Mitigating Backdoor Attacks in Federated Learning

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Abstract
Malicious clients can attack federated learning systems by using malicious data, including backdoor samples, during the training phase. The compromised global model will perform well on the validation dataset designed for the task. However, a small subset of data with backdoor patterns may trigger the model to make a wrong prediction. Previously, there was an arms race. Attackers tried to conceal attacks and defenders tried to detect attacks during the aggregation stage of training on the server-side in a federated learning system. In this work, we propose a new method to mitigate backdoor attacks after the training phase. Specifically, we designed a federated pruning method to remove redundant neurons in the network and then adjust the model’s extreme weight values. Experiments conducted on distributed Fashion-MNIST have shown that our method can reduce the average attack success rate from 99.7% to 1.9% with a 5.5% loss of test accuracy on the validation dataset. To minimize the pruning influence on test accuracy, we can fine-tune after pruning, and the attack success rate drops to 6.4%, with only a 1.7% loss of test accuracy.

1 Introduction
Federated learning systems [10] are vulnerable under attacks from malicious clients [2, 1]. The server does not have access to the data of clients, and thus, cannot verify model updates from clients, especially when the system is augmented with secure aggregation protocols to further protect the privacy of clients [4]. Malicious clients can theoretically send any updates to the server and the server could be easily compromised if it is under no effective protection that identifies malicious updates to the learned weights of the neural networks.

Existing defense methods focus on the federated aggregation process where the server receives model updates from all the clients. These methods try to distinguish malicious updates from benign ones. Byzantine-robust aggregation rules like Krum [3], Bulyan [11], trimmed mean [16] and median [16], all using statistical characteristics of model weights. However, they have failed to detect backdoor attacks in federated learning [1][2][15] because the non-IID distribution of data among different clients creates enough space for the attacker to hide malicious updates from being detected.

Backdoor attacks often trigger “backdoor neurons” which are the neurons that are activated only in the presence of backdoor-ed images [6]. Studies [9][13] have shown that pruning those “backdoor neurons” could greatly mitigate backdoor attacks without hurting too much model performance. However, these pruning methods cannot be directly used in our case because they rely on a reliable sources of “clean” data, which is not guaranteed in federated learning scenarios (which is designed to protect the privacy of clients’ data). We propose a novel federated pruning process that does not require access to the clients’ original data and helps in deciding the pruning sequence of neurons.

We introduce two federated pruning methods by eliminating neurons that are not being activated by clients’ inputs. Our federated pruning method requires clients to rank the dormant level of neurons in the network. Basically, neurons that are not frequently activated by the network are called dormant neurons. The server will decide these dormant neurons based on the information provided by the clients and steadily pruning the neural networks while checking the model performance on a small validation dataset.

Our empirical studies have shown that only a federated pruning process is not enough to thoroughly eliminate backdoor attacks. The success rate of the federated pruning method highly depends on the attacker’s targets. For example, the pruning process can fully eliminate backdoor behavior when the attacker tries to backdoor digit 9 to digit 1, while the same pruning process fails when the attacker tries to backdoor digit 9 to digit 5. The reason is that in some cases, benign and backdoor behaviors are utilizing the same set of neurons. Thus, pruning those neurons will degrade the performance of the model on both clean data and backdoor instances. Liu et al. [9] have also mentioned a similar situation in their work about the pruning-aware attack.

To solve this problem, we propose an assumption that the number of neurons/features that supports backdoor labels is less than the number of neurons/features which support correct labels. Under this
assumption, reversing the correct prediction results to backdoor labels requires extreme values of the inputs or the weights of the neurons. Thus, by limiting the inputs and the weights of the neurons, we can mitigate the backdoor attacks.

The contribution of this paper are as follows:

- We propose two federated pruning methods to remove redundant neurons in the network without degrading accuracy significantly in a scenario where we do not have access to the clients’ private dataset.

- Our experiments show that the defensive effect of pruning neurons highly depends on the target label attacked by the malicious clients. Thus, we propose to adjust extreme weights in the network to degrade the backdoor attacks. Experiments on MNIST and Fashion-MNIST have shown that our method can effectively reduce the average attack success rate from over 99% to be less than 2%.

- We propose a federated fine-tuning process after neuron pruning to improve the model performance on the validation dataset. Experiments show that adjusting extreme weights after fine-tuning can degrade the attack success rate to less than 10% while the global model’s accuracy rate on the validation dataset can improve 5%.

- We provide in-depth explorations and experiments to show the effectiveness of each part of our defense method, including the federated pruning process, fine-tuning process, and adjusting extreme weights process. We conduct experiments on different datasets, data distribution among clients, attack targets, attack patterns, and model architectures.

2 Related Works

2.1 Backdoor Federated Learning

Bagdasaryan et al. [1] introduced the “semantic backdoor” concept that uses rare features in the real world as a trigger and does not require the attacker to modify the input of the model at inference time. For example, an adversary could compromise the global model by predicting car images with racing stripes as birds, whereas other car images would still be predicted as cars. Sun et al. [12] further showed that allowing the non-malicious clients to have correctly labeled samples from the targeted tasks could not prevent such backdoor attacks. Bhagoji et al. [2] showed that with 10% of the clients being compromised, a backdoor can be introduced by poisoning the model sent back to the server, even with the presence of anomaly detectors or Byzantine-resilient aggregation mechanisms used by the server.

2.2 Attacks and Defenses in Federated Learning

Previously proposed byzantine-robust aggregation rules, like Krum [3], Bulyan [11], trimmed mean [10] and median [16], all using statistical characteristics of model weights, have been reported failed to detect backdoor attacks in federated learning [1, 12]. Non-IID distribution of data gives attackers enough space to plug in their backdoor-model updates. Fang et al. [5] have further shown an untargeted attack that by directly manipulating the local model parameters on the compromised client devices during the learning process, the global models with previous byzantine-robust aggregation rules would suffer a worse testing error rate. To better conceal attackers’ updates from being detected, Xie et al. [15] proposed a distributed backdoor attack method that decomposes a global trigger pattern into separate local patterns and embeds them into the training set of different attackers.

Li et al. [8] proposed a spectral anomaly detection based framework that detects the abnormal model updates based on their low-dimensional embeddings, in which the noisy and irrelevant features are removed while the essential features are retained. They showed that in low-dimensional latent feature space, the abnormal (malicious) model updates can be easily differentiated from the normal updates. Most existing defense methods are trying to distinguish attackers’ updates from benign clients’ updates, while the attackers are trying to modify their updates as close to the other updates as possible. It is hard to tell which method is more effective under different datasets and various data distributions. Our work differs from the existing ones by focusing on further mitigating backdoor attacks after the training phase.

2.3 Pruning Against Backdoor Attacks

Gu et al. [6] showed that poisoned data designed to introduce a backdoor often triggers “backdoor neurons”. Based on this assumption, pruning defenses [9, 13] attempt to remove activation units that are inactive on clean data. This method requires “clean” data that is representative of the global dataset being used to identify those “backdoor neurons”, and such “clean” data is typically not approachable by the server in federated learning scenarios. Different from the above work, our work proposes a federated neuron pruning method.

3 Problem Definition

In this section, we introduce our federated learning environment settings, including the aggregation rule, data distribution among clients, and backdoor attack methods employed in this paper.
3.1 Global Model Learning In a federated learning scenario proposed by McMahan et al. [10], data is distributed among a huge number of clients and cannot be shared with others than the client himself. We assume the total number of clients is \( N \) and each client has \( n_i \) number of samples. At each time \( t \), the server randomly selects a portion of clients \( k \cdot N \) (\( 0 < k \leq 1 \)) from all clients and asks them to train the global model on their local dataset. Then, the FedAvg algorithm [10] will update the global model by aggregating the weight updates from these clients as shown below.

\[
\omega_{t+1} = \omega_t + \eta \cdot \frac{\sum_{i=1}^{kN} n_i \Delta \omega_i^{t+1}}{\sum_{i=1}^{kN} n_i}
\]

where \( \omega_t \) is the previous model parameters at time \( t \), \( \omega_{t+1} \) is the updated model parameters at time \( t + 1 \), \( \Delta \omega_i^{t+1} \) is the updated changes of model parameters provided by client \( i \), \( \eta \) is the global model learning rate. In this paper, since our defense method is not focused on the aggregation process, we simplify the above rules to speed up the backdoor attack and make sure the attack is successful. To be more specific, we make some assumptions to simplify the above learning process. Firstly, we set the number of samples \( n_i \) same for every client, because otherwise the attacker can simply strengthen their updates by claiming that they have a large number of samples to overwhelm the updates from others. Secondly, to improve the global training speed and better monitor the attacking process behavior, we set the same learning rate \( \eta \) for each client (including the attacker). Thirdly, we assume all clients will participate in every round of model aggregation so that the random selection of clients process will not affect the performance of the global model and attacks. The global model aggregation rule is simplified as follows.

\[
\omega_{t+1} = \omega_t + \frac{1}{N} \sum_{i=1}^{n} \Delta \omega_i^{t+1}
\]

3.2 Threat Model The goal of the attacker is to ensure the final global model only fails on a specific task while performing reasonably well on designed tasks. For example, on the MNIST dataset [7], the attacker would like to make the global model mispredict images with backdoor patterns as another label selected by the attacker, while the other normal images would still be predicted correctly. Consequently, the server can hardly recognize that the global model has been compromised even with a substantial evaluation dataset. In general, the attacker would like the global model to predict all testing samples \( \{x_i\} \) with correct labels \( y_i = T \) correctly, while corrupted samples with backdoor patterns \( \{x'_i\} \) will be predicted to a wrong label \( F \), where label \( T \) and label \( F \) can both be selected by the attacker.

We make the following assumptions about the attacker in our experiments: (i) According to our federated learning scenario, all the clients participate in every round of model aggregation. So, there will be at least one attacker in each training iteration. (ii) The malicious client only has access to his own dataset and has no access to the testing dataset. The backdoor training samples are created by applying backdoor patterns to the local dataset the attacker owns.

3.3 Backdoor Attack In this paper, we use similar backdoor patterns as in BadNets [6], which changes some pixels in a picture to form a pattern. During the local training phrase, the attacker would train the model with both original images and the backdoored version of those images at the same time. In this way, we can enforce the model to learn the backdoored pattern instead of misclassifying both the original images and the backdoored images. For example, among the images in Fig 1, the original image would still be predicted as "nine", while the backdoored images are predicted as "one" or any other label chosen by the attacker.

After local training, we use the model replacement attack [1] to make sure the updates from the attacker will survive the FedAvg aggregation on the server’s side. The update function of the attacker can be seen in Appendix A.

4 Defense Method

Empirical studies by Gu et al. [6] showed that backdoor inputs trigger neurons that are typically not used by normal clean inputs. These so-called “backdoor neurons” are leveraged by the attacker to recognize backdoor patterns and trigger misbehavior while keeping silent when the input data is clean. Based on this finding, Liu et al. [9] proposed a Fine-Pruning method to re-
move the “backdoor neurons” in the DNN, thus mitigating backdoor attacks. The key to this pruning method is to find the dormant neurons that are not frequently activated in the network. By using clean training inputs to activate the DNN, they record the averaged activation values of each neuron in the last convolutional layer of the network. Then, they can iteratively prune neurons based on the increasing order of averaged activation values and stop before the accuracy on the validation dataset drops below a certain threshold.

However, in federated learning, the server does not have access to the training data of clients. Thus, there is no way to guarantee a source of clean training inputs to activate the network, since attackers hide among the clients. So, in this paper, we propose a federated way of pruning neurons. The key idea is to ask all the clients to record the averaged activation value of each neuron based on their local training dataset. Then, the server will gather such information from all clients to further determine a pruning sequence indicating which neurons are less used and thus can be pruned first. It can test on a small validation dataset to decide the pruning rate (how many neurons need to prune) following this pruning sequence and select the maximum pruning rate with an acceptable test accuracy on the validation dataset. On the other hand, if the server does not have such a validation dataset or its dataset is too small or biased to represent the data in the real world. It can pass the pruning sequence back to every client and ask them to report the test accuracy on each client’s dataset under different pruning rates. The server will collect this feedback and determine the final pruning strategy.

There are two advantages to this method. Firstly, this method does not require access to the clients’ datasets and thus protects the privacy of each client. Secondly, it is computationally efficient in federated learning, since it only requires at most two rounds of communication between server and clients after the learning process has completed. It is even possible to include more clients to participate in this step than in the training process. Along with the advantages, it also comes with shortcomings. For example, we can no longer have guaranteed “clean data”. Since the attackers are also among the clients, they can return any pruning sequence they want along with the test accuracy on their datasets. Thus, we further propose two algorithms to minimize the influence of minority attackers.

4.1 First Approach: Ranking Vote The ideal situation in federated pruning is that the server can directly collect all the average activation records from each client. However, directly passing through the real values may result in both privacy and security problems. For privacy concerns, real values may reveal some information about the clients’ original dataset. For security concerns, the attackers may easily manipulate the final aggregation results by changing the updated values just as they did in the model learning process.

To solve this problem, we propose a ranking vote algorithm, as shown in Fig 2 where each client provides a ranking of all the neurons based on their averaged activation values. Then, the server can create a global dormant ranking of all the neurons by aggregating the ranking positions of individual neurons from all the clients. In the end, the server iteratively prunes neurons in the increasing ranking order until the accuracy on the validation dataset drops below a certain threshold.

On the other hand, if the server does not have sufficient representative validation dataset to determine when to stop pruning, it can send the global neuron ranking back to each client and ask them to test on clients’ local datasets following the same pruning sequence. After collecting the pruning results of each client, the server can decide how many neurons are going to be pruned following this sequence.

4.2 Second Approach: Majority Vote In the above Ranking Vote algorithm, with more neurons in the model, malicious updates of ranking information will make the larger impact. To further limit the impact of potential attackers, we can simplify the updates from the clients to be only zero or one for each neuron. Then, it would be much harder for the attackers to manipulate the final results if they are a minority group. Also, this method can better protect the clients’ privacy by revealing less information about the activation records on the local dataset.

Specifically, the server will provide a pruning rate, say \( p\% \), to all the clients. Each client needs to decide which neurons should be pruned based on their averaged activation records and the pruning rate. If the average activation value of a neuron belongs to the least value group (i.e., the value is below \( p\% \) of all the values), it will be pruned. If the neuron should be pruned, it will be assigned value ‘0’; otherwise, it will be assigned ‘1’. At this point, we can imagine that each client will create a mask for all neurons and the mask only has values ‘0’ and ‘1’. Then, the server will aggregate all the masks from all clients to have a majority vote information about each neuron. Neurons with higher values stand for their importance among clients; neurons with lower values stand for their dormancy among clients. In the last step, the server can iteratively prunes neurons in increasing order of their aggregated values until the
accuracy on the validation dataset drops below a certain threshold.

With the improvement of security and privacy, this method may require more rounds of communication between clients and the server compared with the Ranking Vote algorithm. Because the pruning rate $p\%$ can hardly be selected without any prior knowledge. Although our experiments show that the pruning rate between 30\% and 70\% performs well in various situations, the server may still need to try different pruning rates in a real situation. Thus, extra rounds of calculation and communication between clients and the server may be needed.

### 4.3 Adjusting Extreme Weights

In our empirical study, we find that the pruned network alone cannot guarantee the mitigation of backdoor attacks. The effect of pruning is highly dependent on the data distribution among clients and the target labels chosen by the attackers. To solve this problem, we assume that after the pruning process, most neurons remained in the network are essential for the designated tasks, and the number of neurons/features that support backdoor labels are less than the number of neurons/features that support correct labels. Under this assumption, reversing the correct prediction results to backdoored labels requires extreme values of the inputs or the weights of the neurons. By limiting the input ranges and adjusting extreme weight values in the network, we can mitigate the backdoor attacks.

To limit the input ranges, we perform an input normalization step for all the inputs to the model. Also, we use a batch normalization layer between layers to further limit the input ranges to the next layer of the network. To adjust extreme weight values in the network, we scan all the weights in the last convolutional layer and zero the weights that are larger or smaller than thresholds based on the mean and standard deviation of the weights in that layer. For example, if the mean value of all the weights in layer $i$ is $\mu_i$ and the standard deviation is $\sigma_i$. Then, we set the threshold $s = \mu_i \pm \Delta \cdot \sigma_i$. Finally, all weights that are larger than $\mu_i + \Delta \cdot \sigma_i$ and all weights that are smaller than $\mu_i - \Delta \cdot \sigma_i$ will be set to zero. Empirical studies have shown that this process is effective in reducing the backdoor task success rate to a low level after model pruning.

### 4.4 Fine-tuning

Pruning neurons and adjusting extreme weights will cause a drop in the model’s test accuracy on the validation dataset. We neither want our model to be vulnerable under backdoor attacks nor expect the model to perform poorly on designed tasks. So, we propose a fine-tuning process after pruning neurons. The idea is to continue the federated learning process on the pruned global model and recover its loss of test accuracy as much as possible. Although the attacker may also participate in this process and push the backdoor attack success rate back to its original level, the followed process of adjusting extreme weights can help reduce the attack success rate to a low level.

### 5 Experiments

The experiments are performed on MNIST and Fashion-MNIST dataset with non-i.i.d. data dis-
tributions. We verified our defense method on backdoor tasks in different client data distribution, different backdoor tasks, different model architectures, and under different backdoor patterns. For experiments on MNIST, we use a model that consists of 2 convolutional layers and 2 fully connected layers. For experiments on Fashion-MNIST, we use a model that consists of 3 convolutional layers and 2 fully connected layers.

5.1 Client Data Distribution Our experiments show that the data distribution among clients can significantly influence the federated learning process. We define a $K$-label distribution among all the clients to simulate various real-world situations. $K$-label distribution means each client will be randomly assigned data belonging to $K$ different labels. For example, if $K = 10$, each client will have randomly assigned data from all the 10 labels (MNIST dataset only has 10 different labels, from digit “0” to digit “9”). The data in each client follows the same uniform distribution, which means that every client will have roughly the same number of samples for all labels. In another extreme case, if $K = 1$, each client will have data that belongs to a single label. Given the condition that we only have 10 clients, in this case each client will hold all the data belonging to a unique label. In this extreme situation, the training process would take much longer than the 10-label distribution, and the backdoor attack would also be easier. The performance of the model during the training process of 3-label, 5-label, and 7-label distribution is shown in Figure 3.

5.2 Neuron Pruning Methods Comparison In this paper, we proposed two methods to determine the pruning sequence of neurons. One is the ranking vote algorithm and the other is the majority vote algorithm. Figure 4 shows the performance of ranking vote and majority vote algorithms on 3-label distribution under different numbers of pruned neurons.

Another question that comes with this pruning process is when should we stop. As we can see in Figure 4, the attack success rate decreases after the test accuracy drops. Also, the server does not have backdoor images during testing. Hence, we can only decide the stop point based on the test performance. In this experiment, we determine the pruning stop point when the test accuracy drops over 1% between two testing points.

5.3 Extreme Value Threshold After pruning neurons in the network, the last step is to limit extreme weight values in the same layer that we prune neurons.
We calculate the mean $\mu_i$ and the standard deviation $\sigma_i$ of all the weights in layer $i$. Then, we change all the weights that are beyond the threshold $s = \mu_i \pm \Delta \cdot \sigma_i$ to be zero. Figure 5 shows one example that this pruning process can effectively mitigate backdoor attack without hurting the accuracy of the model on designed tasks. Typically, we can use the same stopping criteria as in the above pruning process. In our experiments, we find that when $\Delta = 3$, there is always a reasonable result, so in the rest of our experiment we set $\Delta = 3$.

5.4 Backdoor Patterns We conduct experiments to study the impact of backdoor patterns on the attack and our defense method. As shown in Figure 4, we implemented five different attack patterns with the backdoor task of changing the prediction results of digit 9 to digit 1 in the MNIST dataset. The experiment results are shown in Table 4. In the extreme weights adjusting process, we fixed the threshold index $\Delta = 3$. Although we could achieve a much lower attack success rate in some patterns (3-pixels and 7-pixels attack patterns) when using methods, as shown in Figure 4 by selecting the $\Delta$ value that test accuracy begins to decrease. To maintain a fair comparison between different attack patterns, we use the fixed $\Delta$ value to conduct the comparison experiment. We can observe that the structure of the attack pattern has some impact on the final attack performance. In other words, some patterns are more resistant to the neuron pruning process, and some are more resistant to the adjusting extreme weights process.

5.5 Defense Method Evaluation Next we show the experiment results of our pruning method under different circumstances. We conduct experiments on the MNIST dataset to show that both the neuron pruning process and the process of adjusting the extreme weights are all essential parts in our defense method. Further experiments on the fine-tuning process are also reported here. In the end, we test the whole defense procedure on the Fashion-MNIST dataset and prove the effectiveness of our method.

5.5.1 Pruning Neurons According to the definition of our threat model, the goal of the attacker is to manipulate the prediction results of some inputs $x_i'$ with backdoor patterns to another label. To be more specific, those inputs $x_i$ should be predicted as label $y_i = T$ without backdoor patterns. However, after adding the backdoor patterns to the original images, $x_i'$ will be predicted as label $y_i' = F$ by the compromised model. Under this attack, the backdoor patterns and the victim label $T$ and target label $F$ should all be determined by the attacker.

The work of Liu et al. [9] has shown that pruning dormant neurons can effectively mitigate the backdoor attack success rate. However, when we pruned neurons in federated learning scenarios, our experiments showed that the success rate of mitigating backdoor attacks depends on the victim label $T$ and target label $F$ selected by the attacker. Detailed experiment results on the MNIST dataset are represented in Table 5 in Appendix.

With the Ranking Vote method, the backdoor attack success rates drop below 10% only in 5 out of 18 cases shown in 5. With the Majority Vote method, the chance of successful defense is 38.9% (7 out of 18). These results show that pruning neurons only is not able to mitigate backdoor attacks effectively. Figure 4 shows that the attack success rate will not decrease until the test accuracy drops to an unacceptable level. This is because some neurons that support backdoor patterns may also perform an essential function in supporting benign inputs.

5.5.2 Adjusting Extreme Weights In the previous section, we show that pruning dormant neurons alone in federated learning is not enough to mitigate backdoor attacks. In this section, we show that adjusting extreme weights alone can mitigate backdoor attacks only when the model structure is concise enough. Specifically, we are using a two-layer convolutional neural network with the first layer containing 8 neurons and the second layer containing 16 neurons to train on MNIST. Detailed experiment results can be seen in Table 3 of Appendix. The success rate of backdoor attacks decrease from over 99% to an average of 3.2% while the accuracy of the model on test datasets remains almost the same. However, if we perform this process on a larger network (e.g.: two-layer convolutional network with the first layer containing 20 neurons, and the second layer containing 50 neurons), the attack success rate will not decrease. The reason could be that the backdoor training samples are leveraging lots of redundant neurons to reverse the correct prediction results while those backdoor neurons do not necessarily have extreme weights since they can dominate through numbers. So, pruning neurons is necessary when there are redundant neurons in the network that can be leveraged by the backdoor attacks.

5.5.3 Fine-tuning Since the neuron pruning process could not eliminate all the backdoor neurons, we can further improve the model performance on a normal test dataset by fine-tuning the pruned models through federated learning. We apply the same procedure in
Table 1: Experiment results of federated pruning performance under different attack patterns. An example of number of pixels attack can be seen in Figure 1. *test acc* stands for the performance of model on the test dataset. *atk acc* stands for the performance of model on backdoor samples. *num* in *pruning neurons* stands for the number of neurons that are pruned during this process. *num* in *adjusting extreme weights* stands for the number of weights that are changed to zero in this process. The experiment data in this table is trained on a two layer convolutional neural network, with the first layer containing 20 neurons and the second layer containing 50 neurons. The backdoor task is trying to backdoor digit 9 in MNIST to digit 1.

| attack pattern | training phase | pruning neurons | adjusting extreme weights |
|----------------|----------------|----------------|--------------------------|
|                | test acc | atk acc | num | test acc | atk acc | num | test acc | atk acc |
| 1              | 98.5    | 99.9   | 22  | 97.3     | 98.7    | 131 | 97.2     | 0.4     |
| 3              | 98.5    | 100    | 30  | 96.6     | 100     | 139 | 97       | 34.8    |
| 5              | 98.4    | 100    | 34  | 97       | 100     | 138 | 95.2     | 1.4     |
| 7              | 98.5    | 100    | 30  | 96.2     | 96.9    | 138 | 96.8     | 32.9    |
| 9              | 98.4    | 99.8   | 30  | 97.6     | 2.3     | 133 | 96.2     | 0.5     |

Table 2: Experiment results of the training process, neuron pruning process, extreme weights adjusting process and pruning with fine-tuning process on distributed Fashion-MNIST dataset. *vic* stands for the victim label that the attackers want to attack. The backdoor pattern used in this experiment is single-pixel backdoor pattern.

| target | training phase | pruning neurons | adjusting extreme weights | defense with fine-tuning |
|--------|----------------|----------------|--------------------------|--------------------------|
|        | vic | atk | test acc | atk acc | test acc | atk acc | test acc | atk acc | test acc | atk acc |
| 9      | 0   | 88.8 | 99.8    | 83.2    | 2.8    | 82.9    | 2.1    | 86.3    | 9.0    |
| 9      | 1   | 88.7 | 99.4    | 82.6    | 6.5    | 82.1    | 0      | 87.0    | 0      |
| 9      | 2   | 87.8 | 99.8    | 82.2    | 2.7    | 82.1    | 3.1    | 85.6    | 12.6   |
| 9      | 3   | 87.5 | 99.6    | 84.4    | 0.3    | 84.4    | 0      | 86.2    | 0.4    |
| 9      | 4   | 87.8 | 99.7    | 81.0    | 2.9    | 80.6    | 0      | 85.8    | 2.3    |
| 9      | 5   | 86.6 | 99.7    | 81.2    | 11.9   | 80.6    | 3.6    | 86.1    | 10.4   |
| 9      | 6   | 86.3 | 99.8    | 82.8    | 93.6   | 82.0    | 0.2    | 86.0    | 3.1    |
| 9      | 7   | 88.5 | 99.7    | 82.9    | 4.3    | 83.1    | 4.6    | 87.0    | 17.1   |
| 9      | 8   | 88.8 | 99.9    | 84.7    | 87.7   | 85.0    | 3.2    | 87.2    | 2.9    |

5.5.4 Experiments on Fashion-MNIST Our experiments on the Fashion-MNIST dataset are shown in Table 2. We have a total of 10 clients and use a 3-label data distribution among all the clients. There is one attacker among the clients. The global model has three convolutional layers and another two fully connected layers. We tested our defense method under different attacking targets selected by the attacker. According to the result, we can also notice that the neuron pruning process can only mitigate backdoor attacks targeting certain labels, but the following adjusting extreme weights can mitigate all backdoor attacks targeting any labels. On the other hand, the fine-tuning process can significantly improve the model performance on the main task, although it may also benefit the attacker since the attacker is also among the group of clients participating in the fine-tuning. Without a fine-tuning process, the average attack success rate drops from 99.7% to 1.9%, and the test accuracy on the validation dataset drops from 88.1% to 82.5%. With the fine-tuning process, the test accuracy on the validation dataset rises up to 86.4%, although the average attack success rate also increases from 1.9% to 6.4%, as a tradeoff between performance and security.

6 Discussion

6.1 Regularization Method The extreme weights adjusting method is trying to eliminate those extreme...
values in the network weights. This method is very similar to the idea of regularization. However, we find that directly applying the L2 regularization penalty of all layers on the loss function will potentially degrade the model’s performance on the test dataset. Instead, using the L2 regularization penalty only on the last convolutional layer can increase the network’s robustness against a backdoor attack. After adding the regularization method in the last convolutional layer, it becomes much more challenging for the attackers to compromise the global model with a sufficient large regularization factor. The related experiment results can be seen in the Appendix. However, such robustness of the model comes with a loss of performance on the designed tasks (test accuracy on the testing dataset). So, there is a trade-off between the robustness against backdoor attacks and the performance of the model. A larger regularization coefficient provides more robustness but will suffer from a loss in the test performance.

6.2 Model Architectures The neuron pruning method tries to simplify the model architectures and ensure that every remaining neuron is essential to the designed task (measured by the test accuracy on the testing dataset). Experiments (in Table 3 of Appendix) have shown that when the model is concise/simple enough, we can even skip the neuron pruning step, while simply adjusting extreme weights in the last convolutional layer can mitigate backdoor attacks. However, it is almost impossible to design a network architecture that perfectly matches the least requirement of the complexity with an unseen dataset. Simple architectures may cause the model to suffer from large bias errors, while complex architectures will make the model more vulnerable to backdoor attacks. That is why we introduced the neuron pruning process to leverage the information from all clients to prune as many unnecessary neurons as possible without hurting the model’s performance on its designed tasks.

7 Conclusion

We proposed a new method to mitigate backdoor attacks in federated learning. We can simplify the model architectures through the federated neuron pruning process while maintaining good performance of the model on designed tasks. Then, adjusting extreme weights in the simplified model can effectively degrade the success rate of backdoor tasks. We evaluated our method with different attack settings (attack targets/labels, backdoor patterns, data distribution among clients, and datasets). Our experiments also showed that the federated fine-tuning process after pruning neurons could further improve the model performance on designed tasks without hurting the defending method’s performance after adjusting the extreme values process.

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A Model Replacement Attack

The basic idea behind model replacement attack is that the attacker wants the global model to be as close to his local trained model as possible. In the ideal situation, the global model will be completely replaced by the attacker’s model as shown below:

\[
x_{atk} = \omega_{t+1} = \omega_{t} + \frac{1}{N} \sum_{i=1}^{n} (x_{i,t+1}^{i} - \omega_{t})
\]

where \(x_{atk}\) is the attacker’s model, \(\omega_{t+1}\) is the global model at time \(t + 1\), \(x_{i,t+1}^{i}\) is the local model trained by client \(i\) at time \(t + 1\), \(N\) is the number of all clients that participate in the federated learning process. So this function means that the global model \(\omega_{t+1}\) is an averaged mean of model updates from \(N\) clients at time \(t + 1\) and the goal of the attacker is to replace this global model \(\omega_{t+1}\) with attacker’s model \(x_{atk}\). We assume \(x_{n,t+1}^{n}\) is the update from malicious client. Then, by solving Equation A.1 we can have the following:

\[
x_{n,t+1}^{n} = N \cdot x_{atk} - N \cdot \omega_{t} - \sum_{i=1}^{n-1} (x_{i,t+1}^{i} - \omega_{t}) + \omega_{t}
\]

where \(x_{n,t+1}^{n}\) is the update results from client \(n\) (which we assume is the attacker) at time \(t + 1\). As assumed in the work of Bagdasaryan et al. \[1\], \(\sum_{i=1}^{n-1} (x_{i,t+1}^{i} - \omega_{t}) \approx 0\). With the convergence of global model, these deviations cancel out, so the attacker’s update can be simplified as following:

\[
x_{n,t+1}^{n} = N \cdot (x_{atk} - \omega_{t}) + \omega_{t}
\]

However, since the deviations do not cancel out in the training process, we replace the \(N\) in the above equation with an attack update amplification coefficient \(\alpha\) \((1 \leq \alpha \leq N)\) here. We find that the \(\alpha\) value is related to the data distribution among clients. If the distribution of dataset is more similar among clients, a higher value of \(\alpha\) is needed to achieve better results on the backdoor tasks.

B Experiments on MNIST

More experiments mentioned in the paper can be found in Table 3, Table 5 and Table 4.

C Regularization Method

In section 6.1 we discussed about using L2 regularization on the last convolutional layer can improve the robustness of the network against backdoor attacks. Related experiment results can be seen on Figure 6.
| attacker target | training phase | prunning without fine-tuning | prunning with fine-tuning |
|-----------------|----------------|-----------------------------|--------------------------|
|                 | vic label      | atk label                  | test acc (%) | atk acc (%) | test acc (%) | atk acc (%) | test acc (%) | atk acc (%) | test acc (%) | atk acc (%) |
|                 | 9              | 0                          | 98.2          | 99.7        | 94.7         | 0.3         | 96.6         | 0.8         | 96.9         | 0.1         |
|                 | 9              | 1                          | 98.6          | 100         | 95.1         | 0.4         | 96.9         | 0.4         | 97.2         | 2.5         |
|                 | 9              | 2                          | 98.2          | 99.9        | 95.7         | 4.1         | 97.2         | 8.8         | 98.1         | 3.5         |
|                 | 9              | 3                          | 98.3          | 99.6        | 95.6         | 36.9        | 97.2         | 2.8         | 94.6         | 2.8         |
|                 | 9              | 4                          | 98.5          | 100         | 97.2         | 5           | 98.1         | 0.1         | 97.5         | 0.1         |
|                 | 9              | 5                          | 98.5          | 99.9        | 86.6         | 14          | 94.6         | 2.8         | 97.5         | 0.1         |
|                 | 9              | 6                          | 98.6          | 99.7        | 96.4         | 0.1         | 97.5         | 0.1         | 98.2         | 0.5         |
|                 | 9              | 7                          | 98.9          | 99.9        | 94.1         | 0.8         | 96.6         | 3.1         | 96.9         | 0.9         |
|                 | 9              | 8                          | 98.5          | 99.9        | 93.9         | 4.5         | 96.6         | 3.1         | 96.9         | 0.9         |

Table 4: Experiment results of the comparison between with and without fine-tuning process on distributed MNIST dataset. *vic label* stands for the victim label that the attackers want to attack. *atk label* stands for the target label that the attackers want the backdoor data being predicted. *test acc* stands for the performance of model on test dataset. *atk acc* stands for the performance of model on backdoor dataset. Backdoor dataset is composed of images that originally belong to *vic label* in the test dataset been added backdoor patterns.

![Figure 6](image.png)

Figure 6: The performance of model with different regularization coefficient $\lambda$ in the last convolutional layer. The model is trained on MNIST dataset in 3-label distribution among 10 clients. The training processes are identical with the same data distribution, 30 epochs of training time and the same attacker’s amplification update coefficient $\alpha = 3$. 
| target | training phase | pruning neurons - Ranking Vote | pruning neurons - Majority Vote |
|--------|----------------|-------------------------------|--------------------------------|
| vic    | atk | test acc | atk acc | num | test acc | atk acc | num | test acc | atk acc |
| 9      | 0   | 98.5     | 100     | 35  | 96.2     | 100     | 40  | 95.7     | 99.9   |
| 9      | 1   | 98.2     | 100     | 37  | 96.2     | 0.4     | 39  | 93.8     | 0.6    |
| 9      | 2   | 98.6     | 100     | 36  | 96.5     | 0.1     | 37  | 95.8     | 0.2    |
| 9      | 3   | 98.6     | 99.6    | 32  | 96.2     | 6.7     | 34  | 96.1     | 2.3    |
| 9      | 4   | 98.7     | 100     | 34  | 94.7     | 100     | 35  | 95.2     | 0.5    |
| 9      | 5   | 98.4     | 99.9    | 39  | 95.7     | 99.9    | 39  | 95.7     | 99.9   |
| 9      | 6   | 98.1     | 99.8    | 33  | 95.6     | 100     | 32  | 96.6     | 99.9   |
| 9      | 7   | 98.8     | 99.9    | 37  | 96.7     | 98      | 37  | 96.1     | 99.2   |
| 9      | 8   | 98.2     | 99.7    | 36  | 96.2     | 99.5    | 36  | 95.5     | 99.7   |
| 0      | 9   | 98.4     | 100     | 40  | 95.3     | 4.1     | 39  | 96.4     | 3.4    |
| 1      | 9   | 98.7     | 99.7    | 38  | 95.9     | 99.9    | 38  | 96.4     | 0.3    |
| 2      | 9   | 98.4     | 99.8    | 32  | 97.5     | 100     | 30  | 97.2     | 100    |
| 3      | 9   | 97.2     | 99.8    | 30  | 90.6     | 100     | 32  | 95.8     | 99.3   |
| 4      | 9   | 97.9     | 100     | 37  | 94.1     | 100     | 38  | 93.6     | 100    |
| 5      | 9   | 98.6     | 100     | 34  | 96.6     | 0.8     | 34  | 96.7     | 0.7    |
| 6      | 9   | 98.6     | 99.9    | 36  | 97       | 99      | 33  | 96.8     | 100    |
| 7      | 9   | 98.8     | 99.7    | 36  | 96.9     | 97.6    | 35  | 97.2     | 98.4   |
| 8      | 9   | 98.3     | 100     | 34  | 96.3     | 97.8    | 37  | 95       | 99.5   |

Table 5: Experiment results of neurons pruning process on distributed MNIST dataset when attackers have different attack targets. *vic* stands for the victim label that the attackers want to attack. *atk* stands for the target label that the attackers want the backdoor data being predicted. *test acc* stands for the performance of model on test dataset. *atk acc* stands for the performance of model on backdoor dataset. Backdoor dataset is composed of images that originally belong to *vic* label in the test dataset been added backdoor patterns. *num* stands for the number of neurons that are pruned during this process. There are 50 neurons in this convolutional layer.