SECURITY-PRESERVING FEDERATED LEARNING VIA 
BYZANTINE-SENSITIVE TRIPLET DISTANCE

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ABSTRACT

While being an effective framework of learning a shared model across multiple edge devices, federated learning (FL) is generally vulnerable to Byzantine attacks from adversarial edge devices. While existing works on FL mitigate such compromised devices by only aggregating a subset of the local models at the server side, they still cannot successfully ignore the outliers due to imprecise scoring rule. In this paper, we propose an effective Byzantine-robust FL framework, namely dummy contrastive aggregation, by defining a novel scoring function that sensitively discriminates whether the model has been poisoned or not. Key idea is to extract essential information from every local models along with the previous global model to define a distance measure in a manner similar to triplet loss. Numerical results validate the advantage of the proposed approach by showing improved performance as compared to the state-of-the-art Byzantine-resilient aggregation methods, e.g., Krum, Trimmed-mean, and Fang.

\textbf{Index Terms}— distributed learning, federated learning, edge computing, privacy-preserved, security-preserved

1. INTRODUCTION

Success of deep learning has been built upon massive utilization of data examples [1] by summarizing the core information into deep neural networks. While traditional deep learning assumes availability of the entire data set at the central server side, such assumption becomes impractical when dealing with private data, e.g., medical data of the patients. Federated learning (FL) [2, 3] mitigates this privacy constraint by sharing the model parameter vector instead of data itself so that multiple distributed users (e.g., hospitals) can achieve a single shared AI model (e.g., disease predictor) as if it were trained with the whole data set.

However, due to the nature of sharing the model parameter vector instead of data set, FL is generally more vulnerable to adversarial settings, which cannot apply robust learning techniques that mitigates outlier that works directly on the data set (see, e.g., [4] for robust loss design via $t$-logarithm). Accordingly, FL is susceptible to a variety of Byzantine failures, e.g., data poisoning [5] and model poisoning [6, 7] attacks, which leads to performance degradation [8] and/or increased communication rounds [9].

To overcome the backdoor attacks in FL, various kinds of aggregation rule at the central server side, namely Krum [10], Trimmed-mean [11], and Fang [12]. Essentially, these approaches mitigate the outliers by comparing the scores of the shared model parameter vectors that are defined based on the pairwise distances between the shared local models. However, as the scoring function is computed only on the basis of the distance between the local models, the pairwise distance may lead to uninformative scoring function. To this end, we propose to also utilize the global model at the previous round, which can play as an anchor that is likely to akin to the benign devices as compared to the compromised devices, to de-
fine a triplet distance as shown in Fig. 1. Furthermore, when computing the proposed triplet distance, instead of using the model parameter itself, we utilize feature vectors, or projected vectors [13, 14, 15], that is obtained by inferring some dummy data to the model parameter vector of interest. In this paper, we generate dummy data following standard Gaussian distribution.

2. PRELIMINARIES

In this section, we summarize existing Byzantine-Resilient aggregation strategies, namely Krum [10], Trimmed-mean [11], and Fang [12]. While Krum and Trimmed-mean work without any additional data set, Fang assumes availability of extra data set so as to further improve the performance of Krum or Trimmed-mean. In the following, we denote $\beta$ as the number of transmitted compromised edge devices known a priori for aforementioned aggregation rules.

**Krum** [10]: Given $M$ locally updated models, Krum selects a single model for aggregation per each global epoch $g_e$. Precisely, Krum first computes the $\ell_2$-pairwise distance across every edge devices’ models to compute the score of the $i$th model as

$$s_{\ell_2,i}^{\text{krum}} = \sum_{\theta^j \in \mathbb{I}_{i, M-\beta-2}} ||\text{vec}(\theta^j) - \text{vec}(\theta^i)||^2,$$

where $\text{vec}(\cdot)$ denotes vectorization operation, and $\mathbb{I}_{i, M-\beta-2}$ is the set of $M - \beta - 2$ models that excludes $\beta - 2$ models that are most apart from the $i$th model in $\ell_2$ distance manner. Then, the central server selects a single model which has the smallest score as

$$\theta^i_{\text{krum}} = \text{arg min}_i s_{\ell_2,i}^{\text{krum}} \quad \text{for} \quad i_{\text{krum}} = \text{arg min}_i s_{\ell_2,i}^{\text{krum}}.$$  

**Trimmed-mean** [11]: Trimmed-mean removes the impact of outliers by taking the mean that excludes extreme models. Similar to Krum, Trimmed-mean first computes the $\ell_2$-pairwise distance scores as

$$s_{\ell_2,i}^{\text{trim}} = \sum_{j=1}^{M} ||\text{vec}(\theta^j) - \text{vec}(\theta^i)||^2.$$  

Note that the score is computed with respect to all available pairs. Then the central server sorts the models in an ascending order based on the computed score $s_{\ell_2,i}$. Once sorted, the central server removes the largest and smallest $\beta$ models and aggregate the remaining $M - 2\beta$ models as

$$\text{trim} = \frac{1}{M - 2\beta} \sum_{\theta^m \in \mathbb{I}_{M-2\beta}} \theta^m,$$  

where $\mathbb{I}_{M-2\beta}$ is the set of $M - 2\beta$ remaining models. Note that the trimming parameter $\beta$ should be smaller than $M/2$.

**Fang** [12]: Unlike Krum or Trimmed mean, Fang utilizes the available global data $D_g$ at the server-side to remove $\beta$ models. While Fang can be built upon both Krum and Trimmed mean, we focus here on Trimmed mean which has been reported to show better performance than application with Krum [12]. In order to compute scoring function for $i$th model based on the available data set, Fang computes two aggregation models, one being the $\text{trmin}_\beta$ (4) with total $M$ models; while the other the $\text{trmin}_\beta$ (4) using $M - 1$ models that excludes the $i$th model. We accordingly denote the corresponding Trimmed mean models as $A_i$ and $B_i$, respectively. Then the central server computes the scoring function $s_{err,i}$ for each edge device $i$ as

$$s_{err,i} = \mathcal{L}(A_i; D_g) - \mathcal{L}(B_i; D_g),$$

where $\mathcal{L}(\theta; D)$ is the loss function of model $\theta$ using data set $D$. Then, the central server discards $\beta$ models which have the lowest scores $s_{err,i}$ to aggregate the $M - \beta$ remaining models $A_{\text{raise}}$ as

$$\text{fang} = \frac{1}{M - \beta} \sum_{\theta^m \in \mathbb{I}_{M-\beta}} \theta^m.$$  

3. SYSTEM MODEL

3.1. Federated setting

In this paper, we focus on the scenario of applying FL under targeted [6] and untargeted [7] model poisoning attacks. The federated learning network consists of $M$ edge devices including $B$ benign devices and $C$ compromised edge devices, communicating through the central server. Each edge device $m = 1, \ldots, M$ holds a different local dataset $D_m$ that possibly contains a different number $|D_m|$ of data points, i.e., $d_{m,1}, d_{m,2}, \ldots, d_{m,|D_m|}$, with $i$th data example for $m$th device $d_{m,i}$. The goal of FL is to train a globally shared model based on the edge devices’ dataset $\{D_m\}_{m=1}^M$ without sending data to the central server. Mathematically, the training objective of FL can be written as $F(\theta) \triangleq \frac{1}{M} \sum_{m=1}^{M} \mathcal{L}(\theta; d_{m,i})$, where $F(\theta)$ is the global empirical loss over the entire edge devices’ dataset $\{D_m\}_{m=1}^M$, with the local empirical loss for edge device $m$ defined as $f_m(\theta) = \frac{1}{|D_m|} \sum_{d_{m,i} \in D_m} \mathcal{L}(\theta; d_{m,i})$, denoting $\mathcal{L}(\theta; d_{m,i})$ as the local loss function for data $d_{m,i}$ computed from the model parameter $\theta$. In order to minimize the training objective $F(\theta)$, FL performs $G$ global epochs, in other words, $G$ communication rounds between edge devices and the central server.

3.2. Benign model update

At each global epoch $g_e$, every benign edge devices locally update their model with their own data based on the shared global model $\theta_{g_e}$ from the central server. Precisely, each benign edge device $b \in B$ initializes $\theta_{g_{e-1}}$ to $\theta_{g_{e-1}}^{b, \text{init}}$ and trains
its model θ^{b,l=0}_{ge} up to local epoch l_e = L with its own local data \( D_b \). Assuming Stochastic Gradient Descent (SGD) optimization [16], at each local epoch \( l_e \leq L \), the local update rule can be written as

\[
\begin{align*}
\theta^{b,l+1}_{ge} & \leftarrow \theta^{b,l}_{ge} - \gamma \nabla_{\theta^{b,l}} L_{ce}(\theta^{b,l}_{ge}; \tilde{D}_b) \\
\theta^{b,l=0}_{ge} & = \theta_{ge},
\end{align*}
\]

with subset \( \tilde{D}_b \) with \( N \) examples, sampled from the local data set \( D_b \). Here, \( \gamma \) is the local learning rate and \( L_{ce}(\cdot) \) denotes the cross entropy loss [16]. Once this local training is finished, benign edge devices transmit their trained models \( \theta^{b,l=0}_{ge} \) to the central server. Note that at the very first global epoch \( g_e = 0 \), the global model parameter \( \theta_{ge=0} \) is randomly initialized.

### 3.3. Compromised model update

We now introduce targeted [6] and untargeted [7] model poisoning updates for compromised edge devices. The goal of targeted model poisoning attack is to modify the global model’s behavior on a small number of samples while maintaining the overall performance [17]. In contrast, the untargeted model only aims to degrade the performance of the global model [8], [18].

**Targeted attack** [6]: In targeted attack, compromised edge devices \( c \in C \) perform additional step from (7) as follows:

\[
\begin{align*}
\theta^{c,l=0}_{ge} & \leftarrow \theta^{c,l=0}_{ge} + \delta^{c}_{ge}, \\
\delta^{c}_{ge} & = \lambda (\theta^{c,l=0}_{ge} - \theta_{ge}),
\end{align*}
\]

with boosting factor \( \lambda \) that is designed to satisfy the compromised edge device’s objective.

**Untargeted attack** [7]: In untargeted attack, compromised edge devices \( c \in C \) transmit the fake update without performing (7) as follows:

\[
\begin{align*}
\theta^{c,l=0}_{ge} & \leftarrow \eta(\theta' - \theta_{ge}), \\
\theta' & \sim \mathcal{N}(0, I),
\end{align*}
\]

where \( \eta \) is the scaling factor and \( \mathcal{N}(0, I) \) denotes the standard multivariate Gaussian distribution.

### 4. DUMMY CONTRASTIVE AGGREGATION

We now present the proposed aggregation method that is designed to alleviate the compromised devices introduced above. First key idea is to define a new scoring function in the projected vector domain unlike Krum or Trimmed mean. Since projected vector requires some input data to obtain the feature vector, we proposed to consider a dummy image as input for computing the scores.

At first, the central server randomly generates \( N \) dummy data \( \{\xi_n\}_{n=1}^{N} \) where each \( n \)th sample has its element generated from the standard normal Gaussian \( \mathcal{N}(0, 1) \). We set the size of each dummy input \( \xi_n \) to be same as the input of the true data example \( d_{m,i} \). With the generated dummy data set \( \{\xi_n\}_{n=1}^{N} \), the projected vector \( p \) of the \( M \) local models and the global model are defined as

\[
\begin{align*}
p_m &= g_{\theta^{m,l=0}_{ge}}(\{\xi_n\}_{n=1}^{N}) \in \mathbb{R}^{N \times O}, \\
p_g &= g_{\theta^{0}}(\{\xi_n\}_{n=1}^{N}) \in \mathbb{R}^{N \times O},
\end{align*}
\]

where \( g_{\theta}() \) denotes the neural network functionality before the last fully connected (FC) layer. Here, \( O \) is the dimension of the projected vector for each dummy input \( \xi_n \), which is determined by the neural network architecture. Then the central server computes the dummy contrastive score \( s_{dc,m} \) for each received model \( \theta^{m,l=0}_{ge} \) as follows:

\[
s_{dc,i} = \sum_{j=1}^{M} \left( L_{bce}(p_{gj}; p_j) + L_{bce}(p_g; p_i) \right),
\]

with the loss \( L_{bce} \) defined as

\[
L_{bce}(x; y) = \frac{1}{O} \sum_{o=1}^{O} -((y_o \cdot \log \sigma(x_o) + (1-y_o) \cdot \log (1-\sigma(x_o))),
\]

with sigmoid function \( \sigma(\cdot) \). Note that in (12), we didn’t consider \( g_{\theta} \) as the probability measure to directly use the unnormalized logit vector \( p_{m} \). Finally, the central server sorts the models in an ascending order according to \( s_{dc,m} \) with respect to the other models. After sorting, the central server removes the largest \( \beta \) models and aggregate the remaining \( M - \beta \) models as follows:

\[
\theta_{ge+1} \leftarrow \frac{1}{M - \beta} \sum_{\theta^m \in M - \beta} \theta^m,
\]

where \( \mathcal{M}_{M - \beta} \) is the set of \( M - \beta \) remaining models. After all, \( \theta_{ge+1} \) is used for the next global epoch \( g_e \) and we repeat the procedure until \( g_e \) reaches the predefined value \( G \).

### 5. EXPERIMENT AND RESULTS

#### 5.1. Experiment setting

We use blood cell images dataset [19] with ResNet-18 [20] classifier. We compare the proposed aggregation rule with Krum, Trimmed-mean, and Fang which are the commonly used methods in FL under adversarial setting. The considered blood cell microscope dataset consists of training set of 11,959 examples, validation set of 1,712 examples and a test set of 3,421 examples. We set the dimension of the projected vector \( O \) as 512. Additionally, we adopt quantized skew [21] over \( M = 10 \) edge devices to take into account for non iid FL setting. Other hyperparameter setting is available at the open source code\(^1\).

\(^1\)https://github.com/yjlee22/byzantineFL
5.2. Results

5.2.1. Without Byzantine attacks.

First, we check whether the proposed robust scheme works well enough as vanilla FL scheme, FedAvg [2], when there is no byzantine attacks. To check the convergence of proposed method, we examine the test accuracy with respect to global epoch \( g_e \). According to Fig. 2, we can observe that the global model trained by the proposed method converge as well as vanilla FedAvg. Therefore, it can be confirmed that the proposed approach can achieve approximately the same performance as the vanilla aggregation with a slight decrease in the rate of convergence.

![Fig. 2: Test accuracy with respect to global epoch \( g_e \) without any Byzantine attacks.](image)

5.2.2. Impact of Byzantine percentage

To check the backdoor attack effect, we examine the minimum test error rate after sufficient global epochs, as a function of the ratio of compromised edge devices \( p := C/M \). Additionally, we set \( \beta \) to \( C \) which is a key parameter for Krum, Trimmed-mean, and Fang. According to Fig. 3, unlike conventional approaches, it is shown that the proposed method works well regardless of the type of model poisoning attack. The proposed method outperforms all the schemes, while reaching the similar performance as compared to Fang, which requires additional global data. Note that our scheme does not require any extra data.

![Fig. 3: Minimum test error rate with respect to the percentage of compromised (model poisoning attacks) edge devices \( p \) after sufficient round \( G \) of communication rounds.](image)

5.2.3. Impact of non-iid degree

To investigate the impact of non-iid degree \( \alpha \) over Byzantine failures, we now compare the minimum test error rate with respect to \( \alpha \) in a logarithmic scale. Note that, the data distribution of edge devices becomes closer to iid as \( \alpha \) increases. In this experiment, the ratio of compromised devices is fixed to \( p = 0.3 \). From Fig. 4, we can observe that the test error rate of proposed method decreases faster than the other Byzantine-resilient methods as \( \alpha \) increases. Unlike the proposed method and krum, we can also see that other techniques have different trends depending on the type of Byzantine attacks. Therefore, it can be confirmed that the proposed method shows a consistent tendency regardless of the type of Byzantine attack and non-iid degree. From this result, we believe that proposed method is more robust to backdoor attacks than existing methods in real-world problems.

![Fig. 4: Minimum test error rate with respect to the non-iid degree \( \alpha \) after sufficient round \( G \) of communication rounds in the presence of Byzantine attacks (model poisoning).](image)

6. CONCLUSIONS

In this paper, we proposed dummy contrastive aggregation via alleviating Byzantine attacks which degrades the performance of FL. Numerical results verify that the proposed approach outperforms the existing byzantine FL techniques, Krum, Trimmed-mean, and Fang, under the blood cell classification dataset, by simply changing the distance measure that is more sensitive to outliers. Future work may consider meta-learning [22, 23] for designing a dummy input to further improve the performance of FL with increased robustness to Byzantine attacks.
7. REFERENCES

[1] Osvaldo Simeone, *Machine Learning for Engineers*, Cambridge University Press, 2022.

[2] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Agueray Arcas, “Communication-efficient learning of deep networks from decentralized data,” in *Proc. AISTAT*, Fort Lauderdale, United States, Apr. 2017.

[3] Tian Li, Anit Kumar Sahu, Ameet Talwalkar, and Virginia Smith, “Federated learning: Challenges, methods, and future directions,” *IEEE Signal Process. Mag.*, vol. 37, no. 3, pp. 50–60, 2020.

[4] Matteo Zecchin, Sangwoo Park, Osvaldo Simeone, Marios Kountouris, and David Gesbert, “Robust PACm: Training ensemble models under model misspecification and outliers,” *arXiv preprint arXiv:2203.01859*, 2022.

[5] Vale Tolpegin, Stacey Truex, Mehmet Emre Gursoy, and Ling Liu, “Data poisoning attacks against federated learning systems,” in *Proc. ESORICS*, Guildford, United Kingdom, Sep. 2020.

[6] Arjun Nitin Bhagoji, Supriyo Chakraborty, Prateek Mittal, and Seraphin Calore, “Analyzing federated learning through an adversarial lens,” in *Proc. ICML*, Long Beach, United States, June 2022.

[7] Xiaoyu Cao and Neil Zhenqiang Gong, “Mpaf: Model poisoning attacks to federated learning based on fake clients,” in *Proc. IEEE/CVF CVPR Workshop*, New Orleans, United States, June 2022.

[8] Eugene Bagdasaryan, Andreas Veit, Yiqing Hua, Deborah Estrin, and Vitaly Shmatikov, “How to backdoor federated learning,” in *Proc. AISTAT*, Virtual Event, Aug. 2020.

[9] Xiang Li, Kaixuan Huang, Wenhao Yang, Shusen Wang, and Zhihua Zhang, “On the convergence of fedavg on non-iid data,” in *Proc. ICLR*, Virtual Event, May 2020.

[10] Peva Blanchard, El Mahdi El Mhamdi, Rachid Guerraoui, and Julien Stainer, “Machine learning with adversaries: Byzantine tolerant gradient descent,” in *Proc. NeurIPS*, Long Beach, United States, Dec. 2017.

[11] Dong Yin, Yudong Chen, Ramchandran Kannan, and Peter Bartlett, “Byzantine-robust distributed learning: Towards optimal statistical rates,” in *Proc. ICML*, Stockholm, Sweden, July 2018.

[12] Minghong Fang, Xiaoyu Cao, Jinyuan Jia, and Neil Gong, “Local model poisoning attacks to byzantine-robust federated learning,” in *Proc. USENIX Security Symposium*, Virtual Event, Aug. 2020.

[13] Qinbin Li, Bingsheng He, and Dawn Song, “Model-contrastive federated learning,” in *Proc. IEEE/CVF CVPR*, Nashville, United States, June 2021.

[14] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton, “A simple framework for contrastive learning of visual representations,” in *Proc. ICML*, Virtual Event, July 2020.

[15] Ting Chen, Simon Kornblith, Kevin Swersky, Mohammad Norouzi, and Geoffrey E Hinton, “Big self-supervised models are strong semi-supervised learners,” in *Proc. NeurIPS*, Virtual Event, Dec. 2020.

[16] Osvaldo Simeone, “A brief introduction to machine learning for engineers,” *Found. Trends Signal Process.*, vol. 12, no. 3-4, pp. 200–431, 2018.

[17] Battista Biggio, Blaine Nelson, and Pavel Laskov, “Poisoning attacks against support vector machines,” in *Proc. ICML*, Edinburgh, Scotland, June 2012.

[18] Yingqi Liu, Shiqing Ma, Yousra Aafer, Wen-Chuan Lee, Juan Zhai, Weihang Wang, and Xiangyu Zhang, “Trojaning attack on neural networks,” in *Proc. NDSS*, San Diego, United States, Feb. 2018.

[19] Andrea Acevedo, Anna Merino, Santiago Alférez, Ángel Molina, Laura Boldú, and José Rodellar, “A dataset of microscopic peripheral blood cell images for development of automatic recognition systems,” *Data Br.*, vol. 30, 2020.

[20] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in *Proc. IEEE/CVF CVPR*, Las Vegas, United States, June 2016.

[21] Qinbin Li, Yiqun Diao, Quan Chen, and Bingsheng He, “Federated learning on non-iid data silos: An experimental study,” in *Proc. IEEE ICDE*, Virtual Event, May 2022.

[22] Sangwoo Park, Hyeryung Jang, Osvaldo Simeone, and Joonhyuk Kang, “Learning to demodulate from few pilots via offline and online meta-learning,” *IEEE Trans. Signal Process.*, vol. 69, pp. 226–239, 2020.

[23] Sangwoo Park, Osvaldo Simeone, and Joonhyuk Kang, “Meta-learning to communicate: Fast end-to-end training for fading channels,” in *Proc. IEEE ICASSP*, Virtual Event, May 2020.