

Federated Learning for Traffic Flow Prediction with Synthetic Data Augmentation

Fermin Orozco
University of Exeter
Exeter, UK
F.Orozco@exeter.ac.uk

Pedro Porto Buarque de Gusmão
University of Surrey
Surrey, UK
P.Gusmao@surrey.ac.uk

Hongkai Wen
University of Warwick
Warwick, UK
Hongkai.Wen@warwick.ac.uk

Johan Wahlström
University of Exeter
Exeter, UK
J.Wahlstrom@exeter.ac.uk

Man Luo
University of Exeter
Exeter, UK
M.Luo@exeter.ac.uk

ABSTRACT

Deep-learning based traffic prediction models require vast amounts of data to learn embedded spatial and temporal dependencies. The inherent privacy and commercial sensitivity of such data has encouraged a shift towards decentralised data-driven methods, such as Federated Learning (FL). Under a traditional Machine Learning paradigm, traffic flow prediction models can capture spatial and temporal relationships within centralised data. In reality, traffic data is likely distributed across separate data silos owned by multiple stakeholders. In this work, a cross-silo FL setting is motivated to facilitate stakeholder collaboration for optimal traffic flow prediction applications. This work introduces an FL framework, referred to as FedTPS, to generate synthetic data to augment each client's local dataset by training a diffusion-based trajectory generation model through FL. The proposed framework is evaluated on a large-scale real world ride-sharing dataset using various FL methods and Traffic Flow Prediction models, including a novel prediction model we introduce, which leverages Temporal and Graph Attention mechanisms to learn the Spatio-Temporal dependencies embedded within regional traffic flow data. Experimental results show that FedTPS outperforms multiple other FL baselines with respect to global model performance.

CCS CONCEPTS

- **Information systems** → *Data streaming; Spatial-temporal systems.*

KEYWORDS

Federated Learning, Traffic Flow Prediction, Synthetic Data Generation

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1 INTRODUCTION

Traffic prediction is an integral aspect of modern Intelligent Transport Systems (ITSs) with innate implications on the safety and productivity of inhabitants; it facilitates the optimisation of traffic management systems, and the dissemination of pertinent information for commuters. This in turn has profound implications on social, environmental, and economic factors. Deep-learning based models have demonstrated exceptional accuracy in their ability to learn spatio-temporal relationships from traffic data and predict future traffic states [5, 12, 22, 25, 28].

The majority of previous works towards spatio-temporal prediction aim to train a model from a centralised perspective where the collective data is available on a single device. Centralising city-wide ITS data in real-world settings is a difficult task; ITSs represent a partnership between transport stakeholders such as local government authorities, ride-sharing companies, and micro-mobility organisations. Sharing journey data has implications on user privacy (GDPR), as well as commercial implications. Therefore, developing frameworks for applicable decentralised data-driven methods is of paramount importance within the ITS sector to enable stakeholder collaboration for the development of traffic prediction models. Federated Learning (FL) [15] provides a solution for training optimal traffic prediction models collaboratively by decentralising the training process of a traffic prediction model. Although recent works in FL demonstrate its capacity to train a global model which learns spatio-temporal dependencies across distributed data, these works do not directly address the issue of data heterogeneity [9], or instead focus on the client selection strategy or parameter aggregation function [14, 16, 18, 29, 31–33].

To tackle the issue of data heterogeneity and imbalanced data partitions across clients, data sharing mechanisms for FL applications in highly heterogeneous settings were explored in [34] wherein a small partition of real data is distributed to clients to augment their local datasets in a cross-device setting. Sharing real data with

clients introduces a compromise between accuracy and privacy of data. Recent works have looked at training generative models within an FL framework for image classification tasks, to augment local client datasets without sharing data that would compromise data privacy [2, 13, 23]. For applications beyond image classification where data contains spatial and temporal dependencies and heterogeneity is principally due to quantity and feature-based skews, limited work exists on the benefits of augmenting FL client datasets using synthetic data.

Emerging research in the field of generative models for trajectory generation have demonstrated the exceptional capacity for diffusion-based models to generate synthetic data that captures spatio-temporal cross-dependencies of traffic data while maintaining the privacy of real data [35]. Leveraging recent works in FL as well as in the field of generative models for spatio-temporal data generation, we present a framework for Federated Traffic Prediction with Synthetic data augmentation (FedTPS). This framework first trains a diffusion-based model for traffic data generation through FL. This model is used to generate a synthetic dataset developed from the learned global data distribution. A traffic flow prediction model is then trained through FL, wherein each client's local dataset has been augmented with the generated synthetic dataset.

In real-world implementations of traffic flow prediction models with data silos, the data owned by separate clients may contain inherent skews, contributing to data heterogeneity across client datasets. The proposed FedTPS framework directly inhibits the negative effects of data heterogeneity when training a global through FL, while also increasing the amount of training data in each client's local dataset. To the best of our knowledge, this work is the first to explore the benefits of exploiting synthetic data for FL in traffic prediction applications.

The main contributions of our work are as follows:

- We assess the performance of several traffic flow prediction models trained under an FL setting. We also develop a novel traffic prediction model, the Graph Attention and Temporal Attention Unit (GATAU), which builds upon the existing spatio-temporal model, the Temporal Attention Unit (TAU) [22], to also leverage Graph Attention mechanisms.
- We propose a novel FL framework, FedTPS, which trains a federated generative model to produce a synthetic dataset. This synthetic data is used to augment client datasets for traffic flow prediction applications, and improve the predictive performance of the FL model.
- Our experiments are validated on a real-world dataset to analyse the impact of data augmentation on traffic flow prediction model performance, and demonstrate improved results relative to multiple other FL frameworks designed to address data heterogeneity across data-silos.

2 RELATED WORKS

2.1 Federated Learning

The distributed nature of the data in a FL setting incurs a detrimental effect on model accuracy relative to centralised training paradigms due to the fact that the data distribution among clients is non-Independent and Identically Distributed (non-IID). In cross-silo FL settings, each client may represent a data center which stores

large amounts of data aggregated from many devices, and owned by a particular organisation. FL has been extended to optimise the training of the global model [19], as well as to improve its applicability in non-IID settings [11]. Yet such methods focus on optimising the FL framework rather than address the data heterogeneity issues directly.

Existing data augmentation approaches for FL focus on image classification tasks, and typically rely on Generative Adversarial Networks (GANs) [2, 13, 23], or on sharing mean latent representations of client data [3, 27]. Unlike image generation applications, traffic data generation requires modelling the dynamics of data over both spatial and temporal dimensions. Differentially-private representations of spatio-temporal data can be produced by altering real data [1, 30], or mixing partial aspects of the data [17]. These processes affect the spatio-temporal characteristics of the data itself, however. Recent work into diffusion-based models for spatio-temporal data generation demonstrate their capacity to generate high-fidelity synthetic trajectories which capture the spatio-temporal characteristics of sample traffic data, while ensuring the privacy of the real data.

DiffTraj [35] is a conditional diffusion-based trajectory generation model which leverages Traj-UNet, a network based on the UNet architecture [20] as well as an intermediary attention-based transition module, to model the noise transitions at each time step in the diffusion model processes. The model embeds additional context, such as the starting region and departure time of a trip, as conditional information which is implanted by a Wide and Deep network [4] to enhance the generative capacity of the model. To avoid memorisation of trajectories based on conditional information, which would implicate the privacy of real data, DiffTraj uses the classifier-free diffusion guidance method [8] which jointly trains an unconditional model to increase the diversity of generated trajectories and avoid deterministic data generation.

2.2 Traffic Flow Prediction

To extract temporal dependencies, deep-learning based models typically employ either Recurrent Neural Networks (RNNs) based architectures [12, 14], temporal Convolutional Neural Networks (CNNs) which convolve around the time dimension of traffic flow data [25, 28], or temporal Attention mechanisms to capture the evolution of the data around the time dimension [22].

Spatial relationships embedded within data can be captured through CNNs which convolve around the spatial dimension of data [22]. Traffic data can also be represented as graph networks, enabling Graph Convolutional Networks (GCNs) to capture spatial relationships within the data. GCN operations are dependent on the graph structure, which demands expert contextual knowledge to adequately capture inter-region relationships. Graph Attention Networks (GATs) [24] implement a self-attention mechanism to learn the relevance between a given node and its neighbouring nodes, and hence are independent of the graph structure. To capture spatio-temporal dependencies within data, models such as STGCN [28] implement GCNs with temporal CNNs to capture spatio-temporal dependencies within data, while DCRNN [12] leverages GCNs with RNN-based models. GraphWaveNet [25] also utilises temporal CNNs and GCNs, however it learns an adjacency matrix for the

graph structured data. The Temporal Attention Unit (TAU) [22] utilises CNNs and temporal Attention mechanisms to capture both spatial and temporal relationships within data.

Existing work on FL applied for traffic prediction implement novel client selection strategies to cluster clients with similar spatial characteristics [16, 31, 33]. Other such works look to adapt the aggregation procedure of the FL setting [18, 29, 32]. FedTDP [9] explores the data heterogeneity issue which may be found in real-world traffic data silos, yet does not propose a method for dealing with the inherent data heterogeneity across client data silos.

3 PROBLEM FORMULATION

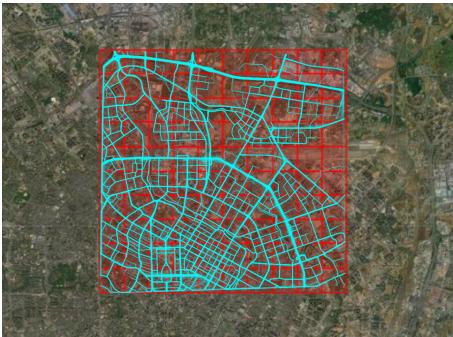


Figure 1: Satellite image of Chengdu, showing a sample of trajectories shown in cyan representing X_c , and where traffic flow into the red regions represents Q_c .

Definition 1 (Data Generation): Trajectory data can be defined as a sequence x of GPS latitude-longitude pairs. The objective of data generation is, given a set of GPS trajectories, $\mathcal{X} = \{x^1, x^2, \dots, x^m\}$, where x^i is a sequence of GPS latitude-longitude pairs, learn a model, G , that can generate a set of synthetic trajectories, $X_{\text{synth}} = \{x_{\text{synth}}^1, x_{\text{synth}}^2, \dots, x_{\text{synth}}^m\}$, where x_{synth}^i is a sequence of synthetic latitude-longitude pairs, and where the synthetic trajectories retain the real data's spatial and temporal characteristics without revealing information pertaining to the real trajectories. To emulate the setting of various organisations each with ownership over separate data silos, the global trajectory dataset, X_{glob} , is partitioned into C clients such that $X_{\text{glob}} = (X_1 \cup X_2 \cup \dots \cup X_C)$, where X_c is the trajectory dataset owned by client c . The FL task is to train model G through FL using the distributed client datasets, and develop a synthetic dataset X_{synth} .

Definition 2 (Traffic Flow Prediction): A city can be discretised into N disjoint regions, and $q_t \in \mathbb{R}^N$ can be defined as the traffic inflow for all regions N at time step t . Given historical traffic flow $Q = (q_1, q_2, \dots, q_T) \in \mathbb{R}^{N \times T}$, train a model to predict the traffic inflow of all regions at future time step $T + \tau$, hence predict $q_{T+\tau}$. Based on the partitioned trajectory data X_{glob} , client c can derive its regional traffic inflow data Q_c , and can also augment its own local dataset using the synthetic dataset X_{synth} . The federated traffic flow prediction task is then to collaboratively train a global prediction model using the distributed client datasets with synthetic data augmentation.

4 METHODOLOGY

This work aims to address a real-world setting of multiple organisations, each with their independent dataset of vehicle trajectories,

collaborating through FL to train a trajectory generation model and subsequent traffic flow prediction model. To emulate this scenario, the trajectory dataset is segmented into subsets to represent local client datasets in a cross-silo FL setting. Within this FL setting, a server acts as a secure, trusted central system which coordinates federated training between clients, and whose role is further detailed in Algorithms 1 and 2. The proposed FedTPS framework first aims to train a generative model through the partitioned vehicle trajectory datasets, and generate a synthetic dataset from the global distribution of data. The second step aims to train a traffic flow prediction model using each client's traffic flow data, and augment each client's data with the synthetic data generated from the first step. This will reduce the effects of data heterogeneity present across the client datasets, and increase the amount of training data available to clients.

4.1 Federated Generative Model

As a probabilistic generative model, a diffusion model aims to generate synthetic data by modeling two sequential processes: 1) A series of forward processes which gradually injects noise into the data, and 2) The reverse of these processes, which learn to capture the original data distribution from a noisier version [21]. Recent works have applied diffusion-based models for high-fidelity data generation in various domains [6, 7, 26]. The forward process is defined as a Markov chain with F Gaussian transitions that map the real data $x_0 \sim g(x_0)$ to x_F , a latent variable with the same dimensionality as x_0 , according to

$$g(x_1, \dots, x_F | x_0) = \prod_{f=1}^F g(x_f | x_{f-1}), \quad (1)$$

$$g(x_f | x_{f-1}) = \mathcal{N}(x_f; \sqrt{1 - \beta_f} x_{f-1}, \beta_f \mathbf{I}), \quad (2)$$

where β_f denotes the variable variances which control the Gaussian noise. Importantly, the forward process allows sampling x_f in closed form from $x_f = \sqrt{\alpha_f} x_0 + \sqrt{1 - \alpha_f} \epsilon$, where $\epsilon \sim N(0, \mathbf{I})$ and $\alpha_f = \prod_{i=1}^f (1 - \beta_i)$. The reverse process can be parameterized as a Markov chain with learned Gaussian transitions

$$p_\theta(x_0, \dots, x_{f-1} | x_F) = p(x_F) \prod_{j=1}^F p_\theta(x_{f-1} | x_f), \quad (3)$$

$$p_\theta(x_{f-1} | x_f) = \mathcal{N}(x_{f-1}; \mu_\theta(x_f, f), \sigma_\theta(x_f, f)^2 \mathbf{I}), \quad (4)$$

where $x_F \sim N(0, \mathbf{I})$, and where $\mu_\theta(x_f, f)$ and $\sigma_\theta(x_f, f)$ are the mean and variance, parameterized by θ . The objective of the diffusion model is to minimise the error between the Gaussian noise ϵ and the predicted noise level $\epsilon_\theta(x_f, f)$, over its training set. For a data sample x_0 , the client loss L_c is given by

$$\mathcal{L}_c(\theta) := \mathbb{E}_{x_0 \in X_c, \epsilon, f} [\|\epsilon - \epsilon_\theta(x_f, f)\|^2]. \quad (5)$$

Conditional diffusion models enable additional information to be embedded into the reverse denoising process as conditional variables into Eq. (4). The diffusion-based generative model DiffTraj [35] is used as the conditional model for synthetic data generation in FedTPS, as illustrated in Algorithm 1.

4.1.1 Federated Framework. In a scenario where trajectory data is segmented across data silos from multiple organisations, a diffusion model cannot be trained under a traditional framework since the training data is not centralised. Given the vast amount of data required to train a conditional diffusion-based model such as DiffTraj, each client may not be able to individually train an accurate data generation model which captures the spatio-temporal characteristics across the city with high fidelity.

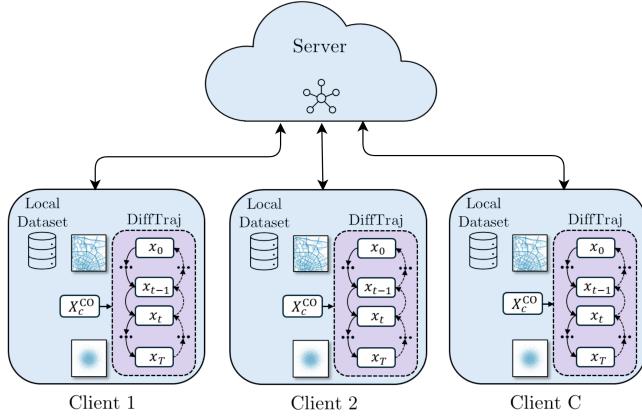


Figure 2: FedTPS Framework for training a federated generative model. X_c^{CO} represents client c 's conditional observations required for the DiffTraj model.

Under a federated setting, the updated parameters from each client's local training on the global model are communicated to a central server which then aggregates the results to update the global model. FedAvg aggregates the parameters based on the number of data samples in a client's partition. The objective of the federated DiffTraj model is to minimise the loss of the model over the cross-client datasets, and can be formalised as

$$\arg \min_{\theta} L(\theta) := \sum_{c=1}^C \frac{|X_c|}{|X_{\text{glob}}|} L_c(\theta) \quad (6)$$

where $|X_c|$ and $|X_{\text{glob}}|$ denote the number of trips in the dataset of client c and in the global set of all clients, respectively. The process of training a federated DiffTraj model is shown in Algorithm 1. After the global model has been trained, each client is queried for conditional information which is then used to generate the central synthetic dataset, X_{synth} . This conditional information can be centralised, since it does not compromise the privacy of the real trajectory data.

To develop X_{synth} , once the federated DiffTraj model is trained, client's can be queried for conditional observations, proportionally based on the amount of orders in their dataset. This will ensure the conditional observations randomly sampled are evenly distributed for the range of clients. $|X_c|$ is available to the server in a FedAvg framework as shown in Equation (6). Synthetic data is only generated for a duration of 10 days, so that the ratio of synthetic regional inflow data to real regional inflow data for each client is 1:3.

4.2 Federated Traffic Flow Prediction Model

Using each client's local individual trajectory dataset X_c , the regional inflow dataset, Q_c , can be constructed, where $Q_c \in \mathbb{R}^{TxN}$, T is the number of regional traffic flow interval samples, and N is the

Algorithm 1 Training the DiffTraj [35] model through FL using FedAvg.

```

1: Server initialises global model  $\theta$ 
2: Server selects all clients for participation,  $c \in C$ 
3: for global round,  $r_{\text{glob}} \in \{1, \dots, R_{\text{glob}}\}$  do
4:   for each client  $c \in C$  in parallel do
5:     Distribute global model to clients,  $\theta \rightarrow c$ 
6:     for local round  $r_{\text{loc}} \in (1, \dots, R_{\text{loc}})$  do
7:       Sample  $x_0 \sim g(X_c)$ 
8:       Sample  $f \sim \text{Uniform}\{1, \dots, F\}$ 
9:       Sample  $\epsilon \sim \mathcal{N}(0, I)$ 
10:      Local updates  $\theta_{r_{\text{loc}}+1}^c \leftarrow \theta_{r_{\text{loc}}}^c - \eta \nabla_{\theta} \mathcal{L}_c$ 
11:    end for
12:    Global updates  $\theta_{r_{\text{glob}}+1} \leftarrow \sum_{c=1}^C \frac{|X_c|}{|X_{\text{glob}}|} \theta_{r_{\text{glob}}}^c$ 
13:  end for
14: end for

```

number of regions captured in the data. Each client can augment their local dataset with the synthetic regional inflow dataset Q_{synth} derived from the synthetic dataset X_{synth} shared by the server. Figure 3 illustrates the structure of the FedTPS framework for the traffic prediction task.

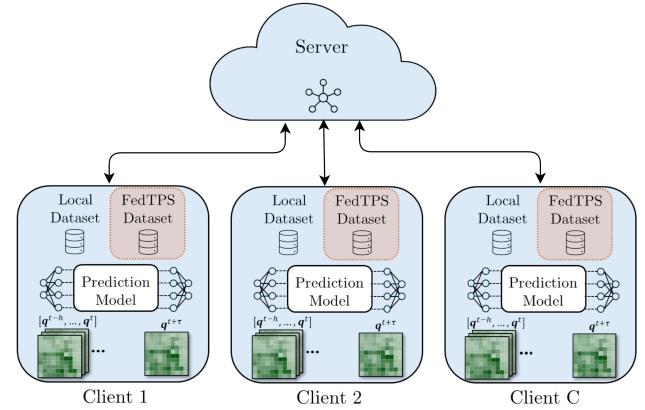


Figure 3: FedTPS framework for training a traffic prediction model in a federated setting, with synthetic data augmentation of each client's local dataset.

The local objective of a traffic flow prediction model is denoted by

$$f_c(\omega) = \frac{1}{|Q_c|} \sum_t (\mathcal{L}(\mathcal{F}_c(\omega; q_{t-h:t}), q_{t+\tau})) \quad (7)$$

where the model is parameterised by ω , h denotes the number of previous traffic flow data samples fed to the model, and τ is the number of time steps in the future for which we will be predicting traffic flow. The global objective is therefore

$$\text{argmin}_f(\omega) := \sum_{c=1}^C \frac{|Q_c|}{|Q_{\text{glob}}|} f_c(\omega) \quad (8)$$

where $|Q_c|$ and $|Q_{\text{glob}}|$ denote the number of regional inflow data samples in the dataset of client c , and in the global set of all clients, respectively.

Algorithm 2 Training a global traffic flow prediction model through FedTPS.

```

1: Server generates synthetic data,  $X_{\text{synth}}$ , from  $\theta$ 
2: Server initialises global model  $\omega$ 
3: Server selects all clients for participation,  $c \in C$ 
4: Server disseminates synthetic data,  $X_{\text{synth}} \rightarrow C$ 
5: for global round,  $r_{\text{glob}} \in \{1, \dots, R_{\text{glob}}\}$  do
6:   for each client  $c \in C$  in parallel do
7:     Distribute global model to clients,  $\omega \rightarrow c$ 
8:     for local round  $r_{\text{loc}} \in (1, \dots, R_{\text{loc}})$  do
9:       Local updates  $f_{r_{\text{loc}}+1}^c(\omega) \leftarrow f_{r_{\text{loc}}}^c(\omega) - \eta \nabla_{\omega} \mathcal{L}_c$ 
10:      end for
11:      Global updates  $\omega_{r_{\text{glob}}+1} \leftarrow \sum_{c=1}^C \frac{|Q_c|}{|Q_{\text{glob}}|} f(\omega)_{r_{\text{glob}}}^c$ 
12:    end for
13:  end for

```

4.3 Proposed Traffic Flow Prediction Model

The Temporal Attention Unit was introduced by Tan et al [22] and poses temporal attention as a combination of statical attention, which occurs within a data sample, and dynamical attention, which occurs between the frames of the data samples. The statical attention can be captured by performing depth-wise convolution, followed by a dilated depth-wise convolution, and finally a 2D convolution. The depth-wise convolution layers learn separate kernel filters for each of the channels in the encoded representation of the input. The dynamical attention is composed of a 2D average pooling layer, followed by a fully-connected layer. The final temporal attention is a result of the product between the statical and dynamical attention components.

An Encoder-Decoder architecture model architecture is presented in this work, wherein the Encoder and Decoder represent stacked 2D convolutional layers that encode a spatial representation of the data. To augment this Encoder-Decoder architecture for the task of traffic prediction, we can model the regional traffic flow data as a sequence of graphs, and employ the Graph Attention model [24] with multi-head attention, to learn multi-channel relationships between regions in the city. Figure 4 compares the model architecture between TAU and GATAU.

Thus, we introduce the Graph Attention with Temporal Attention Unit (GATAU). Figure 5 illustrates the GATAU module in further detail.

Our input data $X \in \mathbb{R}^{N \times T}$, where N is the number of nodes and T is the length of the input sequence, is first processed by a 2D convolutional layer to map the input into a higher dimension feature space. This output is fed into the Multi-Head Graph Attention (MGAT) module. Within the MGAT, attention coefficients are calculated which give a measure of the importance of relationships between nodes. The input into MGAT are node features, $h = \{\vec{h}_1, \vec{h}_2, \dots, \vec{h}_N\} \in \mathbb{R}^{T \times F}$ where F is the input feature size. Attention coefficients for layer l are calculated by

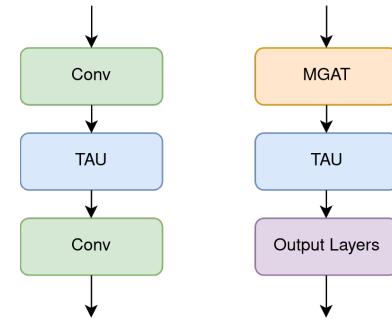


Figure 4: General model architecture comparison of TAU and GATAU.

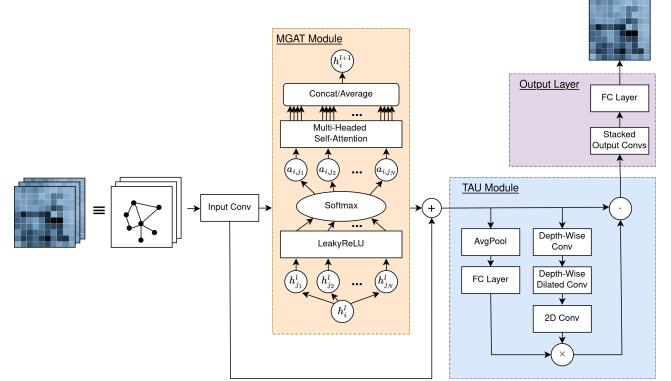


Figure 5: Architecture of the proposed GATAU model.

$$e_{ij}^l = \text{LeakyReLU} \left(\vec{a}^{lT} \left[W^l \vec{h}_i^l || W^l \vec{h}_j^l \right] \right) \quad (9)$$

where $W \in \mathbb{R}^{F' \times F}$ is a learnable weight matrix, F is the feature dimension of the input, F' is the output feature dimension which can be of different cardinality to F , and a is a function which computes the attention score from the concatenation of linearly transformed embedding of neighbouring nodes. We further apply a LeakyReLU activation for the attention coefficients. A fully connected linear single layer is used to represent function a . Then we normalise the attention scores across all connections for a given node through

$$a_{ij}^l = \frac{\exp(e_{ij}^l)}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik}^l)} \quad (10)$$

where \mathcal{N}_i denotes the node connections of node i . The output features for every node are calculated as a linear combination of the normalised attention coefficients from Equation 10 to give

$$h_i^{l+1} = \sigma \left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} W^k \vec{h}_j^l \right) \quad (11)$$

where σ is an ELU activation function. To enhance the stability of the model during training, a multi-head mechanism of attention is utilised for the graph attention module, wherein each attention head trains its own parameters. As per the original work which averages the multi-head outputs at the final layer [24], our model also averages the multi-head outputs after the single-layer MGAT module. The output from the MGAT module is of shape $X \in \mathbb{R}^{N \times T \times F'}$.

A residual connection is used to fuse the output of the initial convolution layer with the output from the MGAT module. The fused hidden layer is then reshaped into $X \in \mathbb{R}^{N \times F' \times H \times W}$ format to be processed by the TAU module, where H and W are the dimensions of the rectangular grid of the city. Our output layer is composed of a convolutional layer, and fully connected layer, which reduce the dimensionality of our processed input's feature space to match our target shape, which is $Y \in \mathbb{R}^N$.

5 EXPERIMENT

5.1 Dataset

The experiments conducted in our work use the ride-sharing dataset published by Didi Chuxing GAIA Initiative. The dataset contains data for over three million journeys made in the city of Chengdu, China over the entire month of November 2016. Table 1 contains details of the dataset.

Table 1: Description of Didi Chuxing dataset for the city of Chengdu.

Dataset	Chengdu
Orders	5,807,001
Drivers	1,136,970
Latitudes	(30.65293, 30.72776)
Longitudes	(104.042135, 104.12959)
Time Span	01/11/2016-30/11/2016

5.2 Data Pre-Processing

Targeting the real-world setting of multiple organisations collaborating to train trajectory generation and traffic flow prediction models through FL, the Didi Chuxing dataset is partitioned into subsets based on the number of clients emulated in the FL setting. It is assumed that each vehicle will collect data for a particular organisation, and hence, trajectories will be grouped according to the driver vehicle, and vehicles will be assigned exclusively to a particular organisation partition. For each client setting we partition vehicles evenly among the clients. Since individual drivers in a ride-sharing context will have preferences over their journeys and the number of orders they are assigned this will embed feature-based skews across the partitions and ensure realistic data distributions.

Once partitioned, we employ the same pre-processing steps as [35] to train the trajectory generation model. Each client also processes their trajectory dataset into regional vehicle inflow format for the traffic flow prediction task. For this step, the city of Chengdu is discretised into a rectangular 10x10 grid. Regional inflows are aggregated into 30 minute windows, and sequences of these windows over 6 hours are joined to be used by the traffic prediction model to predict the regional inflow 3 hours in the future. For the traffic flow prediction task, we segment the regional inflow data into the training, evaluation, and testing datasets by splitting the entire dataset into sets of 60%, 20%, and 20%, respectively.

As a measure of the heterogeneity between the regional inflow datasets, we employ two image-based comparison metrics to assess average similarity across the partitioned client datasets: normalised Root Mean Squared Difference (nRMSD) and Structural Similarity Index (SSI) - whose value ranges from 1 (identical) to -1 (dissimilar).

The properties of the partitions detailed in Table 2 suggest that as the number of clients in a setting increases, data heterogeneity also increases; both metrics show a decrease in data similarity as the client number increases.

Table 2: Metrics assessing the average similarity between the partitioned datasets representing each client's local dataset for each FL setting.

Clients	# Orders per Client Partition	nRMSD	SSI
2	(2904846, 2902155)	0.15	0.95
4	(1452404, 1452464, 1453202, 1448931)	0.21	0.92
6	(969168, 965928, 969817, 968308, 969601, 964179)	0.26	0.88

5.3 Description of Experiments

- (1) **Trajectory Data Generation:** This experiment details the performance of the trajectory generation models as a function of data heterogeneity and number of clients. This is important as it demonstrates the generative capability of a trajectory generation model in federated implementations with greater data heterogeneity..
- (2) **Traffic Flow Prediction** The purpose of this experiment is to assess how traffic flow prediction models perform over a range of different client cases under different FL frameworks, including FedTPS. This study is significant, as it emphasises how different federated mechanisms affect the performance of a global traffic flow prediction model, and highlights the benefits of a federated approach relative to traffic flow prediction models trained independently on separate data partitions.
- (3) **Pre-Training with Synthetic Data:** This study explores the effects of pre-training the global model in an FL framework using synthetic data. This is important, as it provides a method for training traffic flow prediction models in scenarios with limited communication or local training rounds.
- (4) **Single Client Data Augmentation:** In this experiment, the single client case is studied, wherein all data is owned by one organisation. The synthetic data generation method from FedTPS can be employed by the client to augment their dataset. This study emphasises the benefits of increasing the dataset size on the training process of a client.
- (5) **Varying Global and Local FL Training:** The purpose of this study is to explore the benefits of FedTPS when the ratio of local training rounds to global parameter aggregation rounds is increased. Increasing the number of local training rounds per global aggregation can lead to the local training processes of each client to drift from one another, which can detrimentally impact the parameter aggregation process.

5.4 Baselines

Unless otherwise stated, all models are trained using the Adam optimiser with a learning rate of 0.001 and a batch size of 32. For federated training, we use 80 global training rounds where we aggregate the updated client parameters after one local training

round. The following are the settings of the various baselines for the traffic flow prediction task, including our proposed model GATAU.

- (1) **GRU:** A three-layer GRU model [5] with hidden dimensions of 32 is implemented.
- (2) **STGCN:** The STGCN model [28] is implemented with the same model parameters specified in the original work. A distance based adjacency matrix is used for the Graph Convolution operation.
- (3) **DCRNN:** The DCRNN model [12] is implemented with the same model parameters specified in the original work. A distance based adjacency matrix is used for the Diffusion Convolution operation.
- (4) **GWNET:** The GWNET model [25] is implemented with the same model parameters specified in the original work. For the self-adaptive adjacency matrix, the input graph assumes connections for regions within 4 kilometres.
- (5) **TAU:** The TAU model [22] is implemented with the same model parameters specified in the original work.
- (6) **GATAU:** The input convolutional layer is composed of two sequential 2D convolution layers with a hidden size 16. The TAU units have the same model parameters as in the original work [22]. Our output layer is composed of two 2D convolution layers at output with hidden size 16, and a kernel size (1,1), one final linear layer to match dimensions to the output dimension. For the Graph Attention layer, the graph assumes connections between regions within 4 kilometres.

To assess our proposed FL framework FedTPS, we implement a variety of different training frameworks. The cross-silo nature of this application motivates a setting with complete client participation; contributions from every client are critical.

- (1) **Non-FL Setting:** Each client trains traffic prediction model on its own partitioned dataset, and the best performing model is recorded.
- (2) **FedAvg:** FedAvg [15] uses a weighted averaging mechanism, based on relative client dataset sizes, to update the global model based on individual client contributions.
- (3) **FedOpt:** FedOpt [19] builds on FedAvg by implementing server-side adaptive optimisers such as Adam, as well as server-side momentum. For the server, we use a learning rate of 0.01, a momentum parameter of 0.9, and a second moment parameter of 0.99.
- (4) **FedProx:** FedProx [11] utilises a penalty term, μ , to inhibit deviations of clients from the global model. We use a proximal term μ of 0.001.
- (5) **FedTPS:** The proposed framework utilises FedAvg as the parameter aggregation mechanism, and generates a synthetic dataset for the first third of the trajectory dataset, hence generates a synthetic dataset of 10 sequential days.

A server with two NVIDIA RTX 3090 GPUs is used to conduct our experiments. Our code, as well as a list of the pre-requisite packages, is made available at <https://anonymous.4open.science/r/FedTPSC51B/>.

6 RESULTS

6.1 Trajectory Data Generation

Figure 6 depicts trajectories generated by the trajectory generation model for a variety of different client settings. The single client example is equivalent to a centralised training paradigm. As the number of clients increases, the generated trajectories can be observed to be noisier. After converting the generated trajectories into regional inflow data, table 3 shows the similarity between generated samples and real traffic data based on three metrics, averaged over the regional inflow data sequences. Some deviation is expected due to the generational diversity of the DiffTraj model, yet the results show close similarity meaning that the spatio-temporal characteristics of the original data were modelled accurately by the trajectory generation model. In general, increasing the number of clients in the FL setting results in a larger deviation from the real traffic data for the samples generated, as evidenced by the decreasing values of SSI and increasing MAD and nRMSE metrics.

Table 3: Comparison of generated regional inflow data against real regional inflow data for the DiffTraj model trained through FL, with varying client cases.

City	Clients	MAD	nRMSE	SSI
Chengdu	1	11.03	0.10	0.98
	2	12.24	0.10	0.98
	4	12.91	0.11	0.97
	6	13.30	0.11	0.96

Table 2 shows that the data heterogeneity in the partitioned datasets increases in the settings with more client partitions. This can cause the global model to struggle generalising across the multiple data silos, which leads to model performance degradation with higher client numbers. Furthermore, since the client's partitioned datasets decrease in size with more clients, this introduces statistical challenges for the diffusion model stemming from smaller local datasets, which can slow convergence for the global model. Yet the samples generated throughout all client cases demonstrate high degrees of similarity with the real data, as the structural similarity index is very close to 1 and the nRMSE remains low throughout the different cases.



Figure 6: Visualisation of generated trajectories for the city of Chengdu from federated DiffTraj model over varying client cases.

6.2 Traffic Flow Prediction

Table 4 presents the results of the traffic prediction models, trained under different FL paradigms with varying client numbers, with respect to normalised Mean Absolute Error (nMAE) and Mean Absolute Percentage Error (MAPE) metrics. In general, FedTPS

Table 4: Comparison of various Spatio-Temporal model performances for prediction of traffic at 6 time-steps in future. Assessed using nMAE and MAPE metrics, under varying client numbers and varying FL methods.

City	Clients	FL Method	GRU		STGCN		DCRNN		GWNET		TAU		GATAU	
			nMAE	MAPE										
Chengdu	2	Non-FL	0.2479	28.62	0.1509	26.35	0.1535	24.12	0.1442	21.92	0.1180	18.79	0.1203	18.44
		FedAvg	<u>0.2315</u>	<u>23.31</u>	0.1291	22.46	<u>0.1217</u>	<u>19.23</u>	0.1198	19.43	<u>0.1107</u>	<u>17.52</u>	<u>0.1180</u>	18.88
		FedOpt	0.2330	23.68	0.1287	<u>22.22</u>	0.1236	19.81	<u>0.1193</u>	<u>18.93</u>	0.1120	17.78	0.1181	18.72
		FedProx	0.2337	24.02	<u>0.1283</u>	23.44	0.1294	20.75	0.1217	19.89	0.1194	19.66	0.1183	18.30
		FedTPS	0.2308	23.27	0.1229	20.93	0.1184	18.89	0.1148	18.65	0.1096	17.21	0.1144	18.34
	4	Non-FL	0.2613	26.75	0.1731	27.43	0.1760	25.51	0.1699	25.23	0.1527	21.80	0.1468	20.86
		FedAvg	0.2457	<u>24.27</u>	0.1514	<u>23.71</u>	<u>0.1478</u>	<u>21.80</u>	0.1455	21.83	<u>0.1384</u>	20.16	0.1424	20.86
		FedOpt	0.2466	23.92	0.1502	<u>23.24</u>	0.1482	21.84	0.1419	21.78	0.1373	20.59	0.1422	20.42
		FedProx	0.2474	24.21	0.1537	24.68	0.1489	22.06	0.1455	<u>21.23</u>	0.1419	21.44	0.1428	20.95
		FedTPS	0.2470	<u>24.00</u>	0.1487	23.13	0.1434	21.41	0.1405	21.19	0.1428	<u>20.46</u>	0.1405	20.70
	6	Non-FL	0.2719	27.08	0.1868	28.32	0.1928	26.03	0.1851	26.03	0.1825	24.21	0.1660	22.35
		FedAvg	0.2596	24.92	<u>0.1680</u>	24.41	0.1680	23.40	0.1645	22.82	0.1602	<u>22.01</u>	0.1625	22.22
		FedOpt	0.2611	25.30	0.1691	24.89	0.1685	23.52	<u>0.1620</u>	<u>22.50</u>	0.1602	21.81	0.1622	22.30
		FedProx	0.2628	25.47	0.1714	25.47	0.1680	23.62	0.1645	22.71	0.1668	22.84	0.1645	22.33
		FedTPS	0.2611	<u>25.08</u>	0.1654	<u>24.44</u>	0.1637	22.89	0.1600	<u>22.35</u>	0.1668	22.35	0.1591	21.78

consistently outperforms other FL frameworks for the Chengdu dataset. Our reasoning for FedTPS’s improved performance relative to other FL frameworks is due to the increased amount of data available to the clients during training, as well as the reduction of data heterogeneity stemming from the shared synthetic dataset. Through synthetic data augmentation, we ensure that each client’s dataset is more representative of the overall data distribution, and increase the amount of information available to each client. By reducing the degree of data heterogeneity the impact of non-IIDness on client training which may manifest as noise in the gradient updates is ameliorated. This improves the stability of the training by improving the parameter fusion process, and consequently the global model performance.

Comparing FedAvg and FedOpt, there is no noticeable difference between the two mechanisms as FedAvg outperforms FedOpt in 6 cases, while FedOpt outperforms FedAvg in 7 cases. This is consistent with wider research on cross-silo FL with real-world data, which found that no State-of-the-Art FL framework consistently outperformed FedAvg [10]. FedProx generally performs worse than the other FL frameworks. It should be noted that the data augmentation framework of FedTPS can be used in conjunction to other FL framework which optimise the aggregation protocol for global model updates or the client selection strategy, such as any of the FL baselines presented in this work.

With regards to the traffic flow prediction models, TAU consistently outperforms other State-of-the-Art models. When trained with FedTPS, GATAU yields the best results under a six client setting, and has the lower nMAE in a four client setting. The Graph Attention mechanism has more trainable parameters than the convolution operations employed by TAU in its encoder-decoder structure. Therefore data augmentation may be more impactful for this model. At lower client numbers, the benefits of FedTPS are more noticeable. This is likely due to the performance of the trajectory generation model improving at low client numbers, hence leading to higher quality synthetic trajectories generated. Furthermore, as shown in Table 2, data heterogeneity increases when partitioning the data for higher client number cases, and thus, the optimisation

objective in local training for a client varies more. This impacts the global model developed in a federated setting, which may result in worse performing global models.

6.3 Effects of Synthetic Pre-training on Global Model Training

Figure 7 details the training loss and evaluation metrics of select traffic prediction models under FL settings, with and without pre-training. With pre-training, the models can be seen to converge more rapidly than the FL settings without pre-training. However, by global round 60, the models will have generally converged to the same training loss. Hence, while pre-training with synthetic data improves the convergence speed of the global model noticeably, it offers no improved model performance. The random initialisation of model parameters causes the training loss and evaluation metrics at global round 1 to be very high for models without pre-training. However, with synthetic data pre-training, the starting point of the model is competitive, as can be seen from the low evaluation metric scores at global round 1.

6.4 Synthetic Data Augmentation Single-Client Setting

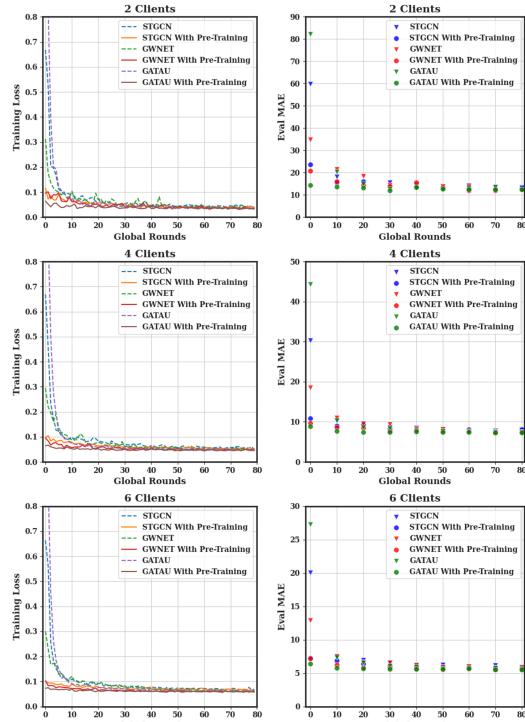
Table 5 details the effects of synthetic data augmentation for multiple traffic flow prediction models in a single client case. For this dataset, it is clear in all cases that synthetic data augmentation can significantly improve model performance. In a single client case, where there is limited traffic regional inflow data, adding synthetic data can increase the amount of information available during training. Furthermore, a single client case would also yield a diffusion model which generates the highest fidelity trajectories; it can be seen from Table 3 that increasing the number of clients leads to a degradation in the quality of the generated trajectories.

6.5 Effect of Client Rounds and Server Rounds

Table 6 illustrates the results of this study, which explores varying the number of local training rounds per global aggregation

Table 5: Comparison of various Spatio-Temporal model performances for prediction of traffic at 6 time-steps in future. Assessed using nMAE and MAPE metrics, when there is a single client.

City	Augmented Data	GRU		STGCN		DCRNN		GWNET		TAU		GATAU	
		nMAE	MAPE										
Chengdu	No	0.2419	34.47	0.1409	28.58	0.1379	23.33	0.1320	21.95	0.1003	17.63	0.1039	16.83
	Yes	0.2338	29.74	0.1323	27.89	0.1263	22.01	0.1247	20.68	0.0928	16.02	0.0952	16.21

**Figure 7: Effects of Pre-Training models with Synthetic Data on model training process.**

step. FedTPS consistently demonstrates lowest error metrics than FedAvg. The decrease in data heterogeneity stemming from the shared synthetic dataset, coupled with the increased information available to each client, means that even in cases where there are greater local training rounds relative to global aggregation rounds, the global model convergence is enhanced. This may be because the synthetic data reduces the variance between client updates and promotes more stable and consistent parameter updates. Thus, FedTPS improves the robustness of the federated learning process against the challenges posed by non-IID data distributions and limited communication rounds.

6.6 Communication Costs

Table 7 presents FedTPS’ communication cost for the distribution of the synthetic data to each federated client in. as well as the communication cost of the model parameters which occurs when the server distributes the global model to clients.

FedTPS distributes the generated synthetic data to clients only at the initial round. Compared to the communication cost for a single round of the global model distribution process, FedTPS increases communication cost from 44.7% for the STGCN model, to 0.8% for

Table 6: Comparison of selected traffic flow prediction models trained in a federated setting employing FedAvg and FedTPS as the ratio of local and global training rounds are varied.

Clients	Model	FL Method	$r_{loc} : r_{glob}$	nMAE	MAPE
2	STGCN	FedAvg	10	0.1301	23.22
		FedTPS	20	0.1327	24.27
	GWNET	FedAvg	10	0.1229	21.84
		FedTPS	20	0.1228	22.03
	GATAU	FedAvg	10	0.1165	19.00
		FedTPS	20	0.1238	21.10
		FedAvg	10	0.1156	19.19
		FedTPS	20	0.1149	19.40
	STGCN	FedAvg	10	0.1183	18.42
		FedTPS	20	0.1230	18.62
		FedAvg	10	0.1179	17.93
		FedTPS	20	0.1169	17.88
4	GWNET	FedAvg	10	0.1573	24.93
		FedTPS	20	0.1564	24.86
		FedAvg	10	0.1489	23.54
		FedTPS	20	0.1534	24.45
	GATAU	FedAvg	10	0.1442	21.44
		FedTPS	20	0.1474	21.84
		FedAvg	10	0.1401	21.27
		FedTPS	20	0.1398	21.08
	STGCN	FedAvg	10	0.1434	20.67
		FedTPS	20	0.1417	20.50
		FedAvg	10	0.1412	21.01
		FedTPS	20	0.1395	20.20
6	STGCN	FedAvg	10	0.1744	26.18
		FedTPS	20	0.1752	26.25
		FedAvg	10	0.1674	24.65
		FedTPS	20	0.1735	25.93
	GWNET	FedAvg	10	0.1643	22.70
		FedTPS	20	0.1646	23.15
		FedAvg	10	0.1608	22.39
		FedTPS	20	0.1622	22.48
	GATAU	FedAvg	10	0.1627	22.53
		FedTPS	20	0.1628	21.95
		FedAvg	10	0.1601	21.86
		FedTPS	20	0.1595	21.84

the TAU model. The global model distribution process is a reoccurring communication cost, and hence over the entire federated training process the added communication cost of FedTPS becomes much less significant.

Table 7 also demonstrates that the GATAU model incurs less communication costs than the TAU model. It should be noted that for cross-silo FL settings, communication bottlenecks are not as prevalent; server-to-client connections represent high-bandwidth data center network connections. Furthermore, complete client

participation is important for cross-silo settings as contributions from every client are critical.

Table 7: Communication costs of FedAvg and FedTPS for selected traffic flow prediction models for different client numbers, in MB.

City	Initial Comm.	Comm. Cost per Client per FL Round			
	Cost per Client FedTPS	STGCN	GWNET	TAU	GATAU
Chengdu	0.38	0.85	1.21	47.83	38.70

7 CONCLUSION

This paper addresses the task of Federated Learning for traffic flow prediction applications, and presents a new framework referred to as FedTPS which facilitates synthetic data augmentation of client datasets. By reducing data heterogeneity among clients and enhancing the information available during local training, FedTPS is able to consistently outperform other FL mechanisms for a variety of different client settings and different traffic flow prediction models. An FL setting to traffic flow prediction tasks is emulated using a large-scale ride sharing dataset for the city of Chengdu. The trajectory data is partitioned into subsets to emulate individual organisations which collect their own data. Organisations can then collaborate to train models in a federated manner, without infringing upon data privacy. FedTPS first trains a federated synthetic data generation model, and then generates a synthetic regional traffic flow dataset from the learned global distribution of trajectories. This synthetic data is then distributed to all clients prior to the traffic flow prediction task so they may augment their local datasets. Future work could apply FedTPS in highly non-IID data settings.

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