FedRME: Federated Road Markings Extraction from Mobile LiDAR Point Clouds

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***Abstract*—Road markings extraction (RME) from 3D point clouds acquired by mobile LiDAR systems has been widely used for road safety and autonomous driving. However, due to the increasing awareness of personal data protection and national information security regulations, most autonomous driving companies are not willing to share their private point clouds data with the community. Therefore, such restriction of centralized training might inevitably inhibit the effectiveness of RME procedure. Federated learning (FL) is a distributed machine learning architecture that could address the aforementioned privacy-accuracy dilemma to collaboratively learn a global RME model from multiple clients without sharing raw data. In this paper, we propose a novel FedRME, a federated road markings extraction system to collaboratively learn a global RME model with multiple privacy-preserved local models from 3D mobile LiDAR point clouds. FedRME adopt the classical FedAvg model to construct a generalizable global feature embedding model without accessing local data. Moreover, to tackle data heterogeneity problem that local models vary in point clouds volumes and categories, we design a dynamic weighting mechanism to optimize the cooperative training effectiveness before server aggregation. Experimental results on three real-world mobile LiDAR point clouds datasets with federated learning settings demonstrate that FedRME not only achieves superior performance but also reduces computation by up to 25%.The source code is available at https://github.com/WwZzz/easyFL#FedRME.**

Keywords—federated learning; cooperative computing; road markings extraction; mobile laser scanning; point clouds.

I. INTRODUCTION

Road markings have long been used to provide driving guidance to road participants. Road markings extraction (RME) is to distinguish the road markings from other road surface elements [1, 2, 3]. As a result, RME in an accurate and timely manner is of vital importance to many applications, such as road safety, intelligent navigation, autonomous driving.

Mobile laser scanning (MLS) systems, such as vehicle-mounted mobile LiDAR system [4, 5], backpacked laser scanning system [6], have been widely used in RME tasks due to their higher retro-reflective property from 3D point clouds data. However, the increasing awareness of personal data protection [7] and national information security regulations have limited the utilization of MLS systems as well as their downstream applications including RME. For example, most automated driving companies are not willing to share their local point clouds data and RME models, that are separately collected and stored in multiple systems, with the community. In short, the restriction of centralized training inevitably inhibits the effectiveness of automated RME procedure.

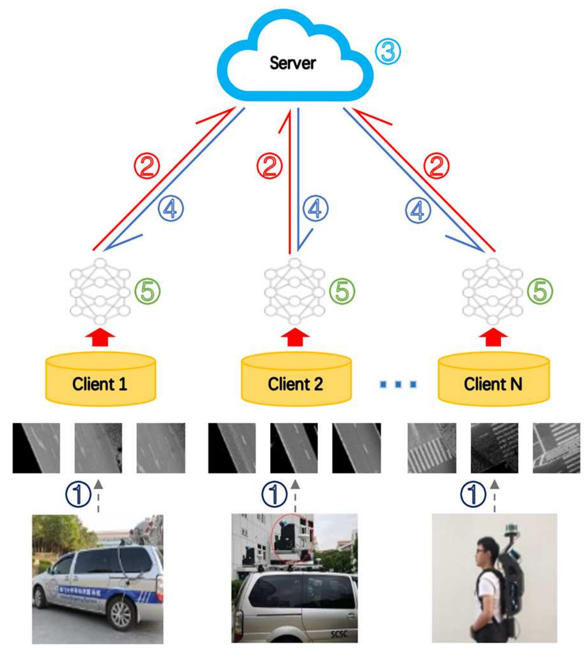

Fig. 1. A scenario of federated learning based road markings extraction. The iterative process are: 1) road marking images extracted from 3D point clouds processing by multiple mobile laser scanning systems (from left to right: RIEGL VMX-450 system, lightweight vehicle-mounted mobile LiDAR system, backpacked laser scanning system); 2) local training and sending gradients; 3) server aggregation; 4) sending back global model; and 5) updating local models.

Federated learning (FL) is emerging as a privacy-aware machine learning paradigm [8, 9, 10, 12, 13]. The architecture of FL are likely to address the aforementioned privacy-accuracy dilemma during RME that distributed clients collaboratively learn a global model without sharing raw data. Fig. 1 shows the motivating scenario of federated road markings extraction.

The iterative process of federated learning based road markings extraction are (as shown in Fig. 1):

1) road marking images are extracted after 3D point clouds processing methods by multiple mobile laser scanning systems, such as RIEGL VMX-450 system (left in the bottom Fig. 1), a

lightweight vehicle-mounted laser scanning system (middle in the bottom Fig. 1), and a self-developed assembled backpacked laser scanning system (right in the bottom Fig. 1);

2) each client performs local training, and sends encrypted gradients without sharing training data with server;

3) server conducts secure aggregation without learning information about any client;

4) server sends back the aggregated global model to each client;

5) each client updates its local model with the decrypted gradients.

The potential benefit of adopting FL to RME tasks is tw ofold. First, since clients cooperatively share model/gradients updates instead of training data with the server [8], federated le arning can effectively mitigate potential privacy leakage risks d uring RME. **Second**, FL could reduce communication overhead by avoiding massive data exchanging from multiple mobile Li DAR systems. However, this novel yet realistic federated settin g brings two unique technical challenges, which have never bee n explored so far.

Challenge 1: **How to cooperatively learn a powerful global model from multiple clients?** In our scenario (Fig. 1), the global model is distributed into a set of small local RME tasks with heterogeneous feature and data distributions. It is yet unclear that how to cooperatively train a separate RME model on each task, in order to capture the global point clouds data distribution under the data access restriction in federated learning. Moreover, training a universal applicable global model is also prone to overfitting.

Challenge 2: **How to cope with data heterogeneity problem of local RME models?** Unlike FL systems in other domain such as CV and NLP, whose data samples of images or texts are independent, data samples in point cloud images vary greatly in point clouds volumes and categories. For example, in the bottom images of Fig. 1, in terms of the spatial density of point clouds, the zebra crossing is denser than the lane line. Therefore, it is still challenging to tackle this heterogeneity issue before server aggregation.

To address the above two challenges, we propose a paradigm **FedRME**, a federated road markings extraction system to collaboratively learn a global RME model with multiple privacy-aware local models from 3D mobile LiDAR point clouds. FedRME adopt the classical FedAvg model to construct a generalizable global feature embedding model without accessing local data. Moreover, to tackle data heterogeneity problem that local models vary in point clouds volumes and categories, we design a dynamic weighting mechanism to optimize the cooperative training effectiveness before server aggregation. Experimental results on three real-world mobile LiDAR point clouds datasets with federated learning settings demonstrate that FedRME achieves superior performance on all evaluation metrics.

The rest of the paper is organized as follows. In Section II, we review related works about RME and federated learning. Section III presents the proposed FedRME method. We conduct extensive experiments and discuss evaluation results in Section IV. Section V summarizes this paper and provides future directions.

II. Related Works

A. Road Markings Extraction and Classification

Road markings extraction (RME) is to distinguish the road markings from other road surface elements, as road markings usually show higher intensities than road surfaces. Recently, threshold-based methods have been commonly used for road markings extraction. The multi-segment threshold strategy [1] first divides point clouds into several blocks. Then, each block is divided into multi-segment structures with a width value. Finally, to extract road markings, the multi-segment structures are segmented separately. Spatial Density Filtering (SDF) distinguishes road marking points from noise by calculating the spatial density at every point. Later, weighted neighboring difference histogram (WNDH) and multiscale tensor voting (MSTV) methods [10] are proposed to segment and extract road markings from noise corrupted Geo-Referenced Feature (GRF) images. Specifically, WNDH first calculates the intensity histogram of the point cloud and obtains a dynamic threshold. Then, MSTV algorithm further filters out noise data in order to extract the correct road markings.

Following the extraction process, the road markings are classified into different groups for further applications. Yu et al. [1] utilizes the Euclidean distance clustering to group markings into clusters based on the Euclidean distances to their neighbors. First, a voxel-based normalized cut segmentation method was used to group road markings into large and small size road markings. Then, a trajectory curb line based method was proposed to classify large-size markings. A Deep Boltzmann Machine (DBM) was used to classify small-size markings. Similarly, Soilán et al. [3] proposes a method based on the Gaussian Mixture Model (GMM). In their method, the intensity distribution of a road that contains road markings can be separated into road surface and road markings that are approximated by Gaussian distributions, with the higher mean distribution representing the intensity distribution of the road marking points. Their method calculates the probability of a point belonging to a road marking by estimating the parameters of the two Gaussian distributions. In addition, Cheng et al. [11] proposed a road markings extraction method, using four geometric features including area, perimeter, estimated width, and orientation. Because this method uses a simple segmentation strategy, it is difficult to handle markings like text. In addition, it is difficult for these four geometric features to correctly represent an incomplete road marking.

However, due to the awareness of personal data protection and national information security regulations, the aforementioned centralized RME methods might face the data access restriction. For example, most automated driving companies are not willing to share their RME models for privacy and competition concerns.

B. Federated Learning

Federated Learning (FL) is an emerging paradigm for cooperatively training with decentralized data without sharing raw data [8, 12]. FedAvg [8] is designed to train a global model collectively from isolated clients under the orchestration of a central server.

Statistical heterogeneity, such as non-IID data, is one of the key challenges of FL [13, 14]. In order to improve non-IID performance, Zhao et al. [15] proposed to share partial data representing global distribution with clients. Yao et al. [16] proposed FedMeta to fine-tune the server model after aggregation using metadata acquired from voluntary clients. Li et al. [17] offer FedProx, a FL model to accelerate the convergence of FedAvg by restricting the local update to be closer to the global model.

To the best of our knowledge, we are the first to explore the implementation of FL algorithm to road markings extraction. Specifically, our proposed FedRME method customizes the FedAvg model to construct a generalizable global feature embedding model without accessing sensitive point clouds data. Moreover, we design a dynamic weighting mechanism to tackle the data heterogeneity issue that local RME models vary in point clouds volumes and categories.

III. THE FEDRME METHOD

A. Overview

We first provide an overview of the architecture of our federated road markings extraction system, FedRME (as shown in Fig. 2). FedRME adopt the classical FL framework, and its main components include data collection and processing, local training in the client side, and server aggregation in the server side (bottom up in Fig. 2).

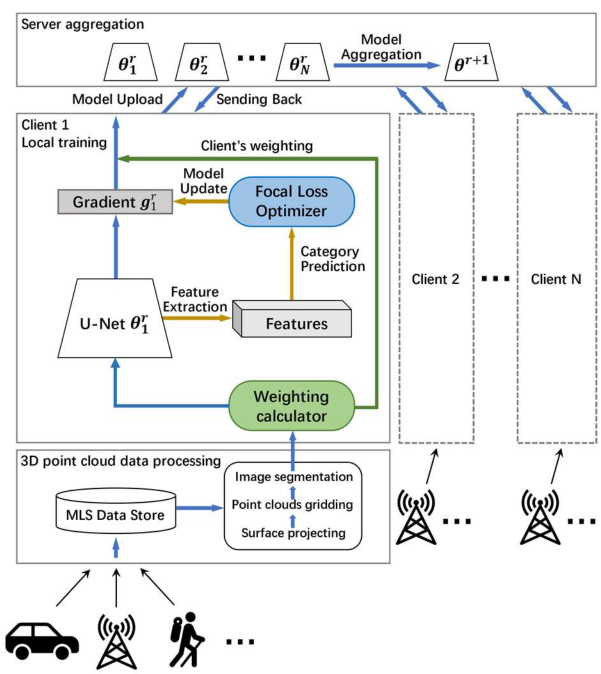

Fig. 2. Architecture of our federated road marking extraction system (FedRME), including 1) data collection and processing; 2) local training in the client side with weighting calculation (WC) and focal loss optimization (FLO) modules; and 3) server aggregation in the server side.

In order to cope with data heterogeneity problem during local training procedure, we design two novel modules in the client side: weighting calculation (WC), and focal loss optimization (FLO). When 3D point clouds processing is finished, a set of road marking images will be introduced to local training for a specific client. On one hand, a weighting calculation (WC) module is applied to compute the weighting factor of the client by evaluating the volumes and categories of road marking images. By using WC module, the potential data heterogeneity problem of the client would be addressed. On the other hand, we utilize U-Net [18] to conduct road markings extraction. Unlike the conventional U-Net model using cross-entropy directly, we introduce a novel Focal Loss (FLO) module as a new loss function, so that model training would pay much attention to hard samples (e.g., zebra crossing) which take much training times. By using FLO module, the training model will raise the priority of these hard samples to optimize the overall model prediction accuracy. The detail design of U-Net, WC, and FLO will be described in the next sub-section.

B. Local Training with Dynamic Weighting Mechanism

1) Road Markings Extraction with U-Net

Since each pixel in the marking images either represents road marking points or non-road marking points, it is reasonable to consider the road markings extraction task as a binary classification problem. Conventional U-Net [18] is an encoder-decoder network, which sets connections between the encoder and decoder. The pipeline of U-Net is illustrated in Fig. 3. The network structure consists of two parts: the contracting part and the expansive part. First, the contracting process consists of four downsampling options. For each step in the downsampling option, there are two 3×3 convolutional layers, following with a rectified linear unit (ReLU) and a 2×2 max pooling layer with stride. Later, the down-sampled results are input into the next encoder layer. Second, the expansive part consists of four upsampling options. For each step in upsampling option, the feature maps are up-sampled by deconvolution, where the size of the deconvolution kernel is 2×2 and the stride is 2×2. Besides, the results of deconvolution are connected with the saved convolution results in corresponding encoder layers. Finally, the segmentation results are output by the feature maps with a 1×1 convolution, a softmax activation function and an argmax function.

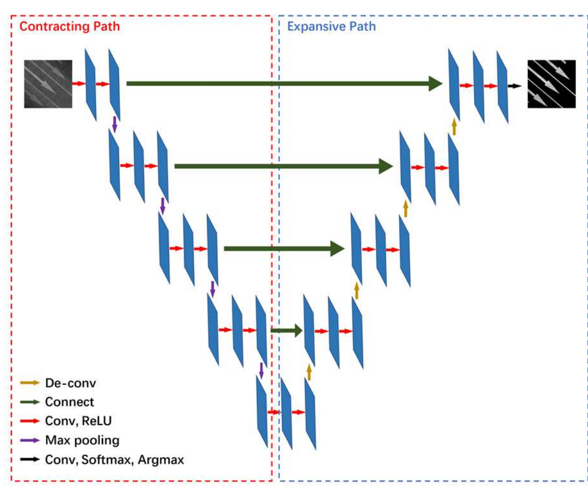

Fig. 3. U-Net structure [18].

In this paper, we modify U-Net [18] to conduct federated road markings extraction. Unlike the conventional U-Net model using cross-entropy directly, we introduce a novel Focal Loss (FLO) module as a new loss function, so that model training would pay much attention to hard samples (e.g., zebra crossing). See more details in the next sub-section (i.e., Focal Loss Optimization).

2) Focal Loss Optimization (FLO)

Unlike the original U-Net model using cross-entropy, we modified the model by applying the Focal Loss (FLO) as a new loss function to achieve superior performance for road markings extraction. In our task, we use a weighting factor w_f to address class imbalance problem. Moreover, we add a modulating factor m_f to the cross entropy loss in order to make the overall model training focus much on hard samples (e.g., zebra crossing) which take much training times. By using FLO module, the training model will raise the priority of these hard samples to optimize the overall model prediction accuracy. The focal loss function for binary classification task is defined as:

$$loss_{fl} = \begin{cases} -w_f(1-p)^{m_f}\log(p), & if \quad y=1 \\ -(1-w_f)p^{m_f}\log(1-p), & otherwise \end{cases} \tag{1}$$

where p is the probability that model predicts positive, and y is the class that model predicts. *1* means positive.

3) Weighting Calculation (WC)

For the client-side, the quantity of each category is quite different, which means the data are not independent and identically distributed (non-IID). However, standard federated algorithms like FedAvg [8] simply aggregates global model by averaging the gradients sent from each client, which may not perform well in scenarios such as road markings extraction because of data heterogeneity among clients. Therefore, we modified the FedAvg framework by calculating each client's weighting using their distribution of categories, instead of averaging clients' gradients with the number of clients. The weighting for each client can be represented as:

$$Weighting_i = \frac{NP_i}{\sum_{k=1}^{n} NP_k} \tag{2}$$

in which i is the client ID that participate in training, n is the total number of the clients. In addition, NP function is defined as:

$$NP_i = \frac{\sum_{k=1}^{M_i} RMPixel_k}{S * M_i} \tag{3}$$

in which i is the client ID as well, $RMPixel_k$ is the quantity of road markings pixel in groundtruth image k, M is the number of training images in client i and S is the training image size.

C. Server Aggregation and Updating Local models

At the end of each training round, the server aggregates the models which are uploaded from all clients with their own weighting factors. After that, the server sends back the global model. Finally, all clients update their local models with global model. By adopting both weighting calculation and focal loss module before server aggregation, both standalone training and server aggregation will focus on the hard and positive samples, which might result in better extraction performance .

In summary, the proposed FedRME model can be described as $Algorithm$ 1:

Algorithm 1: Federated Road Markings Extraction

Input: Local epoch E, batch size B, training round R, number of clients M, local weighting ω

Output: Global model θ^R

for *each client i = 0* to *M-1* **do**
    for *each local epoch e = 0* to *E-1* **do**
        for *b in batch B* **do**
            precision ← (batch predict with θ^{R-1})
            $loss_{fl}$ ← (focal loss calculation with Eqn 1)
        end for
        update $gradient_i$ using $loss_{fl}$
    end for
    upload $gradient_i$ and ω_i to Server
end for
for each client *i = 0* to *M-1* **do**
    update θ^R with $gradient_i$ and ω_i
end for
send back θ^R to *each client i*

IV. Experiments And Evaluations

In this section, we firstly introduce our dataset used in experiments. After that, we describe our experimental settings. Then we present the overall performance of FedRME method compared with FedAvg. Finally, we analyze the optimization methods with ablation studies, computation costs, respectively.

A. Dataset

We evaluate all experiments with nine road MLS point clouds data, including three highway point clouds and six urban road point clouds, which are measured by a RIEGL VMX-450 system [5], a lightweight vehicle-mounted laser scanning system (VLP-32C), and an assembled backpacked laser scanning system [6], respectively. The latter two systems are developed by Xiamen University. Table I lists the statistics of the datasets, including five different categories of road markings. It is noted that these datasets vary greatly in road markings volumes and categories.

TABLE I. Number of road markings in datasets from VMX-450 system, VLP-32C system and backpacked system.

Category	**VMX-450**	**VLP-32C**	**BACKPACKED**
Dashed line	433	286	65
Text	13	6	/
Arrow	15	11	68
Diamond	11	3	/
Zebra crossing	12	20	/
Lane line	106	156	200
Triangle	5	/	23

Moreover, as the datasets are collected from discontinuous roads, their appearances are quite different as well. In short, these characteristics of the datasets simulate data heterogeneity in real scenarios.

Furthermore, to create a non-IID data partition, we extracted 9 road point clouds into 3 parts based on highway, urban and mixed road point clouds dataset settings, respectively.

B. Experimental Setup

1) Evaluation Metrics

Road markings extraction can be evaluated using the following three performance metrics:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (6)$$

In these equations, TP is the number of true positives, FP is the number of false positives and FN is the number of false negatives.

2) Implementation Details

We implement FedAvg and FedRME in Python based on PyTorch framework. We run clients on two NVIDIA RTX3090 GPUs and run the server on Intel Xeon Gold 6142 CPU. Model update and aggregation are conducted through the PyTorch communication backend. For all experiments, we evaluate and save both local models and the global model in each round. Finally, we choose and save the best performance on validation dataset among all rounds.

3) Parameter Settings

The parameter settings are as follows: the focal loss weighting factor $w_f = 0.3$ and $m_f = 2.0$, batch size $B = 32$, total communication round $R = 20$, the initial learning rate L = 0.0001. We set local training epoch $E = 5$ for federated learning experiments, and $E = 100$ for local learning experiments. The number of clients is set as $M = 3$, 5 and 9.

C. Performance Comparison

We demonstrate the effectiveness of FedRME in comparison with standalone training, global training and FedAvg methods. Standalone training means that each client training U-Net model as described in Section III with its dataset without collaborating with other clients. The global training method merges all 9 road point clouds data for training with U-Net model as well. The FedAvg method, which aggregates global model by calculating average loss, then updates the clients' models by replacing them with global model. The comparison of all experiments results is shown in table II. The proposed FedRME outperforms all distributed methods (i.e., LocRME and FedAvg) on all evaluation metrics. Specifically, FedRME achieves superior performance up to 4.67% in terms of precision, 8.13% in terms of recall, and 7.38% in terms of F1-score, respectively.

D. Ablation Studies

To further investigate the effect of two representative components in our model, we compare FedRME with its two variants as follows:

- FedRME w/o FLO: FedRME without the FLO module (i.e., focal loss optimization).
- FedRME w/o WC: FedRME without the WC module (i.e., weighting calculation).

Table III shows the Precision, Recall and F1-Score results of full model compared with two variants, respectively. In general, FedRME outperforms all variants. Especially, FedRME performs better than *FedRME w/o FLO* and *FedRME w/o WC* by a large margin when M=3, indicating that two components (i.e., FLO and WC) are of vital importance for cooperatively federated road markings extraction tasks. In addition, with the increase of clients (i.e., M=5, 9), the performance advantage of FedRME may narrow because the data heterogeneity problem grows in accordance with the increase number of clients in federated learning system.

E. Computation Costs

Table IV compares the computation costs of FedRME with its two variants and FedAvg. We define computation costs as the least communication rounds R, when the global model's predicted results on validation dataset (i.e., intersection over union (IoU)) is greater than 0.8. The greater IoU value means the better results. Compared with FedAvg method, both FedRME w/o FLO and FedRME w/o WC method could achieve the state-of-the-art computation cost. In addition, our proposed FedRME, which is a cooperative optimization method, reduces computation cost up to 25% when M=3.

TABLE II. RESULTS ON DATASETS WITH E=5, R=20, M=3, 5, AND 9 (BATCH SIZE = 8 WHEN M=9, WHILE BATCH SIZE = 32 WHEN M={3,5}).

Model Setting	Precision			Recall			F1-Score		
	M=3	*M=5*	*M=9*	*M=3*	*M=5*	*M=9*	*M=3*	*M=5*	*M=9*
LocRME	52.519%	48.672%	45.976%	35.815%	40.685%	23.304%	42.588%	44.322%	30.930%
FedAvg	67.591%	56.059%	54.200%	42.091%	41.685%	29.681%	51.876%	46.736%	38.270%
FedRME	**72.262%**	**58.603%**	**55.912%**	**50.219%**	**43.035%**	**37.049%**	**59.257%**	**49.627%**	**44.565%**
Global (reference only)	79.004%			92.706%			85.308%		

TABLE III. ABLATION STUDIES WITH E=5, R=20, M=3, 5 AND 9 (BATCH SIZE = 8 WHEN M=9, WHILE BATCH SIZE = 32 WHEN M={3,5}).

Model Setting	Precision			Recall			F1-Score		
	M=3	*M=5*	*M=9*	*M=3*	*M=5*	*M=9*	*M=3*	*M=5*	*M=9*
FedRME w/o FLO	66.901%	55.937%	55.269%	47.218%	41.829%	35.008%	55.362%	47.866%	42.865%
FedRME w/o WC	67.736%	58.049%	54.081%	43.915%	41.946%	33.522%	53.284%	48.700%	41.389%
FedRME	**72.262%**	**58.603%**	**55.912%**	**50.219%**	**43.035%**	**37.049%**	**59.257%**	**49.627%**	**44.565%**

TABLE IV. COMPUTATION COST COMPARISON OF DIFFERENT METHODS WITH IOU THRESHOLD=0.8, M=3, 5 AND 9.

Methods	FedAvg	FedRME w/o FLO	FedRME w/o WC	FedRME
M=3	8	8	9	6
M=5	11	12	10	12
M=9	14	14	13	13

V. CONCLUSION

In this paper, we present *FedRME*, a novel federated road markings extraction system to collaboratively learn a global RME model without sharing sensitive 3D point clouds data. To address the data heterogeneity among clients, we adopt the classical FedAvg model to construct a generalizable global feature embedding model without accessing local data. For cooperative optimizations in clients, we design a dynamic weighting mechanism to enhance the cooperative training effectiveness before server aggregation. Extensive empirical studies on three real-world mobile LiDAR point clouds datasets demonstrate that FedRME effectively elevates performance and reduces computation by up to 25%. In the future, we plan to: 1) consider the system heterogeneity among clients, such as user dropouts; and 2) deploy the federated system on distributed computers rather than simulated nodes.

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