

---

# DeFL: Decentralized Weight Aggregation for Cross-silo Federated Learning

---

**Jialiang Han**

Key Lab of High-Confidence Software Technology, MoE (Peking University), Beijing  
hanjialiang@pku.edu.cn

**Yudong Han**

Key Lab of High-Confidence Software Technology, MoE (Peking University), Beijing  
hanyd@pku.edu.cn

**Gang Huang**

Key Lab of High-Confidence Software Technology, MoE (Peking University), Beijing  
hg@pku.edu.cn

**Yun Ma**

Institute for Artificial Intelligence, Peking University, Beijing  
mayun@pku.edu.cn

## Abstract

Federated learning (FL) is an emerging promising paradigm of privacy-preserving machine learning (ML). An important type of FL is cross-silo FL, which enables a small scale of organizations to cooperatively train a shared model by keeping confidential data locally and aggregating weights on a central parameter server. However, the central server may be vulnerable to malicious attacks or software failures in practice. To address this issue, in this paper, we propose DeFL, a novel decentralized weight aggregation framework for cross-silo FL. DeFL eliminates the central server by aggregating weights on each participating node and weights of only the current training round are maintained and synchronized among all nodes. We use `Multi-Krum` to enable aggregating correct weights from honest nodes and use `HotStuff` to ensure the consistency of the training round number and weights among all nodes. Besides, we theoretically analyze the Byzantine fault tolerance, convergence, and complexity of DeFL. We conduct extensive experiments over two widely-adopted public datasets, i.e. CIFAR-10 and Sentiment140, to evaluate the performance of DeFL. Results show that DeFL defends against common threat models with minimal accuracy loss, and achieves up to 100x reduction in storage overhead and up to 12x reduction in network overhead, compared to state-of-the-art decentralized FL approaches.

## 1 Introduction

In many real-world scenarios, such as e-commerce, medical diagnosis, and Internet of Things (IoT), data are distributed among devices or organizations and the volume of local data is insufficient to train reliable models without over-fitting. To address this limitation, it is a common practice to feed local data into a centralized server and train a global model. Undoubtedly, it raises concerns about data ownership, privacy, security, and monopolies. Recently, emerging federated learning (FL) [35]

mitigates some of these concerns by training a global model without gathering confidential data from each participating node [41]. Cross-silo FL [53, 34] is an important type of FL where 2-100 organizations collectively aggregate weights on a central parameter server, which is assumed to be trusted and reliable among organizations. However, this assumption may not hold in practice. For example, the central server could be malicious, leading to poisoning the model [15, 1, 48, 49], or skewing the model by favoring particular clients [33, 52]. Besides, fatal crashes in central servers could lead to an accuracy drop, convergence time increase, or even training procedure abortion.

To address the preceding problems raised by the central parameter server of FL, some decentralized FL solutions are proposed by eliminating the central server. These solutions can be categorized into two directions. One direction is to dynamically elect a leader, where weights are aggregated and transmitted to other nodes [47, 46, 30, 28]. The leader takes the place of the central server of FL. However, if the dynamically elected leader is detected (probably through overmuch network bandwidth [16]) and then attacked, or if the leader behaves maliciously, the risks of model poisoning and skewing still exist. The other direction is to leverage a blockchain to maintain weights and coordinate the weight aggregation [40, 13, 30, 39, 28, 2, 38, 32, 44, 19]. However, most of them are implemented based on a third-party blockchain platform, such as Ethereum or FISCO, therefore suffering from unnecessary storage and network overhead. The reason is that they maintain the consistency of all history weights due to underlying consensus mechanisms. However, FL requires weights of only the current training round for updating and does not require updates in one round to be recorded in a particular sequence.

To this end, in this paper, we propose DeFL, a novel decentralized weight aggregation framework for cross-silo FL. The key idea of DeFL is in two folds. First, the local updates of all nodes are aggregated on each node so that the reliability concern of a leader or central server can be mitigated. Second, weights of only the current training round are maintained and synchronized so that the storage and network overhead can be significantly reduced. Realizing such an idea faces two challenges. First, the weights aggregated on or updated (local trained) by faulty or adversarial nodes are not reliable. Second, synchronizing weights of only the current round brings in inconsistency in the round number  $round\_id$ . For example, at some specific point in the training procedure,  $round\_id_A$  on client  $A$  with sufficient computation and network resources could be larger than  $round\_id_B$  on client  $B$  with insufficient resources. As a result, aggregating weights of  $round\_id_A$  and  $round\_id_B$  is inconsistent with FedAvg [35] in the standard FL setting, leading to accuracy drop or convergence time increase. To tackle these challenges, we abstract each participating node as two roles, i.e. a client and a replica, as shown in Figure 1. A client enables aggregating *correct* weights from honest nodes with a weight filter based on Multi-Krum [4]. A replica ensures the consistency of  $round\_id$  and weights of the current and last rounds with a synchronizer based on HotStuff [51].

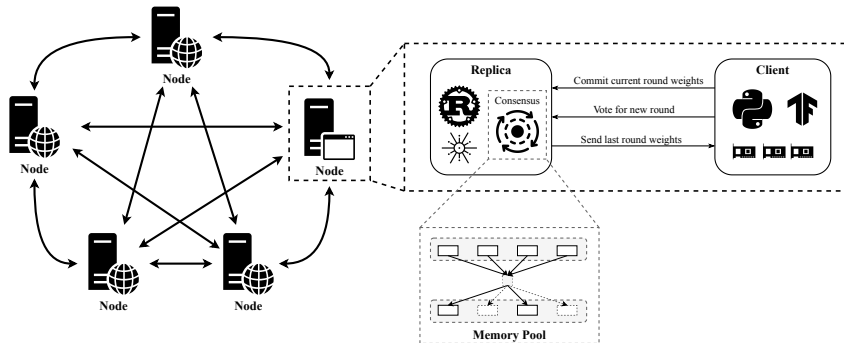


Figure 1: The architecture of DeFL

To evaluate the performance of DeFL, we conduct extensive experiments over two widely-adopted public datasets, i.e. CIFAR-10 and Sentiment140. We comprehensively measure Byzantine fault tolerance and scalability on the accuracy, computational overhead, storage overhead, and network overhead. The results show that DeFL defends against common threat models with minimal accuracy loss, and achieves up to 100x reduction in storage overhead and up to 12x reduction in network overhead, compared to state-of-the-art decentralized FL baselines. We will make the source code of

this paper publicly available online when this paper is accepted. Our contributions of this paper can be summarized as follows.

- We propose a novel decentralized weight aggregation framework for cross-silo FL (DeFL), where weights are aggregated on each node and weights of only the current training round are maintained and synchronized.
- We design a weight filter based on `Multi-Krum` to enable aggregating correct weights and design a synchronizer based on `HotStuff` to ensure consistency of `round_id` and weights.
- We theoretically analyze the Byzantine fault tolerance, convergence, and overhead of DeFL.
- We use public datasets to measure the performance of DeFL and demonstrate its superior to state-of-the-art baselines.

## 2 Related Work

In this section, we introduce related work about federated learning (FL) and decentralized FL.

**Federated Learning.** To allow users to collectively reap the benefits of shared models trained from rich data without transmitting raw data, McMahan *et al.* propose FL [35]. To improve communication efficiency, Konečný *et al.* [24] propose structured update and sketched update. Bonawitz *et al.* [5] introduce the protocol of FL, detailed system design on devices and servers, and some specific challenges of implementation. Yang *et al.* [50] categorize FL into Horizontal FL, Vertical FL, and Federated Transfer Learning. In FL settings, the central parameter server aggregates updates from devices with weights proportional to the size of local datasets, i.e. FedAvg [35]. Therefore, the stability, fairness, and security of the central server are crucial to FL.

**Decentralized Federated Learning.** To mitigate security and fault tolerance concerns of FL, decentralized FL [26, 25] is proposed, where users update their beliefs by aggregating information from their one-hop neighbors. The following literature focuses on aggregating weights of all active nodes and is categorized into two directions.

One direction is to dynamically elect a leader, where weights are aggregated and transmitted to other clients. For example, Swarm Learning (SL) [47, 46] combines decentralized hardware infrastructures, and distributed machine learning (ML) with a permissioned blockchain to securely onboard members, dynamically elect the leader, and merge model parameters. BLADE-FL [28] allows each client to broadcast the trained model to other clients, aggregate its model with received ones, and then compete to generate a block before local training of the next round. In this direction, the network bandwidth of leaders tends to be significantly higher than other nodes [16] and easy to detect. If the leader is attacked or behaves maliciously, these approaches become invalid.

The other direction is to leverage a blockchain to maintain weights and coordinate the model aggregation. For example, Biscotti [40] uses blockchain and cryptographic primitives to coordinate a privacy-preserving ML process. BAFFLE [39] uses Smart Contracts (SC) to coordinate the round delineation, model aggregation, and update tasks in FL. BFLC [30] uses blockchain for global model storage and local model update exchange and devises an innovative committee consensus mechanism to reduce consensus computing and malicious attacks. BFL [38] designs a novel reward and develops a mathematical framework that features the controllable network and parameters for privacy-aware and efficient on-vehicle FL. Lu *et al.* [32] integrate blockchain for maintaining parameters and use reinforcement learning (RL) to solve the resource sharing task. However, most of them are implemented based on a third-party blockchain platform, therefore suffering from unnecessary storage and network overhead.

## 3 Methodology

In this section, we describe the threat models, weight filtering and aggregation on a client, `round_id` and weight synchronization among replicas, and the decoupling-storage-and-consensus design of DeFL.

### 3.1 Threat Model

Following existing Byzantine fault tolerant (BFT) FL approaches [40, 8, 45, 37], we assume the number of participating nodes is  $n > 3f$ , where  $f$  denotes the number of Byzantine nodes while other nodes are honest. In cross-silo FL, where device heterogeneity is relatively low, we assume partially synchronous communication [11], whereby all honest nodes complete a local training round before a *global stabilization time of local training* (GST\_LT).  $f$  Byzantine nodes are faulty or adversarial. Faulty nodes may not always commit transactions promptly. Adversarial nodes can perform three representative poisoning weight attacks, i.e., Gaussian attack [12], sign-flipping attack [29] and label-flipping attack [3]. Adversarial nodes can also commit update transactions with weights of the wrong round or commit aggregation transactions before GST\_LT. Because one node plays the role of both a client and a replica, malicious behaviors are not assumed to exist between the client and replica of the same node.

### 3.2 Weight Filter

A client enables aggregating correct weights with a weight filter based on Multi-Krum [4]. The main idea of Krum is that when data are independent and identically distributed (i.i.d.), the gradient updates from honest clients tend to be close to the correct gradient, while those from the Byzantine clients tend to be arbitrary and are supposed to be omitted for aggregation. Specifically, Krum selects the gradient that minimizes the sum of squared distances to its  $n - f$  closest gradients. Multi-Krum interpolates between Krum and FedAvg, thereby allowing to mix the BFT properties of Krum with the convergence speed of FedAvg. Specifically, Multi-Krum applies FedAvg on top  $k$  gradients that minimizes the sum of squared distances to its  $n - f$  closest gradients.

---

#### Algorithm 1 Local training and weight aggregation on a client

---

```

1: if  $l\_round\_id \leq r\_round\_id$  then
2:    $start\_time \leftarrow clock()$ 
3:    $weight\_agg \leftarrow \text{Multi-Krum}(W_1^{LAST}, \dots, W_n^{LAST})$ 
4:    $weight\_new \leftarrow \text{local\_train}(weight\_agg, l\_data)$ 
5:    $resp \leftarrow \text{commit TX}(\text{"UPD"}, id, r\_round\_id + 1, weight\_new)$ 
6:   if  $resp = \text{OK}$  then
7:      $l\_round\_id \leftarrow r\_round\_id + 1$ 
8:    $end\_time \leftarrow clock()$ 
9:    $\text{sleep}(\max(0, GST\_LT - (end\_time - start\_time)))$ 
10:   $\text{commit TX}(\text{"AGG"}, l\_round\_id)$ 

```

---

Algorithm 1 describes how a client executes writing operations to local data structures that do not require synchronization, i.e. local round number and local weights. When the local training round  $l\_round\_id$  falls behind the global (replica) training round  $r\_round\_id$ , the client is supposed to update local  $round\_id$  and local weights through local training. Within GST\_LT, the client filters and aggregates weights of other clients of the last round in Line 3, trains aggregated weights with local data in Line 4, and commits an UPD transaction (TX) to replicas in Line 5. Then, the client waits until GST\_LT and commits an AGG transaction to replicas in Line 9-10.

### 3.3 Synchronizer

A replica ensures the consistency of  $round\_id$  and weights of the current and last round with a synchronizer based on HotStuff [51]. HotStuff [51] is proposed to address scaling challenge in Practical Byzantine Fault Tolerance (PBFT) [7]. Under the partially synchronous communication model [11], whereby a known bound  $\Delta$  on message transmission holds after some unknown *global stabilization time* (GST), and  $n \geq 3f + 1$ , HotStuff is a leader-based BFT State Machine Replication (SMR) protocol which achieves *linear* view change and optimistic responsiveness by adding a PRE-COMMIT phase to each view in PBFT. Its overall communication complexity per view is  $O(n)$ , which enables large-scale deployment on FL devices.

Algorithm 2 describes how a replica executes writing operations to global data structures that require synchronization, i.e.  $round\_id$  and weights of the current and last rounds. When executing

---

**Algorithm 2** Synchronization among replicas

---

```
1: on execution of TX("UPD",  $id$ ,  $target\_round\_id$ ,  $weight$ )
2:   if  $target\_round\_id = r\_round\_id + 1$  then
3:      $W_{id}^{CUR} \leftarrow weight$ 
4:     respond OK
5:   else
6:     respond AlreadyUPDError
7: on execution of TX("AGG",  $target\_round\_id$ )
8:   if  $target\_round\_id = r\_round\_id + 1$  then
9:      $votes \leftarrow votes + 1$ 
10:    if  $votes$  meets a quorum then
11:       $r\_round\_id \leftarrow target\_round\_id$ 
12:       $votes \leftarrow 0$ 
13:      for  $i \leftarrow 1$  to  $n$  do
14:         $W_i^{LAST} \leftarrow W_i^{CUR}$ 
15:         $W_i^{CUR} \leftarrow \emptyset$ 
16:      respond OK
17:    else
18:      respond NotMeetQuorumWarning
19:   else
20:     respond AlreadyAGGError
```

---

transactions, the replica is supposed to verify that the committed  $round\_id$  is consistent with the current global training round, in Line 2 and Line 8. When executing the UPD transaction, the replica synchronizes the weights of the current round of the corresponding client in Line 3. When executing the AGG transaction, the replica waits until the number of received AGG transactions meets a *quorum*, i.e.  $f + 1$ , in Line 8-10. Then, the replica updates and synchronizes  $round\_id$  and the weights of the current and last rounds in Line 11-16.

### 3.4 Decoupling Storage and Consensus

We construct DeFL in two layers: a communication layer and a storage layer. In the communication layer, processes reliably broadcast their proposals and reach consensus, following the schedule of HotStuff. In the storage layer, weights are stored in a trusted memory pool and can be retrieved by a unique index, which does not require any extra communication.

## 4 Analysis

In this section, we analyze Byzantine fault tolerance, convergence, and overhead of DeFL.

### 4.1 Byzantine Fault Tolerance

**Lemma 1.** *In HotStuff, when  $n \geq 3f + 1$ , if  $t_1$  and  $t_2$  are conflicting transactions, then they cannot be both committed, each by an honest replica.*

This lemma is proven in HotStuff [51]. It means that all honest nodes receive transactions with the same content and in the same sequence. Therefore, each honest node receives the same weights in each round and behaves identically the same when aggregating weights. Therefore, we can treat each honest node as a parameter server and consider one honest node to represent all.

**Lemma 2.** *In Krum, let  $V_1, \dots, V_n$  be any independent and identically distributed (i.i.d.) random  $d$ -dimensional vectors s.t.  $V_i \sim G$ , with  $\mathbb{E}G = g$  and  $\mathbb{E}\|G - g\|^2 = d\sigma^2$ . Let  $B_1, \dots, B_f$  be any  $f$  random vectors, possibly dependent on the  $V_i$ 's. If  $n > 2f + 2$  and  $\eta(n, f)\sqrt{d} \cdot \sigma < \|g\|$ , where*

$$\eta(n, f) \stackrel{\text{def}}{=} \sqrt{2 \left( n - f + \frac{f \cdot (n - f - 2) + f^2 \cdot (n - f - 1)}{n - 2f - 2} \right)} = \begin{cases} O(n), & f = O(n) \\ O(\sqrt{n}), & f = O(1) \end{cases}, \quad (1)$$

then the Krum function KR is  $(\alpha, f)$ -Byzantine fault tolerant where  $0 \leq \alpha < \pi/2$  is defined by

$$\sin \alpha = \frac{\eta(n, f) \cdot \sqrt{d} \cdot \sigma}{\|g\|}. \quad (2)$$

The definition of  $(\alpha, f)$ -Byzantine fault tolerance and the proof of this lemma is in Multi-Krum [4].

**Theorem 1.** In DeFL, when  $n \geq 3f + 3$  and  $\eta(n, f)\sqrt{d} \cdot \sigma < \|g\|$ , there exists  $\alpha$  such that DeFL is  $(\alpha, f)$ -Byzantine fault tolerant.

*Proof.* Let  $f_H \leq f$  be faulty nodes that fail to update weights before GST\_LT,  $f_K \leq f$  be adversarial nodes that update poisoned weights before GST\_LT, where  $f_H + f_K = f$ . Obviously, active nodes  $n_K$  participating in weight synchronization satisfy  $2f + 3 \leq n_K \leq n$ . According to Equation 1,  $\eta(n, f)$  monotonically increases with  $n$ , therefore,  $\eta(n_K, f_K)\sqrt{d} \cdot \sigma \leq \eta(n, f)\sqrt{d} \cdot \sigma \leq \|g\|$ . Therefore, there exists  $\alpha_0$  such that

$$\sin \alpha_0 = \frac{\eta(n_K, f_K) \cdot \sqrt{d} \cdot \sigma}{\|g\|} \leq 1, \quad (3)$$

and the Krum function KR is  $(\alpha_0, f_K)$ -BFT. Let  $f_K = f$ , then DeFL is  $(\alpha_0, f)$ -BFT.

## 4.2 Convergence

Following HotStuff [51], we analyze the convergence of the Stochastic Gradient Descent (SGD) using DeFL. The SGD optimization is formulated as  $w_{t+1} = w_t - \gamma_t \cdot \text{KR}(V_1^t, \dots, V_n^t)$ . For an honest node  $i$ ,  $V_i^t = G(w_t, \xi_i^t)$  where  $G$  is the gradient estimator and  $\xi_i^t$  is a mini-batch of samples. The local standard deviation  $\sigma(w)$  is defined as  $d \cdot \sigma^2(w) = \mathbb{E}\|G(w, \xi) - \nabla Q(w)\|^2$ , where  $Q(w)$  is the loss function.

**Lemma 3.** In HotStuff, after GST, there exists a bounded time period  $T_f$  such that if all honest nodes remain in view  $v$  during  $T_f$  and the leader for view  $v$  is honest, then a decision is reached.

This lemma is proven in HotStuff [51]. It means that synchronization among replicas would only take a bounded time period and have bounded influence on convergence.

**Lemma 4.** In Krum, we assume that (i) the loss function  $Q$  is three times differentiable with continuous derivatives, and is non-negative; (ii) the learning rates satisfy  $\sum_t \gamma_t = \infty$  and  $\sum_t \gamma_t^2 < \infty$ ; (iii) the gradient estimator satisfies  $\mathbb{E}G(w, \xi) = \nabla Q(w)$  and  $\forall r \in \{2, \dots, 4\}, \mathbb{E}\|G(w, \xi)\|^r \leq A_r + B_r \|w\|^r$  for some constants  $A_r, B_r$ ; (iv) there exists a constant  $0 \leq \alpha < \pi/2$  such that for all  $w, \eta(n, f) \cdot \sqrt{d} \cdot \sigma(w) \leq \|\nabla Q(w)\| \cdot \sin \alpha$ ; (v) beyond a certain horizon,  $\|w\|^2 \geq D$ , there exist  $\epsilon > 0$  and  $0 \leq \beta < \pi/2 - \alpha$  such that  $\|\nabla Q(w)\| \geq \epsilon > 0$  and  $\frac{\langle w, \nabla Q(w) \rangle}{\|w\| \cdot \|\nabla Q(w)\|} \geq \cos \beta$ . Then the sequence of gradients  $\nabla Q(w_t)$  converges almost surely to zero.

This lemma is proven in Multi-Krum [4].

**Theorem 2.** In DeFL, when  $n \geq 3f + 3$ , under the five assumptions of Lemma 4, the sequence of gradients  $\nabla Q(w_t)$  converges almost surely to zero.

*Proof.* Note that DeFL influences only Assumption (iv) in Lemma 4 by changing the constraint that  $n \geq 3f + 3, f_H + f_K = f$ , and  $2f + 3 \leq n_K \leq n$ . Due to Assumption (iv) in Theorem 2, there exists a constant  $0 \leq \alpha < \pi/2$  such that for all  $w, \eta(n, f) \cdot \sqrt{d} \cdot \sigma(w) \leq \|\nabla Q(w)\| \cdot \sin \alpha$ . Due to the monotonicity of  $\eta(n, f), \eta(n_K, f_K) \cdot \sqrt{d} \cdot \sigma(w) \leq \eta(n, f) \cdot \sqrt{d} \cdot \sigma(w) \leq \|\nabla Q(w)\| \cdot \sin \alpha$ , which satisfies Assumption (iv) in Lemma 4. According to Lemma 4,  $\nabla Q(w_t)$  converges almost surely to zero in DeFL.

The Byzantine fault tolerance and convergence analysis of DeFL on Multi-Krum is similar to that on Krum, therefore, we omit it in Section 4.1 and Section 4.2 due to the page limit. Note that we have not provided theoretical analysis when the data are non-i.i.d., however, we empirically evaluate this scenario on public datasets in Section 5.

## 4.3 Overhead

**Network bandwidth.** The communication complexity per view is  $O(n)$  in HotStuff [51]. In a training round, an honest node would commit an UPD transaction and an AGG transaction. As the size

of weights  $M$  is much larger than that of  $id$  or  $round\_id$ , we only consider  $M$  here. Therefore, it takes  $O(Mn)$  network bandwidth to synchronize weights of the current round on an honest node. As there are  $O(n)$  honest nodes, the overall network bandwidth of  $T$  training rounds is  $O(MTn^2)$ .

**Storage.** Thanks to the decoupling-storage-and-consensus design, DeFL maintains and caches weights of only some constant  $\tau \geq 2$  training rounds from  $n$  nodes, instead of maintaining the consistency of all history weights. Therefore, the overall storage complexity is  $M\tau n$ , regardless of the number of training rounds.

*Summary: When  $n \geq 3f + 3$ , and the data are i.i.d., DeFL is BFT and reaches convergence in a bounded time period. The network bandwidth of  $T$  training rounds is  $O(MTn^2)$  and the storage complexity is  $M\tau n$ , where  $M$  is the size of weights and DeFL caches  $\tau$  training rounds in storage.*

## 5 Evaluation

In this section, we introduce the experimental setup and measure the fault tolerance and scalability of DeFL.

### 5.1 Experiment Setup

**Datasets.** We use CIFAR-10<sup>1</sup> for image classification under MIT License. It consists of 60,000 32x32 color images in 10 classes, with 6,000 images per class. There are 50,000 training images and 10,000 test images. We use Sentiment140<sup>2</sup> for sentiment analysis. The license of Sentiment140 allows academic use without commercial purposes. Because the size of its official testing set (498) is much smaller than its official training set (1,600,000), the test accuracy would be unstable, especially when this dataset is separated into many nodes. Therefore, we manually remove the labels of 160,000 (10%) samples in the official training set and treat them as the new testing set. Therefore, there are 1,440,000 training sentences and 160,000 testing sentences. The number of positive reviews and negative ones are identical. For CIFAR-10 and Sentiment140, we follow related work [21, 31, 54] to model non-i.i.d. data using a Dirichlet distribution  $\text{Dir}(\alpha)$ , in which a smaller  $\alpha$  indicates higher data heterogeneity. We choose  $\alpha = 1$  to create CIFAR-noniid and Sentiment-noniid datasets. Both datasets do not contain personally identifiable information or offensive content. Note that the experimental results of Sentiment140 and Sentiment-noniid are similar to those of CIFAR-10 and CIFAR-noniid and are present in Section A due to the page limit.

**Models.** For CIFAR-10 and CIFAR-noniid, we use Dense Convolutional Network (DenseNet). The depth of DenseNet is 100 and the growth rate is 12. The batch size is 32. The learning rate is 1e-3. For Sentiment140 and Sentiment-noniid, we use attention-based Bidirectional Long Short-Term Memory (Bi-LSTM). The length, iteration number, and window size of Word2Vec embeddings are 300, 32, and 7, respectively. The number of Bi-LSTM units is 128. The batch size is 1,024. The dropout rate of the fully connected layer and the attention layer is 0.15.

**Environments.** We deploy DeFL and baselines on 4-10 instances, each equipped with an NVIDIA Tesla K80 GPU with 12GB memory, 3 Xeon E5-2678 v3 CPUs, and 8GB RAM. Each setting is repeated 10 times to take the average as reported results.

**Baselines.** We carefully choose 3 aforementioned open-source representative baselines to compare with DeFL, i.e. FL [35], Swarm Learning (SL) [47], and Biscotti [40]. FL has no defense against poisoning attacks. SL uses a blockchain to elect a leader. Biscotti defends against poisoning attacks via Multi-Krum [4] and uses a blockchain to store and maintain the consistency of weights.

### 5.2 Fault Tolerance

As mentioned in Section 3.1, we measure 3 types of poisoning attacks with different attack factors on 1 of 4 nodes. As shown in Table 1, FedAvg-based approaches (FL, SL) share similar accuracy while Multi-Krum-based approaches (Biscotti, DeFL) share similar accuracy. When there is no or a mild attack, i.e. Gaussian attack ( $\sigma=0.03$ ) and label-flipping attack, the accuracy of FedAvg-based

<sup>1</sup><https://www.cs.toronto.edu/~kriz/cifar.html>

<sup>2</sup><http://help.sentiment140.com/for-students>

Table 1: Accuracy on different threat models

Attack	CIFAR-10				CIFAR-noniid			
	FL	SL	Biscotti	DeFL	FL	SL	Biscotti	DeFL
No	0.924	<b>0.926</b>	0.891	0.899	0.922	<b>0.925</b>	0.840	0.836
Gaussian ( $\sigma=0.03$ )	<b>0.905</b>	0.904	0.887	0.888	0.922	<b>0.924</b>	0.891	0.893
Gaussian ( $\sigma=1.00$ )	0.184	0.197	<b>0.899</b>	0.894	0.345	0.338	0.872	<b>0.876</b>
Sign-flipping ( $\sigma=-1.0$ )	0.837	0.843	0.880	<b>0.885</b>	0.799	0.803	<b>0.888</b>	0.883
Sign-flipping ( $\sigma=-2.0$ )	0.453	0.456	0.890	<b>0.893</b>	0.423	0.421	0.878	<b>0.881</b>
Sign-flipping ( $\sigma=-4.0$ )	0.126	0.136	<b>0.896</b>	0.893	0.164	0.175	0.866	<b>0.873</b>
Label-flipping	<b>0.894</b>	0.893	0.889	0.890	<b>0.890</b>	0.884	0.872	0.876

approaches is slightly higher than that of Multi-Krum-based ones. The reason is that Multi-Krum filters outlier weights that might be trained by honest nodes and are supposed to be aggregated. This is also why the accuracy of Multi-Krum-based approaches on CIFAR-noniid is lower than that of CIFAR-10. However, when there is a relatively severe attack, the accuracy of Multi-Krum-based approaches is significantly higher than that of FedAvg-based ones. This indicates that Multi-Krum effectively detects poisoned weights and aggregates with *correct* weights from honest nodes.

Table 2: Accuracy on CIFAR-noniid with sign-flipping attack ( $\sigma=-2.0$ )

Attack	FL	SL	Biscotti	DeFL
4+0 ( $\beta=0.00$ )	0.922	<b>0.925</b>	0.840	0.836
3+1 ( $\beta=0.25$ )	0.423	0.421	0.878	<b>0.881</b>
7+0 ( $\beta=0.00$ )	<b>0.891</b>	0.890	0.823	0.825
6+1 ( $\beta=0.14$ )	0.717	0.722	<b>0.851</b>	0.850
5+2 ( $\beta=0.29$ )	0.380	0.369	0.865	<b>0.874</b>
10+0 ( $\beta=0.00$ )	<b>0.883</b>	0.881	0.832	0.826
9+1 ( $\beta=0.10$ )	0.775	0.779	<b>0.845</b>	0.842
8+2 ( $\beta=0.20$ )	0.631	0.634	0.850	<b>0.855</b>
7+3 ( $\beta=0.30$ )	0.358	0.353	0.874	<b>0.878</b>

We choose sign-flipping attack ( $\sigma=-2.0$ ) on CIFAR-noniid to measure the accuracy under different Byzantine rates  $\beta$ , as shown in Table 2. We scale DeFL on 4, 7, 10 nodes, and "a+b" means there are  $a$  honest nodes and  $b$  Byzantine node(s). As  $\beta$  raises, the accuracy of FedAvg-based approaches drops dramatically, while the accuracy of Multi-Krum-based ones remains stable and significantly higher.

**Summary:** Under most attacks, the accuracy of DeFL and Biscotti is significantly higher than that of FL and SL, no matter the Byzantine rate. However, when there is no or a mild attack, the accuracy of DeFL and Biscotti is slightly lower than that of FL or SL.

### 5.3 Scalability

We scale DeFL and baselines to 4, 7, 10 nodes and measure computation, storage, and network overhead. As shown in Figure 2, as the number of nodes increases, the RAM usage of DeFL and other baselines increases linearly. The RAM usage of DeFL is close to that of Biscotti and FL, and lower than that of SL. The GPU memory usage of DeFL and other baselines is always identical. In terms of storage overhead, we measure the storage usage of only the blockchain for fairness. The storage of DeFL is close to that of FL and SL (nearly 0 GB), and significantly lower than that of Biscotti, thanks to the decoupling-storage-and-consensus design. In terms of network overhead, we change the y-axis into a logarithmic axis for clear presentation. The receiving bandwidth of SL and FL is linear to the number of nodes, while that of DeFL and Biscotti is quadratic to the number of nodes. Besides, the receiving bandwidth of DeFL is much lower than that of Biscotti, though higher than that of FL and SL. Thanks to the shared memory pool, the sending bandwidth of DeFL is linear to the number of nodes and similar to (even slightly lower than) that of FL, while that of other baselines is similar to their receiving bandwidth.



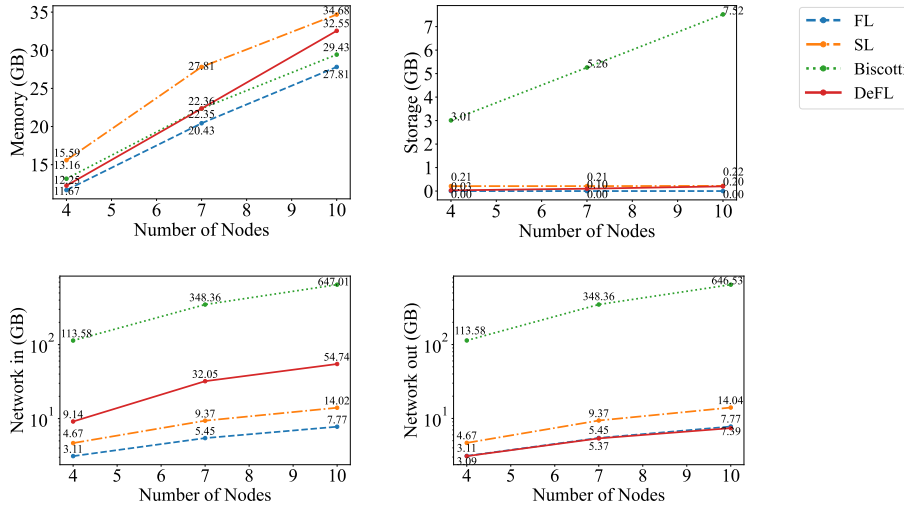


Figure 2: Overhead of different scales on CIFAR-10

**Summary:** The computational overhead of DeFL is similar to that of baselines. The storage overhead of DeFL is almost 0 GB. Although the network overhead of DeFL increases quadratically, it is up to 12x lower than that of Biscotti, which achieves similar accuracy to DeFL under most attacks.

## 6 Threats to Validity

In this section, we discuss some threats to our approach, including limited scalability and competitive literature.

### 6.1 Extend to Cross-device Federated Learning

Note that we limit the scope to cross-silo FL, which makes the following assumptions and results acceptable, (i) partially synchronous communication, (ii) independently local training, (iii)  $O(MTn^2)$  network bandwidth. (i) is the assumption of HotStuff [51], however, in cross-device FL, where device heterogeneity is relatively high, we will consider asynchronous federated learning (AFL) [43] to weaken this assumption in future work. AFL allows the central server to aggregate weights as soon as it receives a local model. (ii) is the assumption of most FL approaches, however, in cross-device FL, where devices are resource-constrained, we will consider on-device training optimizations, like pruning [18], quantization [17], and knowledge distillation [20]. (iii) is the consequence of decentralized aggregation on each node. It could optimize the network bandwidth to reduce the number of synchronizations by designing consensus specialized for FL. For example, DeFL enables updates in one training round to be recorded in a particular sequence, however, this feature is not necessary for FL. We will consider asynchronous Byzantine Atomic Broadcast (BAB) protocols, such as DAG-Rider [23], to slack the sequence constraint.

### 6.2 Difference from Byzantine Fault Tolerant Federated Learning

There are many efforts in defending Byzantine attacks in FL and they can be categorized into proactive and reactive defenses [36]. Proactive defenses include knowledge distillation [27], pruning [22], moving target defense [9], data sanitization [10], and federated multi-task learning [42]. Reactive defenses include Sniper [6], anomaly detection [4], Foolsgold [14]. However, conventional BFT FL approaches are based on the assumption that there exists an honest central parameter server. When the central server is eliminated in DeFL, most of them become invalid.

## 7 Conclusion

In this paper, we propose a novel decentralized weight aggregation framework for federated learning (DeFL), where weights are aggregated on each node and weights of only the current training round are maintained and synchronized. To tackle the weight poisoning and round number inconsistency challenges, DeFL enables aggregating *correct* weights from honest nodes based on `Multi-Krum` and ensures the consistency of the round number and weights based on `HotStuff`. We theoretically analyze the Byzantine fault tolerance, convergence, and overhead of DeFL and evaluate these results over two public datasets. The experimental results validate the effectiveness of DeFL in defending against common threat models with minimal accuracy loss, as well as show the efficiency of DeFL in storage and network usage. In future work, we will leverage asynchronous FL [43] and asynchronous BAB protocols [23] to extend DeFL to cross-device FL.

## References

- [1] Eugene Bagdasaryan, Andreas Veit, Yiqing Hua, Deborah Estrin, and Vitaly Shmatikov. How to backdoor federated learning. In *The 23rd International Conference on Artificial Intelligence and Statistics, AISTATS 2020, 26-28 August 2020, Online [Palermo, Sicily, Italy]*, volume 108 of *Proceedings of Machine Learning Research*, pages 2938–2948, 2020.
- [2] Xianglin Bao, Cheng Su, Yan Xiong, Wenchao Huang, and Yifei Hu. Flchain: A blockchain for auditable federated learning with trust and incentive. In *5th International Conference on Big Data Computing and Communications, BIGCOM 2019, QingDao, China, August 9-11, 2019*, pages 151–159, 2019.
- [3] Battista Biggio, Blaine Nelson, and Pavel Laskov. Poisoning attacks against support vector machines. In *Proceedings of the 29th International Conference on Machine Learning, ICML 2012, Edinburgh, Scotland, UK, June 26 - July 1, 2012*, 2012.
- [4] Peva Blanchard, El Mahdi El Mhamdi, Rachid Guerraoui, and Julien Stainer. Machine learning with adversaries: Byzantine tolerant gradient descent. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 119–129, 2017.
- [5] Kallista A. Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloé Kiddon, Jakub Konečný, Stefano Mazzocchi, Brendan McMahan, Timon Van Overveldt, David Petrou, Daniel Ramage, and Jason Roselander. Towards federated learning at scale: System design. In *Proceedings of Machine Learning and Systems 2019, MLSys 2019, Stanford, CA, USA, March 31 - April 2, 2019*, 2019.
- [6] Di Cao, Shan Chang, Zhijian Lin, Guohua Liu, and Donghong Sun. Understanding distributed poisoning attack in federated learning. In *25th IEEE International Conference on Parallel and Distributed Systems, ICPADS 2019, Tianjin, China, December 4-6, 2019*, pages 233–239, 2019.
- [7] Miguel Castro and Barbara Liskov. Practical byzantine fault tolerance. In *Proceedings of the Third USENIX Symposium on Operating Systems Design and Implementation (OSDI), New Orleans, Louisiana, USA, February 22-25, 1999*, pages 173–186, 1999.
- [8] Jin-Hua Chen, Min-Rong Chen, Guo-Qiang Zeng, and Jian Weng. BDFL: A byzantine-fault-tolerance decentralized federated learning method for autonomous vehicle. *IEEE Trans. Veh. Technol.*, 70(9):8639–8652, 2021.
- [9] Richard Colbaugh and Kristin Glass. Moving target defense for adaptive adversaries. In *2013 IEEE International Conference on Intelligence and Security Informatics, Seattle, WA, USA, June 4-7, 2013*, pages 50–55, 2013.
- [10] Gabriela F. Cretu, Angelos Stavrou, Michael E. Locasto, Salvatore J. Stolfo, and Angelos D. Keromytis. Casting out demons: Sanitizing training data for anomaly sensors. In *2008 IEEE Symposium on Security and Privacy (S&P 2008), 18-21 May 2008, Oakland, California, USA*, pages 81–95, 2008.
- [11] Cynthia Dwork, Nancy A. Lynch, and Larry J. Stockmeyer. Consensus in the presence of partial synchrony. *J. ACM*, 35(2):288–323, 1988.
- [12] Minghong Fang, Xiaoyu Cao, Jinyuan Jia, and Neil Zhenqiang Gong. Local model poisoning attacks to byzantine-robust federated learning. In *29th USENIX Security Symposium, USENIX Security 2020, August 12-14, 2020*, pages 1605–1622, 2020.

- [13] L. Feng, Y. Zhao, S. Guo, X. Qiu, W. Li, and P. Yu. Baf1: A blockchain-based asynchronous federated learning framework. *IEEE Transactions on Computers*, 71(05):1092–1103, 2022.
- [14] Clement Fung, Chris J. M. Yoon, and Ivan Beschastnikh. Mitigating sybils in federated learning poisoning. *CoRR*, abs/1808.04866, 2018.
- [15] Clement Fung, Chris J. M. Yoon, and Ivan Beschastnikh. The limitations of federated learning in sybil settings. In *23rd International Symposium on Research in Attacks, Intrusions and Defenses, RAID 2020, San Sebastian, Spain, October 14-15, 2020*, pages 301–316, 2020.
- [16] Jialiang Han, Yun Ma, and Yudong Han. Demystifying swarm learning: A new paradigm of blockchain-based decentralized federated learning. *CoRR*, abs/2201.05286, 2022.
- [17] Song Han, Huizi Mao, and William J. Dally. Deep compression: Compressing deep neural network with pruning, trained quantization and huffman coding. In *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*, 2016.
- [18] Song Han, Jeff Pool, John Tran, and William J. Dally. Learning both weights and connections for efficient neural network. In *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 1135–1143, 2015.
- [19] Justin D. Harris and Bo Waggoner. Decentralized and collaborative AI on blockchain. In *IEEE International Conference on Blockchain, Blockchain 2019, Atlanta, GA, USA, July 14-17, 2019*, pages 368–375, 2019.
- [20] Geoffrey E. Hinton, Oriol Vinyals, and Jeffrey Dean. Distilling the knowledge in a neural network. *CoRR*, abs/1503.02531, 2015.
- [21] Tzu-Ming Harry Hsu, Hang Qi, and Matthew Brown. Measuring the effects of non-identical data distribution for federated visual classification. *CoRR*, abs/1909.06335, 2019.
- [22] Yuang Jiang, Shiqiang Wang, Bong Jun Ko, Wei-Han Lee, and Leandros Tassioulas. Model pruning enables efficient federated learning on edge devices. *CoRR*, abs/1909.12326, 2019.
- [23] Idit Keidar, Eleftherios Kokoris-Kogias, Oded Naor, and Alexander Spiegelman. All you need is DAG. In *PODC '21: ACM Symposium on Principles of Distributed Computing, Virtual Event, Italy, July 26-30, 2021*, pages 165–175, 2021.
- [24] Jakub Konečný, H. Brendan McMahan, Daniel Ramage, and Peter Richtárik. Federated optimization: Distributed machine learning for on-device intelligence. *CoRR*, abs/1610.02527, 2016.
- [25] Anusha Lalitha, Osman Cihan Kilinc, Tara Javidi, and Farinaz Koushanfar. Peer-to-peer federated learning on graphs. *CoRR*, abs/1901.11173, 2019.
- [26] Anusha Lalitha, Shubhanshu Shekhar, Tara Javidi, and Farinaz Koushanfar. Fully decentralized federated learning. In *Third workshop on Bayesian Deep Learning (NeurIPS)*, 2018.
- [27] Daliang Li and Junpu Wang. Fedmd: Heterogenous federated learning via model distillation. *CoRR*, abs/1910.03581, 2019.
- [28] Jun Li, Yumeng Shao, Kang Wei, Ming Ding, Chuan Ma, Long Shi, Zhu Han, and H. Vincent Poor. Blockchain assisted decentralized federated learning (BLADE-FL): performance analysis and resource allocation. *CoRR*, abs/2101.06905, 2021.
- [29] Liping Li, Wei Xu, Tianyi Chen, Georgios B. Giannakis, and Qing Ling. RSA: byzantine-robust stochastic aggregation methods for distributed learning from heterogeneous datasets. In *The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019*, pages 1544–1551, 2019.
- [30] Yuzheng Li, Chuan Chen, Nan Liu, Huawei Huang, Zibin Zheng, and Qiang Yan. A blockchain-based decentralized federated learning framework with committee consensus. *IEEE Netw.*, 35(1):234–241, 2021.
- [31] Tao Lin, Lingjing Kong, Sebastian U. Stich, and Martin Jaggi. Ensemble distillation for robust model fusion in federated learning. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.

- [32] Yunlong Lu, Xiaohong Huang, Ke Zhang, Sabita Maharjan, and Yan Zhang. Blockchain and federated learning for 5g beyond. *IEEE Netw.*, 35(1):219–225, 2021.
- [33] Lingjuan Lyu, Xinyi Xu, Qian Wang, and Han Yu. Collaborative fairness in federated learning. In Qiang Yang, Lixin Fan, and Han Yu, editors, *Federated Learning - Privacy and Incentive*, volume 12500 of *Lecture Notes in Computer Science*, pages 189–204. Springer, 2020.
- [34] Othmane Marfoq, Chuan Xu, Giovanni Neglia, and Richard Vidal. Throughput-optimal topology design for cross-silo federated learning. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020.
- [35] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Agüera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, AISTATS 2017, 20-22 April 2017, Fort Lauderdale, FL, USA*, 2017.
- [36] Viraaji Mothukuri, Reza M. Parizi, Seyedamin Pouriyeh, Yan Huang, Ali Dehghantanha, and Gautam Srivastava. A survey on security and privacy of federated learning. *Future Gener. Comput. Syst.*, 115:619–640, 2021.
- [37] Safa Otoum, Ismaeel Al Ridhawi, and Hussein T. Mouftah. Blockchain-supported federated learning for trustworthy vehicular networks. In *IEEE Global Communications Conference, GLOBECOM 2020, Virtual Event, Taiwan, December 7-11, 2020*, pages 1–6, 2020.
- [38] Shiva Raj Pokhrel and Jinho Choi. A decentralized federated learning approach for connected autonomous vehicles. In *2020 IEEE Wireless Communications and Networking Conference Workshops, WCNC Workshops 2020, Seoul, Korea (South), April 6-9, 2020*, pages 1–6, 2020.
- [39] Paritosh Ramanan and Kiyoshi Nakayama. BAFFLE : Blockchain based aggregator free federated learning. In *IEEE International Conference on Blockchain, Blockchain 2020, Rhodes, Greece, November 2-6, 2020*, pages 72–81, 2020.
- [40] Muhammad Shayan, Clement Fung, Chris J. M. Yoon, and Ivan Beschastnikh. Biscotti: A blockchain system for private and secure federated learning. *IEEE Trans. Parallel Distributed Syst.*, 32(7):1513–1525, 2021.
- [41] Reza Shokri and Vitaly Shmatikov. Privacy-preserving deep learning. In *Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security, Denver, CO, USA, October 12-16, 2015*, pages 1310–1321, 2015.
- [42] Virginia Smith, Chao-Kai Chiang, Maziar Sanjabi, and Ameet Talwalkar. Federated multi-task learning. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 4424–4434, 2017.
- [43] Michael R. Sprague, Amir Jalalirad, Marco Scavuzzo, Catalin Capota, Moritz Neun, Lyman Do, and Michael Kopp. Asynchronous federated learning for geospatial applications. In *ECML PKDD 2018 Workshops - DMLE 2018 and IoTStream 2018, Dublin, Ireland, September 10-14, 2018, Revised Selected Papers*, volume 967 of *Communications in Computer and Information Science*, pages 21–28, 2018.
- [44] Kentaroh Toyoda, Jun Zhao, Allan NengSheng Zhang, and P. Takis Mathiopoulos. Blockchain-enabled federated learning with mechanism design. *IEEE Access*, 8:219744–219756, 2020.
- [45] Rong Wang and Wei-Tek Tsai. Asynchronous federated learning system based on permissioned blockchains. *Sensors*, 22(4):1672, 2022.
- [46] Stefanie Warnat-Herresthal, Hartmut Schultze, Krishnaprasad Lingadahalli Shastry, Sathyanarayanan Manamohan, Saikat Mukherjee, Vishesh Garg, Ravi Sarveswara, Kristian Händler, Peter Pickkers, N Ahmad Aziz, et al. Swarm learning as a privacy-preserving machine learning approach for disease classification. *bioRxiv*, 2020.
- [47] Stefanie Warnat-Herresthal, Hartmut Schultze, Krishnaprasad Lingadahalli Shastry, Sathyanarayanan Manamohan, Saikat Mukherjee, Vishesh Garg, Ravi Sarveswara, Kristian Händler, Peter Pickkers, N Ahmad Aziz, et al. Swarm learning for decentralized and confidential clinical machine learning. *Nature*, 594(7862):265–270, 2021.

- [48] Chulin Xie, Keli Huang, Pin-Yu Chen, and Bo Li. DBA: distributed backdoor attacks against federated learning. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*, 2020.
- [49] Cong Xie, Sanmi Koyejo, and Indranil Gupta. Zeno: Distributed stochastic gradient descent with suspicion-based fault-tolerance. In *Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA*, volume 97 of *Proceedings of Machine Learning Research*, pages 6893–6901, 2019.
- [50] Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong. Federated machine learning: Concept and applications. *ACM Trans. Intell. Syst. Technol.*, 10(2):12:1–12:19, 2019.
- [51] Maofan Yin, Dahlia Malkhi, Michael K. Reiter, Guy Golan-Gueta, and Ittai Abraham. Hotstuff: BFT consensus with linearity and responsiveness. In *Proceedings of the 2019 ACM Symposium on Principles of Distributed Computing, PODC 2019, Toronto, ON, Canada, July 29 - August 2, 2019*, pages 347–356, 2019.
- [52] Han Yu, Zelei Liu, Yang Liu, Tianjian Chen, Mingshu Cong, Xi Weng, Dusit Niyato, and Qiang Yang. A fairness-aware incentive scheme for federated learning. In *AIES '20: AAAI/ACM Conference on AI, Ethics, and Society, New York, NY, USA, February 7-8, 2020*, pages 393–399, 2020.
- [53] Chengliang Zhang, Suyi Li, Junzhe Xia, Wei Wang, Feng Yan, and Yang Liu. Batchcrypt: Efficient homomorphic encryption for cross-silo federated learning. In *2020 USENIX Annual Technical Conference, USENIX ATC 2020, July 15-17, 2020*, pages 493–506, 2020.
- [54] Zhuangdi Zhu, Junyuan Hong, and Jiayu Zhou. Data-free knowledge distillation for heterogeneous federated learning. In *Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event*, volume 139 of *Proceedings of Machine Learning Research*, pages 12878–12889, 2021.

## Checklist

1. For all authors...
  - (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [\[Yes\]](#)
  - (b) Did you describe the limitations of your work? [\[Yes\]](#)
  - (c) Did you discuss any potential negative societal impacts of your work? [\[No\]](#) The data privacy and security has raised considerable concerns of end-users and this work benefits the data privacy and security of federated learning (FL).
  - (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [\[Yes\]](#)
2. If you are including theoretical results...
  - (a) Did you state the full set of assumptions of all theoretical results? [\[Yes\]](#)
  - (b) Did you include complete proofs of all theoretical results? [\[Yes\]](#)
3. If you ran experiments...
  - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [\[Yes\]](#) We will make the source code of this paper publicly available online when this paper is accepted.
  - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [\[Yes\]](#)
  - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [\[Yes\]](#)
  - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [\[Yes\]](#)
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
  - (a) If your work uses existing assets, did you cite the creators? [\[Yes\]](#)
  - (b) Did you mention the license of the assets? [\[Yes\]](#)
  - (c) Did you include any new assets either in the supplemental material or as a URL? [\[Yes\]](#)

- (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes]
  - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes]
5. If you used crowdsourcing or conducted research with human subjects...
- (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
  - (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
  - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

## A Extended Results for Sentiment140

In this section, we present extended results for Sentiment140 and Sentiment-noniid datasets in fault tolerance and scalability.

### A.1 Fault Tolerance

Table 3: Accuracy on different threat models

Attack	Sentiment140				Sentiment-noniid			
	FL	SL	Biscotti	DeFL	FL	SL	Biscotti	DeFL
No	0.745	<b>0.746</b>	0.744	<b>0.746</b>	0.700	0.699	<b>0.701</b>	0.698
Gaussian ( $\sigma=0.03$ )	0.745	0.743	<b>0.746</b>	<b>0.746</b>	0.699	<b>0.701</b>	0.700	0.699
Gaussian ( $\sigma=1.00$ )	0.737	0.736	0.745	<b>0.747</b>	0.537	0.534	<b>0.701</b>	0.699
Sign-flipping ( $\sigma=-1.0$ )	0.736	0.738	<b>0.749</b>	0.747	0.685	0.686	0.698	<b>0.699</b>
Sign-flipping ( $\sigma=-2.0$ )	0.725	0.722	<b>0.750</b>	0.748	0.699	<b>0.700</b>	0.699	<b>0.700</b>
Sign-flipping ( $\sigma=-4.0$ )	0.655	0.659	0.745	<b>0.748</b>	0.508	0.510	0.697	<b>0.700</b>
Label-flipping	0.719	0.720	<b>0.746</b>	<b>0.746</b>	0.698	0.699	<b>0.701</b>	0.700

As mentioned in Section 3.1, we measure 3 types of poisoning attacks with different attack factors on 1 of 4 nodes. As shown in Table 3, FedAvg-based approaches (FL, SL) share similar accuracy while Multi-Krum-based approaches (Biscotti, DeFL) share similar accuracy. In most settings, especially when the attack is severe, the accuracy of Multi-Krum-based approaches is higher than that of FedAvg-based ones. This indicates that Multi-Krum effectively detects poisoned weights and aggregates with *correct* weights from honest nodes.

Table 4: Accuracy on Sentiment-noniid with Gaussian attack ( $\sigma=1.00$ )

Attack	FL	SL	Biscotti	DeFL
4+0 ( $\beta=0.00$ )	0.700	0.699	<b>0.701</b>	0.698
3+1 ( $\beta=0.25$ )	0.537	0.539	<b>0.700</b>	0.699
7+0 ( $\beta=0.00$ )	<b>0.701</b>	0.700	0.700	<b>0.701</b>
6+1 ( $\beta=0.14$ )	0.624	0.622	<b>0.701</b>	0.700
5+2 ( $\beta=0.29$ )	0.573	0.570	0.700	<b>0.701</b>
10+0 ( $\beta=0.00$ )	<b>0.701</b>	0.699	0.700	<b>0.701</b>
9+1 ( $\beta=0.10$ )	0.656	0.660	<b>0.702</b>	0.701
8+2 ( $\beta=0.20$ )	0.633	0.631	0.701	<b>0.702</b>
7+3 ( $\beta=0.30$ )	0.601	0.604	0.700	<b>0.702</b>

We choose Gaussian attack ( $\sigma=1.00$ ) on Sentiment-noniid to measure the accuracy under different Byzantine rates  $\beta$ , as shown in Table 4. We scale DeFL on 4, 7, 10 nodes, and " $a+b$ " means there are  $a$  honest nodes and  $b$  Byzantine node(s). When the number of nodes is fixed, as  $\beta$  raises, the accuracy of FedAvg-based approaches drops dramatically, while the accuracy of Multi-Krum-based ones remains stable and significantly higher. Besides, when  $\beta$  keeps stable or even slightly raises, as the number of nodes increases, the accuracy of FedAvg-based approaches raises. The reason could be that the higher ensemble property of more nodes contributes to better generalizability and robustness, however, it is beyond the scope of this paper.

**Summary:** Under most attacks, the accuracy of DeFL and Biscotti is significantly higher than that of FL and SL, no matter the Byzantine rate.

### A.2 Scalability

We scale DeFL and baselines to 4, 7, 10 nodes and measure computation, storage, and network overhead. As shown in Figure 3, as the number of nodes increases, the growth trends of overhead of DeFL and baselines are similar to those on CIFAR-noniid, as mentioned in Section 5.3.

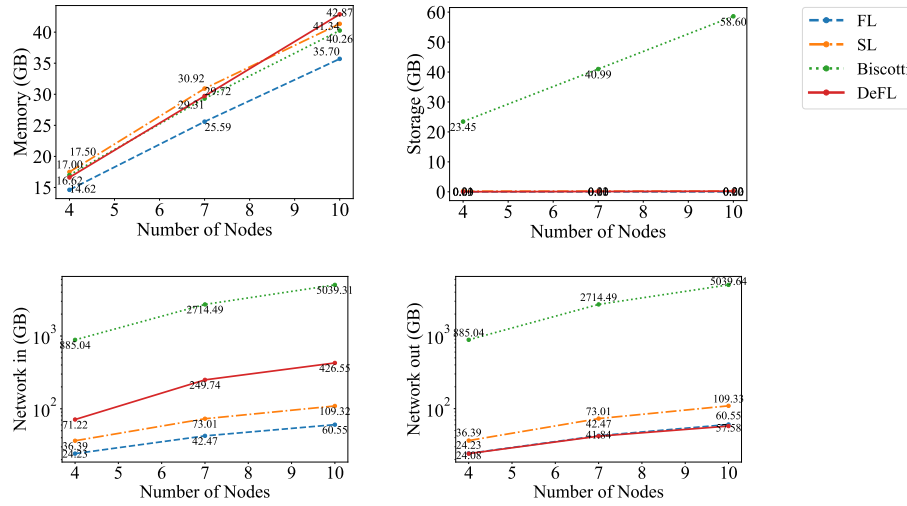


Figure 3: Overhead of different scales on Sentiment-noniid

**Summary:** The computational overhead of DeFL is similar to that of baselines. The storage overhead of DeFL is almost 0 GB. Although the network overhead of DeFL increases quadratically, it is up to 12x lower than that of Biscotti, which achieves similar accuracy to DeFL under most attacks.