Attack-Resistant Federated Learning with Residual-based Reweighting

Shuhao Fu¹ Chulin Xie² Bo Li³ Qifeng Chen¹

¹HKUST, ²Zhejiang University, ³UIUC

Abstract

Federated learning has a variety of applications in multiple domains by utilizing private training data stored on different devices. However, the aggregation process in federated learning is highly vulnerable to adversarial attacks so that the global model may behave abnormally under attacks. To tackle this challenge, we present a novel aggregation algorithm with residual-based reweighting to defend federated learning. Our aggregation algorithm combines repeated median regression with the reweighting scheme in iteratively reweighted least squares. Our experiments show that our aggregation algorithm outperforms other alternative algorithms in the presence of label-flipping and backdoor attacks. We also provide theoretical analysis for our aggregation algorithm.

Introduction

Federated learning is a machine learning methodology for training a global model with decentralized data stored on multiple or millions of devices (McMahan et al. 2017). In federated learning, private data is stored locally in isolated devices and will not be revealed to other parties during training. Federated learning can enable numerous real-world machine learning applications by utilizing massive training data that are privacy-sensitive and scattered on different devices (Bonawitz et al. 2017). For instance, multiple hospitals can collaborate to train a global model for classifying diseases using X-ray images without compromising patient privacy. These hospitals may possess X-ray images in different quantities and varieties, resulting in the non-IID (independent and identically distributed) data distribution that is common in federated learning.

The default federated learning aggregation algorithm *FedAvg* (McMahan et al. 2017) that takes the average of locally updated models is vulnerable to various attacks. We find that federated learning suffers from label-flipping and backdoor attacks in our experiments. When a local model is poisoned, the aggregated global model can also be poisoned and fail to behave correctly.

Mitigating attacks in federated learning or distributed learning has been explored in recent research (Chen, Su, and Xu 2017; Yin et al. 2018; Fung, Yoon, and Beschastnikh 2018; Blanchard et al. 2017). Although the median or trimmed

Copyright © 2021, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

mean aggregation algorithms (Yin et al. 2018) may seem plausible in distributed learning, their performance degrades in federated learning when data is non-IID. FoolsGold (Fung, Yoon, and Beschastnikh 2018) solves non-IID problem by identifying participants with a similar objective as attackers, but this strategy may not work when some harmless participants have similar local data. To make federated learning more attack-resistant, we develop an aggregation algorithm that is robust against label-flipping and backdoor attacks in a general non-IID setting. We derive our aggregation algorithm by adopting the repeated median estimator (Siegel 1982) and the reweighting scheme in iteratively reweighted least squares (IRLS) (Holland and Welsch 1977; Rand R 1997). We estimate the confidence of each parameter in the local models and then the weight of each local model can be computed by heuristically accumulating all the parameter confidence in each local model.

We compare our proposed algorithm to several baselines by conducting experiments on four datasets, the MNIST dataset (LeCun et al. 1998), CIFAR-10 dataset (Krizhevsky, Hinton et al. 2009), Amazon Reviews dataset (Ruining and Julian 2016) and the Lending Club loan dataset (Kan 2019). Our proposed aggregation significantly mitigates the impact of attacked models in non-IID federated learning and outperforms other baselines in our evaluation. Furthermore, we provide theoretical analysis for our aggregation algorithm.

Related Work

Adversarial attacks on federated learning. Several attacks have been studied against federated learning (Wang et al. 2018; Biggio, Nelson, and Laskov 2012; Fung, Yoon, and Beschastnikh 2018; Hayes et al. 2019; Hitaj, Ateniese, and Pérez-Cruz 2017; Melis et al. 2019). The label-flipping attack (Biggio, Nelson, and Laskov 2012) is shown to have great harm to a federated system even with a very small number of attackers (Fung, Yoon, and Beschastnikh 2018). In this attack, the attacker flips the labels of training data from one class to another class and trains the model accordingly. (Bagdasaryan et al. 2018) propose a backdoor attack so that the global model behaves incorrectly on adversarial targeted input. In our work, we mainly focus on defending against label-flipping and backdoor attacks. Note that an attacker can perform any type of attack, such as modifying any model values and training the local model on poisoned data for

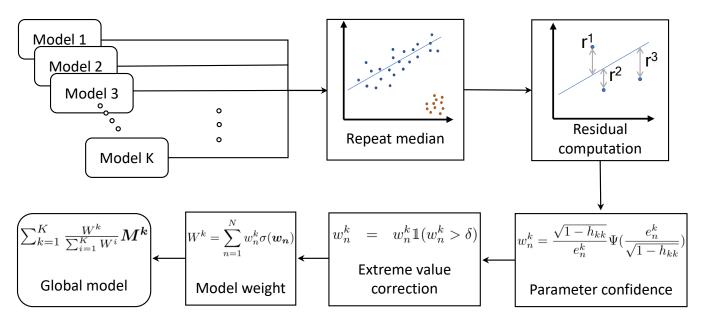


Figure 1: The overview of our aggregation algorithm for attack-resistant federated learning.

arbitrary epochs.

Robust distributed learning. Statistical methods have been studied and applied in robust distributed learning where data is IID (Feng, Xu, and Mannor 2014; Blanchard et al. 2017; Chen, Su, and Xu 2017; Yin et al. 2018; Alistarh, Allen-Zhu, and Li 2018). The median method and the trimmed mean method (Yin et al. 2018) are effective approaches in robust distributed learning but may not be attack-resistant in federated learning where data distribution is non-IID. To tackle the challenge in robust federated learning, we propose a reweighted aggregation algorithm that dynamically assigns weights to the local model based on the residual to a regression line estimated by the repeated median estimator (Siegel 1982).

Defending federated learning. Recently, some researchers have proposed some defense strategies for robust federated learning (Fung, Yoon, and Beschastnikh 2018; Blanchard et al. 2017; Li et al. 2019). FoolsGold (Fung, Yoon, and Beschastnikh 2018) is a defense mechanism against Sybil attacks by adjusting the learning rates of local models based on contribution similarity. The algorithm identifies grouped actions as Sybil attacks and promotes the diversity of local model update. (Gu et al. 2018) proposed a model, CalTrain, that represents data with fingerprints to identify poisoned data and models. (Konstantinov and Lampert 2019) propose to maintain a small reference dataset to justify the quality and accountability of models. While this method is effective, it requires a lot of time to evaluate each model in every single round. Our algorithm does not need an additional reference dataset before or after each aggregation process. On the other hand, some researchers proposed to improve the privacy preservation of federated learning (Bonawitz et al. 2017; Geyer, Klein, and Nabi 2017; Truex et al. 2018; Thakkar, Andrew, and McMahan 2019). (Bonawitz et al. 2017) propose a privacy-preserving protocol for model aggregation

in federated learning. (Geyer, Klein, and Nabi 2017) introduce differential privacy into federated learning. Instead of enhancing privacy preservation, we focus on the robustness of federated learning so that the global model should behave correctly even when there is a large portion of malicious participants.

Our Algorithm

In federated learning, there are multiple rounds of communication between participants and a central server for learning a global model. In each round, the global model is shared among the K participants, and a local model on each device is trained on its local private data with the shared global model as initialization. Then all the K local models are sent to the central server to update the global model with an aggregation algorithm. Suppose the participant k has a local model $M^{(k)}$, and we can update the global model M_{global} by taking the aggregation algorithm of all the K local models.

Aggregation Algorithm

Median is a robust estimator widely used in statistics. However, when the data distribution is non-IID, median often neglects underrepresented data by merely taking a single median value. Hence, in our aggregation algorithm, the global model is designed to be a reweighted average of all the local models where the model weights are estimated robustly.

Algorithm 1 summarizes our aggregation algorithm, and a detailed step-by-step description is provided below. Inspired by the reweighting scheme in IRLS (Rand R 1997), we reweight each parameter by its vertical distance (residual) to a robust regression line. Then the weight of each local model is computed by accumulating the parameter confidence in each local model.

Let $y_n^{(k)}$ be the *n*-th parameter of the *k*-th local model. We use y_n to indicate the list of *n*-th parameters in all the local

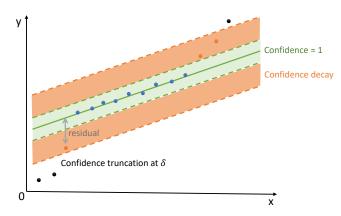


Figure 2: Parameter confidence assignment based on the residual which is the distance from a point to the regression line. In the green area, the parameter confidence is 1; in the orange area, the confidence decays from 1 to δ ; in other areas, the confidence is set to 0.

models. Let x_n be the indices of y_n sorted in an ascending order. Then (x_n, y_n) is a point set in 2D with increasing values in the y direction.

Repeated median. We use the repeated median estimator (Siegel 1982) to estimate a linear regression line y = $\beta_{n0} + \beta_{n1}x$. The slope β_{n1} and intercept β_{n0} are estimated as follow,

$$\beta_{n1} = \text{median median } \frac{y_n^{(j)} - y_n^{(i)}}{x_n^{(j)} - x_n^{(i)}}$$
(1)
$$\beta_{n0} = \text{median median } \frac{x_n^{(j)} y_n^{(i)} - x_n^{(i)} y_n^{(j)}}{x_n^{(j)} - x_n^{(i)}}$$
(2)

$$\beta_{n0} = \underset{i \neq j}{\text{median median}} \frac{x_n^{(j)} y_n^{(i)} - x_n^{(i)} y_n^{(j)}}{x_n^{(j)} - x_n^{(i)}}$$
 (2)

where $i, j \in \{1, 2, ..., K\}$.

Residual computation. We can calculate the residuals of the n-th parameters in all the local models:

$$\boldsymbol{r_n} = \boldsymbol{y_n} - \beta_{n0} - \beta_{n1} \boldsymbol{x_n}.$$

Since r_n can be very different in magnitude for different parameters, we can normalize r_n similar to the reweighting scheme in IRLS (Rand R 1997):

$$\tau_n = \gamma |\widetilde{r_n}| (1 + \frac{5}{K - 1}), \tag{3}$$

$$|\widetilde{r_n}| = \operatorname{median}(|r_n|).$$
 (4)

where γ is a constant. We set $\gamma = 1.48$ recommended by Wilcox et al. (Rand R 1997). Then the normalized residuals become

$$e_n^{(k)} = \frac{r_n^{(k)}}{\tau_n}. (5)$$

Parameter confidence. After obtaining the normalized residuals, the parameter confidence can be determined accordingly (Rand R 1997):

$$w_n^{(k)} = \frac{\sqrt{1 - h_{kk}}}{e_n^{(k)}} \Psi(\frac{e_n^{(k)}}{\sqrt{1 - h_{kk}}}), \tag{6}$$

Algorithm 1 Our aggregation algorithm

Input: Models $M^{(1)}, M^{(2)}, ..., M^{(K)}$, with parameters $y_n^{(\bar{1})}, y_n^{(2)}, ..., y_n^{(K)}$

Output: The global model M_{global}

- 1: **for** n-th parameter where $n=1 \rightarrow N$, and let $\boldsymbol{y_n} = [y_n^{(1)}, y_n^{(2)}, ..., y_n^{(K)}]^T$ **do** 2: $\boldsymbol{x_n} \leftarrow \text{indices of } \boldsymbol{y_n} \text{ sorted in an ascending order}$
- $\beta_{n0}, \beta_{n1} \leftarrow RepeatedMedian(\boldsymbol{x_n}, \boldsymbol{y_n})$ robust line estimation
- $r_n \leftarrow y_n \beta_{n0} \beta_{n1}x_n$
- $|r_n| \leftarrow Median|r_n|$ 5:
- $\tau_n \leftarrow \gamma \widetilde{|r_n|} (1 + \frac{5}{K-1})$ ▷ normalize residuals
- 7:
- $egin{aligned} oldsymbol{H_n} \leftarrow & x_n (x_n^T x_n)^{-1} x_n^T & riangle ext{compute Hat matrix} \ oldsymbol{w_n} \leftarrow & rac{\sqrt{1 diag(oldsymbol{H_n})}}{e_n} \Psi(rac{e_n}{\sqrt{1 diag(oldsymbol{H_n})}}) & riangle ext{compute} \end{aligned}$ 9: parameter confidence
- 10: $y_n, w_n \leftarrow \mathsf{CorrectExtremeValue}(y_n, w_n)$
- $\boldsymbol{w_n} \leftarrow \boldsymbol{w_n} \sigma(\boldsymbol{w_n})$ > reweight confidence by its 11: standard deviation

- $\begin{array}{ll} \text{12: } \textbf{for } \text{each } k = 1 \rightarrow K \ \textbf{do} \\ \text{13: } & W^{(k)} \leftarrow \sum_{n=1}^{N} w_{n}^{(k)} & \rhd \text{ accumulate weights} \\ \text{14: } & M_{\boldsymbol{global}} \leftarrow \sum_{k=1}^{K} \frac{W^{(k)}}{\sum_{i=1}^{K} W^{(i)}} M^{(k)} \\ \end{array}$

where $w_n^{(k)}$ is the confidence of the *n*-th parameter in $M^{(k)}$, $\Psi(x) = max\{-Z, min(Z, x)\}$ with $Z = \lambda \sqrt{2/K}$ and λ is a hyperparameter. We find $\lambda = 2$ is already very robust in all our experiments. Ψ here acts as a trusted interval and we can expand or shrink the interval by tuning λ . h_{kk} is the k-th diagonal element of matrix in H_n :

$$\boldsymbol{H_n} = \boldsymbol{x_n} (\boldsymbol{x_n^T x_n})^{-1} \boldsymbol{x_n^T}, \tag{7}$$

where $x_n = [x_n^{(1)} \ x_n^{(2)} \ \dots \ x_n^{(K)}]^T$.

Extreme value correction. Extremely large values, even multiplied with a small weight in model aggregation, can damage the global model. We address this issue by involving a a threshold δ . If a parameter has a confidence value lower than δ , then it should be corrected to the robust line estimation as follows,

$$w_n^{(k)} = w_n^{(k)} \mathbb{1}(w_n^{(k)} > \delta), \tag{8}$$

$$y_n^{(k)} = y_n^{(k)} \mathbb{1}(w_n^{(k)} > \delta) + (\beta_{n0} + \beta_{n1}x_n^{(k)}) \mathbb{1}(w_n^{(k)} \le \delta)$$
(9)

Model weight. To obtain the weight of each local model, we can simply aggregate the parameter confidence in the local model but this is not ideal. Imagine an attacker trains a model honestly, but then alters only 10% of the parameters to some extremely large values. This adversary model still receives about 90% of the parameter confidence. To address this problem, we measure the importance of a parameter by the standard deviation of w_n . A confidence assignment with a large standard deviation indicates a great disagreement among this parameter in all models and should be more

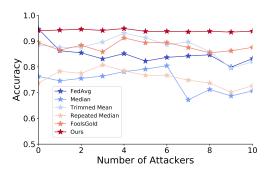


Figure 3: Results of label-flipping attacks on the MNIST dataset. The number of participants is 100, within which 0 to 10 of them are attackers.

critical when being accumulated towards model weights:

$$W^{(k)} = \sum_{n=1}^{N} w_n^{(k)} \sigma(\boldsymbol{w_n}), \tag{10}$$

where $W^{(k)}$ is the weight for model k, N is the number of parameters, $\boldsymbol{w_n} = [w_n^{(1)} w_n^{(2)} \dots w_n^{(K)}]^T$.

Global model. Finally, we can obtain the updated global model by

$$M_{global} = \sum_{k=1}^{K} \frac{W^{(k)}}{\sum_{i=1}^{K} W^{(i)}} M^{(k)}.$$
 (11)

Experiments

We compare our approach with other aggregation algorithms, including FedAvg (McMahan et al. 2017), the coordinate-wise median method (Yin et al. 2018), the coordinate-wise trimmed mean method (Yin et al. 2018), FoolsGold (Fung, Yoon, and Beschastnikh 2018), and a coordinate-wise repeated median approach we adopt from (Siegel 1982). We perform experiments on the MNIST handwritten digit dataset (LeCun et al. 1998), the Amazon Reviews dataset (Ruining and Julian 2016), the CIFAR-10 dataset (Krizhevsky, Hinton et al. 2009), and the Lending Club loan dataset (Kan 2019). We implement attack strategies and defense algorithms in PyTorch (Paszke et al. 2017).

We use a two-layer convolutional neural network (CNN) for our MNIST experiments. With this simple CNN model, our goal is to evaluate different aggregation algorithms for defending federated learning in the presence of attacks. On the CIFAR-10 dataset, we use ResNet-18 (He et al. 2015) for image classification. The text classification model FastText (Joulin et al. 2016) is adopted for evaluation on the Amazon Reviews dataset. It is a two-layer deep neural network where the first layer is an embedding layer, and the second layer is a fully connected layer. For the Lending Club loan dataset, we use a simple neural network with three fully-connected layers to classify loan status. We use the last two models to demonstrate that our algorithm can be generalized to a natural language processing task and to a real-work financial problem. All the evaluation results are the average of running the same experiments 3 times.

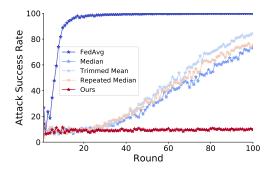


Figure 4: Result of backdoor attack success rate on CIFAR-10 under different aggregation algorithms. Ours outperforms other baselines.

Datasets

MNIST dataset. The MNIST dataset contains 70,000 real-world handwritten images with digits from 0 to 9. We evaluate different methods by learning a global model on these training images distributed on multiple devices in a non-IID setting with adversarial attacks.

CIFAR-10 dataset. The CIFAR-10 dataset contains 60,000 natural images in ten object classes. The experimental setup is also non-IID on CIFAR-10.

Amazon Reviews dataset. The Amazon Reviews dataset (Ruining and Julian 2016) contains product reviews and ratings collected from the Amazon website. Every review is paired with a sentiment rating from 1 to 5. We categorize comments with rating 1 or 2 as negative and comments with rating 4 or 5 as positive. We discard reviews with rating 3, and we only train a binary classifier. We only use the book reviews from the Kindle Store. 20% of the reviews are used for testing, while the rest is for training. We obtain a training set of 86,164 reviews and a test set of 13,260 reviews.

Lending Club Loan dataset. The Lending club dataset LOAN (Kan 2019) contains financial information such as credit scores and the number of finance inquiries for loan status prediction (such as "Current", "Late", or "Fully Paid"). There are 1,808,534 data samples in 9 types of loan status. We divide them by US states to simulate the federated learning scenarios with non-IID data distribution where each state represents a participant.

Results on Label-flipping Attacks

We evaluate the overall classification performance of different aggregation methods on three datasets under label-flipping attacks, the MNIST dataset (Biggio, Nelson, and Laskov 2012), the CIFAR-10 dataset (Krizhevsky, Hinton et al. 2009), and Amazon Reviews dataset (Ruining and Julian 2016). In label-flipping attacks, attackers flip the labels of training examples in the source class to a target class and train their models accordingly.

In the MNIST experiment, we simulate federated learning with 100 participants, within which 0 to 10 of them are attackers. Each participant contains images of two random digits. The attackers are chosen to be some participants with images of digit 1 and another random digit since they are flipping the

Number of attackers	0	1	2	3	4
FedAvg (McMahan et al. 2017)	88.96%	85.74%	82.49%	82.35%	82.11%
Median (Yin et al. 2018)	88.11%	87.69%	87.15%	85.85%	82.01%
Trimmed Mean (Yin et al. 2018)	88.70%	88.52%	87.44%	85.36%	82.35%
Repeated Median (Siegel 1982)	88.60%	87.76%	86.97%	85.77%	81.82%
FoolsGold (Fung, Yoon, and Beschastnikh 2018)	9.70%	9.57%	10.72%	11.42%	9.98%
Ours	89.17%	88.60%	86.66%	86.09%	85.81%

Table 1: Results of label-flipping attacks on CIFAR-10 dataset with different numbers of attackers. The total number of participants is 10.

Number of attackers	0	1	2	3	4
FedAvg (McMahan et al. 2017)	91.81%	86.91%	24.97%	12.52%	9.78%
Median (Yin et al. 2018)	91.73%	91.87%	91.79%	91.43%	91.17%
Trimmed Mean (Yin et al. 2018)	91.81%	91.82%	91.82%	91.49%	91.26%
Repeated Median (Siegel 1982)	91.55%	88.41%	23.22%	11.70%	9.62%
FoolsGold (Fung, Yoon, and Beschastnikh 2018)	50.79%	49.45%	47.44%	49.71%	49.95%
Ours	91.71%	91.79%	91.76%	91.67%	91.38%

Table 2: Results of label-flipping attacks on Amazon Reviews dataset with different numbers of attackers. The total number of participants is 10.

label of 1 to 7. We run 200 synchronization rounds with δ set to 0.01. In each round of federated learning, each participant is supposed to train the local model for 5 epochs, but the attackers can train for arbitrary epochs. The results are shown in Figure 3 where attackers train the models with 5 more epochs to enhance the attacks. Our algorithm outperforms all other methods and is robust when the number of attackers increases. Median methods (Median and Repeated Median) have relatively low accuracy even without any attackers due to their discarding most of the information in model aggregation. Our algorithm, on the other hand, takes the reweighted average of all local models and thus gathers more information in an unsupervised way. We also compare our algorithm with the state-of-the-art algorithm FoolsGold (Fung, Yoon, and Beschastnikh 2018). Though their algorithm also maintains a low attack success rate, our algorithm is more stable and surpasses FoolsGold by 6% on average.

For the CIFAR-10 experiment, following (Bagdasaryan et al. 2018), we adopt a Dirichlet distribution (Minka 2000) with a hyperparameter 0.9 to generate non-IID data distribution for totally 10 participants. The experimental setup is the same for the CIFAR-10 and MNIST experiments under backdoor attacks in Section . The attackers flip the label of "cat" to "dog" since they are the most similar classes in CIFAR-10. The experiment results can be found in Table 1. In this experiment, baseline methods perform fairly well because the data distribution is not immensely non-IID., where each user has all the labels but in different amounts. FoolsGold (Fung, Yoon, and Beschastnikh 2018) fails because they assume that the gradients of honest models are very different because of the non-IID data, and the gradients of outliers are close because they share the same objective. However, it may not always be the case when the data distribution is not so extremely non-IID, such as the CIFAR-10 case. FoolsGold may think these honest users are close and decide they are outliers. Our algorithm, on the other hand, can adapt to extremely non-IID cases, such as the MNIST experiments, where all baseline methods fail, and is also suitable for common non-IID situations such as the CIFAR-10 and the Amazon Review experiments.

In the experiment on Amazon Reviews, there are 10 participants, where 0 to 4 participants are attackers who flip all their labels. Attackers also train for 5 more epochs. We run 10 synchronization rounds in the experiment. The result is summarized in Table 2. Our algorithm achieves comparable state-of-the-art results, and our performance does not degrade when there are less than 50% attackers.

Results on Backdoor Attacks

For pixel-pattern backdoor attacks (Gu et al. 2019) in federated learning(Bagdasaryan et al. 2018), attackers manipulate their local models so that the learned global model predicts some backdoor target label for any image embedded with certain patterns. An example is shown in Figure 5. The global model can behave normally for clean data. We choose "bird" in CIFAR-10 and "2" in MNIST as the backdoor target labels. Similarly, for the preprocessed LOAN dataset that contains 92 features, we manipulate 6 features by assigning certain large values to them and change the labels of manipulated data to "Does not meet the credit policy. Status:Fully Paid."

The training data is mixed with manipulated data and clean data to fit both the backdoor task and the main task. We compare the performance of aggregation algorithms under two backdoor attack scenarios, which are called the naive approach and the model replacement in (Bagdasaryan et al. 2018). For the naive approach, an attacker poisons its local model and submits the malicious update in every round. For the model replacement, an attacker only poisons in one round to embed some patterns into the global model, so the attacker needs to scale up its malicious update before submission. In





Clean image

Backdoored image

Figure 5: There is a white color pattern in the left uppe corner of the backdoored image.

our experiment, the malicious participant attacks in round 6 and scales up its update by 100. We run 200 rounds for MNIST and 100 rounds for CIFAR and LOAN.

Table 3 summarizes the results of backdoor attacks. Our method is the highest in terms of accuracy on MNIST under both backdoor attack scenarios. Moreover, on the more challenging CIFAR-10 dataset, our algorithm is the only one that can defend the naive approach backdoor attack. In Figure 4, we plot the attack success rates over time under different aggregation algorithms except for FoolsGold because it completely fails in both main and backdoor tasks. Intuitively, backdoor attacks can easily succeed under FedAvg, and other baselines slow down the process but still reach high attack success rate into over 70% within 100 rounds. Our algorithm effectively defends the attack and remains stable with 9.65% attack success rate when being attacked continuously for 100 rounds. On the LOAN dataset, our method achieves higher accuracy 94.50% (FedAvg 93.65%) and 0.00% attack success rate (FedAvg 99.71%) under the naive approach attack after 100 rounds. Similarly, our method has 95.06% accuracy (FedAvg 94.11%) and 0.00% attack success rate (FedAvg 98.96%) under model replacement attacks after 100 rounds. Other baselines also have 0.00% attack success rate in two attacking scenarios except FoolsGold, whose attack success rate is 99.96% under the naive approach attack.

It is also interesting to notice that all the baselines fail on the CIFAR-10 dataset for the naive backdoor attack approach while they perform fairly well on the MNIST dataset. This is because the model used for CIFAR-10 experiments, ResNet-18, is more complicated and has more parameters $(1000\times)$ than the simple CNN used for the MNIST dataset. To explore the effect of complex models, we also train a ResNet-18 model on the MNIST dataset and performed the same backdoor attack on it. The results are shown in Figure 6 except for FoolsGold because it completely fails in both main task (about 10.00% accuracy) and backdoor task. The results are similar to the same model on the CIFAR-10 dataset. All the baselines fail to defend, but our algorithm remains stable. Besides, most baseline methods (FedAvg, Median, Trimmed Mean, and Repeated Median) are coordinatewise operations, while our algorithm accumulates a weight for each model rather than each parameter. We believe the model-wise reweighting scheme preserves the structure of the parameters and can perceive higher-level information.

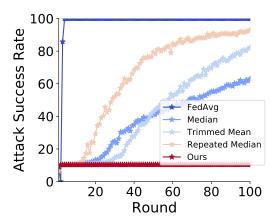


Figure 6: Results of backdoor attack success rate on the MNIST dataset with ResNet-18. Our algorithm is still stable while others fail for the complicated model.

Hyperparameters

We have two hyperparameters in our method, λ and δ , where λ controls the confidence interval, and δ controls the clipping threshold. We perform a grid search to prove that the hyperparameter selection is robust and efficient. The results can be found in Table 4. Basically, a larger δ means that it has a lower tolerance of differences and thus may eliminate some of the honest models when data is non-IID while increasing λ brings insensitivity to the variance of δ . When outliers are easy to be identified (e.g., in IID settings), a large λ yields good results with great stability. In the non-IID experiments, however, the models are more diverse, so it is important to find a balance between excluding adversarial models while embracing models trained on different data distributions. In summary, λ and δ are robust in a large range, as shown in Table 4.

Controlled Experiments

Although our algorithm is inspired by the reweighting scheme from IRLS (Rand R 1997), some alternative linear estimators and weighting schemes can replace the original ones. In this section, we replace the repeated median estimator in our algorithm with the Theil-Sen estimator or the median estimator and replace the weighting scheme with a zero-mean Gaussian function where smaller residual means larger weight. We tune the λ (in the Gaussian weighting it is the variance σ), and the results are shown in table 4. The experiments are performed on the MNIST dataset with label-flipping attacks. The median and Theil-Sen estimators achieve similar results as the Repeated Median estimator, but they can be attacked in a few cases. For example, $\lambda=5$ and $\delta=0.01$ for the median estimator and $\lambda=5$ and $\delta=0.05$ for the Theil-Sen estimator. The Theil-Sen estimator, especially, only has a relatively low breakdown point than Repeated Median, meaning that it will more easily be broken when the number of attackers increases. The alternative Gaussian weighting scheme is fairly robust against label-flipping attacks. This demonstrates that the robustness comes from our algorithm rather than intricate hyperparameter tuning.

Dataset		MN	IST		CIFAR-10			
	Naive approach		Model replacement		Naive approach		Model replacement	
	Accuracy	A.S.R	Accuracy	A.S.R	Accuracy	A.S.R	Accuracy	A.S.R
FedAvg	99.08%	99.71%	98.75%	17.85%	87.44%	99.91%	69.72%	38.59%
Median	98.91%	10.34%	98.87%	10.35%	88.58%	73.06%	87.22%	10.01%
Trimmed Mean	98.97%	10.34%	98.81%	10.34%	88.38%	84.56%	87.30%	9.85%
Repeated Median	98.96%	10.36%	98.82%	10.32%	88.22%	75.25%	87.57%	9.79%
FoolsGold	96.20%	12.51%	97.96%	10.27%	10.00%	0.00%	10.00%	0.00%
Our	98.97%	10.35%	98.88%	10.31%	88.89%	9.65%	87.43%	9.56%

Table 3: Results of backdoor attacks on MNIST and CIFAR-10. There are 10 participants, 1 of whom is an attacker. We denote the attack success rate as A.S.R.

		Original		Median Estimator		Theil-Sen Estimator		Gaussian Weighting	
		Number of attackers		Number of attackers		Number of Attackers		Number of Attackers	
λ (or σ in Gaussian)	Delta	0	9	0	9	0	9	0	9
1	0.01	94.41%	94.54%	94.46%	95.19%	93.76%	92.87%	84.32%	92.22%
1	0.05	93.36%	91.15%	93.37%	93.79%	94.43%	92.70%	87.33%	90.65%
1	0.1	86.93%	89.39%	83.77%	90.93%	92.77%	94.31%	88.31%	89.23%
1	0.2	84.77%	91.40%	70.84%	80.79%	93.28%	93.63%	83.22%	90.28%
2	0.01	94.95%	94.86%	93.34%	94.36%	94.38%	49.28%	91.07%	92.70%
2	0.05	91.45%	93.14%	93.41%	94.86%	95.62%	91.65%	90.85%	93.00%
2	0.1	93.08%	91.84%	94.02%	93.48%	92.29%	93.07%	88.61%	93.15%
2	0.2	86.09%	91.43%	88.84%	92.68%	92.21%	91.70%	90.54%	90.80%
3	0.01	93.83%	94.89%	94.67%	94.68%	94.45%	75.83%	92.46%	93.18%
3	0.05	93.76%	95.86%	93.67%	94.52%	94.86%	94.72%	93.30%	94.25%
3	0.1	94.74%	94.13%	93.11%	91.30%	92.32%	94.70%	92.09%	93.65%
3	0.2	89.11%	93.25%	93.67%	93.76%	94.00%	93.20%	90.88%	93.26%
5	0.01	92.62%	93.77%	93.68%	84.26%	94.69%	93.27%	94.10%	93.58%
5	0.05	94.53%	95.28%	94.23%	94.72%	93.67%	79.91%	92.78%	93.69%
5	0.1	94.23%	94.47%	94.88%	94.69%	94.60%	92.85%	92.81%	93.83%
5	0.2	92.60%	94.23%	92.90%	93.87%	93.51%	91.41%	91.72%	92.93%

Table 4: The results of the controlled experiments by replacing the linear estimator or the weighting scheme with alternative methods. All the experiments are performed on the MNIST dataset with label-flipping attacks.

Theoretical Analysis

For simplicity, we consider the bound of the error rate for training a single-parameter model on K devices, each storing S IID samples of data. We define the parameter of the local model i as $\hat{y}^{(i)}$. Suppose that training data points are sampled from some unknown distribution \mathcal{D} . Let f(y;x) be a loss function of the parameter $y \in \mathcal{Y}$ associated with the data point x, where \mathcal{Y} is the parameter space, and $F(y) := \mathbb{E}_{x \in \mathcal{D}}[f(y:x)]$. Our goal is to learn an optimal model defined by the parameter that minimizes the population loss

$$\mu = \arg\min_{y \in \mathcal{Y}} F(y).$$

The parameter space $\mathcal Y$ is assumed to be convex and compact with diameter D, i.e., $||y-y'||_2 \leq D, \, \forall y,y' \in \mathcal Y.$ Suppose that there are K devices and U of them are corrupted. We denote the set of adversarial devices as $\mathcal B$ and the corruption ratio $\alpha = \frac{U}{K}$. Based on our algorithm, the residuals can be simplified as $(\hat y^{(i)} - \tilde y)$, where $\tilde y$ is the median of $\{\hat y^{(i)}\}$ for i=1,2,...,K. Let |r| be the median of absolute residuals,

i.e., $\widetilde{|r|}=\mathrm{median}(|\hat{y}^{(i)}-\tilde{y}|).$ Then, the normalized residual can be expressed as

$$e^{(i)} = \frac{\hat{y}^{(i)} - \tilde{y}}{\gamma |\tilde{r}| (1 + \frac{5}{K - 1})},\tag{12}$$

and the parameter confidence is defined as

$$z^{(i)} = \begin{cases} 1, & \text{if } \left| e^{(i)} \right| \le \frac{\sqrt{2}\lambda}{\sqrt{K}} \\ \left| \frac{\sqrt{2}\lambda}{\sqrt{K}e^{(i)}} \right|, & \text{if } \frac{\sqrt{2}\lambda}{\sqrt{K}} < \left| e^{(i)} \right| \le \left| \frac{\sqrt{2}\lambda}{\sqrt{K}\delta} \right| \\ 0, & \text{if } \left| e^{(i)} \right| > \left| \frac{\sqrt{2}\lambda}{\sqrt{K}\delta} \right| \end{cases}$$
(13)

Then we will prove that the error of the global model $M_{global} := \frac{1}{\sum_{i=1}^K z^{(i)}} \sum_{i=1}^K z^{(i)} \hat{y}^{(i)}$ is bounded:

$$\left| \frac{1}{\sum_{j=1}^{K} z^{(j)}} \sum_{i=1}^{K} z^{(i)} \hat{y}^{(i)} - \mu \right| = \tilde{\mathcal{O}}(\frac{1}{\sqrt{S}} + \frac{1}{\sqrt{SK}} + \frac{1}{S} + \frac{1}{\sqrt{K}\delta}).$$
(14)

Proof. We adopt assumptions 1, 2, 3, and 6, Theorem 8 and Lemma 3 from (Yin et al. 2018) here. We can separate Equation 14 into two sets with adversarial participant \mathcal{B} and normal users $[K] \setminus \mathcal{B}$ where $[K] = \{1, 2, \dots, K\}$.

$$\begin{split} \left| \frac{1}{\sum_{j=1}^{K} z^{(j)}} \sum_{i=1}^{K} z^{(i)} \hat{y}^{(i)} - \mu \right| &\leq \frac{1}{\sum_{j=1}^{K} z^{(j)}} \sum_{i=1}^{K} z^{(i)} \left| \hat{y}^{(i)} - \mu \right| \\ &\leq \frac{1}{\sum_{j=1}^{K} z^{(j)}} \left(\sum_{i \in [K] \setminus \mathcal{B}} z^{(i)} \left| \hat{y}^{(i)} - \mu \right| + \sum_{i \in \mathcal{B}} z^{(i)} \left| \hat{y}^{(i)} - \tilde{y} + \tilde{y} - \mu \right| \right) \\ &\leq \max_{i \in [K] \setminus \mathcal{B}} \left\{ \left| \hat{y}^{(i)} - \mu \right| \right\} + \frac{1}{\sum_{j=1}^{K} z^{(j)}} \sum_{i \in \mathcal{B}} z^{(i)} \left| \hat{y}^{(i)} - \tilde{y} \right| + |\tilde{y} - \mu| \,. \end{split}$$

$$\tag{15}$$

Now we state here the assumptions and theorems from (Yin et al. 2018).

Assumption 1 (Smoothness of f and F, Assumption 1 from (Yin et al. 2018)). For any $x \in \mathcal{D}$, the derivative of f(y; x) is L-Lipschitz, and the function f(y; x) is L-smooth.

Assumption 2 (Sub-exponential gradients, Assumption 6 from (Yin et al. 2018)). We assume that the derivative of f(y; x) with respect to y is v-sub-exponential.

Proposition 1 (Theorem 8 from (Yin et al. 2018)). Define the median of $y^{(i)}$: $\tilde{y} = \text{median}\{y^{(i)}: i \in [K]\}$. Suppose that Assumption 1 holds, F(y) is λ_F -strongly convex. Then, with probability at least $1 - \frac{4}{1 + SKLD}$, we have

$$|\tilde{y} - \mu| \le \tilde{\mathcal{O}}\left(\frac{1}{SK} + \frac{1}{\sqrt{S}}\left(\alpha + \sqrt{\frac{\log(1 + SKLD)}{K(1 - \alpha)}} + \frac{1}{\sqrt{S}}\right)\right) = \tilde{\mathcal{O}}\left(\frac{\alpha}{\sqrt{S}} + \frac{1}{\sqrt{SK}} + \frac{1}{S}\right)$$
(16)

Proposition 2 (Lemma 3 from (Yin et al. 2018)). Suppose that the derivative of the loss function f is i.i.d. v-subexponential. Then with a high probability, we have

$$\max_{i \in [K] \setminus \mathcal{B}} \{ |\hat{y}^{(i)} - \mu| \} \le \frac{2v}{\sqrt{S}} \sqrt{\log(1 + SKLD) + \log K} = \tilde{\mathcal{O}}(\frac{1}{\sqrt{S}})$$
(17)

(Yin et al. 2018) prove the difference between the median of models and the optimal model is bounded in Proposition 1, and the maximum difference between an honest model and the optimal model is bounded in Proposition 2 with a high probability, which are exactly the third and the first term respectively in Equation 15.

Now let us consider $\frac{1}{\sum_{j=1}^{K} z^{(j)}} \sum_{i \in \mathcal{B}} z^{(i)} |\hat{y}^{(i)} - \tilde{y}|$. For an attacker $a \in \mathcal{B}$, there are two cases:

• $|e^a| \leq \frac{\sqrt{2}\lambda}{\sqrt{K}}$. From Equation 12 and $|e^a| \leq \frac{\sqrt{2}\lambda}{\sqrt{K}}$, we have $|\hat{y}^{(a)} - \tilde{y}| \leq \frac{C}{\sqrt{K}}$, where $C = \gamma \sqrt{2}\lambda |\widetilde{r}| (1 + \frac{5}{K-1})$.

• $|e^a| > \frac{\sqrt{2}\lambda}{\sqrt{K}}$. If $|e^a| > \left|\frac{\sqrt{2}\lambda}{\sqrt{K}\delta}\right|$ then it can be eliminated from Equation 13. From Equation 12 and $|e^a| > \frac{\sqrt{2}\lambda}{\sqrt{K}}$, we have $\frac{C}{\sqrt{K}} < \left|\hat{y}^{(a)} - \tilde{y}\right| \leq \frac{C}{\sqrt{K}\delta}$.

Combine two cases, we know that $|\hat{y}^{(a)} - \tilde{y}| \leq \frac{C}{\sqrt{K}\delta}$, and we have the following inequality,

$$\frac{1}{\sum_{j=1}^{K} z^{(j)}} \sum_{a \in \mathcal{B}} z^{(a)} \left| \hat{y}^{(a)} - \tilde{y} \right| \le \sup_{a \in \mathcal{B}} \left| \hat{y}^{(a)} - \tilde{y} \right| \le \frac{C}{\sqrt{K}\delta}. \tag{18}$$

Therefore, we prove that

$$\left| \frac{1}{\sum_{j=1}^{K} z^{(j)}} \sum_{i=1}^{K} z^{(i)} \hat{y}^{(i)} - \mu \right| = \tilde{\mathcal{O}}\left(\frac{1}{\sqrt{S}} + \frac{1}{\sqrt{SK}} + \frac{1}{S} + \frac{1}{\sqrt{K}\delta}\right). \tag{19}$$

Conclusion

Federated learning utilizes private data on multiple devices to train a global model, but the simple aggregation algorithm in federated learning is vulnerable to malicious attacks. To tackle this problem, we present a novel aggregation algorithm with residual reweighting. Our experiments on computer vision, natural language processing, and financial data show that our approach is robust to label-flipping and backdoor attacks while prior aggregation methods are not. Our algorithm is easy to implement and readily incorporated into existing federated learning frameworks. We hope our proposed aggregation algorithm can make federated learning more practical and robust in the future.

References

- Alistarh, D.; Allen-Zhu, Z.; and Li, J. 2018. Byzantine Stochastic Gradient Descent. In *Advances in Neural Information Processing Systems*.
- Bagdasaryan, E.; Veit, A.; Hua, Y.; Estrin, D.; and Shmatikov, V. 2018. How to backdoor federated learning. *arXiv preprint arXiv:1807.00459*.
- Biggio, B.; Nelson, B.; and Laskov, P. 2012. Poisoning Attacks against Support Vector Machines. In *ICML*.
- Blanchard, P.; Guerraoui, R.; Stainer, J.; et al. 2017. Machine learning with adversaries: Byzantine tolerant gradient descent. In *Advances in Neural Information Processing Systems*.
- Bonawitz, K.; Ivanov, V.; Kreuter, B.; Marcedone, A.; McMahan, H. B.; Patel, S.; Ramage, D.; Segal, A.; and Seth, K. 2017. Practical Secure Aggregation for Privacy-Preserving Machine Learning. In *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*.
- Chen, Y.; Su, L.; and Xu, J. 2017. Distributed Statistical Machine Learning in Adversarial Settings: Byzantine Gradient Descent. *POMACS* 1(2): 44:1–44:25.
- Feng, J.; Xu, H.; and Mannor, S. 2014. Distributed Robust Learning. *CoRR* abs/1409.5937.
- Fung, C.; Yoon, C. J.; and Beschastnikh, I. 2018. Mitigating sybils in federated learning poisoning. *arXiv preprint arXiv:1808.04866*.
- Geyer, R. C.; Klein, T.; and Nabi, M. 2017. Differentially private federated learning: A client level perspective. *arXiv* preprint arXiv:1712.07557.
- Gu, T.; Liu, K.; Dolan-Gavitt, B.; and Garg, S. 2019. BadNets: Evaluating Backdooring Attacks on Deep Neural Networks. *IEEE Access* 7: 47230–47244.
- Gu, Z.; Jamjoom, H.; Su, D.; Huang, H.; Zhang, J.; Ma, T.; Pendarakis, D.; and Molloy, I. 2018. Reaching Data Confidentiality and Model Accountability on the CalTrain. *arXiv preprint arXiv:1812.03230*.
- Hayes, J.; Melis, L.; Danezis, G.; and De Cristofaro, E. 2019. LOGAN: Membership inference attacks against generative models. *Proceedings on Privacy Enhancing Technologies* 2019(1): 133–152.
- He, K.; Zhang, X.; Ren, S.; and Sun, J. 2015. Deep Residual Learning for Image Recognition.
- Hitaj, B.; Ateniese, G.; and Pérez-Cruz, F. 2017. Deep Models Under the GAN: Information Leakage from Collaborative Deep Learning. In *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, CCS*.
- Holland, P. W.; and Welsch, R. E. 1977. Robust regression using iteratively reweighted least-squares. *Communications in Statistics-theory and Methods* 6(9): 813–827.
- Joulin, A.; Grave, E.; Bojanowski, P.; and Mikolov, T. 2016. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.

- Kan, W. 2019. Lending Club Loan Data. URL https://www.kaggle.com/wendykan/lending-club-loan-data.
- Konstantinov, N.; and Lampert, C. 2019. Robust Learning from Untrusted Sources. *arXiv preprint arXiv:1901.10310*.
- Krizhevsky, A.; Hinton, G.; et al. 2009. Learning multiple layers of features from tiny images. Technical report, Citeseer.
- LeCun, Y.; Bottou, L.; Bengio, Y.; and Haffner, P. 1998. Gradient-based learning applied to document recognition. *Proceedings of the IEEE* 86(11): 2278–2324.
- Li, L.; Xu, W.; Chen, T.; Giannakis, G. B.; and Ling, Q. 2019. RSA: Byzantine-Robust Stochastic Aggregation Methods for Distributed Learning from Heterogeneous Datasets. In *AAAI*.
- McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; and y Arcas, B. A. 2017. Communication-Efficient Learning of Deep Networks from Decentralized Data. In *AISTATS*.
- Melis, L.; Song, C.; Cristofaro, E. D.; and Shmatikov, V. 2019. Exploiting Unintended Feature Leakage in Collaborative Learning. In *IEEE Symposium on Security and Privacy*.
- Minka, T. 2000. Estimating a Dirichlet distribution.
- Paszke, A.; Gross, S.; Chintala, S.; Chanan, G.; Yang, E.; DeVito, Z.; Lin, Z.; Desmaison, A.; Antiga, L.; and Lerer, A. 2017. Automatic differentiation in PyTorch.
- Rand R, W. 1997. *Introduction to Robust Estimation and Hypothesis Testing*. Elsevier.
- Ruining, H.; and Julian, M. 2016. Ups and Downs: Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering .
- Siegel, A. F. 1982. Robust regression using repeated medians. *Biometrika* 69(1): 242–244.
- Thakkar, O.; Andrew, G.; and McMahan, H. B. 2019. Differentially Private Learning with Adaptive Clipping. *arXiv* preprint arXiv:1905.03871.
- Truex, S.; Baracaldo, N.; Anwar, A.; Steinke, T.; Ludwig, H.; and Zhang, R. 2018. A Hybrid Approach to Privacy-Preserving Federated Learning. *arXiv preprint arXiv:1812.03224*.
- Wang, Z.; Song, M.; Zhang, Z.; Song, Y.; Wang, Q.; and Qi, H. 2018. Beyond Inferring Class Representatives: User-Level Privacy Leakage From Federated Learning. *arXiv* preprint *arXiv*:1812.00535.
- Yin, D.; Chen, Y.; Ramchandran, K.; and Bartlett, P. 2018. Byzantine-Robust Distributed Learning: Towards Optimal Statistical Rates. In *ICML*.