DemoFL: Democratic Federated Learning Based on Multi-party Computation and Consensus Algorithm

Zhaoyang Han, Chunpeng Ge, Zhe Liu*, and Chuan Ma

***Abstract*—Federated Learning (FL) is a framework based on which numerous parties can train a machine learning model cooperatively without leaking their training data. However, attackers can reconstruct FL parties' data through the information leaked when the model is trained. Therefore, the privacy problem in FL is critical. Current precautionary measures in FL rely on the parties to establish a secure channel between each other, which leads to a heavy communication overhead. Moreover, establishing ample secure channels between parties in FL may be unrealistic in some scenarios.**

In this paper, we propose Democratic Federated Learning (DemoFL), which is a privacy-preserving FL framework based on secure multi-party computation (MPC) and simplified consensus algorithms. Our method adopts secret sharing techniques to hide local model parameters and runs a consensus algorithm to ensure that the communication is reliable and the system is robust. DemoFL utilizes a hierarchical structure to reduce the time complexity of set-up from $O(n^2)$ to approximatively $O(n)$, and realizes high security and robustness without reducing accuracy. We also conduct performance evaluations to demonstrate the practicality and efficiency of our proposed framework.

***Index Terms*—Federated Learning, Secure Aggregation, Machine Learning, Multi-party Computation, Consensus algorithm**

I. Introduction

Mobile devices in daily life are equipped with increasingly powerful computing and storage abilities, which enables individual devices to accumulate enormous valuable information. It facilitates a huge number of rising technologies such as edge computing and smart home. Meanwhile, the accumulated data in users' devices can be used to train models for various practical purposes due to the flourishing of machine learning. In traditional machine learning frameworks, data needs to be gathered into a central server in order to execute the learning process. As most data collected by mobile devices is sensitive, users may refuse to send their private data to others, such as a learning center. This phenomenon impedes the development of distributed learning among common users.

Since the computing ability of mobile devices is powerful enough to run small-scale machine learning tasks, FL [1], which is a distributed machine learning framework, becomes possible. FL's main purpose is to address the privacy problem in learning tasks and it is developing rapidly with an increasing number of applications. For example, Google's keyboard query suggestions [2] project is an effective application of FL. It trains a model that can predict users' input precisely without uploading users' private data. Figure 1 illustrates the structure of FL. Parties receive a global model from the server and train their models based on their own data respectively. Afterwards, each party sends the parameters of their models to the server while the server runs a particular aggregation algorithm to compute the global model based on these parameters. In such frameworks, users do not need to send their data to the learning server, and thus the privacy of participants is to some extent protected.

Though FL can protect users' data, attackers can still eavesdrop on a party's parameter during the training process and then establish inference attacks [3], [4], [5] to reveal users' training data. Leaking these private data may cause severe consequences. We take a hospital's diagnostic model as an example. If the diagnostic model is compromised, the patients' private medical-related information will be exposed, and this could result in potentially serious consequences. Additionally, as the server is provided by an untrusted third party, the untrusted party can easily obtain all participants' parameters in the aggregation process and conduct attacks. It is because in the conventional FL framework [5], parameters are directly sent to the server, and this enables the server to gather all information easily. Therefore, sending parameters to the server directly faces the threat of inference attacks. This kind of attack is quite severe as it can be established by any malicious or untrusted participant in the FL process. Therefore, how to conduct joint learning without leaking parameters to others comes into focus.

To tackle the privacy problem in FL, researchers proposed numerous secure aggregation protocols [6], [7], [8], [9], [10] based on cryptography or other techniques. These protocols enable a group of parties with private information to compute a function of these private data without revealing them. Therefore, employing secure aggregation in FL can help to protect models' intermediate parameters from being known by others. However, current solutions still have some shortcomings and deficiencies. A trivial solution is to employ homomorphic encryption (HE) to implement secure aggregation, Shi *et al*. [6] utilized HE methods to achieve secure addition in FL. With the data encrypted, attackers cannot obtain any useful information from leaked messages. However, HE algorithms suffer from low efficiency which is hardly acceptable in FL [11]. Another feasible approach to implement secure aggregation is Differential Privacy (DP). DP-based frameworks add noises to the parameters in order to deceive the attackers. The problem

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is that these noises also have an influence on the learning result [12], therefore, there remains a trade-off problem between the performance and security levels for DP methods in FL. What's more, the effects of DP-based methods are barely satisfactory [13]. Blockchain-based methods [14], [15], [16] are also promising and provide high security, yet blockchain-based methods are still inefficient and implement-unfriendly so far.

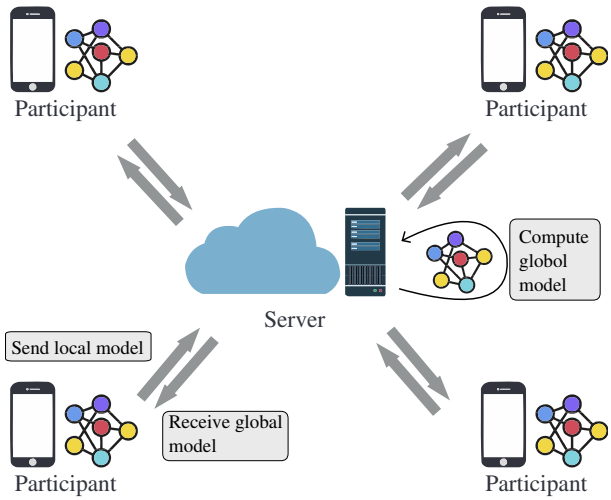


Fig. 1. The structure of FL. Participants train local models respectively and send their parameters to the server for aggregation. The server compute the new global model based on received parameters and sends it to participants. This process usually will be repeated numerous times.

One may think that the multi-party computation (MPC) [17] technique can be leveraged to implement secure aggregation directly. However, most MPC protocols rely on the prerequisite that all participants are able to communicate with each other privately. In practice, participants of an FL task are unknown to each other, which means one party cannot communicate with another directly. Moreover, it is more unpractical to expect there are secure channels between these participants. This is a severe obstacle that prevents implementing MPC in FL. Bonawitz *et al*. [18] utilized Diffie-Hellman key exchange to generate pairwise secret masks, however, this method has a dissatisfactory efficiency. The high communication overhead within MPC demands a prompt solution. A recent work [19] also analyzed the MPC process in FL and tried to reduce the overheads by introducing a scheme named "aggregation committee", yet this method still has a high price on set-up. In addition, Bonawitz's work also pointed out that the robustness of FL frameworks is also significant because most MPC protocols will fail if there are some participants dropping out, and it usually costs a lot to recover from situations where several nodes are dropping out or crashed. In practice, mobile devices' communications are usually not stable enough, therefore, breakdowns and delays take place quite frequently. In summary, employing traditional MPC methods in a system with a large number of users is faced with a problem with efficiency and instability.

A. Motivation

Prior works suffer from low efficiency, reducing accuracy, or complex structures. Therefore, a secure, efficient, and implement-friendly FL framework is desired. We aim to design an FL framework that:

1) protects users' privacy by employing cryptography techniques while solving the problem that participants are unknown to each other.
2) has a low communication overhead, avoiding constructing overmuch pairwise connections.
3) is secure under semi-honest environments, where all users and the server may eavesdrop on information.
4) has high robustness with the capability to handle emergencies where several participants may lose connection.
5) has no negative influence on the quality of the trained model.

B. Our contribution

1) We propose Democratic Federated Learning (DemoFL), a novel FL framework that protects users' privacy with very low overhead. DemoFL employs a smart additive secret sharing protocol to realize MPC, which helps to hide intermediate parameters.
2) We utilize a hierarchical structure design in DemoFL to reduce the communication demands and improve efficiency. It has a low time complexity as $O(n)$.
3) We design a consensus scheme to achieve "democracy" and high robustness. The consensus scheme helps to handle unexpected situations where a leader node or a common user is crashed. It selects leaders from all clients democratically and rapidly when such situations happen.
4) We conduct a series of experiments and verified that DemoFL has satisfactory efficiency and robustness without reducing accuracy.

C. Roadmap

In Section II we introduce the background and some definitions. Next, we introduce related work and some platforms of FL in Section III. Section IV detailedly illustrates our proposed framework including the attack model. Evaluations for efficiency and security are stated in Section V, followed with experimental results in Section VI. Finally, we give the conclusion and future expectations in Section VII.

II. Background

In this section, we introduce the concepts of key exchange, Federated Learning, multi-party computation, and consensus algorithms, which are used in our proposed framework.

A. Key Exchange

Key exchange protocols allow several parties to share secret keys under unsafe conditions. Diffie-Hellman [20] (DH) is a prestigious key exchange protocol. We introduce how DH protocol helps two parties to achieve agreement: suppose a

and b want to obtain a secret key by means of DH. First they select a group G of order q, and randomly choose a number x_a and x_b respectively. Then a calculates $g_a = g^{x_a}$, where g is a generator of G, and b calculates $g_b = g^{x_b}$. a sends g_a to b, and b sends g_b to a. Finally they can calculate the shared secret s_{ab} respectively:

$$s_{ab} = g_b^{x_a} = g_a^{x_b} = g^{x_a x_b}$$

In this scheme, only g_a and g_b are sent under an unsafe condition. Attackers cannot infer s_{ab} from g_a and g_b, therefore a and b can communicate privately by means of s_{ab}. DH is lightweight and efficient, and it can be expanded to multi-party versions easily in order to enable more parties to share pairwise keys.

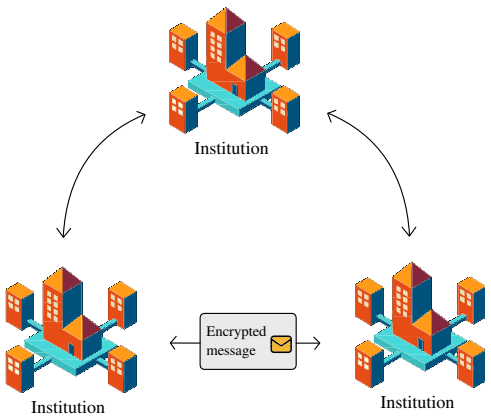
B. Federated Learning

FL enables a number of users to jointly train a model. In each round of FL, each user will train the model based on its data and get the model's parameter. Denote the i-th user's local parameter in the t-th round by W_i^t. When all users have trained their model in the t-th round, an aggregation algorithm Agg will be called to compute the global model's parameter $Agg(W_1^t, W_2^t, ..., W_n^t)$, where n is the total number of users. For example, weighted average was adopted as Agg in FedAvg [1]. FL not only helps to protect users' privacy but also deals with the "data in form of isolated islands" problem for companies or institutions. Yang *et al.* also categorized FL into horizontal, vertical, and hybrid styles based on the fact that whether the data shares the same feature space or entities [21].

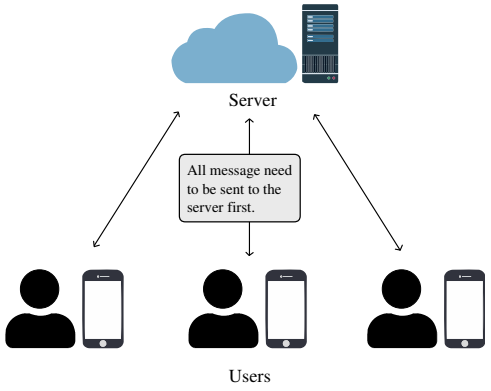
Federated Learning can be generalized to two work environments:

1) **Among-institutions:** In this situation, FL is usually used to help companies or other institutions solving the "Isolated Data Island" problem, where data of different institutions are with different distributions and even different categories of features. This is a severe problem in traditional machine learning, while FL can solve these kinds of problems by the well-designed aggregation algorithm.
   Generally, companies and institutions are responsible social individuals. Therefore, we can suppose Public Key Infrastructure (PKI) is already enabled, and one party can communicate with any other one privately, i.e., P2P communication is already enabled in this environment.
2) **Server-based:** In this case a company or institution aims to train a model based on their users' data while protecting their privacy. The communications of FL parties always need to go through the server. Under this situation, all information may be eavesdropped on by the server if it is untrusted.
   However, the users of an institution usually do not know each other. It means that two parties can hardly exchange information privately without the help of a server. Therefore, the confidence problem is severe in such environments.

Figure 2 illustrates the structures of two environments. Executing MPC protocols and consensus algorithms are at a low price in the first environment. In the second environment, if local parameters need to be protected, we need to run some key-exchange protocols first to construct secure channels among users. One of our contributions is that we solved the problem in the second environment by building connections selectively and efficiently.



(a) Among-institutions



(b) Server-based

Fig. 2. The structures of two work environments in FL. The first is the "Among-institutions" model where institutions can communicate with others directly, and the second is "Server-based" model where parties exchange information in virtue of the server.

C. Multi-party Computation

Secure MPC is a branch of cryptography which enables several parties to compute a particular function without leaking their own data (inputs). Suppose there are n parties employing MPC to compute a function F, and the i^{th} party has its parameter A_i. Their goal is to compute $R = F(A_1, A_2, ..., A_n)$. MPC has the feature that participants can only obtain R from the process and the party P_i has no idea about parameter $A_j (j \neq i)$. This feature fits the aggregation algorithm in FL greatly.

Most MPC protocols depend on two cryptography technologies: secret sharing [22] and oblivious transfer [23]. MPC can be implemented with garbled circuits, multi-party circuit-based protocols, or hybrid methods [24]. It also benefits from fully homomorphic encryption (FHE) algorithms. Garbled circuits

and FHE suffer from complicated design and poor efficiency. Therefore, secret sharing methods are more favored to solve the privacy-preserving problem in FL. A secret sharing scheme involves a secret s, a set of n parties, and a collection A of subsets of parties. Each party has its share of s. The secret sharing scheme ensures any subset in A can reconstruct s [25].

SPDZ [26] (speedz) is a practical and secure secret-sharing-based MPC protocol introduced by Damgard *et al*. It supports addition and multiplication by means of the triples [27], which are generated by somewhat homomorphic encryption (SHE). Our method does not require multiplication and hence we do not need to generate the triples. We adopt the resharing method used in SPDZ to achieve secure addition in DemoFL, which is essential in the aggregation phase of FL.

D. Consensus Algorithms

In a distributed or multi-party system, there is always a problem with consensus, i.e., in such systems parties always need to achieve agreement on a certain value. This could be difficult without any strategy because different parties may be in different statuses and have multifarious matters. Consensus algorithms are adopted to address such problems. It is widely used in blockchain and various famous areas.

Paxos was the first consensus algorithm introduced by Lamport [28]. It helps the nodes of a cluster to select several leaders democratically and reach a consensus with the help of these leaders. Paxos is used in a lot of famous projects such as Ceph [29]. Raft is a modification of Paxos which is more implement-friendly [30]. It contains two phases: leader election and log replication. Parties can achieve agreements based on leaders. Considering that FL models are semi-decentralized systems, our framework can utilize Raft algorithm to select several leaders, based on which MPC protocols can be executed efficiently and robustly.

III. Related Work

In this section, we introduce some prior works on addressing the privacy problems in FL together with some famous FL platforms.

HE based solutions are intuitively effective to solve aggregation problems, and there are many researchers tried to reduce the overhead caused by HE. Stephen *et al*. [31] designed an additively homomorphic encryption method for FL in 2017. However, the encryption method is too complicated that it does not reach high efficiency. The state-of-the-art HE method was proposed by Zhang and Li [32]. It reduced the encryption overhead greatly at the cost of trivial loss of accuracy. However, it still costs much time on computation compared to MPC based and DP based methods.

DP based solutions have better performance than HE based solutions. However, Wei *et al*. [33] has indicated that there is a trade-off between the performance and security levels, which means it needs numerous adjustments and tunning to adopt DP methods efficiently. Robin *et al*. [34] tested DP in FL in 2017 and the result showed that DP's influence on accuracy is untrivial. Following their work, Bayesian differential privacy [35] was proposed in 2019. Bayesian differential privacy considered the probability and distribution of data and is effective for machine learning models whose data are often restricted to a particular type. While it may be inefficient in vertical FL situations. Moreover, all these DP-based methods did not prove DP does not impact the accuracy in other more complicated and large-scale models, which means it is different to find a universal DP method for all machine learning models. Additionally, Bargav *et al*. [13] indicated that the guarantees of DP are essentially meaningless and DP implementations may provide unacceptable utility-privacy trade-offs in practice.

MPC based methods have the least computation cost but require more communications. A typical MPC FL model is implemented by Google [18]. It requires pairwise key exchange among all clients, which results in enormous overhead on communication. It also provides robustness by means of a mask mechanism with some random numbers. However, these mechanisms bring about more overhead. To overcome such problems, other researches present hybrid methods [36], [37]. These hybrid methods combine MPC with either HE or DP and adjust the trade-off between computation and communication. However, these hybrid methods are also unsatisfactory whether in efficiency or feasibility.

FL is becoming increasingly practical nowadays and there are already many FL platforms. FATE [38] is an open-source FL project proposed by Webank's AI Department. It adopts both MPC and HE to implement secure aggregation, while it is still absorbing state-of-the-art methods for privacy-preserving. Pysyft [39] is another open-source FL framework presented by OpenMined. It is based on Pytorch and offers HE, DP, and MPC as alternative methods to realize privacy-preserving. However, the cost of time of Pysyft is dozens of times than pure Pytorch, which indicates that privacy-preserving methods of current FL platforms need to be improved.

IV. Democratic Federated Learning

In this section, we introduce the attack model and the detailed design of the proposed framework Democratic Federated Learning. Figure 3 illustrates the overview of the proposed framework. At the very first, participants of DemoFL will elect several leaders, who will be responsible for forwarding information. Key exchange phase is followed after leaders are elected. Each participant will conduct key exchange protocol with all leaders in order that they can communicate privately. Then, participants start secure training phase, which is similar to other FL frameworks. The difference is that, in the aggregation process, participants will send their data pieces to leaders instead of the whole data to the server. Meanwhile, the consensus system is always monitoring the learning process, and it will take measures when incidents are detected. The detailed framework will be introduced later.

To make it easier to understand our subsequent description, some symbols that will be used are listed below:

- **N**: The total number of users in the FL system, and the i-th party is marked as P_i.
- **S**: The server, which is the host of federated learning and helps other users to forward messages.

- **frac**: The fraction of users that will participate in the learning process each round.
- **n**: The number of users that will be chosen to train the model in each epoch. $n = N * frac$.
- $\mathbf{N}_l$: Number of leaders selected from all N users.
- **L**: The set of leaders. $L = L_i$.
- **W**: The parameters of a machine learning model. W_i means the i-th party's local parameter, and W_{global} is the global model's parameter.
- **C**: The total number of training data. $C = \sum_{i=1}^{n} C_i$, where C_i is the number of training data of the i-th party P_i.

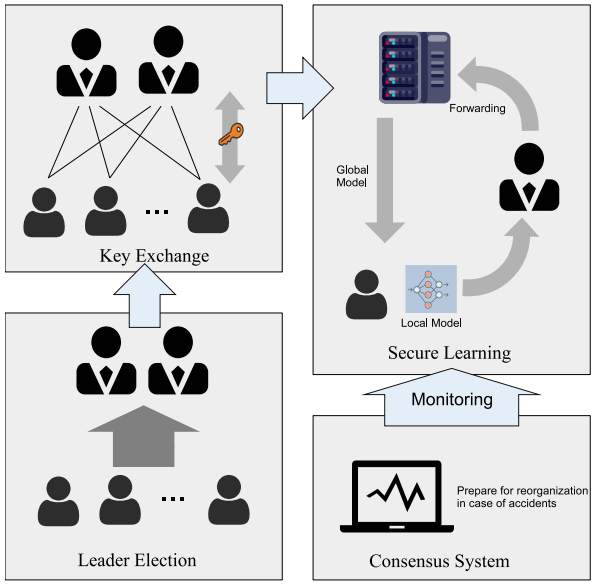


Fig. 3. The overview of DemoFL. It contains 4 modules: leader election, key exchange, secure learning and reorganization. Secure learning process is a loop, and it usually happens a number of times.

Our framework uses the same aggregation scheme as FedAvg, which computes the weighted average of local parameters as the global parameter. In epoch $t+1$, the server's target is to compute the following formula:

$$W_{\text{global}}^{t+1} = \sum_{i=1}^{n} \frac{C_i}{C} W_i^t \tag{1}$$

Although some works protect C_i from semi-honest attackers by means of multi-party multiplication [40], leakage of C_i does not help attackers to reconstruct any data. In addition, C can also be aggregated based on multi-party addition since it only needs addition to compute C from all the components $C_i, i \in [1, n]$. Thus, we can introduce $G_i = C_i * W_i$ to simplify the expression and computation, i.e., multi-party multiplication is unnecessary in this framework. Then the goal of each epoch is adjusted to:

$$W_{\text{global}}^{t+1} = \frac{\sum_{i=1}^{n} G_i^t}{C} \tag{2}$$

So far, we modeled the FedAvg algorithm to a form where only secure multi-party addition is needed to enable privacy-preserving. When the server obtains C and the sum of G_i by means of multi-party addition, it is able to compute W_{global} locally. However, in DemoFL, the server can only receive sums of some users' G_i instead of one particular user's single one because of the leader regime, which enhanced the security.

A. Attack Model

In our settings, an attacker can be either a participant or the server, and we assume the attackers are **honest-but-curious** (or semi-honest) [41]. An honest-but-curious attacker gathers the information it receives instead of deviating from protocols. The attackers may establish several types of attacks:

- **Membership inference attack**: With this attack, the attack's purpose is to reconstruct a user's data based on the information he can eavesdrop on, such as the victim's local parameter [42].
- **Model extraction attack**: The attacker attempts to a model similar to the one trained from FL as possible. Apparently, the local parameters are extremely helpful to the attackers [43].
- **Model inversion attack**: This kind of attack uses some APIs provided by the machine learning system to obtain some preliminary information, based on which attackers try to reverse the model in order to obtain some private data [44].

All these attacks can exploit the local parameters which have a high probability of being eavesdropped by the attacker. If the attacker is the server, we can suppose all the communications are monitored by it. We also assume that there can be collusions among attackers, however, they do not have the authority and ability to cheat on some processes such as the election.

B. Framework Design

We take the server-based situation for example. DemoFL consists of four processes: **leader election**, **key exchange**, **secure learning** and **reorganization**. In the leader election phase, the participants elect several leaders who will gather incomplete information in MPC protocols. In the key exchange phase, all participants build secure channels with the elected leaders, based on which a participant can privately communicate with leaders without leaking any information to the server. In the secure learning process, the whole system executes MPC enabled federated learning. The reorganization process is activated when a node is crashed. And, if crashes of nodes are detected, the reorganization process will generate a new leader as the replacement. The four processes are elaborated as follows:

*1) **Leader election**:* A server-based federated learning system is different from other multi-party systems such as blockchains, where users are equal. Therefore, consensus algorithms can be adjusted more compatible with federated learning models. Our consensus algorithm adopted two prominent features of Raft: "heartbeat" and "self-recommendation". "Self-recommendation" is the key to "democracy". At the very first, every participant sends the "self-recommendation" message to the server, and the first N_l messages to arrive will

be chosen as leaders. To address the inequities caused by the network differences, each party will wait for a short random time before it sends a "self-recommendation" message. This short random time does not need to be long to protect democracy, and it can be set within 5 seconds.

When all N_l leaders have been picked out, the server generates a set L consisting of the identifiers of leaders. Then it sends L to all participants who will participate in the federated learning process. Those participants who are not leaders are called **common users** or **common clients**. Afterward, Key exchange protocols will be executed to construct secure channels between common participants and leaders. Note that the secure channels will be constructed between leaders with all N participants instead of n participants.

The technique of "heartbeat" is used permanently to detect whether a leader is active: we set an interval t_h. The server will send a "heartbeat" to all leaders every t_h passed. If the server does not receive the response in time, it can determine that the leader is crashed and start the reorganization process.

To provide higher security, "leader-tenure" is adopted. I.e., the system will revoke one's leadership regularly, and randomly select another common party as the new leader. This method can prevent collusion attacks when the server selects leaders dishonestly. Details will be discussed later in Section IV.

In the among-institutions environment, the election process is different because there is not a server helping to forward information about leaders. Therefore, the leader election process is more Raft-like: first, the parties act as candidates and send "self-recommendation" to the others with different delays. Then, a party will vote for the first N_l parties that sent it "self-recommendation". The N_l parties with the most votes become leaders. The detailed algorithm can be referred to as Raft algorithm [30].

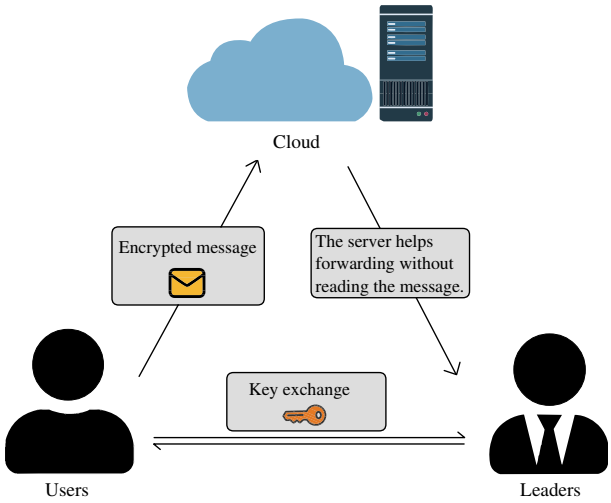


Fig. 4. The institution can communicate with all users directly while all the leader-user pair share a secret key used for private communication. The server helps to forward encrypted messages from which it can know nothing.

*2) **Key exchange**:* When the parties receive L, they will know who the leaders are. In order to communicate with the leaders privately, the parties need to run key-exchange protocols to share secret keys. We employ Diffie-Hellman protocol [20] to realize it.

In a server-based environment, a server can communicate with any clients while the parties are unfamiliar with each other. Therefore, the key exchange process should be conducted in virtue of the server. In the premise that the server is honest-but-curious, parties can exchange keys in a "man-in-the-middle" scheme, where the "man" is the honest server. The server delivers information for users to help them complete DH protocol. This process is secure because information leaked to the server in key-exchange protocols is useless.

After the key exchange process, each party-leader pair, a party P_i with a leader L_j will share a secret key K_{ij}. By means of K_{ij} the party P_i and leader L_j can encrypt their data against the honest-but-curious attacker. The message m can be encrypted as $Enc_{K_{ij}}(m)$. Figure 4 illustrates the institution-leader-user structure. Normally, the institution and the common users only need to communicate with the leaders.

*3) **Secure learning**:* The aggregation algorithm is the same as FedAvg [1]. A secure multi-party addition protocol is used to realize privacy-preserving. There are N_l leaders in the system. Without loss of generality, we suppose $N_l = 3$. The flow chart of secure learning process is shown in Figure 5 and the process is illustrated as below:

1) All the selected parties train the model locally. And a party P_i will get a parameter G_i.
2) Each G_i is divided into 3 pieces G_i^1, G_i^2 and G_i^3, where $G_i = G_i^1 + G_i^2 + G_i^3$. Then G_i^j is sent to the j-th leader L_j respectively.
3) A leader L_j will record a set B_j, which consists of the parties that have sent messages to L_j. When all the parties' parameters are sent or time is up, the leaders will send all B_j to the server and the server will compute the intersection as B. Then B is sent back to all leaders. Each leader reserve parameter shares according to B in case that some parties did not send parameter pieces to all leaders successfully. Parties not included in the intersection are then removed.
4) Leader L_j then computes the sum of the parameters:
$$A_j = \sum_{i=1}^{n} G_i^j \tag{3}$$
Afterwards, A_j will be sent to the server.
5) The server computes:
$$W_{\text{global}} = \frac{A_1 + A_2 + A_3}{C} = \frac{\sum_{i=1}^{n} G_i}{C} \tag{4}$$
and it is the target of FedAvg algorithm. W_{global} is used to update the global model and the server will prepare for the next learning round.

C can be obtained in the same manner: replace G_i with C_i and the server can get C privately. In fact, C_i and G_i are sent to leaders at the same time. Alternatively, each C_i can also be directly sent to the server without encryption since it does not help attackers understanding the parameters. When the system decides to discard a party P_i due to B, it also needs to discard C_i, which will change the amount of training data C.

The pseudocode of secure learning is illustrated in Algorithm IV-B3. Neither the server nor any leader can figure out what exactly a certain party's parameter is based on the information it can receive.

Algorithm 1 Secure Learning Algorithm

Require: G_i, L, K_i (the set of secret keys for party P_i), E_{max} (the maximum epoch for federated learning)

function SPLIT_PARAMETER(G_i)
  $r \leftarrow \text{RANDOM}(0, 0.5)$
  $G_i^1 \leftarrow G_i * r$
  $r \leftarrow \text{RANDOM}(0, 1 - r)$
  $G_i^2 \leftarrow G_i * r$
  $G_i^3 \leftarrow G_i - G_i^1 - G_i^2$
  return G_i^1, G_i^2, G_i^3
end function

function PARTY_SEND(G_i, L, K_i)
  $G_i^1, G_i^2, G_i^3 \leftarrow$ SPLIT_PARAMETER(G_i)
  for $j \in$ indexes of L **do**
    $E_{ij} \leftarrow \text{ENC}(K_{ij}, G_i^j)$
    if Sends E_{ij} to L_j not successfully **then**
      Report "L_j is crashed" to S
    end if
  end for
end function

function LEADER_SEND(K_j)
  $B_j \leftarrow \emptyset$
  Receive E_{ij}s from all possible P_i and add i to B_j
  Send B_j to S
  Receive B from S
  Remove E_{ij}s whose i is not included in B
  $G_i^j \leftarrow \text{DEC}(K_{ij}, E_{ij})$ for each E_{ij}
  $A_j \leftarrow \sum_{i=1}^{n} G_i^j$
  Sends A_j to S
end function

function SERVER_AGGREGATION(e)
  if $e \geq E_{max}$ **then**
    return $True$
  end if
  Receive A_js from leaders
  $W_{\text{global}} \leftarrow \frac{A_1 + A_2 + A_3}{C}$
  UPDATE($Model_{global}, W_{\text{global}}$)
  // Next epoch
  Select n users to participate in the next epoch
  Send W_{global} to these n users
  return SERVER_AGGREGATION(e+1)
end function

*4) **Reorganization**:* The reorganization process provides the robustness for the framework. Normally, the server will notice a leader's crash within a heartbeat cycle. Meanwhile, a party will report to the server if it finds a leader is crashed. After noticing a leader is crashed, the server sends "pause" signals to all users, which will pause the learning processes. Then all users will perform an election campaign according to the consensus algorithm: they send "self-recommendation" signals to the server. The server will receive numerous signals and the first one to arrive will be chosen as the new leader. L will be updated and sent to all common users. Finally, the learning process will be restarted.

C. Among-institutions Model

Since secure P2P communication is already constructed, the key exchange process is removed in this situation. In addition, consensus algorithms can be executed naturally in such an environment as it is in a decentralized system where users are equal. Therefore, leaders are elected by voting as the original Raft does. The leader-tenure and reorganization processes also vote for new leaders instead of getting leaders from a server.

V. Efficiency and Security Evaluation

A. Communications

As illustrated in Section III, our framework only adopts lightweight algorithms to enhance security. Therefore, the execution overhead can be ignored compared to the communication overhead. Notice that any communication in our framework goes through the server. E.g., if P_i wants to send encrypted message c to L_j, c will be sent to server S first. Afterwards S will forward c to L_j. In general, our P2P communications are emulated with client/server communications. This method accelerates communication greatly because it costs much for two strangers to exchange messages directly. E.g., if two users want to communicate directly, both of them need to store the addresses, confirm the "accept" signal after each message-exchange, *et al*. However, with a powerful server helping to forward, these things are no longer concerns for users.

In each round, there are n common users and N_l leaders. To analyze the communication overhead clearly and without loss of generality, we can suppose there is no common user that is also a leader at the same time. Common users, leaders together with the server S are all users requiring communication. Generally, N_l is a very small number such as 3, therefore we can treat it as a constant number. Our framework can be categorized into **set-up** and **secure-learning** two phases. We analyze these two phases respectively:

- **Set-up:** First, all n users will send "self-recommendation" messages to decide who the leaders are, then $n - N_l$ common users need to construct secure channels with all N_l leaders. Afterwards, the server will send L to all n users. Suppose it needs D communications in each DH protocol, then the amount of communications of the set-up phase is $n + n + D * (n - N_l) * N_l$. The time complexity is $O(n)$ based on the fact that D and N_l are small constant numbers.
  In the reorganization process, $n - N_l$ common users will send "self-recommendation" messages to decide a new leader. The new leader then conducts DH protocols with all $n - N_l - 1$ users, which is $D * (n - N_l - 1)$ communications. Therefore, a reorganization process also costs $O(n)$ communications.

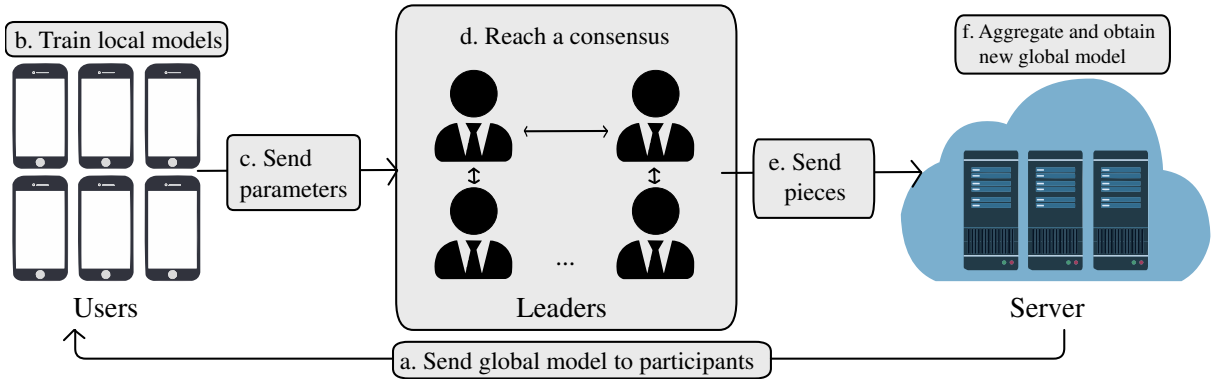


Fig. 5. The flow chart of the secure learning process. It is based on the fact that common users have already constructed secure communication channels with leaders. Note that a participant can be a leader and a common user at the same time, and the averaging was already done by leaders, therefore, the server only needs to summarize the global parameter pieces. After step f, the process will enter the next epoch and restart from step a if the current epoch has not reached the $epoch_{max}$.

- **Secure-learning:** In each epoch, S sends the current W_{global} to n users, which cost n communications. Then each common user sends W_{ij} to N_l leaders respectively, which cost $n * N_l$ communications. Afterwards, each leader sends B_j to the server and waits for the intersecion, which cost $2 * N_l$ communications. Finally leaders send Aj to S, which cost N_l communications. Thus the total cost of one epoch is $n + n * N_l + 3 * N_l$, which is $O(n)$.

In the time complexity aspect, our framework does not result in higher overhead expect for an $O(n)$ preprocessing compared to the original FedAvg algorithm. In the vertical aspect, our framework does not require more message-exchanges for any party-leader pair.

B. Security Evaluation

The evaluation is based on the fact that our adversaries are all honest-but-curious. Since our framework is based on MPC researches, the proof of security against message-leakage can be referred [22], [45], [46]. And the security of using MPC in FL has been proved by Zhu *et al.* [40] The riskiest threat is the collusion attack. Colluding with a common party has no contribution to an attack because it lets out nothing but the information about this common party, which belongs to the attacker side. Therefore, we only discuss collusions among the server and leaders.

Apparently, the attacker must collude with all leaders in order to reconstruct one party's parameter. Since the leaders are assigned randomly based on the consensus algorithm, it is hardly possible for all attackers to be insincere at the same time. However, it is necessary to discuss the situation where the server cheats to select leaders as its wish by other means such as slowing down the sincere users' network. In such situations, the leaders are always selected by the unreliable server. To address this problem, we introduced "leader-tenure" in Section III, which forces the system to change leaders regularly. Since it needs all leaders' betrayal to attack successfully, the system only needs to change one leader regularly. Changing one leader is equivalent to a reorganization process, whose time cost is $O(n)$. Therefore, our framework has high security against collusive honest-but-curious attackers.

VI. Experimental Results

A. Implementation

Our framework is implemented with Pytorch. We used AES-CFB-128 as the authenticated encryption algorithm as Bonawitz *et al.* did [18]. We adopted MNIST and CIFAR-10 as datasets, which are also used in the original FedAvg [1]. We trained a simple convolutional neural network for the classification task. Our experiments are carried on a PC with an Intel i7-8700 CPU (3.2GHz), 16 GB of RAM, and a GTX 1080 GPU. The model was executed in a single thread to facilitate comparing and analysis. The optimizer was stochastic gradient descent (SGD) and the learning rate is 0.01. The $fraction$ is set as 0.1 which means that 10% of clients will be chosen to carry on the training process in each epoch.

B. Accuracy

Although our work does not modify the learning module compared to other federated learning frameworks, we still conducted a series of experiments to observe the accuracy. We compared FedAvg with our framework on both independently identically distribution (IID) data and non-IID data to verify the effectivity. Since this experiment aims to prove validity instead of high accuracy, the models were not trained to obtain high accuracy. We conducted experiments with MNIST in non-IID and CIFAR-10 in IID, and Figure 6 shows the result. With IID data, our framework obtains a similar performance compared with FedAvg. With non-IID data, the two systems did not match as well as they were with IID data when the $epoch$ was small. However, they finally converged to the same stable scope with the same speed, which confirmed the differences were caused by biases. Therefore, our framework can achieve the same learning goal as FedAvg while providing privacy guarantees and system robustness.

C. Set-up Overhead

In the set-up phase, our system selects several clients as leaders, and the number of leaders impacts the efficiency and a particular leader's load because a common user needs to build secure communication channels with all leaders. To

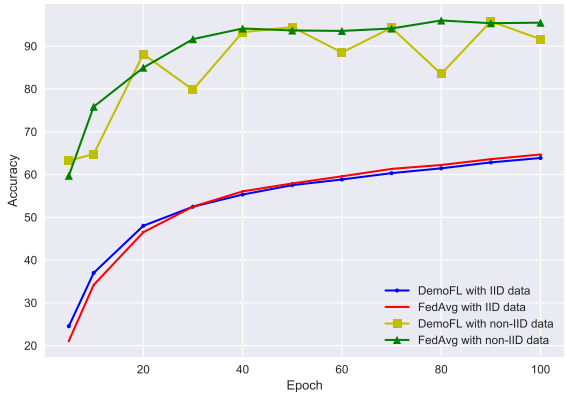


Fig. 6. The accuracy of FedAvg [1] and DemoFL with IID data from CIFAR-10, and non-IID data from MNIST. The horizontal axis *epoch* means the total rounds that the federated learning system has been trained for.

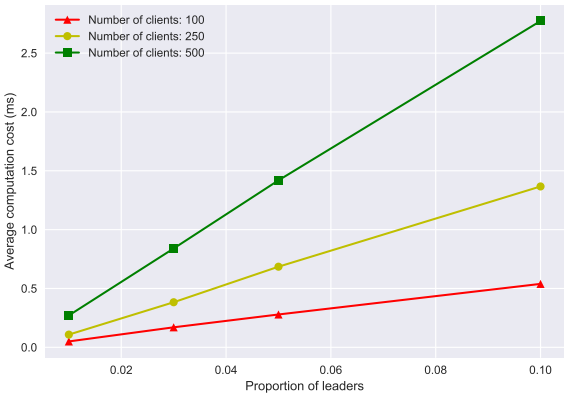


Fig. 7. The average time spent on computation in set-up process DemoFL VS different proportions of leaders.

discover the relation between the number of leaders and the computation overhead, we set the number of clients on different levels and conducted experiments with different numbers of leaders. Figure 7 shows the linear relationship between each user's computation time spent on Diffie Hellman key-exchange protocol and the number of leaders. The overhead of time in the set-up process is also very low because DemoFL has no complex calculations as Bonawitz *et al*. [18]'s secure aggregation scheme does. In Bonawitz's scheme, participants need to calculate secret keys for all other users and generate t-out-of-n secret shares for the pseudorandom generator (PRG) seed and their secret keys. The comparison is illustrated in Figure 8. Since Bonawitz's scheme has a time complexity of $O(n^2)$, the computation overhead of it is much higher than DemoFL. Method of Kanagavelu *et al*. [19] performs the same as Bonawitz's scheme because they also have an $O(n^2)$ set-up. Therefore, employing fewer leaders can help to improve efficiency, and in contrast, employing more leaders can are beneficial to security because a successful attack requires all leaders compromised.

Meanwhile, with more leaders, one common user needs to store more keys for leaders. Apparently, the relationship between the number of leaders and one user's storage overhead is also linear. However, in Bonawitz's scheme, a client needs to storge two t-out-of-n secret shares for all others. The storage complexity of DemoFL and Bonawitz's scheme is $O(N_l)$ and $O(n)$ respectively, where $N_l \ll n$. Therefore, DemoFL has a very trivial set-up overhead on both time and storage, which is friendly to individual participants such as smartphones.

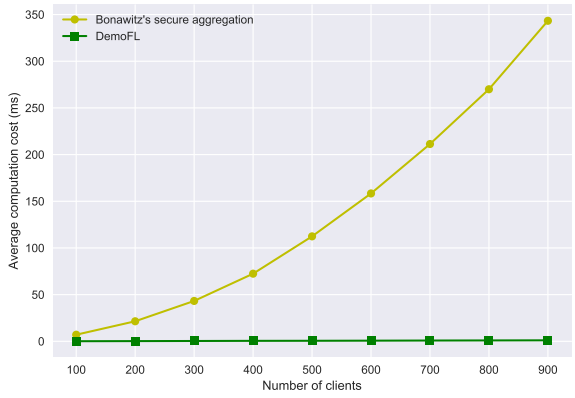


Fig. 8. The average time spent on computation in set-up process of Bonawitz's secure aggregation [18] and DemoFL VS the number of clients. The proportion of leaders is set to 3%.

D. *Efficiency*

Our framework primarily addresses the server-based situation, where a participant's computing capability is far weaker than the server. And for the server, the overhead of computations such as MPC is insignificant compared to the communication overhead because of its powerful computing capability. Therefore, we carried out experiments to evaluate the computation overheads for participants only, and communication overheads for both participants and servers in DemoFL and Bonawitz's secure aggregation scheme. Experiments in this subsection are with the assumption that there are no dropouts or crashes.

To evaluate the computation overheads, we fixed the number of clients to 100 and the proportion of leaders to 3 and tested the average running time of a single participant. In DemoFL, participants are divided into two categories: common users and leaders, and a participant can hold both identities at the same time. While in Bonawitz's secure aggregation scheme, all users are treated equally. The result is displayed in Figure 9. It suggests that participants of DemoFL have obvious advantages on computation overhead. The reason is that participants of Bonawitz's secure aggregation scheme need to carry out more encryptions/decryptions for unmasking.

Measuring the communication overheads with wall clock time is difficult because it has biases large enough to mislead the judgment. Therefore, we evaluate the communication overhead with the number of communications. We conducted experiments to count up the communications and tried to

compare the overheads of DemoFL and Bonawitz's secure aggregation scheme. Since there are no dropouts or crashes, the number of communications in each epoch is fixed. Therefore, we computed the ratio of overheads of Bonawitz's secure aggregation scheme and DemoFL with the number of clients set as 100 and the number of leaders as 3, and the result is 1.184. And if the number of leaders gets larger, this ratio will decrease towards 1. Since the number of leaders will never be set too large, the communication overhead of DemoFL is advantageous.

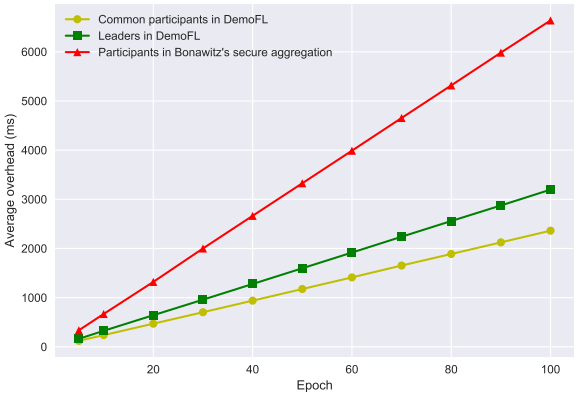


Fig. 9. The average running time per participant in the learning process VS epoch. Without dropouts and reorganization processes.

E. Robustness

1) Crash: The robustness of DemoFL is mainly based on the reorganizing process, which happens when a leader is crashed. We discuss crashes for leaders because a crash of a common user is equivalent to a dropout. Crashes can hardly be completely avoided, therefore, we introduced $crash\_rate$, which is the possibility for each leader that it would crash during one epoch, to help to measure the robustness. Generally, we consider $crash\_rate$ is quite small because compared to dropouts, crashes rarely happen in nowadays smart devices/servers. Therefore we can consider $crash\_rate$ would not be larger than 10%. Since a crash causes a reorganizing process, which helps the system by communications, we still adopt the number of communications to evaluate the extra overhead. We conducted several experiments on how $crash\_rate$ impacts efficiency. First, we set the number of clients to 100 and the $crash\_rate$ to 10%, which is the worst case. Then we counted up the number of communications in a situation without crashes. Finally, we counted up communications in other situations with different numbers of clients and different numbers of leaders. We consider the ratio of communications in these situations with the original one as their overheads, and the result is shown in Figure 10.

The number of clients hardly affects the overheads. In contrast, the number of leaders is very influential. Therefore, we suggest setting the number of leaders as smaller as possible. Generally, 3 or 5 could be sufficient choices.

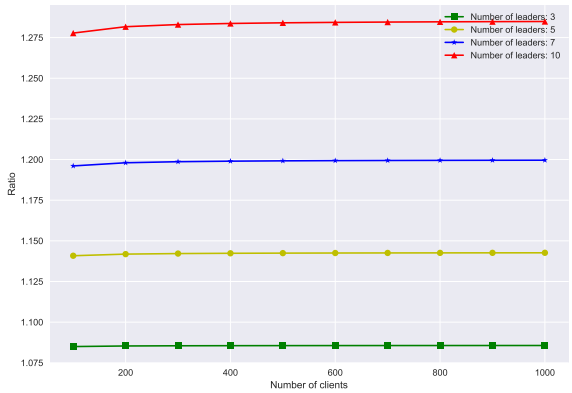


Fig. 10. The ratio of communications VS number of clients and leaders.

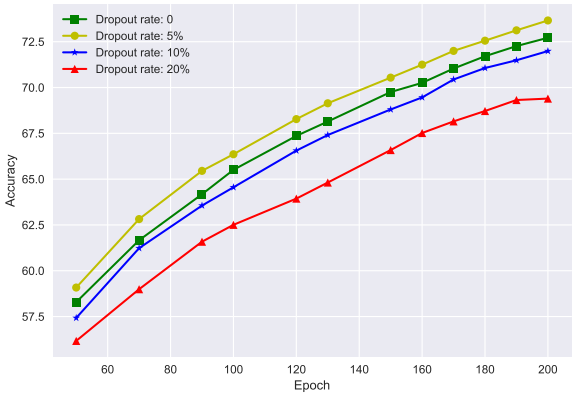


Fig. 11. The accuracy VS different $dropout_rate$s.

2) Network Delay and Dropout: Sometimes several packets cannot be received in time due to network delays or dropouts. Bonawitz *et al.*'s method [18] has considered this issue and it has a "double-masking" scheme to address it, which has a high computation overhead. In DemoFL's secure learning process, a leader will not be waiting for participants' parameters permanently. It has a time limit, over which the leader will abandon waiting and send the current B_j to the server (introduced in Section IV). Under this circumstance, some common parties will be recognized as having lost connection and removed from the participant-group without contributing to the learning process. However, if a party does not lose the connection while its message reached the leader late because of network delay, discarding it may influence the target model's accuracy. Since the leaders will compute the intersection no matter there are dropouts or not, the dropouts have no negative effect on efficiency. We set the $dropout\_rate$ to show the probability that a common party fails to send its parameters to leaders due to packet loss or network delay in one epoch. We then carried out several experiments to observe how package losses impact the learning process. The result is shown in Figure 11. The result indicates that the influence of

dropouts on accuracy is acceptable when $dropout\_rate$ is no more than 10%: when the $Epoch$ gets larger than about 160, the accuracy gap between no-dropout models and with-dropout models becomes insignificant. In addition, the accuracy of the model learned in the situation with 5% $dropout\_rate$ is even better than the model learned in the situation without $dropout\_rate$, which may be caused by biases, or the inherent defects of federated learning's aggregation scheme, and this might be one of our future researches. In summary, DemoFL has a strong resistance to packet loss considering that most machine learning tasks have a large enough $Epoch_{max}$.

VII. Conclusion and Future Works

In this paper, we proposed a novel, efficient, and privacy-preserving federated learning framework named Democratic Federated Learning. DemoFL adopted MPC-based secret sharing methods to achieve privacy-preserving against honest-but-curious adversaries. It also employs consensus algorithms to help users electing leaders democratically, reducing the communication cost, and providing higher efficiency and robustness. Our experiments showed that DemoFL has a linear time complexity VS either the number of clients or training rounds. And it has a high resistance to crashes and dropouts. DemoFL is lightweight and easy-deploying for many existing federated frameworks such as Pysyft and FATE.

However, it remains a problem for federated learning that malicious attackers are more harmful and difficult to defend against compared to honest-but-curious attackers. A malicious attacker can deviate from designed protocols or cheat on data that would go through it. Enhanced MPC protocols such as SPDZ [26] may help to deal with malicious attackers, which could be future work. Therefore, detecting malicious nodes is challenging work. In addition, other federated learning schemes besides FedAvg may contain algebraic calculus more than only addition and multiplication, which means existing MPC based methods will gain high overhead on those schemes. Some blockchain techniques are inspiring to solve malicious attacks such as poisoning and adversarial examples, which may be adopted to enhance DemoFL to provide higher security by preventing fraud. It would be significant and interesting for future work to find more approaches to improve the security and efficiency of federated learning.

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