Shielding Federated Learning: Mitigating Byzantine Attacks with Less Constraints

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Abstract—Federated learning is a newly emerging distributed learning framework that facilitates the collaborative training of a shared global model among distributed participants with their privacy preserved. However, federated learning systems are vulnerable to Byzantine attacks from malicious participants, who can upload carefully crafted local model updates to degrade the quality of the global model and even leave a backdoor. While this problem has received significant attention recently, current defensive schemes heavily rely on various assumptions, such as a fixed Byzantine model, availability of participants’ local data, minority attackers, IID data distribution, etc.

To relax those constraints, this paper presents Robust-FL, the first prediction-based Byzantine-robust federated learning scheme where none of the assumptions is leveraged. The core idea of the Robust-FL is exploiting historical global model to construct an estimator based on which the local models will be filtered through similarity detection. We then cluster local models to adaptively adjust the acceptable differences between the local models and the estimator such that Byzantine users can be identified. Extensive experiments over different datasets show that our approach achieves the following advantages simultaneously: (i) independence of participants’ local data, (ii) tolerance of majority attackers, (iii) generalization to variable Byzantine model.

Index Terms—Federated Learning, Byzantine Attacks, Byzantine Robustness, Privacy Protection

1. Introduction

Recently emerged federated learning (FL) [29] is a new computing paradigm that trains a global machine learning model over distributed data while protecting participants’ privacy. By distributing the model learning process to participants, FL constructs a global model from user-specific local models, such that participants’ data never leaves their own devices. In this way, the bandwidth cost is significantly reduced and user privacy is well protected.

Due to the decentralized nature, FL is vulnerable to Byzantine attacks [12], [22], where malicious participants can falsify real models or gradients to damage the learning process, or directly poison the training data to make the global model learn wrong information or even leave a backdoor. In the literature, various attack methods have been proposed to demonstrate the vulnerabilities of FL. For example, pixel-pattern backdoor attack [9] adds a pre-defined pixel pattern to a fraction of training data and modifies the corresponding labels. Label flipping attack [7] will train the local model by combining correct samples with flipped labels. These two attacks aim at reducing the recognition rate of the local models by tampering with the training data. Another kind of attack method focuses on manipulating the local models, such as bit-flip attack [27] which modifies a part of the local model parameters by flipping specified bits, and sign-flipping attack [14] which flips the signs of local model parameters and enlarges the magnitudes. Recently a distributed backdoor attack [24] is proposed to show the possibility of uniting multiple participants to conduct an attack, where a backdoor trigger can be decomposed and embedded into different adversarial parties.

To mitigate Byzantine attacks, a mounting number of defense schemes have been proposed [2], [3], [18], [23], [26]. They mainly focused on comparing participants’ local models to remove anomalous ones before aggregating them. These solutions, however, suffer from various limitations that make them unsuitable to be applied in practice. For example, the famous defense scheme Multi-Krum [2] assumes that data is independently and identically distributed (IID) and cannot deal with Non-IID datasets. FABA [23] assumes a fixed Byzantine model and needs to know the number of malicious participants in advance before detection. DiVerSeFL [18] requires a part of participants’ local dataset to help detect anomalous models, which apparently violates the privacy principle of FL. The most recently proposed defense FLTrust [4] is not able to identify the Byzantine participants. A comprehensive comparison among existing defensive schemes is shown in Table 1.

To get rid of these limitations, we propose Robust-FL, the first prediction-based Byzantine-robust FL scheme. Different from existing works that focus on making use of local models in the current iteration, Robust-FL aims to construct an estimator based on the historical global models from previous rounds. The local models that significantly differ from the current estimator are expected to have a higher possibility of being malicious, and will be discarded. In detail, we first make use of exponential smoothing to
construct the estimator, which enjoys a high efficiency for
detection, especially when there are large-scale clients in
federated learning. We then propose using a small public
dataset (i.e., less than 10 samples) to train an initial global
model, which is crucial for improving the detection accuracy.

In summary, we make the following contributions:

- We propose a new Byzantine-robust federated learning
  scheme called Robust-FL. To the best of our
  knowledge, Robust-FL is the first predication-based
  defense scheme that can mitigate Byzantine attacks
effectively and efficiently without relying on any
  fallacious assumptions.
- We propose incorporating clustering algorithms to
  adaptively adjust the differences between the estima-
tor and local models, such that a boundary between
  benign and malicious models can be effectively af-
firmed to identify Byzantine participants.
- We conduct extensive experiments to evaluate
  Robust-FL. The results show that Robust-FL is still
effective even more than 50% participants are com-
  promised, the Byzantine models are variable, and the
  participants’ data are not available, while all existing
defenses are invalid under this severe scenario.

2. Related Work

In order to resist Byzantine attacks, researchers have
proposed many defensive schemes in recent years. We divide
them into three categories according to the principles that the
server relied on to detect or evade anomalous local models.

Distance-based defenses: The first category focuses on
comparing the distances between the local models to find
out anomalous ones. Krum [2] aims to choose one local
model that is closest to its $K - f - 2$ neighbors, where
$K$ is the number of participants and $f$ is the number of
malicious users. Since Krum converges slowly, the authors
introduced its variant Multi-Krum, which chooses $K - f$
local models for aggregation rather than just one. Similar
to Multi-Krum, FABA [23] iteratively removes the local
model that is farthest from the average model until the
number of eliminated models is $f$. FoolsGold [7] uses cosine
similarity to identify malicious models and then assigns
them smaller weights to reduce their impact on the averaged
global model. Sniper [3] selects local models for aggregation
based on a graph which is constructed according to the
Euclidean distances between the local models. The PCA
scheme [20] projects local updates into two-dimensional
space and uses a clustering algorithm to find malicious
updates. MAB-RFL [21] is also equipped with PCA and
clustering algorithm to identify malicious updates, in add-
ition, a momentum based approach is applied to tackle
the data heterogeneity (i.e., Non-IID) challenge. All these
solutions (except MAB-RFL), however, only work well over
independently and identically distributed (IID) data, and
they cannot tolerate more than 50% attackers. Besides, most
of them need to know the number of attackers in advance.

Statistics-based defenses: The second category exploits
the statistical characteristics to remove statistical outliers.
Instead of performing detection-then-aggregation, Trimmed
Mean [30] directly uses all the local updates to obtain a
new global model, by computing the median or the trimmed
mean of all local models in each dimension. Geometric
Median [25] intends to find a new update that minimizes
the summation of the distances between the update and each
local model. The RFA scheme [17] computes the geometric
median of the local models with an alternating minimization
approach to reduce the computational overhead. Bulyan [16]
first uses Multi-Krum to remove malicious models and
then aggregates the rest models based on Trimmed Mean.
SLSGD [26] also adopts Trimmed Mean as the aggrega-
tion rule, and then uses a newly proposed moving-average
method, which considers global models in this round and the
last round. Nevertheless, the above schemes cannot identify
Byzantine users, and they perform poorly when there are
more than 50% Byzantine users.

Performance-based defenses: The last category de-

deps on the validation dataset to evaluate the performance
of the uploaded parameters. Li et al. [14] proposed using a pre-trained autoencoder to detect malicious models.
Zeno [27] computes the stochastic descendant score for each
gradient based on a validation dataset and then removes
the gradients with low stochastic descendant scores. Cao
et al. [5] proposed a Byzantine-robust distributed gradient
algorithm, which computes a noisy gradient based on a clean
dataset, and a gradient is accepted only when its distance
between the noisy gradient satisfies a pre-defined condition.
Prakash et al. [18] proposed DiverseFL, which first com-
putes a guiding gradient for each user based on the data
the user shares, and then two similarity metrics (Direction
Similarity and Length Similarity) between the local gradient
and the corresponding guiding gradient are considered, only
when both metrics are satisfied will the gradient be accepted.
FLTrust [4] bootstraps trust with a clean training dataset
collected by the server. More specifically, the RELU-clipped
cosine-similarity between each local update and the server
update (calculated on the cleaning dataset) is employed to
reweight the local update, such that malicious updates have
a limited impact on the global model. However, algorithm
[14] requires a lot of data to obtain benign models and trains
autoencoder based on the benign models, but in reality, it is
difficult to obtain so much data. Although the rest four schemes
require few data, they have other limitations. For instance,
Zeno needs to know the number of attackers in advance;
scheme [5] relies on an appropriate hyper-parameter to dis-
tinguish benign gradients from malicious ones; DiverseFL
compels users to share their private data, which violates the
original intention of FL; FLTrust cannot identify Byzantine
users, which means that malicious updates can also partici-
pate in aggregation to deteriorate the accuracy of the global
model.
TABLE 1: A comprehensive comparison among existing defensive schemes. $T(k, d)$: the average running time corresponding to the number of users $K$ and the model dimension $d$. Note that for Bulyan $C$ means the time complexity of the aggregation algorithm, and $f$ denotes the number of attackers. **Non-IID Data**: whether the training data is distributed heterogeneously (Non-IID). **50%-Byzantine**: whether the percentage of compromised users is larger than 50%. **N-Independence**: whether the number of attackers is NOT required in advance. **D-Independence**: whether the shared data that derived from users is NOT required in advance. **Byzantine Identifiability**: whether the Byzantine users can be identified.

| Scheme | $T(k, d)$ | Non-IID Data | 50%-Byzantine | N-Independence | D-Independence | Byzantine Identifiability |
|--------|-----------|--------------|---------------|----------------|-----------------|---------------------------|
| Multi-Krum [2] | $O(K^2d)$ | $\times$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| FABA [23] | $O(K^2d)$ | $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| PCA [20] | $O(K^2d + K^4)$ | $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| MAB-RFL [21] | $O(K^2d + K^4)$ | $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Trimmed Mean, Median [30] | $O(Kd \log K)$ | $\times$ | $\times$ | $\times$ | $\times$ | $\times$ |
| Bulyan [16] | $O((K-f)C + Kd)$ | $\times$ | $\times$ | $\times$ | $\times$ | $\times$ |
| RFA [17] | $O(Kd)$ | $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Sniper [3] | $O(Kd)$ | $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Resampling [11] | $O(K^2d)$ | $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| RSA [13] | $O(Kd)$ | $\checkmark$ | $\times$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| DiverseFL [18] | $O(Kd)$ | $\checkmark$ | $\checkmark$ | $\times$ | $\times$ | $\times$ |
| FLTrust [4] | $O(Kd)$ | $\checkmark$ | $\checkmark$ | $\times$ | $\times$ | $\times$ |
| Zeno [27] | $O(Kd)$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Our scheme | $O(Kd)$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |

3. Background

3.1. Federated Learning

We consider a general FL system, consisting of a central server and $K$ users. Each user $k$ ($k = 1, 2, ..., K$) has a dataset $D_k$, the size of which is denoted as $|D_k| = n_k$. It is worth noting that each local dataset may be subject to a different distribution, that is, the users’ data may be distributed in a Non-IID way. The users aim to collaboratively train a shared global model $w$. Apparently, the problem can be solved via minimizing the empirical loss, i.e., $\arg\min_{D_k} f(D, w)$, where $D = \bigcup_{k=1}^{K} D_k$ and $f(D, w)$ is a loss function (e.g., mean absolute error, cross-entropy). However, the optimization requires all the users to share their raw data to a central server, which would result in a serious threat to user’s privacy. Instead, FL obtains $w$ by optimizing $\arg\min_{w} \sum_{k=1}^{K} f(D_k, w)$. Specifically, the FL system iteratively performs the following three steps until the global model converges:

**Step 1.** In the $t$-th iteration, the central server broadcasts a global model $w_t$ to the users.

**Step 2.** After receiving $w_t$, each user $k$ trains a new local model $w_{t+1}^{k}$ over $D_k$ by solving the optimization problem $\arg\min_{w_{t+1}^{k}} f(D_k, w_{t+1}^{k})$ and then uploads it to the server;

**Step 3.** The server aggregates all the local models according to user’s proportional dataset size as follows:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^{k},$$

where $n = \sum_{k=1}^{K} n_k$.

3.2. Exponential Smoothing

Exponential smoothing [8] is a well-known lightweight forecasting algorithm over time series data. It has been widely used in production or economic development forecasting because of its low computational complexity and high precision. Next, we present two definitions that are the cornerstones of exponential smoothing.

**Definition 1 (First Order Exponential Smoothing):** If $w_t$ is the global model in the $t$-th iteration, and $s_{t-1}^{(1)}$ is the first order exponential smoothing value in the $(t-1)$-th iteration, then the first order exponential smoothing value for iteration $t$ is defined as:

$$s_t^{(1)} = \alpha w_t + (1 - \alpha)s_{t-1}^{(1)},$$

where $\alpha$ is an empirically determined parameter ranging between 0 and 1, which adjusts the importance of the latest global models. If $\alpha = 1$, then the first order exponential smoothing value is completely determined by the latest global model $w_t$, independent of previous global models. On the contrary, if $\alpha = 0$, then the first order exponential smoothing value is independent of global models, and it is always a constant that is determined by the initial value $s_0^{(1)}$.

**Definition 2 (Second Order Exponential Smoothing):** Based on the first order exponential smoothing value, the second order exponential smoothing value in the $t$-th iteration is defined as:

$$s_t^{(2)} = \alpha s_t^{(1)} + (1 - \alpha)s_{t-1}^{(2)},$$

where $s_{t-1}^{(2)}$ is the second order exponential smoothing value in the $(t-1)$-th iteration. Similarly, we can define $p$-th order exponential smoothing value.

4. Problem Setup

4.1. Attack Model

As is typical in off-the-shelf Byzantine robust defenses [4], [19], [21], we assume that an adversary can control numerous users. It is noteworthy that the adversary...
may control more than 50% users. However, the FL system must contain at least one benign participant. The adversary can arbitrarily manipulate the training data and the model parameters of the users it controls, corresponding to data poisoning attack and model poisoning attack respectively. Nevertheless, the central server and benign users are not under the control of the adversary. Thus the only way the adversary can distract the global model accuracy is by uploading poisoned local models through the compromised users. Note that the adversary can launch collusion attack, where all malicious models are similar or even identical (e.g., LIE attack [1]), to guarantee the stealthiness of the attack.

4.2. Defense Model

Our defense is deployed on the central server and expected to mitigate all kinds of Byzantine attacks with less constrains (as described in Table 1). Specifically, the server does not access the raw local training data and is agnostic about the number of compromised users. In addition, the defense should identify Byzantine users accurately so as to reduce the frequencies that these users are selected in further iterations [21]. Furthermore, the defense is required to tolerate more than 50% attackers and guarantee the quality (i.e., high accuracy) of the global model in both IID and Non-IID scenarios, with a comparable computation overhead with that in FedAvg [15].

Note that the central server is equipped with a small size guiding dataset like many existing defenses [4], [6], [27], [28]. We highlight that, in real-world scenarios, it is toilless for the server to gather such a guiding dataset without sacrificing user privacy (e.g., acquiring from publicly available datasets, manual labeling, or offering voluntarily by users).

5. Robust-FL: Defending Against Byzantine Attacks via Estimation

5.1. Key Insight

After reviewing the existing defenses, we conclude that the main reason behind their limitations is that they focus on making use of the information of the current data in each iteration to detect anomalies, which is indeed a difficult problem. For instance, Multi-Krum tends to remove local models that are far from the overall distribution of the problem. For instance, Multi-Krum tries to remove local models in each iteration to detect anomalies, which is indeed a difficult problem. In this iteration, Robust-FL first constructs an estimator based on previous global models, and then compares the local models with the estimator. The models that are far away from the estimator will be regarded as malicious and discarded. Then the server aggregates the local models to obtain a new global model and updates the estimator for the next iteration. A brief overview of our scheme is illustrated in Fig. 1. In the next sections, we will show how to construct the estimator by using exponential smoothing and address the two main technical challenges when applying it.

5.2. Constructing the Estimator

Robust-FL employs exponential smoothing to construct an estimator, rather than using advanced deep learning algorithms to realize the function of prediction. This is because the server only maintains a sequence of discrete data that is far from enough to train a deep predictive model. Moreover, exponential smoothing enjoys a low computation overhead that enables the server to perform the anomaly detection with high efficiency. In this section, we will show how the server computes the estimator \( \hat{\omega}_t \) in the \( t \)-th iteration. Based on the exponential smoothing algorithm, we first derive the following lemma:

**Lemma 1.** The estimator \( \hat{\omega}_t \) and its \( p \)-th order exponential smoothing value \( s_t^{(p)} \) satisfy the following property:

\[
 s_t^{(p)} = \sum_{i=0}^{n} \left(-1\right)^i \frac{\omega_t^{(i)}}{i!} \frac{\alpha^p}{(p-1)!} \sum_{j=0}^{\infty} j^i \left(1-\alpha\right)^j \frac{(p-1+j)!}{j!} ,
\]

where \( \omega_t^{(i)} \) is the \( i \)-th order derivative of the estimated model \( \hat{\omega}_t \) for \( i \in [0, n] \).

Lemma 1 establishes the relationship between \( \omega_t^{(i)} \) and \( s_t^{(p)} \), such that we can obtain \( \omega_t^{(i)} \) with \( s_t^{(p)} \), which are much easier to compute based on Definition 1 and 2 in Section 3.2.
In Robust-FL, we only consider second order exponential smoothing. Let \( p = 1 \) and \( p = 2 \), we can have:

\[
\begin{aligned}
    s_t^{(1)} &= \hat{w}_0 \alpha \sum_{j=0}^{\infty} (1-\alpha)^j - \hat{w}_t^{(1)} \alpha \sum_{j=0}^{\infty} j(1-\alpha)^j, \\
    s_t^{(2)} &= \hat{w}_t^{(0)} \alpha^2 \sum_{j=0}^{\infty} (1+j)(1-\alpha)^j - \hat{w}_t^{(1)} \alpha^2 \\
    &\quad \sum_{j=0}^{\infty} j(j+1)(1-\alpha)^j.
\end{aligned}
\]  

(4)

Rearranging Eq. (4) we can easily obtain:

\[
\begin{aligned}
    \frac{\hat{w}(0)}{\hat{w}(1)} &= \frac{2s_t^{(1)} - s_t^{(2)}}{s_t^{(1)} - s_t^{(2)}}, \\
    \hat{w}(1) &= \frac{\alpha}{1-\alpha} \left( s_t^{(1)} - s_t^{(2)} \right).
\end{aligned}
\]  

(5)

On the other hand, according to Taylor series, we can set the estimator \( \hat{w}_{t+T} \) after \( T \) iterations as follows:

\[
\hat{w}_{t+T} = \sum_{i=0}^{n} \frac{\hat{w}_i}{i!} T^i.
\]  

(6)

In federated learning, the global model \( w_t \) is always adjusted towards the direction of convergence and the estimator \( \hat{w}_t \) only needs to predict the global model for the next iteration, so it is reasonable to assume that \( \hat{w}_{t+T} \) in Eq. (6) is linear, in other words, we have

\[
\hat{w}_{t+1} = \hat{w}_t^{(0)} + \hat{w}_t^{(1)},
\]  

(7)

where we set \( T = 1 \).

Combining Eq. (5) and Eq. (7), we have

\[
\hat{w}_{t+1} = \frac{2-\alpha}{1-\alpha} s_t^{(1)} - \frac{1}{1-\alpha} s_t^{(2)}.
\]  

(8)

In summary, we can use \( s_t^{(1)} \) and \( s_t^{(2)} \) to update \( \hat{w}_{t+1} \) easily. Note that it is not required to store all the historical global models on the central server, only \( s_t^{(1)} \) and \( s_t^{(2)} \) are needed to obtain the estimator. Therefore, our scheme does not incur additional storage overhead.

### 5.3. Initializing Correct Bias Model

One of the main challenges in Robust-FL is how to generate the initial estimator \( w_0 \). When using exponential smoothing to detect anomalous local models, a bad \( w_0 \) will make the estimator converge towards the malicious local models.

The traditional exponential smoothing usually takes the average of the first several true values as the initial values for \( s_0^{(1)} \) and \( s_0^{(2)} \), and then recursively computes \( s_0^{(1)} \) and \( s_0^{(2)} \). However, the solution does not apply to our scheme, because in the federated learning scenario, there does not exist a true global model at all. Another solution is to use a randomly initialized global model \( w_0 \) to compute \( s_0^{(1)} \) and \( s_0^{(2)} \). According to Eq. (8) the estimator for the first iteration is \( \hat{w}_1 = w_0 \), which means that \( \hat{w}_1 \) is also random. However, the random \( \hat{w}_1 \) cannot guide the server to accurately identify malicious local models as the server might select a lot of malicious models at first, causing the estimated model to be biased towards malicious models in the subsequent iterations.

5.4. Identifying Byzantine Users

Accurately identifying byzantine users and discarding their anomalous local models is of great importance to improve the accuracy of the global model. However, how to find the boundary between normal and abnormal updates is challenging. Most of the existing solutions for identifying byzantine users rely on the assumption that the byzantine model is fixed and the number of attackers is known by the server in advance, which makes it much easier to find the boundary. For instance, FABA iteratively eliminates a local model that is farthest from the average model until the number of eliminated models is equal to the number of attackers. Without the assumption, FABA cannot determine how many local models should be eliminated.

To identify byzantine users without relying on any assumption, Robust-FL incorporates a clustering algorithm (e.g., k-means) based on the bias model. Specifically, we observe that our bias model is able to force the estimator to converge to benign models, making the benign models get much closer to the estimator than malicious ones. Therefore we expect that the biased model will gradually generate a boundary between benign and malicious models. In light of this, Robust-FL first calculates the distances between local models and the estimator, and then makes use of k-means to categorize them into two classes. The class which has a larger distance with the estimator is regarded as the byzantine users.

5.5. Robust-FL: A Detailed Illustration

Algorithm 1 gives a complete description for Robust-FL. Unlike the traditional FL that broadcasts a randomly initialized global model to users, Robust-FL trains the initial model with a small amount of public guiding data to make the estimator be biased towards benign local models (lines 2 to 4). After receiving all the local models, the central server constructs an estimator based on Eq. (8) (line 6).
Algorithm 1 A Detailed Description of Robust-FL

Input: The local models in t-th iteration $w^k_1, w^k_2, \ldots, w^k_N$; the smoothing factor $\alpha$; the first and second order exponential smoothing values $s^{(1)}_t, s^{(2)}_t$; the public guiding dataset $D_g$; the randomly initialized global model $w_0$; the number of training iterations over the guiding dataset $T_g$.

Output: The global model for the $(t+1)$-th iteration: $w_{t+1}$. 

1: $\text{benign}_\text{model} \leftarrow \{\emptyset\}$.
2: if $t = 0$ then
3: $w_0 = \text{SGD}(w_0, D_g, T_g)$;
4: $s^{(1)}_0 = w_0$, $s^{(2)}_0 = w_0$.
5: else
6: Construct estimator $\hat{w}_{t+1}$ using Eq. (8).
7: for $k = 1, 2, 3, \ldots, K$ do
8: Calculate the difference scores: $\text{score}^k_t = \|w^k_t - \hat{w}_{t+1}\|_2$.
9: end for
10: Apply $k$-means based on $\text{score}^k_t$ to obtain two clusters. Define the class with larger distance with $\hat{w}_{t+1}$ as $lc$, otherwise as $sc$: $lc, sc = \text{KMeans}(\text{score}^1_t, \text{score}^2_t, \ldots, \text{score}^K_t)$.
11: for $k = 1, 2, 3, \ldots, K$ do
12: if $|\text{score}^k_t - sc| < |\text{score}^k_t - lc|$ then
13: $\text{benign}_\text{model} \leftarrow \text{benign}_\text{model} \cup \{w^k_t\}$.
14: end if
15: end for
16: $w_{t+1} = \text{FedAvg}(\text{benign}_\text{model})$.
17: end if
18: Calculate $s^{(1)}_{t+1}$ and $s^{(2)}_{t+1}$ according to definitions in Section 3.2.
19: return $w_{t+1}$.

Intuitively, benign models will be less different from the estimator compared with malicious ones. So we utilize Euclidean distance (we call it difference score) to measure the differences between each local model and the estimator (lines 7 to 9). Then the $k$-means algorithm is applied to divide the local models into two clusters according to their difference scores (lines 10 to 15). The cluster with smaller difference scores will be regarded as benign and used for aggregation, while another cluster will be discarded (line 16). Note that when performing the aggregation, Robust-FL uses FedAvg [15] to save the communication cost and speed up the training process.

6. Experiments

6.1. Experimental Setup

1) Datasets and models: We use MNIST and CIFAR-10 to evaluate Robust-FL under different settings. MNIST is a 10-class handwritten digit recognition classification dataset contains 60k training and 10k testing grayscale handwritten digits of size 28×28. CIFAR-10 consists of 50k training and 10k testing three-channel color images of 10 different items of size 32×32. The training samples are evenly assigned to the users in a random way. We train different types of global models on different datasets to show the generality of Robust-FL. Specifically, for MNIST, following previous work [15], we train a convolutional neural network (CNN) as the global model. For CIFAR-10, we use the widely used ResNet20 architecture [10] as the global model.

2) Parameter setting: For MNIST, we set the number of users $K = 30$, and consider the increasing percentage of attackers, i.e., 40%, 50% and 60%. We set the size of guiding dataset $D_g$ to 10. The randomly initialized global model will be trained on $D_g$ for 10 epochs before broadcasting. To reduce the communication overhead, each user trains locally with 3 iterations to obtain the local model in each epoch. There are 100 epochs in total. For CIFAR-10, we set the number of users $K = 60$, and consider the percentage of attackers is 30%, 40% and 50%. The size of $D_g$ is set to 20 and 25 iterations are required at the beginning. The local iterations and global epochs are set to 3 and 1,000 respectively.

3) Evaluated poisoning attacks: In the literature, the poisoning attacks against federated learning can be divided into data poisoning attack and model poisoning attack. For data poisoning attack we consider the popular label-flipping attack where attackers flip their labels from $i$ to $9 - i$. For model poisoning attack we evaluate the representative sign-flipping attack where the attackers directly multiply the local model weight with a reverse constant $-c$ to flip the signs of model and adjust its magnitudes. In our experiments, we set a small value $c = 0.8$ to reinforce its stealthiness. Furthermore, we also consider a stronger model poisoning attack LIE (short for “A little is enough” [1]), which adds a very small amount of noises to a benign model.

6.2. Experimental Results

We compare our proposed Robust-FL with Zeno [27], Multi-Krum [2], FABA [23], Median [30] and Resampling [11]. In addition, we also implement the baseline where all users are benign.
Impact of $\alpha$ on global model accuracy: In our design, $\alpha$ determines the portion of the latest global models. It is therefore necessary to figure out the $\alpha$ that provides the best performance. Fig. 2(a) shows the accuracy of the global model after 30 epochs when $\alpha$ varies from 0.1 to 0.9. The experiment is conducted on the MNIST dataset where the percentage of label flipping attackers is 50%. We can see that the accuracy of global model is lower than 45% when $\alpha$ is smaller than 0.3. This is because there is a large deviation between the estimator and the benign local model. When $\alpha$ increases to 0.8, Robust-FL performs best (with the accuracy of 96%). But a larger $\alpha$ does not necessarily indicate a better performance. For example, when $\alpha = 0.9$, the accuracy decreases to 83%. We owe this to the fact that the estimator has approached to the global model, and the historical information cannot be fully utilized, which also leads to the deviation. Therefore we set $\alpha = 0.8$ in our subsequent experiments.

Computation overhead: From Fig. 2(b), we can see that the computation overhead of Robust-FL is almost the same as that of FedAvg, while the other schemes need much more time to converge, which is consistent with our time complexity analysis in Table 1. For instance, Robust-FL took 16.05 hours to converge, whereas Zeno, Median, FABA, Multi-Krum and Resampling took 20.52, 16.57, 17.33, 17.41, and 17.67 hours, respectively.

Robustness against label-flipping attack: The experimental results over the MNIST dataset in Fig. 3 show that Robust-FL strengthens the plain federated learning and outperforms state-of-the-art solutions under label-flipping attack. Specifically, Robust-FL achieves about 98% accuracy with minor fluctuations, which implies that Robust-FL has almost the same performance as the baseline (i.e., without attacker). Zeno performs similar to our scheme. Multi-Krum performs well for 40% attackers, but its performance drops dramatically when the number of malicious users is no less than 50%. FABA and Median perform barely satisfactorily in the case of 40% attackers. However, similar to Multi-Krum, these two schemes also perform much worse when the attacker dominates. When the percentage of attackers becomes large (e.g., 40% – 60%), Resampling fluctuates heavily because it has a high probability to average a new sampling point between the normal models and the malicious models, making it difficult for the central server to decide whether the point should be chosen for aggregation.

Robustness against sign-flipping attack: Fig. 4 demonstrates that Robust-FL is resistant to sign-flipping attack. To be specific, Robust-FL and Zeno perform comparably with the baseline. Multi-Krum, FABA, and Median perform well in the case of 40% attackers, but these schemes become defenceless when the attackers are no less than 50%. This is due to the fact that these schemes tend to choose the majority of models with similar behavior for aggregation. Hence the central server is more likely to choose malicious local models when the number of attackers is relatively large. For these reasons, Resampling performs the worst among the existing defences.

Robustness against LIE attack: Fig. 5 displays the accuracy of different FL defenses under LIE attack on the CIFAR-10 dataset. Our Robust-FL significantly outperforms the existing solutions. Zeno, FABA, Multi-Krum and Resampling have a similar performance in the case of 30% and 40% attackers, with the accuracy of 10% – 15% lower than Robust-FL. However, when the percentage of attackers is 50%, all the schemes become invalid. Under LIE attacks, Median performs the worst all the time. This indicates that LIE attack can circumvent existing defenses by adding a small amount of disturbances, while Robust-FL can effectively resist LIE attack.

Evaluation over Non-IID data: Fig. 6 evaluates the performance of Robust-FL on Non-IID local training data. We consider label flipping and sign flipping attacks on MNIST, where the percentage of attackers is 50%. We generate the Non-IID data in the same way as [4]. Specifically, the Non-IID degree is controlled by a hyper-parameter $q$ between 0 and 1. A larger $q$ indicates a higher degree of Non-IID. In the experiments, we consider a strong Non-IID degree where $q = 0.95$. We observe that our scheme performs much better than any other defense and is close to the baseline. Zeno, which performs very well in the case of IID setting, has an accuracy of 15% – 30% lower than Robust-FL. The other defenses are completely uncompetitive.

7. Conclusion

This paper focused on defending against Byzantine attacks with relaxed assumptions. We proposed the first estimator-based Byzantine-robust scheme Robust-FL, which constructs an estimator based on the historical global models and then eliminates the model updates that significantly differ from the estimator. In addition, we utilized clustering algorithms to adjust the acceptable differences between the model updates and estimator adaptively such that Byzantine users can be identified. Experiments on different datasets showed Robust-FL achieved the following advantages si-
multaneously (i) tolerance of majority attackers, (ii) generalization to variable Byzantine model, (iii) lower computation overhead.

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References

[1] Baruch, G., Baruch, M., Goldberg, Y.: A little is enough: Circumventing defenses for distributed learning. In: Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems (NeurIPS’19). pp. 8632–8642 (2019)
[2] Blanchard, P., Mhamdi, E.M.E., Guerraoui, R., Stainer, I.: Machine learning with adversaries: Byzantine tolerant gradient descent. In: Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems (NeurIPS’17). pp. 119–129 (2017)
[3] Cao, D., Chang, S., Lin, Z., Liu, G., Sun, D.: Understanding distributed poisoning attack in federated learning. In: Proceedings of the 25th IEEE International Conference on Parallel and Distributed Systems (ICPADS’19). pp. 233–239 (2019)
[4] Cao, X., Fang, M., Liu, J., Gong, N.Z.: Flrust: Byzantine-robust federated learning via trust bootstrapping. In: Proceedings of the 28th Annual Network and Distributed System Security Symposium (NDSS’21). (2021)
[5] Cao, X., Lai, L.: Distributed gradient descent algorithm robust to an arbitrary number of byzantine attackers. IEEE Trans. Signal Process. 67(22), 5850–5864 (2019)
[6] Dong, Y., Chen, X., Li, K., Wang, D., Zeng, S.: FLOD: oblivious defender for private byzantine-robust federated learning with dishonest-majority. In: Proceedings of the 26th European Symposium on Research in Computer Security (ESORICS’21), vol. 12972, pp. 491–518 (2021)
[7] Fung, C., Yoon, C.J.M., Beschastnikh, I.: The limitations of federated learning in sybil settings. In: Proceedings of the 23rd International Symposium on Research in Attacks, Intrusions and Defenses (RAID’20), pp. 301–316 (2020)
[8] G.Brown, R., F.Meyer, R.: The fundamental theorem of exponential smoothing. Operations Research 9(5), 673–685 (1961)
[9] Gu, T., Dolan-Gavitt, B., Garg, S.: Badnets: Identifying vulnerabilities in the machine learning model supply chain. CoRR abs/1708.06733 (2017)
[10] He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR’16). pp. 770–778 (2016)
[11] He, L., Karimireddy, S.P., Jaggi, M.: Byzantine-robust learning on heterogeneous datasets via resampling. CoRR abs/2006.09365 (2020)
[12] Hu, S., Lu, J., Wan, W., Zhang, L.Y.: Challenges and approaches for mitigating byzantine attacks in federated learning. CoRR abs/2112.14468 (2021)
[13] Li, L., Xu, W., Chen, T., Giannakis, G.B., Ling, Q.: RSA: byzantine-robust stochastic aggregation methods for distributed learning from heterogeneous datasets. In: Proceedings of the Thirty-Third AAAI Conference on Artificial Intelligence (AAAI’19). pp. 1544–1551 (2019)
[14] Li, S., Cheng, Y., Liu, Y., Wang, W., Chen, T.: Abnormal client behavior detection in federated learning. CoRR abs/1910.09933 (2019)
[15] McMahan, B., Moore, E., Ramage, D., Hampson, S., y Arcas, B.A.: Communication-efficient learning of deep networks from decentralized data. In: Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS’17). vol. 54, pp. 1273–1282 (2017)
[16] Mhamdi, E.M.E., Guerraoui, R., Rouault, S.: The hidden vulnerability of distributed learning in byzantium. In: Proceedings of the 35th International Conference on Machine Learning (ICML’18), vol. 80, pp. 3518–3527 (2018)
[17] Pillurla, V.K., Kakade, S.M., Harchaoui, Z.: Robust aggregation for federated learning. CoRR abs/1912.13445 (2019)
[18] Prakash, A., Avetisian, A.S.: Mitigating byzantine attacks in federated learning. CoRR abs/2010.07541 (2020)
[19] Shejwalkar, V., Houmansadr, A.: Manipulating the byzantine: Optimizing model poisoning attacks and defenses for federated learning. In: Proceedings of the 28th Annual Network and Distributed System Security Symposium (NDSS’21). (2021)
[20] Tolpegin, V., Truex, S., Gursky, M.E., Liu, L.: Data poisoning attacks against federated learning systems. In: Proceedings of the 25th European Symposium on Research in Computer Security (ESORICS’20). vol. 12308, pp. 480–501 (2020)
[21] Wang, W., Hu, S., Lu, J., Zhang, L.Y., Jin, H., He, Y.: Shielding federated learning: Robust aggregation with adaptive client selection. In: Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence (IJCAI’22). pp. 753–760 (2022)
[22] Wang, W., Lu, J., Hu, S., Zhang, L.Y., Pei, X.: Shielding federated learning: A new attack approach and its defense. In: IEEE Wireless Communications and Networking Conference (WCNC’21). pp. 1–7 (2021)
[23] Xia, Q., Tao, Z., Hao, Z., Li, Q.: FABA: an algorithm for fast aggregation against byzantine attacks in distributed neural networks. In: Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence (IJCAI’19). pp. 4824–4830 (2019)
[24] Xie, C., Huang, K., Chen, P., Li, B.: DBA: distributed backdoor attacker aggregation against federated learning. In: Proceedings of the 8th International Conference on Learning Representations (ICLR’20). (2020)
[25] Xie, C., Koyejo, O., Gupta, I.: Generalized byzantine-tolerant sgd. Journal of Environmental Sciences (China) English Ed (2018)
[26] Xie, C., Koyejo, O., Gupta, I.: SLSGD: secure and efficient distributed on-device machine learning. In: Proceedings of Machine Learning and Knowledge Discovery in Databases - European Conference (ECML PKDD’19). vol. 11907, pp. 213–228 (2019)
[27] Xie, C., Koyejo, S., Gupta, I.: Zeno: Distributed stochastic gradient descent with suspicion-based fault-tolerance. In: Proceedings of the 36th International Conference on Machine Learning (ICML’19). vol. 97, pp. 6893–6901 (2019)
[28] Xie, C., Koyejo, S., Gupta, I.: Zeno++: Robust fully asynchronous SGD. In: Proceedings of the 37th International Conference on Machine Learning (ICML’20). vol. 119, pp. 10495–10503 (2020)
[29] Yang, Q., Liu, Y., Chen, T., Tong, Y.: Federated machine learning: Concept and applications. ACM Trans. Intell. Syst. Technol. 10(2), 12:1–12:19 (2019)
[30] Yin, D., Chen, Y., Ramchandran, K., Bartlett, P.L.: Byzantine-robust distributed learning: Towards optimal statistical rates. In: Proceedings of the 35th International Conference on Machine Learning (ICML’18). vol. 80, pp. 5636–5645 (2018)