Communication-Efficient Cluster Federated Learning in Large-scale Peer-to-Peer Networks

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Abstract—A traditional federated learning (FL) system allows clients to collaboratively train a global model under the coordination of a central server, which sparks great interests in exploiting the private data distributed on clients’ local devices. However, once the central server suffers from a single point of failure, it will lead to system crash. In addition, the FL system usually involves a large number of clients, which requires expensive communication costs. These challenges inspire a communication-efficient design of decentralized FL systems. In this paper, we propose an efficient and privacy-preserving global model training protocol in the context of FL in large-scale peer-to-peer networks, CFL. The proposed CFL protocol aggregates local model update parameters hierarchically by a cluster-based aggregation mode, as well as a leveraged authenticated encryption scheme to ensure the security communication, whose key is distributed by a modified secure communication key establishment protocol. Theoretical analyses show that the proposed CFL protocol guarantees the privacy of local model update parameters, as well as integrity and authenticity under the widespread internal semi-honest and external malicious threat models. In particular, the proposed key revocation based on public voting can effectively defend against external adversaries hijacking honest participants to ensure the confidentiality of the communication keys. In addition, the modified secure communication key establishment protocol indeed achieves high network connectivity probability to ensure transmission security of the system. Moreover, experimental results on the Trec06p and Trec07 datasets show that the final global model trained through the proposed CFL protocol can achieve an accuracy of 99.32% after 14 training rounds, which is comparable to the accuracy and convergence speed of the PPT protocol. The proposed CFL protocol is equally excellent even facing dropout clients. Compared with the PPT protocol, the CFL protocol improves communication efficiency by 43.25% and computational efficiency by 0.87%.

Index Terms—federated learning, peer-to-peer network, communication efficiency, privacy-preserving.

I. INTRODUCTION

MACHINE learning (ML) has injected vitality into many aspects of modern society, such as speech recognition [1], image recognition [2], natural language processing [3], etc. Traditional ML is featured by collecting raw data to train a centralized global model. However, gathering all data to a central database becomes increasingly complicated, especially when the data is created at a rapid rate, as well as the limited bandwidth and high communication overhead in the era of big data. Meanwhile, people and governments are increasingly concerned about data security and user privacy. For instance, the General Data Protection Regulation (GDPR) [4], which is introduced in 2018, limits the usage of user data strictly.

Traditional ML seems to meet a dilemma of user data between communication efficiency and privacy preservation [5]. Fortunately, Federated learning (FL) [6] emerges as a state-of-the-art ML system to solve the dilemma, which allows clients to collectively reap the benefits of shared models without centrally storing data. In FL, clients train their personalized models locally, then a central server aggregates local contributions, such as local models, local gradients or local model update parameters. The local data containing client privacy always stay on the clients’ local devices, which guarantees the privacy of clients. In addition, the local contributions uploaded by clients greatly reduces the scale of raw data, which also guarantees the communication efficiency of the system.

However, such parameter server settings do not always exist in the real world. Some typical scenarios, e.g., Internet of Things (IoT) [7], Smart Home [8] and Ad Hoc [9], are characterized by decentralization. As a result, how to deploy FL in such decentralized networks deserves deep research. In addition, a central server may even become a bottleneck when facing massive clients [10], and thus the decentralized environments indeed motivate the design of the next generation of FL system [11].

Consequently, some decentralized FL works involving algorithms and frameworks are proposed subsequently [12], [13], [14], [15], [16], [17], [18]. Specifically, [12], [13] and [14] consider the ML algorithms for decentralized settings, while [15], [16], [17] and [18] consider the frameworks for FL in decentralized networks. Besides, [19], [20] and [21] research decentralized vertical FL. However, these works discussed above are coarse-grained for decentralized FL. Recently, Chen et al. [22] propose a fine-grained PPT protocol, which is claimed the first communication-efficient and privacy-preserving global model training protocol in the context of FL in peer-to-peer (P2P) networks. However, PPT has obvious shortcomings facing massive clients. First, PPT aggregates local model update parameters by a so-called cyclic transmission manner, which is inefficient when facing massive clients. Second, the key distribution scheme in PPT may lead to same contribution among different pairs of clients, which leaves a potential trouble to the system. Third, the signature scheme in PPT requires extra storage space and heavy computational power. Therefore, a more practical protocol for large-scale decentralized FL is still an urgent need, but the question is how to efficiently and securely aggregate local contributions without a central aggregator in large-scale P2P networks.

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To answer this question, we propose a Cluster Federated Learning (CFL) global model training protocol in large-scale P2P networks. Specifically, we consider a specific decentralized FL settings, where large amounts of clients are distributed in a P2P network, and only a few clients are connected to a server responsible for coordinating FL tasks. To improve the communication efficiency of the system, CFL aggregates local model update parameters hierarchically. For the purpose of further enhancing the privacy and security of the system, CFL adopts the authenticated encryption scheme to ensure the integrity and authenticity of local model update parameters, whose key is established by a modified random pairwise keys scheme, which improves the security facing malicious adversaries hijacking honest participants. The main contributions are as follows:

**An FL global model training protocol in large-scale P2P networks.** We design a cluster FL global model training protocol in large-scale P2P networks, which comprises a secure communication key establishment protocol and an inner-cluster model aggregation protocol. Based on these interactional protocols, high efficiency and privacy-preserving performance of the global model training in large-scale P2P networks is achieved.

**A secure and privacy-preserving protocol.** We analyze the security and privacy ability CFL achieves under the widespread internal semi-honest and external malicious threat models. In detail, the proposed CFL protocol can protect the privacy of the client’s individual local contributions by a generated noise, and ensure the integrity and authenticity of local contributions by the leveraged authenticated encryption scheme. Particularly, our security analysis shows that CFL can guarantee the security of the communication key even facing a malicious adversary hijacking honest participants. Moreover, we analyze the network connectivity, and formally give the reference of key ring size and voting threshold, which proves that the network connectivity of the proposed CFL protocol can guarantee the transmission security.

**Experimental evaluation.** We conduct experiments on the Trec06p and Trec07 datasets, which demonstrates that the proposed CFL protocol can ultimately ensure the convergence of the global model, and the final global model has good classification and generalization ability, even if a dropout situation occurs. More importantly, CFL improves communication efficiency by 43.25% and computational efficiency by 0.87% compared with PPT.

The rest of the paper is organized as follows. In Section II, we formalize the system model, security requirements and design goal. Section III formally describes some preliminaries of our work. We elaborately describe the proposed CFL in Section IV, and give security analysis and network connectivity analysis in Section V. Section VI specifically states our experimental design, and gives the experimental results and evaluation. Section VII lists the related works. We conclude this paper in Section VIII.

II. SYSTEM MODEL, SECURITY REQUIREMENT AND DESIGN GOAL

In this section, we formalize the system model, propose the security requirement and set the design goal.

A. System Model

In this paper, we consider a context of FL in large-scale P2P networks. Specifically, a large group of potential clients with constant wireless communication ranges are distributed in a P2P network, which can be expressed as \( U = \{ u_i \mid i = 1, 2, \cdots, Z \} \). The clients truly participate in the global model training process are called target clients, and expressed as \( C = \{ c_i \mid i = 1, 2, \cdots, N \}, C \subset U \). Each target client \( c_i \) has a local dataset \( D_i \) of size \( |D_i| \) containing private training data. Besides, a server connecting with a few potential clients is responsible for coordinating FL tasks, which means that it cannot aggregate clients’ local contributions directly. The goal of target clients is to collaboratively train a global ML model \( W \) under the orchestration of the server.

Specifically, the collaborative training process is an iterative process. For clarity, we take the \( t \)-th round as an example to describe the iterative process. First, the server sends the global model \( W_t \) to the potential clients connected to it directly, and these potential clients pass \( W_t \) to other potential clients subsequently. After receiving the global model, each target client \( c_i \) initializes the local model as the global model \( W_t \), and trains it with its local dataset \( D_i \) to obtain the local model \( w^t_i \), which is simply expressed as:

\[
 w^t_i \leftarrow \text{Train}(W_t, D_i), \quad (1)
\]

where the local model is a \( d \)-dimensional vector. Then, each target client \( c_i \) calculates its local model update parameters \( x^t_i \), shown as:

\[
 x^t_i = w^t_i - W_t. \quad (2)
\]

Next, all target clients aggregate local model update parameters and upload the aggregation result to the server to update the global model, which is expressed as:

\[
 W^{t+1} = W^t + \sum_{i=1}^{N} p_i x^t_i, \quad (3)
\]

where \( p_i = \frac{|D_i|}{\sum_{i=1}^{N} |D_i|} \), which is the aggregation weight for \( c_i \), and \( W^{t+1} \) is the updated global model. All participants under our consideration perform the above training process periodically until the global model converges to an optimal result, i.e. the final converged global model \( W^* \).

**Communication model.** Inherited from the communication characteristics of P2P networks, all data in the system is transmitted by public communication channels. In addition, all target clients can only communicate with their single-hop neighbor clients within their constant wireless communication ranges, and only a few clients could communicate with the server directly.
B. Security Requirement

In the context of FL in large-scale P2P networks, security and privacy are the most important concerns. Thus, we consider two widely used threat models in FL, i.e., the internal semi-honest threat model and the external malicious threat model [11] [22] [25] [26].

In the internal semi-honest threat model, participants execute prescribed operations honestly but are curious about others’ local model update parameters, which means clients could infer private information from others’ local model update parameters by executing model inversion attacks [27] and membership inference attacks [28]. In particular, honest-but-curious potential clients may execute eavesdropping attacks [29] to obtain the private local model update parameters from target clients.

In the external malicious threat model, a malicious adversary $A$ from outside the system can execute active attacks to obtain the privacy of participants. Specifically, $A$ could execute tampering attacks [29] to threaten the integrity of aggregated local contributions, and $A$ could also execute impersonation attacks [29] to threaten the authenticity of aggregated local contributions. More seriously, $A$ could hijack honest participants to execute active attacks to obtain the communication keys in the system, so that it can pretend to be an honest participant and tamper with the aggregated model update parameters in secret transmission, resulting in serious breaches of system security. As a result, our protocol should meet the following security requirements:

Privacy preservation. Neither an honest-but-curious server nor clients can obtain the individual local model update parameters. Aggregated model update parameters can only be obtained by neighbor clients in the aggregation route.

Data integrity and authenticity. Ensure that local model update parameters are indeed sent by an honest client and have not been tampered during transmission. That is, active attacks executed by $A$ should be detected and resisted.

Confidentiality of the communication key. The communication key used to protect the aggregated model update parameters during transmission can only be obtained by two target clients in communication. In other words, hijack attacks executed by $A$ should be detected and resisted.

C. Design Goal

In this paper, we consider an FL setting in large-scale P2P networks. All potential clients are distributed in a large-scale P2P network, and only a few potential clients are directly connected to the server. Our design goal is to achieve an efficient and privacy-preserving FL global model training protocol. Specifically, the following objectives should be achieved in the proposed protocol:

- Privacy and security. Neither a server nor clients can obtain the privacy of clients from aggregated model update parameters. Besides, active attacks in the network can be detected and resisted. In other words, the integrity and authenticity of the local model update parameters are always maintained during transmission.

- Efficiency. All target clients distributed in P2P networks can aggregate local model update parameters through an efficient aggregation route. In addition, the low computational cost of a single client ensures the computational efficiency.

III. PRELIMINARIES

A. Random Pairwise Keys Scheme

The random pairwise keys scheme [23] is initially employed to establish communication keys in distributed networks. The basic idea is to associate the two potential clients with a pair of keys through their identities. The steps of the random pairwise keys scheme are described as follows:

1. **Step-1.** All potential clients generate their unique identities, expressed as $ID = \{ID_i | i = 1, 2, \ldots, Z\}$.

2. **Step-2.** Each potential client randomly matches its identity with $M$ other identities, and each client pair obtains a pair of keys $k$ from a key pool $K$.

3. **Step-3.** The pair of keys $k$ is stored in both clients’ key rings, along with the identity of the other client that shares the pair of keys. Each potential client’s key ring is represented as $R_i = \{(ID_{i\alpha}, k_{i\alpha}) | \alpha = 1, 2, \ldots, M\}$.

4. **Step-4.** Through secret communication, each potential client uses its key ring to establish communication keys with other potential clients that have the common key knowledge.

B. Authenticated Encryption

Authenticated encryption (AE) [24] is an encryption system that provides both privacy and authenticity in communication, which comprises three algorithms: a key generation algorithm $AE.Gen(\cdot)$, an encryption algorithm $AE.Enc(\cdot)$ and a decryption algorithm $AE.Dec(\cdot)$. The detailed steps of the authenticated encryption are as follows:

1. $AE.Gen(\cdot)$ generates a symmetric key $K$, which is shown as:

   $$K \leftarrow AE.Gen(1^\kappa),$$

   where $\kappa$ is a security parameter, i.e. the length of the symmetric key, which is consistent with the length of each dimension of the local model.

2. $AE.Enc(\cdot)$ inputs the plaintext $X$ and the key $K$ to output the ciphertext $Y$ and an authentication tag $\sigma$, usually in the form of a message authentication code (MAC), which is shown as:

   $$(Y||\sigma) \leftarrow AE.Enc(X, K),$$

   where $||$ represents the string concatenation operator.

3. $AE.Dec(\cdot)$ inputs the ciphertext $Y$ and the same key $K$ to output the plaintext $X$, which is shown as:

   $$X \leftarrow AE.Dec((Y||\sigma), K).$$

Otherwise, $AE.Dec(\cdot)$ outputs a special symbol indicating that the ciphertext is invalid or not authentic.
IV. SYSTEM DESIGN

In this section, we propose an efficient and privacy-preserving global model training protocol for FL in large-scale P2P networks. Our protocol mainly comprises the following five parts: cluster division, communication key establishment, local model training, aggregation within a single cluster and aggregation and update across clusters. The comprehensive system architecture is shown in Fig. 1.

A. Cluster Division

There are large amounts of clients distributed in a P2P network under our consideration, where the complex connections among clients may bring huge communication latency and costs. Therefore, we first divide all potential clients into several clusters $\mathbb{L} = \{L_h | h = 1, 2, \ldots, \lambda\}$ based on the constant wireless communication range of a single potential client to reduce communication overhead of the system. In each cluster, only a few potential clients are directly connected to the server, and the potential clients and their connections within the cluster can also be regarded as a P2P network.

We consider a specific cluster $L_h \in \mathbb{L}$, where all potential clients $U_h = \{u_{h,i} | i = 1, 2, \ldots, z_h\}$ may participate in the global model training process, and all $U_h (h = 1, 2, \ldots, \lambda)$ make up $\mathbb{U}$, which is expressed as:

$$\mathbb{U} = \bigcup_{h=1}^{\lambda} U_h.$$  \hspace{1cm} (4)

While the clients that actually participate in a specific round of global model training are target clients $C_h = \{c_{h,i} | i = 1, 2, \ldots, n_h\}$, $C_h \subseteq U_h$, and all $C_h (h = 1, 2, \ldots, \lambda)$ make up $\mathbb{C}$, which is expressed as:

$$\mathbb{C} = \bigcup_{h=1}^{\lambda} C_h.$$  \hspace{1cm} (5)

B. Communication Key Establishment

In order to enhance the security while transmitting local model update parameters, we propose a secure communication key establishment protocol to establish communication keys for the potential clients within the same cluster, which is an important part of the proposed CFL protocol and comprises three phase, i.e., communication key establishment, key revo-cation and re-keying.

- Communication key establishment. Specifically, we take the cluster $L_h$ as an example. First, each potential client $u_{h,i}$ generates a unique identity $ID_{h,i}$. Then, $u_{h,i}$ randomly matches its identity with $m_h$ other identities, and each client pair obtains a pairwise key $k$ from a key pool $K$ containing sufficient keys. As a result, $m_h$ sets of identities and the corresponding pairwise keys make up the key ring $R_{h,i} = \{(ID_{h,i\alpha}, k_{h,i\alpha}) | \alpha = 1, 2, \ldots, m_h\}$, which is stored locally in advance on potential clients. Note that the above offline operations do not involve communication overhead.

Afterwards, all potential clients $u_{h,i}$ discover other potential clients that have shared keys with them through the challenge-response mechanism. Specifically, $u_{h,i}$ broadcasts a plaintext $a_{h,i}$ and $m_h$ messages $\{A_{h,\alpha} | \alpha = 1, 2, \ldots, m_h\}$ encrypted by $m_h$ pairwise keys $\{k_{h,i\alpha} | \alpha = 1, 2, \ldots, m_h\}$ in $R_{h,i}$, which is shown as:

$$A_{h,i\alpha} \leftarrow \text{CK.Enc}(k_{h,i\alpha}, a_{h,i}).$$

After that, every other potential clients $u_{h,j}$ ($j \neq i$) attempts to decrypt the ciphertexts successively with the locally stored $m_h$ pairwise keys in its key ring, and compares the decryption result $a'_{h,j}$ with the plaintext $a_{h,i}$, seeking for a proper key to disclose the plaintext $a_{h,i}$, which is shown as:

$$a'_{h,j} \leftarrow \text{CK.Dec}(k_{h,i\alpha}, A_{h,i\alpha}).$$

Similarly, $u_{h,j}$ repeats the above encrypted broadcast operation to mutually confirm that they do have the common key. Thus, the shared key becomes their communication key $K_{h,i,h,j}$. As a result, each potential client in the same cluster can establish $m_h$ secure connections with $m_h$ distinct potential clients.

Fig. 1: System architecture of CFL global model training protocol.
• Key revocation. In the external malicious threat model under our consideration, an adversary \( A \) can hijack honest potential clients to execute active attacks, which could compromise the communication keys to threaten the security of the FL system. Thus, we design a compact and efficient key revocation phase based on public voting. Specifically, once a potential client observes active attacks from the client \( A' \) hijacked by \( A \), it broadcasts a negative vote. We define the voting members as \( \{ u_{h,A'\alpha} | \alpha = 1, 2, \cdots , m_h \} \), who are the neighbor clients that can communicate directly with \( A' \). Once \( A' \) is voted against more than \( t_h \), all voting members \( u_{h,A'\alpha} \) will cut off all possible connections to \( A' \) for revocation, and thus eliminating the \( A' \)'s influence on the system.

In particular, the neighborhood broadcast [31] mechanism is used for every public vote in the network. The mechanism adopts broadcasts between neighbors to hierarchically reach a consensus in the network. We stipulate that all voting members need to broadcast any public votes received to maximize the probability of successful transmission to adjacent voting members. All broadcasts are in plaintext, and the public voting itself needn’t protect voters’ identities.

• Re-keying. To ensure the long-term security of the system, the communication keys used for a period of time need to be updated. When the keys expires, the re-keying phase will start. That is, all affected clients restart the communication key establishment phase to rebuild new communication keys.

In conclusion, the whole communication key establishment process by a proposed secure communication key establishment protocol in Fig. 2.

C. Local Model Training

After establishing communication keys, all potential clients are able to collaboratively train the global model. Since the global model training is an iterative process, we take the \( t \)-th round as an example. The server first distributes a global model \( W^t \) to the potential clients directly connected to it. These potential clients subsequently pass \( W^t \) to other potential clients within the same cluster. After receiving \( W^t \), each target client \( c_i \) initializes the global model \( W^t \) as the local model, and trains it with its local dataset \( D_i \). The local model training process is shown as:

\[
\hat{X}_{h,1}^t \leftarrow \text{Train}(D_i, W^t).
\]

Then, \( c_i \) calculates the local model update parameters, shown as:

\[
x_{h,1}^t = w_{i}^t - W^t.
\]

Afterwards, \( c_i \) calculates its weighted local model update parameters \( X_{h,1}^t = p_{i}x_{h,1}^t \), and prepares to aggregate local model update parameters collaboratively.

D. Aggregation within a Single Cluster

After local training, all target clients aggregate their local model update parameters within their clusters respectively. Specifically, we still take the cluster \( L_1 \) as an example to describe the aggregation process of the \( t \)-th round. The server randomly selects a target client directly connected to it as the leader client, namely \( c_{h,1} \). Afterwards, \( c_{h,1} \) generates a random noise \( s_{h,1}^t \) to disturb its weighted local model update parameters \( \hat{X}_{h,1}^t \), which is shown as:

\[
\hat{X}_{h,1}^t \leftarrow \hat{X}_{h,1}^t + s_{h,1}^t,
\]

where the length of \( s_{h,1}^t \) is consistent with the length of each dimension of the local model. Then \( c_{h,1} \) attaches a timestamp \( \tau_{h,1} \) to the disturbed model update parameters, which is represented as \( \hat{X}_{h,1}^t || \tau_{h,1} \). Next, \( c_{h,1} \) randomly selects a neighbor client \( c_{h,2} \) and encrypts the message with their communication key \( K_{h_1,h_2} \), which is shown as:

\[
(Y_{h,1}^t || \sigma_{h,1}^t) \leftarrow \text{AE.Enc}(\hat{X}_{h,1}^t || \tau_{h,1}^t, K_{h_1,h_2}).
\]

Then, \( c_{h,1} \) sends the encrypted message \( Y_{h,1}^t \) and the authentication tag \( \sigma_{h,1}^t \) to \( c_{h,2} \). After receiving the ciphertext, \( c_{h,2} \) recovers it to a plaintext, which is shown as:

\[
(\hat{X}_{h,1}^t || \tau_{h,1}^t) \leftarrow \text{AE.Dec}(Y_{h,1}^t || \sigma_{h,1}^t, K_{h_1,h_2}).
\]

At this point, \( c_{h,2} \) validates the authentication tag \( \sigma_{h,1}^t \) and
the timestamp $t_{h,1}$. Once verified, $c_{h,2}$ aggregates its own weighted model update parameters, which is shown as:

$$X^t_{h,2} \leftarrow X^t_{h,1} + X^t_{h,2}.$$ 

Afterwards, $c_{h,2}$ selects a new neighbor client $c_{h,3}$, and performs the encryption and transmission operations as $c_{h,1}$ does. The remaining target clients perform the same decryption, aggregation, encryption and transmission operations successively until all the target clients are traversed within the cluster.

Note that the aggregation route follows the depth-first traversal algorithm in the graph [30], that is, each target client prefers to select the target clients that have not yet participated in the aggregation. In the end, the final client $c_{h,n_h}$ sends the aggregated model update parameters back to $c_{h,1}$ according to the planned aggregation route. Then $c_{h,1}$ subtracts the noise $s^t_h$ to obtain the aggregation result within its cluster as:

$$\text{sum}^t_h \leftarrow \sum_{i=1}^{n_h} X^t_{h,i}. \quad (8)$$

To reach a consensus in the network, we also adopt neighborhood broadcast [31] mechanism during transmission. We stipulate that each target client broadcasts its behaviors to all adjacent clients, and the receivers broadcast to their neighbors in the same way until all target clients in P2P networks receive the broadcast. For instance, when a target client drops out, because its upstream target client can’t receive the broadcasts from other clients, it selects a new target client to transmit the aggregated model update parameters.

In summary, the process of the model aggregation within a single cluster is described as the inner-cluster model aggregation protocol in Fig. 3.

### E. Aggregation and Update Across Clusters

After finishing the model aggregation within each cluster, each leader client $c_{h,1}$ obtains the inner-cluster aggregation result $\text{sum}^t_h$. Then, all leader clients upload $\text{sum}^t_h$s directly to the server, as they are all connected to the server. Consequently, the server aggregates all $\text{sum}^t_h$s as:

$$\text{SUM}^t = \sum_{h=1}^{\lambda} q_h \text{sum}^t_h, \quad (9)$$

where $q_h$ denotes the aggregation weight of the cluster $L_h$, and generally defined as $q_h = \frac{\sum_{t \in L_h} |D_t|}{\sum_{h=1}^{\lambda} |D_h|}$.

Next, the server updates the global model with the global model update parameter $\text{SUM}^t$, which is represented as:

$$W^{t+1} = W^t + \text{SUM}^t. \quad (10)$$

Finally, the server distributes the updated global model to all target clients, and they iteratively train and aggregate until the global model converges to $W^*$. For clarity of description, we summarize the integrated global model training process from a high-level view in Fig. 4.

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### Inner-Cluster Model Aggregation Protocol

1. **Local Model Training:**
   - $c_{h,1}$ performs local model training and holds weighted local model update parameters $X^t_{h,1}$ to be uploaded.
   - $c_{h,1}$ broadcasts that it has been prepared to participate in the global model update.

2. **Model Disturbance:**
   - The server randomly chooses a leader client $c_{h,1}$.
   - $c_{h,1}$ randomly generates a noise $s^t_h$, which is shown as $X^t_{h,1} \leftarrow X^t_{h,1} + s^t_h$.

3. **Transmission and Aggregation:**
   - $c_{h,1}$ chooses a neighbor $c_{h,2}$ and broadcasts $B^t_{h,1}$ to all its neighbors.
   - $c_{h,1}$ encrypts $X^t_{h,1}$, which is shown as $(Y^t_{h,1}||\sigma^t_{h,1}) \leftarrow \text{AE.Enc}(X^t_{h,1}||\sigma^t_{h,1}, K_{h_1,h_2})$.
   - $c_{h,1}$ sends the ciphertext to $c_{h,2}$.
   - $c_{h,2}$ decrypts the ciphertext received, which is shown as $(X^t_{h,1}||\tau^t_{h,1}) \leftarrow \text{AE.Dec}(Y^t_{h,1}||\sigma^t_{h,1}, K_{h_1,h_2})$.
   - $c_{h,2}$ calculates $X^t_{h,2} = X^t_{h,1} + X^t_{h,2}$.
   - $c_{h,2}$ performs the same operations as $c_{h,1}$ does in step 3.
   - The remaining target clients successively perform the same operations as $c_{h,2}$ does until $c_{h,n_h}$.
   - $c_{h,n_h}$ gets $X^t_{h,n_h}$, which is shown as $X^t_{h,n_h} = \sum_{i=1}^{n_h} X^t_{h,i} + \epsilon^t_h$.

4. **Cluster model Aggregation:**
   - $c_{h,n_h}$ sends $X^t_{h,n_h}$ back to $c_{h,1}$.
   - $c_{h,1}$ subtracts $s^t_h$ and calculates $\text{sum}^t_h = \sum_{i=1}^{n_h} X^t_{h,i}$.

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### Cluster Federated Learning Global Model Training Protocol in Large-Scale P2P Networks

Step 1. All potential clients distributed in the P2P network are divided into several clusters according to their constant wireless communication range.

Step 2. The potential clients in each cluster establish communication keys according to the secure communication key establishment protocol.

Step 3. All target clients in each cluster perform local model training.

Step 4. All target clients in each cluster perform model aggregation according to the Inner-cluster model aggregation protocol.

Step 5. All target clients perform model aggregation across clusters to obtain global model update parameters.

Step 6. The server uses the global model update parameters to perform global model updates.

Step 7. The server distributes the updated global model to all target clients.

Step 8. Determine whether the global model converges. If so, stop training. Otherwise, go to step 3.

**Notes:**

1. The neighborhood broadcast mechanism is adopted to record the behaviors of all clients in the protocol.
2. A newly joined client $w_{new}$ will perform step 2-8.

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Fig. 3: Detailed description of the inner-cluster model aggregation protocol.

Fig. 4: High-level description of integrated global model training protocol.
V. ANALYSIS

In this section, we analyze the security of the proposed CFL protocol. Particularly, we analyze the network connectivity, which is critical for secure communication among clients.

A. Security Analysis

During the training process of the global model, we mainly focus on the privacy and security CFL achieves. Therefore, we analyze how the proposed CFL protocol meets the security requirements discussed in the section II.

First, we analyze the security of the proposed CFL protocol under the internal semi-honest threat model, mainly including three aspects: a server, target clients and potential clients. The detailed security analysis is as follows:

The proposed CFL protocol is privacy-preserving facing an honest-but-curious server. An honest-but-curious server may infer or extract the privacy of individual target client from the aggregation results. To defend against such attacks, the proposed CFL protocol aggregates local contributions through multi-party collaboration. The final aggregation result is the sum of weighted local model update parameters from all target clients. Therefore, the server can only obtain the aggregation result, rather than the private local model update parameters of any individual target client.

The proposed CFL protocol is privacy-preserving facing honest-but-curious target clients. An honest-but-curious target client may execute model inversion attacks [27] or membership inference attacks [28] to threaten the privacy contained in the local datasets. To resist such attacks, a random noise is introduced to protect aggregated model update parameters. When all target clients follow the protocol, the aggregated local contributions are disturbed by a noise $s_h$. All target clients can only get disturbed local contributions or their intermediate aggregation result, rather than the privacy of the individual target client.

The proposed CFL protocol is privacy-preserving facing honest-but-curious potential clients. An honest-but-curious potential client may execute eavesdropping attacks [29] to obtain the intermediate aggregation result. To protect against such attacks, the proposed CFL protocol adopts the secure communication key establishment protocol to provide the communication keys in the system, and adopts authenticated encryption to protect aggregated model update parameters. The uniqueness of the communication key ensures the security of authenticated encryption scheme, thus ensuring the communication security. Therefore, only the client pair owning the communication key can decrypt the intermediate aggregation result, and an honest-but-curious potential client cannot obtain the private key used for decryption nor the intermediate aggregation result.

Furthermore, we analyze the security of the proposed CFL protocol under the external malicious threat models. The detailed security analysis is as follows:

The proposed CFL protocol guarantees the integrity and authenticity of the aggregated model update parameters. A malicious adversary can execute active attacks to threaten the integrity and authenticity of the aggregated model update parameters. In order to defend against such attacks, the proposed CFL protocol adopts authenticated encryption to protect aggregated model update parameters. All target clients encrypt the aggregated model update parameters to be uploaded, where the authentication tag can effectively resist unauthorized tampering of messages and verify whether the sender is a trusted source.

The proposed CFL protocol guarantees the confidentiality of the communication key. More importantly, a malicious adversary can hijack honest participants to execute active attacks, which may lead to the leakage of the communication keys. In order to defend against such attacks, the proposed CFL protocol adopts the key revocation phase based on public voting to reduce the impact of malicious adversaries on the system. When the active attacks from the hijacked client are observed, the hijacked client’s voting members can participate in its revocation resolution. When the revocation condition is met, all potential clients cut off the connections with the hijacked client, thereby eliminating the possibility of the malicious adversary stealing communication keys. Therefore, the confidentiality of the communication key is ensured.

B. Network Connectivity Analysis

In our protocol, we use the secure communication key establishment protocol to establish communication keys for potential clients. We analyze the network connectivity of the protocol in Theorem 1, which is the basis of secure transmission.

Theorem 1: For a cluster $L_h$, according to the secure communication key establishment protocol, the size of the key ring for each potential client only needs to be $m_h$ to ensure a high network connectivity probability.

Proof 1: We first formalize the network in cluster $L_h$ as a random graph $G(n_h, r_h)$, where $n_h$ is the size of the network, that is, the number of potential clients in cluster $L_h$, and $r_h \in [0, 1]$ is the probability that any two potential clients in the network are connected.

To explain $r_h$, we recall Lemma 1.

Lemma 1 [32]: Given a desired connectivity probability $P_c$ for a graph $G(n_h, r_h)$, the threshold function $r_h$ is defined by:

$$P_c = \lim_{n_h \to \infty} \Pr[G(n_h, r_h) \text{ is connected}] = e^{-e^{-e}},$$

(11)

where $r_h = \frac{\ln(n_h)}{n_h}$ and $c$ is any real constant.

According to Lemma 1, given a high connectivity probability (e.g., 0.999), we can calculate $r_h$ as follows:

$$r_h = \frac{\ln(n_h)}{n_h} + \frac{-\ln(-\ln(P_c))}{n_h}.$$ 

(12)

According to the properties of the graph $[33]$, we can infer a graph with $n_h$ vertices has at most $\binom{n_h}{2}$ edges. Assume that $G$ has $e$ edges, then we can interpret $r_h$ as:

$$r_h = \frac{e}{\binom{n_h}{2}}.$$ 

(13)

Next, we can calculate the key ring size $m_h$ of the potential client (i.e. the expected degree of $G$) as:

$$m_h = \frac{2e}{n_h}.$$ 

(14)
Therefore, according to the formulas (13) and (14), we can figure out the relationship between $m_h$ and $r_h$ as:

$$m_h = r_h \times (n_h - 1) \sim r_h \times n_h,$$

(15)

where $\sim$ represents an equivalence symbol.

As a result, according to the formula (12), we can calculate the key ring size $m_h$ as:

$$m_h = \ln(n_h) - \ln(-\ln(P_c)),$$

(16)

Theorem 1 indicates that under the condition that the network connectivity probability is as high as possible, the size of key ring for each potential client only needs to be $m_h = \ln(n_h) - \ln(-\ln(P_c))$. In other words, given the size of the key ring $m_h$, all aggregation results can be transmitted in ciphertext with a high probability.

In the proposed secure communication key establishment protocol, we design key revocation phase to reduce the influence of malicious clients on the network, which may affect network connectivity probability. Therefore, we analyze the influence of the value of voting threshold $l_h$ on network connectivity in Theorem 2.

Theorem 2: In the proposed secure communication key establishment protocol, the voting threshold $l_h$ for revoking the clients hijacked by malicious adversaries is a suitable small value between 1 and $m_h$.

Proof 2: After the communication key establishment phase, each potential client in cluster $L_h$ establishes $m_h$ connections with other potential clients.

If $l_h > m_h$, less than $l_h$ voting members will result in the failure of revocation.

If $l_h$ is too small, it is likely that a small number of hijacked clients will cause the revocation of multiple honest clients.

Therefore, we can get the value range of $l_h$ as:

$$l_h \in (1, m_h).$$

(17)

According to the formula (16), we can determine the value range of $l_h$ as:

$$l_h \in (1, \ln(n_h) - \ln(-\ln(P_c))).$$

(18)

The formulas (16) and (18) tell us that the key ring size $m_h$ increases slowly with the network size $n_h$, which means that $l_h$ is a small value and voting costs would not be significant. Theorem 2 shows that we only need minimal voting cost to minimize the impact of malicious adversaries on the network without affecting the network connectivity.

VI. Experiments and Evaluation

In this section, we conduct the experiments in a spam classification scenario. All experiments are implemented on the same computing environment (Linux Ubuntu 16.04, Intel i7-6950X CPU, 64 GB RAM and 5TB SSD) with Tensorflow, Keras and PyCryptodome.

A. Experimental Design

Dataset. The datasets used in our experiments consists of two parts, Trec06p and Trec07, which are all English e-mails from the real world. The Trec06p dataset contains 12910 hams and 24912 spams in the main corpus with messages, and the Trec07 dataset contains 25220 hams and 50199 spams.

Network connectivity topology. In our experiments, there are 200 potential clients distributed in five clusters $L_A$, $L_B$, $L_C$, $L_D$ and $L_E$, with 100 target clients. Specifically, as is shown in Fig. 5, there are 39, 46, 21, 58 and 36 potential clients in these five clusters respectively, of which 19, 22, 12, 31 and 16 target clients represented as gray nodes. We illustrate the connections among potential clients based on the communication keys as the gray lines. Furthermore, we illustrate the leader clients as black nodes, and the aggregation routes as the red lines.

Parameter tuning. In our experiment, the server distributes an original global model. All clients use the local datasets and the original global model to collaboratively train a global model according to the proposed CFL protocol. It is worth mentioning that the Trec06p dataset is divided into the Trec06p training set and the Trec06p testing set according to the ratio of 3:1, and the Trec06p training set is adopted to train the original global model. In addition, the Trec07 dataset is divided into two parts, a part is assigned to 100 target clients as their training sets to train their local models, where the training set of each client obeys the normal distribution of mean 600 and variance 100, and the rest part serves as the Trec07 testing set. The original global model and local models have the same structure, which consists of two convolution layers, two pooling layers and three fully connected layers. We set the loss function as the cross-entropy error and the active function as the ReLU. We use the mini-batch SGD algorithm for gradient descent, with batch size of 64, and set the learning rate as 0.2. Local training is performed 64 epochs per aggregation. Besides, we use the AES-GCM-128bit algorithm for authenticated encryption.

B. Experimental Results and Evaluation

In order to validate the convergence of the final global model, we evaluate the accuracy and loss value of the final global model in Fig. 6. After 14 rounds of global model

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1We give the download link as: https://trec.nist.gov/data/spam.html.
training following the proposed CFL protocol, the global model converges, and the accuracy and loss value of the final global model are 99.32% and 0.0356 in the Trec07 testing set. The results show that the proposed CFL protocol can guarantee the convergence of the global model with good classification ability.

Moreover, we compare the performances of the original global model and the final global model by illustrating the receiver operating characteristic (ROC) curve and the area under the curve (AUC) in both Trec06p and Trec07 testing sets in Fig. 7. Specifically, Fig. 7(a) and Fig. 7(c) reflect the global model performance in the Trec06p testing set and the Trec07 testing set. The final global model outperforms the original global model in both the Trec06p and Trec07 testing sets, and it is not overfitting, which shows that the final global model of the CFL protocol has good generalization ability.

Besides, in order to validate the dropout robustness of the proposed CFL protocol, we randomly set 15% dropout clients in each training round. In this case, the global model converges after 16 rounds of training, at which point the accuracy and loss value of the global model are 99.26% and 0.0343, as shown in Fig. 6. It shows that even in the event of dropout clients, our protocol still ensures that the final global model has favourable performance. Similar results can also be observed in Fig. 7. Specifically, Fig. 7(b) and Fig. 7(d) reflect the global model performance with dropout clients in Trec06p testing set and Trec07 testing set. The final global model respectively obtains AUC value of 0.97 and 0.98 in the Trec06p and Trec07 testing sets, which exceeds the original global model and is not overfitting. The results means that the CFL protocol is robust to dropout clients.

Besides, in order to demonstrate the communication efficiency of the proposed CFL protocol, we also record the communication times with dropout clients in the system, and compare it with the PPT protocol under the same conditions in TABLE I. Obviously, compared with the PPT protocol, the proposed CFL protocol improves the communication efficiency by 43.25%. Such results benefit from the cluster-based division in our protocol. It is worth mentioning that the communication times are not necessarily negatively correlated with the number of dropout clients, which is related to the distribution of network topology.

Moreover, in order to reflect the computational efficiency of the proposed CFL protocol, we record the time of operations of a client in TABLE II, where the authenticated encryption (decryption) adopted in our protocol takes less time than the encryption (decryption) and signature (verification) used in the PPT protocol. This benefits from the superiority of the authenticated encryption scheme which combines confidentiality and authentication. At this point, our protocol improves the computational efficiency of a single client by 0.87%. In addition, TABLE II shows the time for a single leader client in our protocol to perform noise generation, addition, and subtraction operations. In summary, our protocol shows better computational performance than PPT.

### TABLE I: Communication Times

| Percentage of dropout clients | 0   | 1   | 2   | 5   | 10  | 15  |
|------------------------------|-----|-----|-----|-----|-----|-----|
| CFL's communication times    | 105 | 106 | 104 | 105 | 102 | 92  |
| PPT's communication times    | 191 | 186 | 185 | 184 | 172 | 164 |

We randomly set 0-15% dropout clients in each round of aggregation and record the corresponding communication times.

### TABLE II: Computational Times

| Component | Time (ms) |
|-----------|-----------|
| Auth. Enc. (Dec.) | 80 |
| Encryption (Dec.) | 120 |
| Signature (Ver.) | 200 |

VII. RELATED WORKS

**Centralized FL**. FL is proposed by McMahan *et al.* [6] for training a global model from data distributed on different mobile clients, so as to preserve data privacy. Other works build on FL by improving communication efficiency [85], improving system scalability [26] and improving system privacy-preserving performance [25]. At the algorithmic level, centralized FL mainly uses two model aggregation algorithms, FedSGD [6] and FedAvg [6]. In the above works, a central server coordinates the training process and receives local contributions from all clients. However, as Lian *et al.* [10] have demonstrated, the central server may even become a bottleneck when the number of clients is very large. A decentralized
TABLE II: Computational Performance

| Index | Operations $^*$ | Time (ms/1000byte) |
|-------|-----------------|---------------------|
| 1     | Encryption(AES-128bit) | 170.8248$^*$          |
| 2     | Decryption(AES-128bit) | 0.0282$^*$             |
| 3     | Signature(Elgamal-2048bit) | 0.0003$^*$          |
| 4     | Verification(Elgamal-2048bit) | 0.0071$^*$         |
| 5     | Encryption(AES-GCM-128bit) | 169.3596          |
| 6     | Decryption(AES-GCM-128bit) | 0.0163$^*$            |
| 7     | Noise generation | 1.2368               |
| 8     | Noise addition | 0.087                |
| 9     | Noise subtraction | 0.1316               |

$^*$ We execute a series of operations on a 114MB file of local model update parameters in the form of plaintext, and the file size of the encrypted result is 428.8MB.

$^\dagger$ Based on the same experimental settings, we directly use the results of relevant operation time in the PPT protocol [22] for comparison.

A decentralized FL. Subsequently, a series of FL frameworks and algorithms without a central aggregator have been proposed. As for the algorithm, Baidu proposes in [12] a bandwidth optimization algorithm Ring AllReduce for training, which allows the gradient to be averaged effectively on distributed devices. Yang et al. [13] exploit the signal superposition property of wireless multiple-access channel to achieve locally computing updates in FL by over-the-air computation. Combining PushSum gossip algorithm with stochastic gradient updates, Assran et al. [14] propose SGP (Stochastic Gradient Push) and OSGP (Overlap Stochastic Gradient Push) to accelerate distributed training of deep neural networks.

As for the framework, Ramanan et al. [15] propose a blockchain based free FL framework, BAFFLE, which achieves high scalability and computational efficiency in a private Ethereum network. However, FL on the blockchain is still a challenge to clients’ local computational power. Hu et al. [16] address the decentralized FL problem by aggregating the local model segments based on gossip protocol. The gossip-based framework allows asynchronous algorithms for collaborative learning but requires high communication overhead. Dubey et al. [17] devise FEDUCB for P2P FL to solve the contextual linear bandit problem. Li et al. [18] propose SimFL to build decision trees with bounded errors, which leverages locality-sensitive hashing (LSH) to collect similarity information. Chen et al. [22] propose a so-called efficient and privacy-preservation FL global model training protocol, PPT protocol, which adopts the aggregation route of cyclic transmission. However, the PPT protocol is inefficient facing a large number of clients.

In a word, in the existing FL framework in P2P networks, the fine-grained decentralized FL system design, as well as enhancing the communication efficiency and privacy-preserving performance of the system in large-scale scenarios are urgently needed. To the best of our knowledge, our proposed CFL protocol can ensure communication efficiency and privacy-preserving performance for FL in large-scale P2P networks.

In order to solve the problems of single point of failure and high communication cost in centralized FL system, this paper studies the FL global model training protocol in large-scale P2P networks, focusing on the communication efficiency and privacy-preserving performance of the system. We develop a cluster FL global model training protocol CFL based on the previous works. Our experiments on two real datasets show that the CFL protocol is robust and efficient. Much work remains to be done in the future.

The basis of network division. The division of the network in this paper is still coarse-grained, and more refined network division from the client perspective is urgently needed. How the clients choose the network hierarchy directly affects the network topology. Therefore, it is worth discussing to study the client’s own preference and its geographical location to determine a more reasonable network division.

Dynamic topology consideration. This paper studies static P2P networks without considering dynamic changes of the clients. Mobile clients may destroy the network connectivity topology, thus affecting global model training. In fact, this situation often occurs in the context of the Internet of Things, and dealing with it will improve the flexibility and scalability of the system.

Realizable homomorphic encryption. Future developments in technology will constantly improve the performance of hardware. The introduction of new privacy-preserving technologies will be possible, such as homomorphic encryption. The implementation of homomorphic encryption technology with high local computational power can take into account communication efficiency while ensuring privacy-preserving performance.

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