Abnormal Client Behavior Detection in Federated Learning

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Abstract

In federated learning systems, clients are autonomous in that their behaviors are not fully governed by the server. Consequently, a client may intentionally or unintentionally deviate from the prescribed course of federated model training, resulting in abnormal behaviors, such as turning into a malicious attacker or a malfunctioning client. Timely detecting those anomalous clients is therefore critical to minimize their adverse impacts. In this work, we propose to detect anomalous clients at the server side. In particular, we generate low-dimensional surrogates of model weight vectors and use them to perform anomaly detection. We evaluate our solution through experiments on image classification model training over FEMNIST dataset. Experimental results show that the proposed detection-based approach significantly outperforms the conventional defense-based methods.

1 Introduction

Federated learning, first proposed by Google in [1, 2], is a new paradigm that enables multiple data owners (a.k.a. clients) to collaboratively train a machine learning model without sharing their privacy-sensitive data on a server. The federated setting is a natural fit for distributed multi-task learning [3]. Thanks to its potential for ensuring privacy, federated learning has already found its applications in various fields, such as mobile internet, finance, insurance, healthcare and smart cities [4–6].

In a typical horizontal federated learning system [1, 2, 4], there is one server and multiple clients. Each client performs model training using its own data and transfers local update to the server for aggregation. The aggregated model update (a.k.a. global update) is then pulled back from the server by the clients. This training process repeats iteratively until the model converges or the maximum number of training rounds is reached. In such a federated setting, the federated averaging (FedAvg) algorithm is widely-used for federated model training, which takes either the model average or the gradient average of the local model weight or gradient updates from the clients [2, 7–10].

In contrast to its counterpart in distributed machine learning system, the server in a federated learning system has no access to the clients’ data, nor does it have a full control of the clients’ behaviors. As a consequence, a client may deviate from the normal behaviors during the course of federated learning, which is originally called Byzantine attacks and is referred to as abnormal client behavior in this work. Abnormal client behavior may be caused intentionally, e.g., by a malicious attacker disguised as a normal client, or unintentionally, e.g., by a client with hardware and/or software defects. It is

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important to detect such abnormal clients, so as to: (i) minimize the impact of anomalous clients; (ii) report abnormal clients; (iii) avoid model leakage to unintended clients; and (iv) prevent from allocating reward or incentive to abnormal clients [11]. Traditional Byzantine-tolerant algorithms are defense-based and sometimes fall short in the federated learning settings with accuracies deteriorated as demonstrated in our experiments. The crux of performance degradation is due to the untargeted defense adopted in existing methods, defending against the attackers at a cost of honest clients.

In this work, we propose a new approach that leverages a pre-trained anomaly detection model to detect abnormal client behaviors and eliminate their adverse impacts. We employ an anomaly detection model at the server to run over the local model weight updates received from the clients. We apply FedAvg algorithm [2] to aggregate the model weight updates. Our approach widely applies to scenarios where the model weight update is sent from a client to the server in various manners, e.g., with no encryption [2], with additive masking protection [12], with differential privacy [13, 14], and in a trusted execution environment (TEE) [15]. Since the model weight of a deep learning model can easily be oversized, we utilize dimensionality reduction techniques to generate surrogates of the local model weight updates at the server for anomaly detection. Experimental results show that the proposed detection-based approach outperforms the conventional defense-based methods, e.g., achieving an improvement of 10% or more in model accuracy for the jointly trained model.

2 Related Work

Defending against malicious attackers has been extensively studied in the context of distributed machine learning, e.g., popular defense-based methods including GeoMed [16], Krum [17], and Trimmed Mean [18]. For federated learning, there also exist several defense-based schemes for minimizing the impact of malicious attackers, such as the work of [19]. The authors of [20] proposed a detection-based approach for collaborative machine learning. The work of [20] is based on the assumption that the distribution of the masked features of the training data preserves the distribution of the training data, which is, however, not applicable to federated learning. To our knowledge, this is the first work that applies a detection-based approach to the federated learning framework.

3 Abnormal Client Behavior Detection

3.1 Problem Definition

We consider a horizontal federated learning system consisting of one server and $K$ clients that collaboratively train a model using the FedAvg algorithm [2]. Due to space limit, we only present the case where each client sends local model weight update to the server without encryption, while leaving the case with additive masking [12], differential privacy [13, 14], and targeted model poisoning [21, 22] to the full version of this work. Our goal is to use an anomaly detection model at the server to detect the anomalous clients and to eliminate their impact on federated model training.

3.2 The Detection-Based Approach

The key idea of our detection-based approach is that each client in the federated learning system is assigned a credit score, which is calculated based on the anomaly score produced by the anomaly detection model. Assuming $K$ clients participate in federated learning, each client has a number of $n_k$ training data points and a local model weight $w_{k,t+1}$ in the $(t+1)$-th global iteration (a.k.a. round). The aggregation in the FedAvg framework [2] is given by

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

where $w_{t+1}$ represents the global model weight update (i.e., the aggregated model weight update), and $n$ denotes the total number of data points at $K$ clients and we have $\sum_{k=1}^{K} n_k = n$.

We propose to replace term $\frac{n_k}{n}$ in Eq. (1) with $\alpha_{k,t+1}$, which may differ in different rounds:

$$w_{t+1} = \sum_{k=1}^{K} \alpha_{k,t+1} w_{k,t+1}.$$
Given the anomaly score $A_{t+1}^k$ is assigned to client $k$ in round $t + 1$, the credit score $\alpha_{t+1}^k$ of client $k$ in round $t + 1$ is defined as

$$\alpha_{t+1}^k = \frac{n_k (A_{t+1}^k)^{−L}}{\sum_{j=1}^{K} n_j (A_{t+1}^j)^{−L}}, \quad \forall j = 1, 2, \cdots, K,$$

(3)

In addition to the fraction of training data points owned by a client, the credit score $\alpha_{t+1}^k$ takes the anomaly score into consideration, leading to targeted defense against abnormal clients. The constant $L$ in Eq. (3) is a hyperparameter, for tuning the influence of $A_{t+1}^k$ in calculating $\alpha_{t+1}^k$. The value of $L$ should be large if one of the clients owns a large proportion of data. Note that, the anomaly score $A_{t+1}^k$ can be calculated by various anomaly detection models [23]. In this paper, we present an autoencoder-based anomaly detection [24], while leaving other anomaly detection schemes to the full version of this work.

Note that since $\sum_{k=1}^{K} \alpha_{t+1}^k = 1$, the convergence of the proposed iterative model averaging procedure in Eq. (2) is guaranteed as long as the convergence of the Fedavg algorithm in Eq. (1) is ensured. This is because it essentially scales down the learning rate.

### 3.3 Autoencoder-Based Anomaly Detection

In the proposed approach, we employ a pre-trained autoencoder model at the server to detect abnormal model weight updates from the clients and hence to detect anomalous clients. Autoencoder model is known to be effective for anomaly detection [23], especially for high-dimensional data [24].

Denote $D = \{w_{1}^{−1}, w_{2}^{−1}, \cdots, w_{N}^{−1}\}$ as the set of model weights for training the autoencoder model, where subscript $-1$ indicates that these model weights are accumulated at the server before the time point for conducting anomaly detection. An autoencoder model can then be pre-trained with this dataset $D$. In the training process, a data point $w_{i}^{−1}$ is firstly compressed into a lower dimensional latent vector by the encoder network and then reconstructed as $\tilde{w}_{i}^{−1}$ by the decoder network [24]. The reconstruction error (a.k.a. mean squared error (MSE)) of the $i$-th data point is given by

$$Err (w_{i}^{−1}) = \| w_{i}^{−1} - \tilde{w}_{i}^{−1} \|^2.$$  

(4)

We can then define anomaly score $A_{t+1}^k$ of client $k$ in round $t + 1$ as

$$A_{t+1}^k = \frac{1 + Err (w_{t+1}^k)}{1 + \sigma_{t+1}},$$

(5)

where $\sigma_{t+1}$ is defined as $\sigma_{t+1} = \min_j \{ Err (w_{t+1}^j), j = 1, 2, \cdots, K \}$.

For deep learning models, the dimension of the model weight $w_{t+1}^k$ can be extremely large, which may lead to prohibitive computational complexity for training the autoencoder model and for anomaly detection. To reduce the computational complexity, we apply dimensionality reduction to the model weight $w_{t+1}^k$ to generate low-dimensional surrogates and use them as input to the autoencoder model. We may apply several existing dimensionality reduction techniques here [25]. For instance, when the dimension of the model weight $w_{t+1}^k$ is $M$, we may randomly take $\overline{M}$ out of $M$ elements from $w_{t+1}^k$ to form a surrogate vector [26], with $\overline{M}$ being much smaller than $M$. For a specific neural network model, we may take the weight of a particular layer from the model weight $w_{t+1}^k$, e.g., the weights of the last convolutional layer [27].

After obtaining the anomaly scores of the clients, we can proceed to calculate the credit scores as in Eq. (3) and run the aggregation operation. We may further make hard decisions on which clients are abnormal via thresholding, which essentially follows the same procedure as for binary classification. The credit score $\alpha_{t+1}^k$ is set to zero if the anomaly score $A_{t+1}^k$ is strictly larger than the threshold $A_{t+1}^{th}$, and $\alpha_{t+1}^k$ is set to $\frac{\alpha}{n}$ otherwise. The threshold $A_{t+1}^{th}$ can be chosen as, e.g., the average value or the median of the anomaly scores $\{A_{t+1}^j, j = 1, 2, \cdots, K \}$.
4 Experiments

4.1 Experimental Settings

We evaluate our solution with a 62-class image classification task over Federated Extended MNIST (FEMNIST) dataset [28]. There are in total 801,074 samples distributed unevenly among 3,500 writers in FEMNIST. Each writer has an average of 229 samples with standard deviation 89.6. Similar to [8, 28], each writer in the FEMNIST dataset represents a client, resulting in a heterogeneous federated setting. During each global round, $K = 20$ writers will be selected and run mini-batch gradient descent locally with a batch size of 16 and a learning rate of 0.06. Each client performs local model weight update for 20 epochs. The percentage of abnormal clients is set to be 30% in every global round. The anomaly score is defined by equation 5 and the credit score is defined by equation 3. In "Credit Score" approach, we aggregate the clients’ model weights by equation 2. In "Thresholding" approach, we set the threshold value to be the average value of the anomaly scores.

The image classification model trained in federated learning is a CNN model with two convolutional layers, both with $3 \times 3$ kernel, 32 channels, and $2 \times 2$ max-pooling, followed by a fully connected layer with 1024 units, and a final 62-dimensional softmax output layer. ReLu activation is used in the hidden layers. This model has a similar architecture as LeNet-5 [29].

The autoencoder model used at the server for anomaly detection has four hidden layers. The input of the autoencoder is a vector with dimensionality of 3000 randomly taken from the last convolutional layer and the number of units in each hidden layer is 64, 32, 32, 64, respectively. ReLu activation is used in the hidden layers. The autoencoder model is trained with accumulated local model weight updates at the server, with the loss function being reconstruction error (i.e., MSE), a batch size of 32 and a dropout rate of 0.2. For calculating credit score, the hyperparameter $L$ in Eq. (3) is set to 2.

4.2 Experimental Results

Following [17] and [30], we consider three adversarial attack models, namely sign-flipping, additive noise and gradient ascent. Sign-flipping attack flips the sign of the model weight, and additive noise attack adds Gaussian noise to the model weight. In gradient ascent attack, the anomalous clients run gradient ascent locally, instead of gradient descent.

As shown in Fig. 1, the proposed methods ("Thresholding" and "Credit Score") outperform the baseline schemes in terms of model accuracy in all settings. It is interesting to see that, by taking out the abnormal updates (i.e., "Thresholding"), the proposed detection-based approach achieves almost the same performance as the FedAvg algorithm without attackers. While GeoMed [16] performs the best among the defense-based methods, the proposed detection-based approach has an improvement of 10% or more in model accuracy over GeoMed under sign-flipping attacks, as illustrated in Fig. 1(a). Further, as discussed in [17], GeoMed cannot defend against the large values sent by abnormal clients. Krum [17] does not perform well in defending against the considered attacks because it is not applicable in federated learning, where data is not identically and independently distributed (iid). Only selecting one most appropriate local model weight update among all the updates received from the clients leads to high bias in model aggregation in non-iid federated settings. Similarly, Trimmed Mean [18] is not effective in defending against the considered attacks in non-iid federated settings. Further, Trimmed Mean and Krum require the knowledge of the fraction of the attackers, which can not be known apriori in federated learning.

Figure 1: Model performance under sign-flipping (a), additive noise (b), gradient ascent (c) attacks
5 Summary

We have shown that autoencoder based anomaly detection can be adopted at the server to detect abnormal local model weight updates from the clients in a federated learning system. The detection-based approach offers the option to opt-out the anomalous clients. Experimental results demonstrate superior performance of the proposed detection-based approach over the defense-based methods.
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