ABSTRACT
Federated Learning (FL) is an emerging decentralized artificial intelligence paradigm, which promises to train a shared global model in high-quality while protecting user data privacy. However, the current systems rely heavily on a strong assumption: all clients have a wealth of ground truth labeled data, which may not be always feasible in the real life. In this paper, we present a practical Robust and Communication-efficient Semi-supervised FL (RC-SSFL) system design which can enable the clients to jointly learn a high-quality model that is comparable to typical FL’s performance. In this setting, we assume that the client has only unlabeled data and the server has a limited amount of labeled data. Besides, we consider malicious clients can launch poisoning attacks to harm the performance of the global model. To solve this issue, RC-SSFL employs a minimax optimization-based client selection strategy to select the clients who hold high-quality updates and uses geometric median aggregation to robustly aggregate model updates. Furthermore, RC-SSFL implements a novel symmetric quantization method to greatly improve communication efficiency. Extensive case studies on two real-world datasets demonstrate that RC-SSFL can maintain the performance comparable to typical FL in the presence of poisoning attacks and reduce communication overhead by $2 \times \sim 4 \times$.

KEYWORDS
Decentralized AI, Privacy and Security, Federated Learning, Semi-supervised Learning, Robust Aggregation, Communication Efficient

1 INTRODUCTION
Federated Learning (FL) [35] is an emerging decentralized training paradigm that allows the clients (e.g., mobile phones, mobile vehicles, and IoT devices) to jointly train a shared global model. In FL, the clients are asked to upload the model updates to a server while keeping their data locally during training, which prevents from sharing the raw data and achieves privacy protection [33]. However, the current FL-based systems are based on an unrealistic assumption: that is, the local datasets of all clients are labeled data. In the real world, it is not common for each client to have rich labeled data. For example, during the COVID-19 epidemic, inter-geographic hospitals may not be able to train a high-precision COVID-19 diagnostic model because some of them do not have enough labeled data [24]. Furthermore, in most cases, putting together a properly labeled dataset for a given federated learning task is a time-consuming, expensive, and complicated endeavor [45]. In the above example, annotating lung X-rays requires professional doctors with specific domain knowledge and consumes much time.

Motivated by the above challenges, we aim to answer the following question: How to design a FL system under the limitation of clients’ unlabeled dataset to achieve model performance comparable to that of the benchmark FL [35]? Inspired by the success of previous semi-supervised learning techniques, in this paper, we aim to design a semi-supervised federated learning (SSFL) system.

However, directly adapting semi-supervised techniques into the FL system will greatly increase the communication overhead of the system. Since the client in the SSFL system holds unlabeled data, the SSFL system needs to adapt a loss function that can foster local training and pseudo-label unlabeled data [23]. In this way, the convergence speed of the SSFL system is much slower than that of the FL system [19], which will increase the number of training rounds in the SSFL system. As known, the communication overhead has always been one of the bottlenecks in FL, because the clients and server periodically exchange model parameters (i.e., size of model updates) to train a shared global model [20]. Therefore, the adoption of semi-supervised techniques makes the communication issue in FL even more serious.

On the other hand, poisoning attacks are one of the most serious security threats when FL system is deployed [6, 9, 12, 13, 17, 18, 29, 42]. In a poisoning attack, the attacker poisons the system by
manipulating data sets or model updates, thereby downgrading the system performance and even causing system training fail [9, 12, 17, 43]. In fact, the SSFL system is more susceptible to poisoning attacks than the common FL systems. In the scenarios of SSFL, the client’s dataset is unlabeled, and the clients are required to use pseudo-labeling to label unlabeled data [19]. This creates an attack surface for malicious clients to arbitrarily generate wrong labels or modify the labels of the dataset. If the pseudo-labels given to the training samples are wrong or inappropriate, these samples will become poisoned samples to compromise the modeling training.

In this paper, we tackle the above challenges by presenting a new Robust and Communication-efficient Semi-Supervised Federated Learning system (termed RC-SSFL). Specifically, we design a practical semi-supervised federated learning system to deal with a real-life scenario, i.e., the client lacks labeled data. For the inherent challenge of the fact that communication overhead and poisoning attacks affect the performance of the proposed system, RC-SSFL is designed with the following features. Firstly, RC-SSFL implements a minimax optimization-based client selection strategy to select the clients who hold high-quality updates, thereby reducing the impact of poisoning attacks. Secondly, RC-SSFL leverages the Geometric Median Aggregation (GMA) algorithm to achieve robust model updates aggregation. Thirdly, RC-SSFL designs a novel symmetric quantization method to greatly reduce communication overhead. In particular, the contributions of this paper are summarized as follows:

- We design a practical semi-supervised federated learning system that allows clients to hold unlabeled datasets to collaborate with the server holding small-scale labeled datasets to train a shared global model. Specifically, we use the pseudo-label method to set pseudo-labels for the client data and use data augmentation methods to increase the diversity of client data, thereby improving the performance of the system.
- We design a minimax optimization-based client selection strategy to select the clients who hold the high-quality updates. Specifically, we minimize the difference between the client’s updates and the server’s global model updates, while maximizing the cosine similarity and Wasserstein distance between the client’s updates and the server’s global model updates. Furthermore, we introduce the Geometric Median Aggregation algorithm to robustly aggregate the updates of selected clients.
- We propose a symmetric quantization technique to compress the updates of each client, thereby improving the communication efficiency of the system. Specifically, we introduce Maximum Mean Discrepancy to find the best clipping threshold to ensure that the quantization is symmetric. Such a quantification technique is symmetric, so it will not affect the client selection strategy.
- We conduct an extensive evaluation over two real-world datasets. Experimental results show that the performance of the designed SSFL system is comparable to the FL system. Besides, our system is shown robust to poisoning attacks under i.i.d and non-i.i.d settings. Furthermore, our system improves the communication efficiency by $2 \times \sim 4 \times$ compared to the prior SSFL systems.

# BACKGROUND & RELATED WORK

## 2.1 Semi-supervised Federated Learning

Considering that the labeled data is scarce and precious, many researchers have turned their attention to the semi-supervised federated learning (SSFL) paradigm. In [23], the authors pointed out a more practical scenario in FL setting that users might not have ground-truth labels. The recent works [19, 22, 53] most related to our work have made a preliminary exploration of the design of the SSFL system. Unlike [19, 22, 53], we consider more complex scenarios where the client might be unreliable or malicious and studied the non-iid case with unlabeled client data. Meanwhile, we also address the critical challenge of communication overhead in the SSFL system.

## 2.2 Attack-resistant Federated Learning

To cope with poisoning attacks in FL, several abnormal client detection methods have been developed in recent years, mainly to use anomaly detection methods to identify malicious clients [49]. Although researchers have proposed many detection methods for abnormal clients, these methods can be divided into two categories: dimensionality reduction-based methods and neural network-based methods. In [29, 31, 49], they reduced the dimensionality of the update vector of the client to a two-dimensional space, and then divide the client into an honest group and a malicious group using a binary classification method. The researchers transformed the task of detecting abnormal clients into a high-dimensional binary classification problem. In [28, 40, 42], they used autoencoders and variants to classify high-dimensional weight vectors to achieve malicious client detection. However, the above methods are impractical in real life. This is because the above methods require the server to implement complex dimensionality reduction techniques or train a large-scale deep learning model, which is obviously impractical for the FL system.

## 2.3 Communication-efficient Federated Learning

To reduce the harmful effects of expensive communication overhead on the performance of the FL system, many researchers have proposed many advanced methods that focus on the model update, efficient stochastic gradient descent (SGD), and gradient compression. In FL setting, the asynchronous model update methods [15, 48, 50, 51] improve communication efficiency by reducing the computing time of edge devices. However, the asynchronous update methods rely on an assumption that the model update delay time is bounded, but this assumption may be impractical in FL setting. In this case, the delay may range from a few hours to a few days, or it may be completely unlimited [30]. The efficient SGD methods [2, 3, 21, 54] optimize the classic SGD methods to increase the speed of local updating, thereby improving communication efficiency. In the distributed optimization community, gradient compression methods (including gradient sparsification [4, 32, 44, 46] and gradient quantization [3, 26, 34, 41, 55] techniques) are generally used to reduce the size of the updated gradients (or update weights) to improve communication efficiency. However, the above methods are all asymmetric compression methods, which are not conducive to
the combination of the compression scheme and other techniques that help improve the performance of the FL system.

3 PRELIMINARIES

In this section, we overview the Federated Learning pipeline, threat model, and design goal.

3.1 Federated Learning Pipeline

In the federated learning setting, we consider a server $S$ and $m$ clients $C_i$, $i \in [1, m]$, participating in training a shared global model $\omega^*$. We assume that each client holds a data sample $z$ with data distribution $\mathcal{D}$ (e.g., i.i.d or non-i.i.d). For the model parameters $\omega \in \mathbb{R}^d$ and a data sample $z$, let $t(\omega; z)$ be the loss function at the client. So let $L(\omega) = \mathbb{E}_{z \sim \mathcal{D}}[t(\omega; z)]$ be the loss function at the server. In particular, the client holds the data locally and only periodically exchanges updates (weights or gradients) with the server to learn this global model. Therefore, the goal of FL is to minimize the following objective function:

$$\min_{\omega} L(\omega), \text{ where } L(\omega) := \sum_{k=1}^{m} p_k L_k(\omega), \quad (1)$$

where $p_k \geq 0$, $\sum_k p_k = 1$ is a user-defined term which indicates the relative influence of each client on the global model.

To minimize the above objective function, the server and clients cooperatively run a $T$-round FL protocol. Specifically, the server randomly selects a certain proportion $q$ ($0 < q < 1$) of clients from all clients to participate in this learning task and sends the initialized global model $\omega_0$ to each selected client. Each client uses a local optimizer (e.g., SGD, AdaGrad, or Adam) on the local dataset $\mathcal{D}$ to train the received initialized global model $\omega_0$ and upload the updates (updated weights $\omega_0^{(k)}$ or gradients $g_0^{(k)}$) to the server. The server collects all the updates uploaded by the clients and runs an aggregation algorithm (e.g., FedSGD [35], FedAVG [35]), i.e., $\omega_T = \omega_0 + \frac{1}{m} \sum_{k=1}^{m} \omega_0^{(k)}$ (or $g_0^{(k)}$) to obtain an optimized global model $\omega_T$. The above steps are repeated for $T$ rounds until the global model converges.

3.2 Threat Model and Design Goal

3.2.1 Threat Model. In this paper, we consider a more practical scenario where there are at most $c$ clients that are malicious and the server $S$ is semi-honest, and these clients can launch poisoning attacks that harm the performance of the system. In the poisoning attacks, the attackers poison the system by modifying the pseudo-label of the local dataset or modifying the model updates of the client. But the server is subject to laws and regulations and will not attack this system. Specifically, we assume that the update generated by the $c$ clients is $\omega' = \theta(\omega^{c1}, \omega^{c2}, \ldots, \omega^{cm})$, and the update generated by other clients is $\omega = \theta(\omega^{s1}, \omega^{s2}, \ldots, \omega^{sm})$. Therefore, the attack goal of these $c$ clients is to maximize the following objective function:

$$\max_{\omega' \neq \omega} s^T(\omega - \omega'), \quad (2)$$

where $s$ represents the change direction vector of global model parameters. Specifically, when there is no attack, we use $s_j = 0$ to indicate the direction of change of the $j$-th global model parameter in the current iteration, where $s_j = 1$ or $-1$. $s_j = 1$ (or $s_j = -1$) means that the $j$-th global model parameter increases (or decreases) in the previous iteration. In short, these malicious clients disrupt the training task by generating updates in the opposite direction to the global model.

3.2.2 Design Goal. In this paper, our goal is to design an attack-resistant and communication-efficient SSFL system. Similar to most SSFL systems, the proposed system needs to achieve performance comparable to typical FL systems on unlabeled client data. First, the proposed system needs to design a solution to prevent poisoning attacks. Specifically, our goal is to minimize Eq. (2) while selecting clients with high-quality model updates. Second, our system can significantly improve communication efficiency by using a symmetric quantization method. Third, our system uses GMA aggregation rule to robustly aggregate noisy updates.

4 SYSTEM DESIGN

In this section, we elaborate on our designs. First, we introduce the SSFL system. Second, we demonstrate the proposed minimax optimization strategy to find clients with high-quality model updates in the proposed system. Third, we design a symmetric quantification method to improve communication efficiency in the proposed system.

4.1 Semi-supervised Federated Learning System

In this section, we present a semi-supervised federated learning (SSFL) system, as illustrated in Fig. 1. In our SSFL setting, the server $S$ holds a labeled dataset $D_1 = \{(x_1, y_1)\}_{i=1}^{N_1}$, $N_1$ denotes the number of samples in the labeled dataset. For $m$ clients $C_i$, $i \in [1, m]$, $k$-th client holds an unlabeled dataset $D_k = \{(x_i)\}_{i=1}^{N_k}$, $N_k$ denotes the number of samples in the local unlabeled dataset). Similar to the typical FL [35], the goal of the server and clients in the SSFL system is to collaboratively train a global model in high quality. Note that it is challenging for SSFL to achieve the above goal because SSFL is limited by the fact that the client has unlabeled data. Therefore, we aim to design a new training method to make the performance of SSFL comparable to the typical FL. The steps of our proposed training method for SSFL are as follows:

- **Phase 1, Initialization:** First, the server selects a certain proportion $q$ ($0 < q < 1$) of clients from all participating clients to participate in an SSFL task (e.g., prediction tasks or classification tasks). Second, unlike the typical FL, the server not only aggregates the updates uploaded by the clients, but also trains an initialized global model $\omega_0$ on its own labeled dataset $D_1$. On the server side, the goal is to minimize the following objective function:

$$\min_{\omega} L_s(\omega), \text{ where } L_s(\omega) := \frac{1}{N_1} \sum_{(x_i, y_i) \in D_1} t(y_i, f(\phi(x_i); \omega)), \quad (3)$$

where $L_s(\omega)$ is the loss function, $t(\cdot, \cdot)$ is the cross-entropy loss, and $\phi(\cdot)$ is the data augmentation function (e.g., Flip-and-shift Augmentation [7] and RandAugment [16]). Third,
Semi-supervised Federated Learning Workflow

Figure 1: Overview of the proposed semi-supervised federated learning system.

the server broadcasts the initialized global model $\omega_0$ to assign pseudo labels to the selected clients.

- **Phase 2, Local Training:** Each client trains the received global model $\omega_0$ on its own unlabeled dataset $D_k$. Specifically, the client utilizes the global model $\omega_0$ to pseudo-label the unlabeled dataset to train the local model $\omega_k$. In the semi-supervised learning, one generally uses pseudo-labels generated by weak data augmentation methods (e.g., flip-and-shift) to train samples generated by strong data augmentations methods (e.g., shift and crop) [39]. The reason is that these data augmentation methods can generate a wide variety of samples, which can improve the performance of semi-supervised learning. Thus, we follow [39] to define the following objective function:

$$\min_{\omega_k} L_k(\omega),$$

$$L_k(\omega) := \frac{1}{N_k} \sum_{i \in D_k} y(\max(\tilde{y}_i) \geq \lambda) \ell(\arg \max(\tilde{y}_i), f(\phi(x_i); \omega))$$

where $\lambda$ is the threshold hyperparameter, which helps the model to decide which samples have high confidence to be correctly labeled, $\phi(\cdot)$ is the strong data augmentation function, $\psi(\cdot)$ is the indicator function, and $\tilde{y}_i = f_k(\phi(x_i); \omega)$ is the prediction of the model $f_k$ on the augmented sample generated by weak data augmentation methods $\phi(\cdot)$. Then all clients upload the updates to the server.

- **Phase 3, Aggregation:** The server uses an aggregation algorithm like FedAVG [35], i.e., $\omega_t = \omega_{t-1} + \frac{1}{m} \sum_{k=1}^{m} \omega_t^{(k)}$ to aggregate the updates, to aggregate all the updates to obtain a new global model $\omega_t$. Furthermore, the server continues to train the global model on the dataset $D_s$.

Remark: For Eq. (3) and Eq. (4), we need to use SGD with momentum over a mini-batch to optimize. For aggregation algorithms, we can use other aggregation algorithms depending on the specific application scenario. All the above steps are repeated until the global model converges.

4.2 Optimization-based Client Selection Strategy

In our SSFL setting, we assume that there are $c$ clients that are malicious to launch poisoning attacks (refer to Sec. 3.2.1) to the server so as to damage the performance of the global model. To mitigate this attack, we design a minimax optimization-based defense strategy that can select clients who hold high-quality updates. Note that high-quality model updates indicate that such model updates help the global model to improve accuracy.

Observation: As shown in Fig. 2, we explore the difference between the aggregated updates and weight values distribution between malicious clients and honest clients. First, in Fig. 2 (left), we find that the update direction of the aggregated update vectors of the honest clients is close to the update direction of the aggregated global update vectors of the server. On the contrary, the update direction of the aggregated update vectors of the malicious clients is different from the update direction of the server. Second, in Fig. 2 (right), from the distribution of weight values, the distribution of updates generated by malicious clients is obviously very different from the distribution of updates generated by honest clients (including server).

Strategy: Motivated by the above observations, we can use the distribution difference (direction difference) between the client’s weight value (aggregated update vectors) and the server’s weight values (aggregated update vectors) as an indicator to measure the quality of the update held by the client. In this way, the server only needs to aggregate model updates uploaded by clients with high-quality updates to obtain the best performing global model. Thus, the formal definition of the minimax optimization strategy is
The second term of Eq. (5) means that we choose as many clients whose update direction is close to the global model update direction as much as possible whose distance or distribution is close to the weights of the honest client and server's model updates, \( \Delta \), represents a measure to indicate the update quality of cosine similarity we designed and the typical cosine similarity is that we use the sum of the client's historical updates. The reason is that the sum of historical updates can better reflect the reputation of the client [18, 25]. Note that the client’s reputation is used to measure the historical behavior of this client.

Second, if we regard the client’s update as a distribution, then the formal definition of the method using Wasserstein distance as the metric is as follows:

\[
\Delta_{i,t} = -W(w, \sum_{t=1}^{T} w_{i,t}) = - \inf_{\gamma \in \Pi} \int_{x} \int_{y} E(x,y) \gamma(x) \gamma(y) \, dx \, dy,
\]

where \( \gamma \) is the joint distribution of \( w \) and \( \sum_{t=1}^{T} w_{i,t} \).

**Aggregation:** In this paper, we use the geometric median aggregation (GMA) algorithm instead of FedAvg aggregation algorithm to aggregate model updates uploaded by the clients. The reason is that the FedAvg aggregation algorithm is susceptible to noise updates. First, the data distribution between clients is generally non-independent and identically distributed (non-i.i.d) in the SSFL system, which means that model updates shared between clients may include noisy updates [30]. Second, the stochastic gradient descent optimizer is a commonly used optimizer in the SSFL system which introduces random noise updates during the gradient descent process to harm the performance of the system [53]. Noisy updates cause the server to get incorrect aggregation results and harm the performance of the system.

As shown in Fig. 3, if there are some noise gradients, the average gradient produced by the FedAvg aggregation algorithm is quite different from the true gradient. On the contrary, the geometric median aggregation algorithm is robust to the noise gradients and the aggregation result is closer to the true gradient. Next, we give the definition of GMA as follows:

**Definition 1.** Geometric Median Aggregation (GMA): Let \( \{ z, z \in Z \} \) be a subset of the space of natural numbers, thus, the
Algorithm 1: Robust semi-supervised federated learning algorithm.

Input: The labeled dataset $D_\ell$ on the server, the unlabeled dataset $D_u (k \in [1, m])$ on the client, the threshold hyperparameters $\delta$ and $\lambda$, and the cross-entropy loss $f(\cdot, \cdot)$.

Output: Optimal global model $\omega^*$.

Server:
1. foreach round $t = 1, 2, \cdots, T$ do
2. Train the global model $\omega_{t-1}$ on the labeled dataset $D_\ell$ by using $f(\cdot, \cdot)$ (Refer to Eq. (3));
3. Broadcast the global model $\omega_{t-1}$ to all the clients;
4. Client:
5. foreach client $C_i, i \in [1, m]$ do
6. Receive global model $\omega_{t-1}$;
7. Train the local model $\omega_{t-1}^k$ on the local unlabeled dataset $D_k$ by using Eq. (4);
8. Use data augmentation methods to generate diverse labeled data;
9. Upload the update $\omega_{t-1}^k$ to the server;
10. foreach round $t = 1, 2, \cdots, T$ do
11. Set the threshold hyperparameters $\delta$ and $\lambda$;
12. Utilize minimax optimization strategy to select clients with high-quality updates by using Eq. (5)–Eq. (7);
13. Use Geometric Median Aggregation to aggregate the selected updates, i.e., $\omega_{t+1} = \omega_k + \frac{1}{m} \sum_{i=1}^{m} \text{geomed}(\omega_i)$;
14. Broadcast the global model $\omega_k$ to all the clients;
15. return $\omega^*$.

The geometric median is defined as follows:

$$\text{geomed}(z) := \arg \min_{y \in \mathbb{Z}} \sum_{z \in \mathbb{Z}} |y - z|.$$ (9)

Referring to FedAvg [35], the formal definition of Geometric Median Aggregation is as follows:

$$\omega_{t+1} = \omega_k + \frac{1}{m} \sum_{i=1}^{m} \text{geomed}(\omega_i).$$ (10)

Based on the above-designed defense strategy and aggregation algorithm, our novel SSFL algorithm is summarized in Algorithm 1.

4.3 Symmetric Quantization for Communication Efficiency

Expensive communication overhead hinders the widespread promotion of FL system, which is a key challenge that FL system needs to solve. In the distributed learning optimization community, researchers generally use compression techniques (e.g., sparsification and quantization) to compress the updates of interaction between the client and the server to improve communication efficiency [15, 37]. The most commonly used techniques to improve communication efficiency in FL systems are quantification-based methods. Specifically, these quantization methods are mainly used to compress model updates associated with the local model size to reduce the size of update uploads of the client. However, they are not designed for model update aggregation and defense attacks in FL [52], and they cannot be applied to our SSFL system. The reason is that compressed updates are asymmetrical, i.e., the distribution of updates will change, which prevents us from using the minimax optimization strategy we designed to resist malicious attacks. We scrutinize the constraints, and summarize the requirements for quantization as follows:

- **Symmetric Range**: Asymmetric quantization range can lead to incorrect aggregation results, which can make SSFL training fail [52]. On the other hand, in order to make the minimax optimization strategy function effectively, we expect a symmetric quantification method to ensure that the difference between the client’s update and the global model’s update can be accurately calculated.

- **Bounded Range**: In SSFL training, gradient explosions sometimes occur, i.e., the value of the gradient becomes unbounded [3], which also leads to incorrect aggregation results. Therefore, we aim to find an effective way to clip the updates into a bounded range before aggregation.

In this paper, we propose a symmetric quantization method to quantify the updates associated with the local model size uploaded by the clients for communication efficiency.

First, we assume that $w_{ij} \in [\min, \max]$ is the weight value of the $i$-th row and $j$-th column in the weight values vector $w$ which is quantized into an $r$-bit (e.g., $r = 2, 4, 8, 16$) unsigned integer, thus, the quantized value of $w_{ij}$ is:

$$Q(w_{ij}) = \left\lfloor \frac{(2^r - 1) \cdot w_{ij} - \min}{\max - \min} \right\rfloor,$$ (11)

where $Q(\cdot)$ denotes the quantization function. We use clipping technique to make $w_{ij} \in [-\alpha, \alpha]$, which ensures that $w_{ij}$ is in a symmetrical range. Note that $\alpha$ is the threshold hyperparameter. Let $q_n$ be the quantized result, the formal definition of dequantization is as follows:

$$Q^{-1}(q_n) = q_n \cdot (\max - \min)/(2^r - 1) + \min.$$ (12)

Referring to Eq. (11) and Eq. (12), the value of $\alpha$ determines whether our quantization method can achieve symmetric quantization. Therefore, we need to use a suitable optimization method to find the best threshold $\alpha$.

Next, we present our method of optimizing the threshold. Specifically, we follow [10, 11, 47, 52] to assume that $w \sim N(0, \sigma^2)$. Based on the above setting, previous works generally used KL divergence [10], clipping technique ACIQ [11, 52] and convergence rate [47] methods to optimize the selection of the threshold. However, these methods are not suitable for SSFL systems trained using the mini-batch method. The reasons are two-fold: 1) The above methods need to learn the distribution of samples from a large number of samples; 2) The samples included in the mini-batch training method are limited. Therefore, the above methods are not accurate using mini-batch training with a small number of samples. Inspired by the Maximum Mean Discrepancy (MMD) [14] method in transfer learning, we use this method to optimize our threshold to minimize the accumulated error caused by the clipping technique. The definition of MMD is as follows:
**Definition 2. Maximum Mean Discrepancy (MMD):** Let \( p \) and \( q \) denote the distribution of source sample \( X \) and target sample \( Y \), respectively. There is a random projection function \( f : \chi \rightarrow \mathbb{R} \), thus, MMD is:

\[
\text{MMD}(\mathcal{F}, p, q) := \sup_{f \in \mathcal{F}} \{ E_p[f(x)] - E_q[f(y)] \}.
\]

\[
\text{MMD}(\mathcal{F}, X, Y) := \sup_{f \in \mathcal{F}} \left\{ \frac{1}{m} \sum_{i=1}^{m} f(x_i) - \frac{1}{n} \sum_{i=1}^{n} f(y_i) \right\},
\]

where \( \mathcal{F} \) represents the set of all functions \( f \) that map the feature space \( a \) to the real number set \( \mathbb{R} \).

MMD cannot be directly used in SSFL settings, we need to improve it to be suitable for mini-batch training. Specifically, we assume that \( w \sim \mathcal{N}(0, \sigma^2) \) and \( Q(w) \) denotes the quantized weight vector. We introduce Reproducing Kernel Hilbert Space [36] to use the dot product in space \( \mathcal{H} \) to represent the mapping of function \( f \), i.e., \( f(x) = (f, \psi(x))_\mathcal{H} \) where \( \psi(\cdot) \) represents a map of \( \chi \rightarrow \mathcal{H} \), thus, mini-batch-based MMD distance is:

\[
\text{MMD}^2(\mathcal{F}, w, Q(w)) := \langle \psi(w + \mathcal{Q}(w) \omega), \psi(w) \rangle_{\mathcal{H}} \quad \text{where} \quad \psi(\cdot) \text{represents the mapping of function} \quad f(\cdot), \quad \mathcal{M} \quad \text{denotes the entire model}.
\]

**Experimental Results**

### 5.1 Experimental Setup

In this section, we evaluate our design on MNIST and CIFAR-10 datasets for performance analysis. All experiments are implemented on the same computing environment (Linux Ubuntu 18.04, Intel i5-4210M CPU, 16GB RAM, and 512GB SSD) with Pytorch and PySyft [38].

**Models:** In this experiment, we use a simple deep learning model (i.e., CNN with 2 convolutional layers followed by 1 fully connected layer) for classification tasks on the MNIST datasets and use AlexNet [27] model for classification tasks on the CIFAR-10 dataset.

**Datasets:** MNIST is a handwritten digital image dataset, which contains 60,000 training samples and 10,000 test samples. Each picture consists of 28 \times 28 pixels, each pixel is represented by a gray value, and the label is one-hot code: 0–9. The CIFAR-10 dataset consists of 10 types of 32 \times 32 color pictures, a total of 60,000 pictures, each of which contains 6,000 pictures. Among them, 50,000 pictures are used as the training dataset and 10,000 pictures are used as the test dataset. The pixel values of images in all datasets are normalized into \([0, 1]\) and the label is one-hot code: 0–9. Note that in our SSFL system, we remove the label information of the local dataset on the client side.

**Settings:** For data assignment procedures, we assign \( N \) labeled training samples to the server, and the remaining unlabeled training samples are assigned to \( m \) clients. For the i.i.d data distribution setting, we evenly assign the unlabeled data of \( d \) classes to each client. For the non-i.i.d data distribution setting, we evenly distribute the unlabeled data to each client while keeping only two classes of unlabeled data for each client. Note that the classes of each client in the non-i.i.d setting is randomly assigned.

**Parameters:** We set the number of clients \( m = 100 \), proportion of client participation \( P = 0.1 \), training round \( T = 250 \), local training epoch \( E = 5 \), learning rate \( \eta = 0.001 \), mini-batch size \( B = 32 \), and the number of training samples \( N_c = 10,000 \) on the server-side. For the symmetric quantization method, the optimal threshold \( \alpha = 0.5 \). For the SSFL setting, we follow [53] to set the threshold hyperparameter \( \lambda = 0.95 \). Furthermore, we use SGD with momentum over a mini-batch to optimize our model.

**Attacks:** In this experiment, we consider there are \( c \) malicious clients in two typical poisoning attacks: label-flipping attack (a.k.a a data poisoning attack) [9, 12] and Gaussian attack (a.k.a model poisoning attack) [17, 49]. For a label-flipping attack, a malicious client modifies only one class of pseudo-label of the local dataset to another class. Specifically, for the MNIST dataset, a malicious client changed all the training samples with the pseudo label “1” to the pseudo label “7” for the CIFAR-10 dataset, a malicious client changed all the training samples pseudo labels “dog” to the pseudo label “cat”. For a Gaussian attack, a malicious client upload its update of \( \omega \) from a Gaussian distribution with mean \( \frac{1}{m-c} \sum_{i=1}^{m} \omega \), variance 10. Although malicious clients have different attack methods, their attack goal is the same, i.e., \( \max_{\omega \in \mathbb{R}^d} s^T(\omega - \omega') \) (refer to Eq. (2)). Note that the above attack methods are practical and easy to implement in our SSFL system. The reason is that the client in the SSFL system has complete autonomous control over its own dataset and model updates.

### 5.2 System Performance

We first present a comparison of the performance of the proposed system with other benchmark schemes. In this experiment, we use FL with FedAvg [35], FL with FedSGD [35], FL with GMA [49], SSFL with FedAvg [53], and SSFL with FedSGD [22] as the benchmark schemes for comparison of our systems. Note that the typical FL systems are supervised learning paradigms and these benchmark schemes are the most common and typical of existing FL and SSFL systems. Furthermore, we conduct performance comparison...
Table 1: Performance comparison between the proposed system and the benchmark schemes on the i.i.d setting of the MNIST and CIFAR-10 datasets.

| Dataset   | Data Distribution | Learning Method | Aggregation Method | Accuracy  |
|-----------|-------------------|-----------------|--------------------|-----------|
| MNIST     | i.i.d             | Supervised Learning | FedAvg             | 99.33%    |
|           |                   | Supervised Learning | FedSGD            | 99.21%    |
|           |                   | Supervised Learning | GMA                | 99.39%    |
|           |                   | Semi-supervised   | FedAvg             | 98.17%    |
|           |                   | Semi-supervised   | FedSGD            | 97.84%    |
|           |                   | Semi-supervised   | GMA + Client Selection | 99.16%  |
| CIFAR-10  | i.i.d             | Supervised Learning | FedAvg             | 73.97%    |
|           |                   | Supervised Learning | FedSGD            | 72.89%    |
|           |                   | Supervised Learning | GMA                | 74.08%    |
|           |                   | Semi-supervised   | FedAvg             | 65.84%    |
|           |                   | Semi-supervised   | FedSGD            | 64.41%    |
|           |                   | Semi-supervised   | GMA + Client Selection | 69.84%  |

Table 2: Performance comparison between the proposed system and the benchmark schemes on the non-i.i.d setting of the MNIST and CIFAR-10 datasets.

| Dataset   | Data Distribution | Learning Method | Aggregation Method | Accuracy  |
|-----------|-------------------|-----------------|--------------------|-----------|
| MNIST     | non-i.i.d         | Supervised Learning | FedAvg             | 98.04%    |
|           |                   | Supervised Learning | FedSGD            | 98.04%    |
|           |                   | Supervised Learning | GMA                | 98.32%    |
|           |                   | Semi-supervised   | FedAvg             | 97.18%    |
|           |                   | Semi-supervised   | FedSGD            | 97.16%    |
|           |                   | Semi-supervised   | GMA + Client Selection | 98.00%  |
| CIFAR-10  | non-i.i.d         | Supervised Learning | FedAvg             | 66.37%    |
|           |                   | Supervised Learning | FedSGD            | 66.08%    |
|           |                   | Supervised Learning | GMA                | 66.54%    |
|           |                   | Semi-supervised   | FedAvg             | 61.05%    |
|           |                   | Semi-supervised   | FedSGD            | 60.71%    |
|           |                   | Semi-supervised   | GMA + Client Selection | 64.98%  |

Figure 4: Performance comparison of the SSFL system with and without the client selection scheme on label-flipping attacks.

First, we evaluate the performance of our system and benchmark schemes on the i.i.d and non-i.i.d settings of the MNIST and CIFAR-10 datasets. As shown in Table 1 and Table 2, we find that the performance of the proposed system is close to that of the best-performing benchmark scheme, i.e., the supervised learning-based FL with GMA and exceeds the state-of-the-art SSFL schemes. The supervised learning paradigm-based FL systems rely on rich labeled information to achieve superior performance on the MNIST and CIFAR-10 datasets. Nevertheless, such FL systems are difficult to deploy. The reason is that labeling datasets are a time-consuming and expensive task in real life. On the other hand, the proposed SSFL system does not rely on rich labeled information and its performance...
We explore the robustness of the proposed system against two typical poisoning attacks (i.e., label-flipping attacks and Gaussian attacks) on the MNIST and CIFAR-10 datasets. We assume that there are $c = 30$ malicious clients and the malicious clients can collide with each other to launch attacks. Recall that, the attack goal of the malicious client is $\max s^T(\omega - \omega')$, i.e., to poison the model by generating updates that are in the opposite direction of the global model update.

First, one aims to find the optimal threshold hyperparameters in the proposed client selection strategy. Thus, we explore the impact of different threshold values on the performance of the system, especially the data augmentation methods, which increase the diversity of client data.

Second, we explore the impact of different aggregation methods on the performance of the FL system and SSFL system. From the experimental results, the performance of the scheme using the GMA method is better than the benchmark schemes using FedAvg and FedSGD. There are two reasons why GMA is better than the benchmark methods: (1) FL and SSFL systems use stochastic gradient descent method to optimize, but the variance of stochastic gradient descent will introduce update noise to harm the performance of the system. (2) The GMA method can alleviate the adverse effects of update noise caused by stochastic gradient descent. In particular, we design an optimization-based client selection strategy before GMA aggregation, which helps the system select clients with high-quality updates.

### 5.3 System Robustness

We explore the robustness of the proposed system against two typical poisoning attacks (i.e., label-flipping attacks and Gaussian attacks) on the MNIST and CIFAR-10 datasets. As shown in Table 3, for the MNIST and CIFAR-10 datasets, the proposed system is comparable to FL. Although the proposed SSFL system does not hold a labeled dataset on the client side, we use the pseudo-labeling methods and data augmentation methods to improve the performance of the system, especially the data augmentation methods, which increase the diversity of client data.

Table 4: The impact of different quantization levels on the update size of the model.

| Model       | Quantification Level | Size of Model Updates |
|-------------|----------------------|-----------------------|
| CNN         | 32-bit               | 0.083 M               |
|             | 16-bit               | 0.0415 M              |
|             | 8-bit                | 0.021 M               |
| AlexNet     | 32-bit               | 1.25 M                |
|             | 16-bit               | 0.625 M               |
|             | 8-bit                | 0.3215 M              |
MNIST dataset, the system performance is the best when $\delta = 0.90$; for the CIFAR-10 dataset, the system performance is the best when $\delta = 0.85$. This is because the model updates generated on different datasets are different, so one needs to set different thresholds for different datasets.

Second, we evaluate the performance of the proposed system against label-flipping attacks on the MNIST and CIFAR-10 datasets. In Fig. 4(a) and Fig. 4(b), we show the performance comparison between the SSFL system with the client selection scheme and the SSL system without the client selection scheme on the i.i.d and non-i.i.d MNIST datasets. Specifically, the SSL system without our client selection scheme is affected by the label-flipping attacks and becomes unstable or even unable to converge in non-i.i.d scenarios. On the contrary, the SSL system with our client selection scheme mitigates the adverse effects of such malicious attacks by selecting clients with high-quality updates. In the client selection strategy we designed, the server selects the honest clients by comparing the cosine similarity and distribution similarity between the clients’ updates and its own updates, which prevents malicious clients from participating in SSL training. For i.i.d and non-i.i.d CIFAR-10 datasets, we can also find in Fig. 4(c) and Fig. 4(d) that the proposed client selection strategy can defend against such data poisoning attacks while maintaining good performance.

Third, we evaluate the performance of the proposed system against Gaussian attacks on the MNIST and CIFAR-10 datasets. In this attack, malicious clients will collude with each other to launch a model poisoning attack. Specifically, these malicious clients obtain the global model $\omega_{t-1}$ for the $t$-th round of training, and then collude with each other to use the updated mean of the honest clients as the mean of the Gaussian attack, i.e., $\frac{1}{m-1} \sum_{c=1}^{m} \omega_{t-1}$ to poison the global model. We show the accuracy evaluation results on the i.i.d and non-i.i.d of the MNIST dataset in Fig. 5(a) and Fig. 5(b), which demonstrate that the designed client selection strategy can help the system maintain accuracy and convergence in the presence of Gaussian attacks. We can find the same results in Fig. 5(c) and Fig. 5(d). On the other hand, from the experimental results, Gaussian attacks (i.e., model poisoning attacks) have a stronger ability to poison the global model than label-flipping attacks (i.e., data poisoning attacks). Although we have a client selection strategy to mitigate these model poisoning attacks, the training process of the system is not stable. The reason is that the model poisoning attack provides a poisoned update that obeys the Gaussian distribution to poison the model update and the attackers can collude with each other to enhance the effect of the attack.

### 5.4 System Communication Efficiency

In this section, we explore the influence of the quantization level in the symmetric quantization method we designed on the communication efficiency and performance of the system. We set the quantization level $r \in \{32\text{-}bit, 16\text{-}bit, 8\text{-}bit\}$ in which $r = 32\text{-}bit$ as baseline method. We use the CNN and AlexNet models as the local models of the MNIST and AlexNet datasets, respectively.

First, we summarize the relationship between different quantization levels and the size of the corresponding model updates. As shown in Table 4, we find that $\frac{1}{r}$ is the size of model updates. In this way, we reduce the communication overhead by reducing the size of model updates for each round of client-server interaction. In Fig. 6, the experimental results show that the convergence speed of the system using the symmetric quantization scheme (i.e., $r \in \{16\text{-}bit, 8\text{-}bit\}$) is close to that of the system without the symmetric quantization scheme (i.e., $r = 32\text{-}bit$). For example, for the MNIST non-i.i.d dataset, both the 8-bit quantization scheme and the benchmark scheme reached convergence in the 200-th round of training. Furthermore, when $r = 8\text{-}bit$, each round of system training can reduce communication overhead by $\frac{1}{4}$.

Second, we evaluate the performance of the system using the symmetric quantization scheme on the i.i.d and non-i.i.d settings of the MNIST and CIFAR-10 datasets. We show the accuracy evaluation result in Fig. 6, which demonstrates that the symmetric quantization scheme we designed will not affect the performance and convergence of the system. Therefore, the symmetric quantization scheme can only increase the communication efficiency by $2x \sim 4x$, but also maintain the performance of the system.

### 6 Conclusion

In this paper, we present a system design for semi-supervised federated learning, which is robust to two typical poisoning attacks and improves communication efficiency by $2x \sim 4x$. First, our system introduces the pseudo-labeling methods in the semi-supervised learning community to implement a more practical SSL system. Second, our system designs a minimax optimization-based client selection strategy to use cosine similarity and Wasserstein distance to select clients with high-quality updates, thereby removing malicious clients with low-quality updates to defend against poisoning attacks. Third, to improve our system’s communication efficiency, our system designs a asymmetric quantization method for compressing individual model updates and introduces the MMD distance to find the best gradient clipping threshold. We conduct an extensive evaluation of popular benchmark datasets, and the results validate the practical performance of our system. Specifically, experimental results show that the performance of the designed SSL system is comparable to the FL system. Besides, our system is robust to poisoning attacks under i.i.d and non-i.i.d settings.

### REFERENCES

[1] Jonas Adler and Sebastian Lunz. 2018. Banach wasserstein gan. In Advances in Neural Information Processing Systems. 6754–6763.
[2] Naman Agarwal, Ananda Theertha Suresh, Felix Xinnan X Yu, Sanjiv Kumar, and Brendan McMahan. 2018. qsgd: Communication-efficient and differentially-private distributed sgd. In Advances in Neural Information Processing Systems. 7564–7575.
[3] Dan Alistarh, Denjus Gruhic, Jerry Li, Ryota Tomioka, and Milan Vojnovic. 2017. QSGD: Communication-efficient SGD via gradient quantization and encoding. In Advances in Neural Information Processing Systems. 1709–1720.
[4] Dan Alistarh, Torsten Hoefler, Mikael Johansson, Niko Konstantinov, Sarit Khurmat, and Cédric Renggli. 2018. The convergence of sparsiﬁed gradient methods. In Advances in Neural Information Processing Systems. 5973–5983.
[5] F. Ang, L. Chen, N. Zhao, Y. Chen, W. Wang, and F. R. Yu. 2020. Robust Federated Learning With Noisy Communication. IEEE Transactions on Communications. 68 (2020), 3452–3464.
[6] Yoshinori Aono, Takuya Hayashi, Lihua Wang, Shihou Moriai, et al. 2017. Privacy-preserving deep learning via additively homomorphic encryption. IEEE Transactions on Information Forensics and Security. 12 (2017), 1333–1345.
[7] Eric Azaiez, Diego Ortego, Paul Albert, Noel E.O’Connor, and Kevin McGuinness. 2020. Pseudo-labeling and conﬁrmation bias in deep semi-supervised learning. In 2020 International Joint Conference on Neural Networks (IJCNN). IEEE, 1–8.
[8] Martin Arjovsky, Soumith Chintala, and Léon Bottou. 2017. Wasserstein gan. arXiv preprint arXiv:1701.07875 (2017).
