edges in the Bay Area from 2017/1/1 to 2017/5/31.
  - **PeMSD7M:** It is a sub-sample of PeMS published as part of [100], also collected from PeMS. It covers 228 traffic sensors with a 5-minute sampling rate corresponding to 2012/5/1 to 2012/6/30.
- **NY-Bike [2]:** Spanning a period of ten years, from June 2013 to January 2023, this dataset includes comprehensive information about daily bike orders by people in New York City and is regularly updated. More specifically, it contains information about bike trips, such as duration, starting and ending point, and location, as well as details about bikers, including user type, gender, and year of birth.
- **Yelp [65]:** It is a collection of businesses, reviews, and user data extracted from the Yelp platform. This dataset is regularly updated and contains almost 7 million reviews of over 150,000 businesses located in 11 metropolitan areas across the United States and Canada. The data includes information on individual users such as their name, the number and nature of their reviews, and their list of friends. Additionally, the dataset also includes check-ins, which provide information about the frequency and duration of customer visits to businesses.

#### 4.2.3 Grid based Approaches

In grid-based approaches, the input data into the model is a sequence of locations over time. These approaches mainly focus on deep neural models such as RNN, GRU and LSTM to capture past historical traffic information as a predictor for future instances.

**FedGRU [64]** Liu et al. proposed a Gated Recurrent Unit (GRU) based federated learning algorithm for highway flow prediction. They also proposed a novel aggregation function that provides improvement over FedAvg. They evaluate their approach using real-world data collected from the Caltrans Performance Measurement System (PeMS) [15], which includes 39K individual sensors in real-time monitoring the freeway system across all major metropolitan areas of the State of California. They showed a similar performance to the centralized baseline of GRU model and several others including

**FedTSE [102]** In FedTSE, authors proposed a framework for Travel State Estimation (TSE). They design a long short-term memory (LSTM) model as the local training model for joint prediction of vehicular speed and traffic flow. A unique characteristic of FedTSE is that it relies on the deep reinforcement learning (DRL)-based algorithm to adjust model parameter uploading/downloading decisions such that it improves the estimation accuracy of local models and balances the tradeoff between computation and communication cost. They evaluate their approach on the England Freeway Dataset which includes flow and speed for the entire year of 2014. They also consider three different aggregation strategies corresponding to *FedTSE-Syn* with identical numbers for training epochs, *FedTSE-Asyn* with a different number of training epochs for each RSU, and *Weighted FedTSE-Asyn* that considers the weight of contribution in training (measured per epoch).

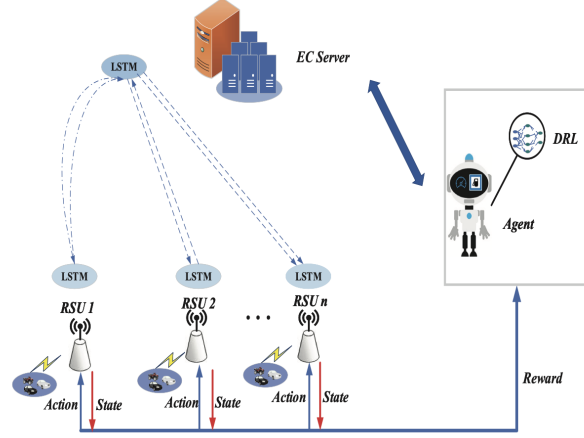


Figure 3: Figure from FedTSE [102] showing the interactions between Edge Computing (EC) Server and Road Side Units (RSU) acting as a cross-silo unit. The LSTM model weights are aggregated using FedAvg, and a Deep Reinforcement Learning (DRL) Agent to maximize reward.

Table 6: Number of parameters and performance of baseline centralized models on PEMS7M [100] dataset.

Model	Year	Number of Parameters	Performance (MAPE%)
STGCN [100]	2017	330K	5.02%
MTGNN [95]	2020	433K	5.02%
DCRNN [58]	2017	610K	5.33%

**MVFF [23]** proposes a vertical federated learning framework for mobility data forecasting for cross-silo applications where each organization holds a partial subset of data. Using a local learning model, each organization extracts the embedded spatio-temporal correlation between its locations. To account for global learning, a global model synchronizes with the local models to incorporate the correlation between all the organizations' locations.

**Fed-NTP [86]** proposed an LSTM model implemented in FL to predict network traffic based on the most influential features of network traffic flow in the Vehicular Ad-Hoc Network (VANET). Even though this work is *not* aiming in predicting vehicle traffic and focuses on network flow, it has some relevance with the existing models such as FedGRU [64]. Fed-NTP shows to outperform FedGRU on the same V2V dataset. Other similar works that have focused on network traffic prediction such as FedDA [104] exist in the literature. However, as they solely focus on network traffic problems and are not intended for mobility applications, we do not review them in the survey. We encourage the reader to refer to [45] for a full survey of network traffic prediction techniques in FL.

#### 4.2.4 GNN Based Approaches

State-of-the-art multi-layer GNNs have been used to address the spatial-temporal nature of traffic prediction in centralized settings. In FL setting a challenge with GNN-based approaches is regarding vertical FL and in scenarios where each silo has a partial (overlapping) view of the graph. Many of the works in this domain are motivated by intelligent transportation systems often referred to as Road Side Units (RSU) where each unit has its own distribution of traffic patterns across the same city (Figure 3). One of the challenges with applying GNN based model for traffic forecasting is the large number of parameters that these models have and in the context of FL, the aggregation becomes a bottleneck for such models. For instance, while a simple Auto-Regressive Integrated Moving Average (ARIMA) model relies on a low number of parameters (order of 100s), the more complex models have an enormous number of parameters. Table 6 shows the magnitude of parameters for baseline traffic prediction models over the PEMS7M dataset [100]. The following works described below aim to tackle this problem by proposing alternative aggregation functions.

**FedSTN [101]** The FedSTN approach as formalized by Yuan et. al is a newly proposed solution to solving the traffic flow prediction (TFP) problem. To accomplish this task, authors proposed a Graph-based Representation Learning for Cross-Silo Federated Learning using three main modules: a Recurrent Long-term capture Network (RLCN) module, an Attentive Mechanism Federated Network (AMFN) Module, and a Semantic Capture Network module (SCN). The

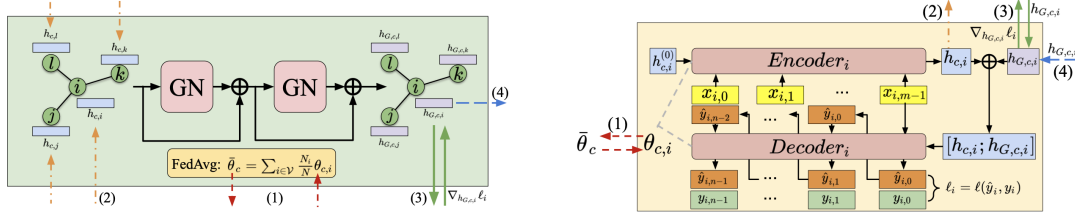


Figure 4: Figure from CNGNN [76] presents (a) the server-side graph neural network with a systematic overview of training steps: (1) Federated learning of on-node models. (2) Temporal encoding update. (3) Split Learning of GN. (b) Client  $i$  Auto-encoder architecture.

RLCN module is responsible for learning long-term traffic behaviors as geometric time series data of fixed long-term interval  $p$ . The data as input into this module is comprised of inflow-outflow values for certain grid spaces, as initially computed for the data.

The AFMN module is responsible for learning short-term spatial-temporal features in a privacy-preserving manner. This module includes long-term contextual data such as meteorology and federated graph attention (FedGAT). Lastly, there is the SCN module, which takes into account Point of Interest Feature Components (POI) and non-euclidean connection relationships. Points of interest and their interactions have significant effects on TFP but are not incorporated into the raw time series prediction data. Furthermore, transportation networks also have methods of connection outside adjacent-grid connections, such as trains, highways, etc. These flows also have an important effect on TFP that is not incorporated elsewhere, so this module is to address this issue. The output of all these modules is then connected via an FC layer followed by a Tanh activation function for the final output.

**CNFGNN [76]** Meng et al. proposed a new architecture named Cross Node Federated Graph Neural Network (CNFGNN) to predict the flow. CNFGNN works by decomposing the problem into two stages: first, it uses an encoder-decoder network to extract temporal features locally, and then a GNN to capture spatial relations across devices. On each training step, the server processes a temporal encoding update, a partial gradient update, and an on-node graph embedding update. Each iteration updates the client side weights and then ships the model, hidden layer, and gradients back to the server.

One large issue of the proposed approach is the communication overhead in the training stage, with split learning requiring the global model to fetch all hidden states from each node, and ship gradients of node embeddings to each node. Then, it must receive gradients of node embedding and send gradients of hidden states in the back-propagation step. To mitigate this, they propose an alternative training approach in which the temporal encoder-decoder and the node embeddings are trained separately. First, the node embeddings are fixed optimization is performed on the encoder-decoder. Then, after a fixed interval, the global model is updated fixing the node-level models. This drastically reduces communication overhead. The FL local models and the GNN model with only a local objective function. They perform alternating optimization to update clients' model weights with GNN model weights fixed and then update GNN model weights with the FL local model weights fixed, over multiple rounds.

**CTFL [107]** proposes a Clustering-based hierarchical and Two-step- optimized FL (CTFL), to overcome the large number of parameters that are needed for aggregation in the GNN-based models such as STGCN [100], DCRNN [58] and MTGNN [95]. CTFL employs a divide-and-conquer strategy, clustering clients based on the closeness of their local model parameters. It also accounts for optimization by applying a two-step strategy where the central server uploads only one representative local model update from each cluster, thus reducing the communication overhead associated with model update transmission in the FL.

Finally, it is worth noting that other works similar to flow prediction exists which are focused on identifying travel modality inference (TMI). For instance [108] proposes MTSSFL which trains a deep neural network ensemble under a novel semisupervised FL framework. It achieves a highly accurate score for a crowdsourced TMI without depending on the availability of massive labeled data.

### 4.3 Clustering Based Approaches

Most existing works in clustering in federated learning are focused on methods to identify and self-organize devices into communities are so to conduct model sharing within those communities. In [13], authors introduce and evaluate a hierarchical clustering for vision models, where the local model is a Convolutional Neural Network (CNN) that is

Table 7: RMSE metric for reviewed Federated Learning models and centralized baselines over various benchmark datasets.

	<i>NY Bike</i>	<i>Taxi-NY</i>	<i>Yelp</i>	<i>Taxi BJ</i>	<i>PeMS</i>	<i>PEMS-BAY (5mn)</i>	<i>METR-LA (5mn)</i>
Centralized Approaches							
ARIMA	10.07	12.43	-	22.78	-	5.59	7.66
ST-RESNET [111]	6.33	9.67	-	16.69	-	-	-
GRU	-	-	-	-	9.97	4.12	11.78
GRU+NN	-	-	-	-	-	3.81	11.47
Federated Approaches							
FedSTN [101]	-	9.32	-	24.22	-	-	-
FedGRU [64]	17.14	-	1.22	-	11.04	-	-
Federated-LSTM [88]	17.24	-	1.24	-	-	-	-
MVFF (GRU+GNN) [23]	6.79	-	0.96	-	-	-	-
CNFGNN [76]	-	-	-	-	-	3.82	11.48

trained under *supervised* learning. The extensive evaluation presents the improvement that hierarchical clustering can bring to federated learning under a non-iid setting where each client holds partitioned data. In [50], the authors propose the dynamic GAN-based clustering in FL to improve the time series forecasting for cases such as cell tower handover prediction. Their proposed approach accounts for the adaptive clusters and non-iid data. IFCA proposed by [36] starts by randomly initializing  $k$  models, one per cluster. Each client assigns itself to a cluster at the start of each round of training by evaluating all  $k$  models on its local data and choosing the model with the lowest loss to train for  $m$  epochs. At the end of each round, the server performs federated averaging within each cluster of clients separately.

Although this theoretical line of work is receiving a great deal of attention from the Federated Learning research community we have seen almost no adaptation, except one, to the spatial-temporal models in FL. F-DEC [70] proposed a deep embedded clustering for urban community detection in federated learning. They expanded on the centralized model proposed by [31] and trained an autoencoder based on heatmap images of mobility trajectories transformed using the frequency of visits (where brighter pixels show more frequently visited areas). They then used a KL divergence loss for clustering similar heatmaps together. Furthermore, this work is the only early evidence that we found that measures the computational complexity of such algorithms when it is deployed on ordinary smartphones.

## 4.4 Other Approaches

### 4.4.1 Location-Based Recommendation Models

The primary challenge in location-based recommendation systems is to recommend the top-K relevant points of interest (POIs) for a given user. One approach to address this challenge, presented in [5], extends the Bayesian pairwise ranking (BPR) algorithm to the federated setting. This approach provides a flexible framework for factorization models, enabling clients to share subsets of their model parameters while maintaining model convergence. Another work, described in [38], focuses on optimizing the aggregation process in federated learning. The authors pre-train reliable deep models consisting of a graph convolutional network (GCN) and a gated recurrent unit (GRU) connected to a multilayer perceptron (MLP), to estimate the system parameter space, which is then optimized at the server level using a reinforcement learning algorithm. The authors view the parameter sets from clients as an agent that searches for the optimum, with the action representing aggregation strategies and the reward indicating the utility acquired by the selected update operations. Their solution outperforms traditional centralized deep models due to the added optimization step based on reinforcement learning.

Various system architectures have been proposed to improve the efficiency of federated POI recommendations. For instance, [81] introduces a framework that leverages social relationships between users to create more personalized models. The authors first train a global model using federated learning and then use a trusted third party to find similar users based on encrypted embeddings, which will be used for the personalized aggregation step. In [6], personalization of POI models is emphasized through the aggregation step, while a gossip communication protocol is used to eliminate the central federated learning server. Nodes gossip about their models with their neighbors and aggregate them after evaluating their contribution. The authors also introduce a peer-sampling protocol that acts as a clustering over time, ensuring each node has similar users in its neighborhood. The experiments demonstrate that fully decentralized federated learning can be competitive with centralized solutions while offering scalability and personalization.

Another use case that has been explored in the context of location-based recommendation systems is the driver recommendation use case, as tackled by [91]. In this work, cab companies use federated learning to strengthen roadside

units (RSUs) with the computational capability to develop an intelligent recommender system that recommends the appropriate driver for a subsequent trip. To this end, they consider both the driver’s stress and past behavioral patterns.

**PREFER [37]** Guo et al. proposed a two-set recommendation model training. First, for privacy purposes, they propose to train the user-dependent model parameters strictly locally. Subsequently, user share and aggregate less sensitive parameters (i.e., user-independent) in a multiple-edge server architecture, instead of remote cloud servers, with an aim to improve real-time response capability and reduce transmission distance. They validate their approach both analytically and empirically on two standard POI recommendation models, namely, Distance2Pre [18] and PRME-G [28], and two check-in datasets, Foursquare [99] and Gowalla [17], and show the competitiveness of their approach with centralized and federated competitors.

#### 4.4.2 Privacy in Spatial-Temporal FL Models

Federated learning was initially designed to protect user privacy by sharing model parameters instead of data. However, research has shown that sharing these parameters can still reveal sensitive information, especially in models that use embeddings/latent features to capture user or point-of-interest semantics. To address this issue, researchers have proposed mainly three approaches: i) "a share less" policy, ii) injecting noise using techniques like Differential Privacy (DP), and iii) using cryptographic methods like Secure Multi-Party Computation (SMPC). Various studies have proposed solutions using each of these approaches, but each approach has its limitations. For instance, [37, 5] proposed sharing only user-independent embeddings to be learned in a federated manner while training user embeddings locally. [27] first proposed a practical attack, demonstrating that user check-ins can be easily inferred by a curious FL server based on POIs embeddings. Later on, they proposed to alleviate this attack by training these embeddings on noisy data generated using DP. They show that if the rest of the network (i.e., non-sensitive layers) is frozen during this noisy training, and is pre-trained on real data, then the performance remains reasonable. Nevertheless, they did not quantify the impact of their attack nor the degree of protection provided by their solution. Another line of work, [81], opts for the third approach and uses SMPC to hide the individual contributions of the users from a curious FL server. Unfortunately, this approach opens the door to malicious users, whose goal would be to corrupt the learning, and who would be difficult to detect due to SMPC.

A more privacy-oriented solution was proposed by [16]. They aggregated less sensitive embeddings using SMPC and categorized sensitive embeddings into two parts: those related to POIs and those related to users. They used Local DP to add noise at the user level to the POI-related embeddings before sharing them with the server. They also proposed to share the user-dependent embeddings in a peer-to-peer fashion using secret sharing. To reduce overhead and the attack surface, they considered geographic information to build the peer neighborhood. Thus, a user shares its sensitive embeddings only with geographically close neighbors. This solution has competitive prediction performances with non-private solutions and undeniably provides more privacy guarantees. However, the impact of the assumption that sensitive embeddings can be safely shared with nearby users is still unclear.

Another type of attack that has received significant attention in recent mobility research is re-identification attacks [68, 32]. The fundamental concept behind such attacks is that a malicious service provider could exploit background knowledge to associate anonymized user traces with their respective owners, thereby compromising users’ anonymity. To address this issue, Khalfoun et al. proposed a federated protocol for assessing the risk of re-identification on mobility data. This protocol involves training a re-identification model in a federated manner using users’ traces and subsequently utilizing this model to select the optimal combination and hyperparameters of location privacy protection mechanisms (LPPMs) that can protect a user’s privacy whenever they transmit their data to an untrusted Mobile Crowd Sensing Server (MCS). Notably, this solution appears to be the only privacy risk assessment mechanism for mobility data that does not necessitate the presence of a trusted curator, to the best of our knowledge. For a full survey of privacy and security techniques in Federated Learning see [78].

## 5 Discussion and open research challenges

Based on the review of the above papers, we see the following opportunities and roadmaps for the research community to explore.

**Semantic Location Embedding and Context-Awareness Modelling.** One of the biggest opportunities that we see in continuing research on location and point trajectory predicting, is in regards to integrating more semantic and contextual information about types of places instead of focusing primarily on coordinates. For example, this contextual

information can include information on whether a point in trajectory represents someone’s workplace, their frequently visited locations, or a potential point of interest in a new town. This contextual information can then be learned over time on users’ devices, maintaining users’ privacy while allowing for better-personalized models.

**Realistic Cross-silo Spatial Temporal Datasets for Benchmarking.** Existing approaches that we reviewed are mostly evaluated with ST data partitioned artificially. Nevertheless, the long-term development of this field still requires realistic and large-scale federated datasets to be made available to support experimental evaluations under settings close to practical applications. For instance, in the reviewed literature, there is a lack of research on how the geographic distribution of silos can lead to a geographically distinct flow of information. Establishing policy-based scenarios in order to guide how the data should be partitioned across silos to reflect real-world data ownership challenges is a direction that we believe the research community will be working closely with other stakeholders in the future.

**Trust, Fairness, and Accountability.** In addition to trust and accountability, another challenge that we see spatial temporal mobility models will face under a federated setting is fairness. That is to what extent the models that are trained on location traces are equitable? Especially models that are designed for the purpose of mobility flow prediction and allocation of transport options. For instance, mobility demand prediction algorithms have been shown to offer higher service quality to neighborhoods with more white people [14]. Indeed, as recent evidence from the broader machine learning domain has shown, the systematic discrimination in making decisions against different groups has been shifted from people to autonomous algorithms [48, 41]. In many applications, discrimination may be defined by different protected attributes, such as race, gender, ethnicity, and religion, that directly prevent favorable outcomes for a minority group in societal resource allocation, education equality, employment opportunity, etc [85]. Measuring fairness of mobility models is a dimension that has been vastly overlooked in applications of spatial-temporal mobility models, with exception of a few works [97, 98, 34] and with little consensus on how fairness should be defined and measured for spatial-temporal applications. One way of controlling for fairness of mobility models under the FL setting is to create auditing systems that can infer information about the training without having access to location data of the devices or the global model at the FL server [71, 69]. We believe future work will focus on dynamic middle-wares that can leverage solutions such as clustered FL to offer interpretability of the underlying models [112, 36, 55] are crucial to transition exiting solutions from research to practice.

**Transition to Real-world Deployment Through Dedicated Frameworks.** Finally, we believe that just as crowd-sensing research was successful a decade ago through frameworks such as AWARE [29], which reduced the burden of app development for data collection, frameworks specifically designed for federated mobility models will facilitate the transition from limited research to in-wild deployments. To achieve this transition, it is crucial to i) provide benchmarks for mobility applications and ii) develop mobility-centered federated learning frameworks, as was the case for graph applications [40] and IoT applications [109]. This will allow the research community to effectively evaluate and compare the performance of federated learning models on mobility data. We foresee that the transition between the current research efforts to real deployment will happen over stages where first multi-disciplinary research will focus on understanding users’ attitudes towards using their location data for training models. After all, similar research on crowd-sensing applications has shown that location information is a top concern of users’ involvement in these applications [3]. To the best of our knowledge, currently, there are no existing works in understanding users’ privacy concerns when their data is not shared externally but is still used in creating predictive models. As a next step, we envision a slow transition between fully centralized models to decentralized models. Rather than training models focused on end-user prediction tasks, generative models that allow synthetic trace generation by learning from user mobility traces will be used to update and de-bias centralized datasets.

## 6 Conclusion

In this paper, we surveyed the federated learning models in the domain of mobility prediction as well as the widely used datasets for spatial temporal models. We described the challenges that exists in applying common deep learning techniques in the decentralized settings and discussed the opportunities for the research community to consider for future work. Our work indicates rapid growth and interest in this space, with promising future directions both in terms of theoretical frameworks and models, and practical applications and usecases. We hope both academics and practitioners find this survey useful for choosing the appropriate approach for their individual scenarios.

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