TrustAggFL: Enhancing Federated Learning with Trusted Client Aggregation for Improved Security

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ABSTRACT

Federated Learning (FL) has emerged as a promising approach for training machine learning models across individual devices while preserving data privacy. However, FL faces many challenges, specifically a vulnerability to adversarial attacks due to its strict adherence to ensuring individual client model and data privacy. To mitigate these issues, dynamic clipping techniques have been proposed which dynamically adjust the gradient clipping threshold during model aggregation. However current iterations depend on specific and often intensive calculations to determine a clipping threshold which can lead to an over fitting to a specific data set or attacker model. In this paper, we address the limitations of existing FL and dynamic clipping approaches by introducing a novel method that incorporates a group of trusted users during the aggregation of client models for a global update. By identifying and utilizing a subset of trusted clients, our method enhances the robustness of model aggregation against malicious updates. This approach not only maintains the model's performance but also improves its resistance to adversarial influences. We demonstrate the effectiveness of our proposed method through extensive experiments thus showcasing its superiority and simplicity in achieving enhanced model security in federated learning settings.

KEYWORDS

federated learning, backdoor attacks, dynamic clipping, static clipping, noising

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1 INTRODUCTION

Federated Learning (FL), an innovative use of machine learning, has emerged as a cornerstone solution for collaborative model training while preserving the privacy of user data [9]. This approach is particularly relevant with the current landscape of data protection regulations as it allows various entities to engage in collective learning without compromising the data confidentiality of their individual and more often than not unique users. Contrasting to normal machine learning where an individual client is only able to train on their individual user data, FL's framework empowers the collaboration of independent groups to glean valuable insights from their respective data sources that previously would've been impossible and illegal. This collaborative effort fosters informed decision-making and innovative strategies for all participants to benefit from such as spam email detection for corporate use [12] and training language models for Google [11].

Despite the merits of collaboration, FL faces challenges such as controlling client models and mitigating vulnerabilities introduced by adversarial attacks. Notably, FL's decentralized nature and privacy preserving foundation makes it difficult to directly review individual client training as a central aggregator/server. This design characteristic renders the model susceptible to poisoning attacks from individual malicious clients [7]. For example, the absence and/or weaknesses of centralized data filtering mechanisms can expose the global model to biases/backdoors originating from a malicious client's individual dataset [4]. Specific to security concerns, the emergence of backdoor attacks, including pixel pattern-based methods, poses additional risks [3]. These attacks compromise of inserting a designated pixel pattern onto images during the training phase of an individual client model so that it misclassifies the images with the pattern backdoor. When this model is selected and aggregated to the global model, the global model will also misclassify any image it comes across with the same pattern backdoor.

This paper introduces a novel methodology, named TrustAggFL, which strategically integrates a subset of trusted users during the client model aggregation process. This approach aims to mitigate vulnerabilities and fortify the security posture of federated learning environments, including defense against backdoor attacks. By harnessing the contributions of trustworthy clients, TrustAggFL seeks to bolster the integrity of aggregated models and enhance resistance against adversarial influences, specifically pixel pattern-based attacks. This contribution extends FL's capabilities, offering an innovative solution to its inherent limitations and emerging security challenges, making it well-suited for privacy-conscious collaborative learning scenarios.

2 BACKGROUND ON PRIVACY-PRESERVING DEFENSES

Differential Privacy is a solution in addressing privacy concerns in model training. It trains models without ever exposing the individual data from users. The process involves privacy-preserving mechanisms such as noise injection and data clipping that are used by aggregators. These techniques not only mask the client models, safeguarding individual data contributors [2, 15], but also act as a strong defense against potential malicious backdoor adversaries attempting to insert backdoors into the central model [10].

2.0.1 Clipping. Differential privacy can employ a technique known as "difference clipping" to control the amount of information shared during model updates. This process involves limiting the magnitude of individual model parameter changes before their aggregation [6]. By introducing noise to the updates within a bounded range, differential privacy prevents malicious actors from extracting sensitive information about individual data contributors [2]. Difference clipping strikes a balance between accurate model convergence and protecting the privacy of participants, thus enabling federated learning to harness the power of diverse data sources while upholding stringent privacy standards.

Difference clipping is typically divided into two groups: static and dynamic [10]. While both have the same goal of being privacy preserving while maintaining overall task accuracy, the parameters used for them are created in two different distinct approaches.

- Static: This method requires for a human (often the aggregator) to set a **fixed** predetermined value to clip by as to limit the size of the individual client updates. Although it is simple and evenly clips all updates to the same "length", this also becomes its Achilles Heel as the model converges and model updates shrink [5, 10]. It's difficult to achieve a balance of clipping and preserving the model's effectiveness as past research [5] has shown. We also demonstrate this finding in (**Fig. 4**). Over clipping (having a small parameter preset shown by **Fig. 1a**) will hinder the contributions of benign clients and the model fails to converge (reach a high accuracy rate). Conversely, under clipping (having a large parameter preset shown by **Fig. 1b**) results in a failure to do its purpose of reducing the effectiveness of backdoors (backdoor effectiveness stays high).

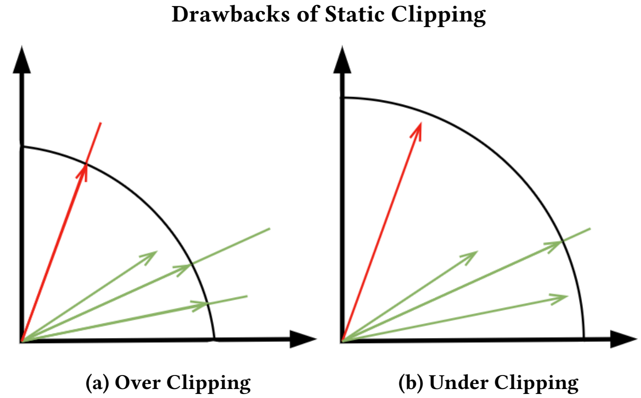


Figure 1: Green lines represent benign updates while the red is a malicious backdoor update. The circle represents the preset clipping parameter. Finally, the arrow on the lines represent where the model update "magnitude" is clipped.

- Dynamic: This method, on the other hand, adjusts the clipping threshold based on the data or size of the updates. This more logical approach takes into account the data characteristics within each training round, ensuring that larger updates (start of training) receive a more relaxed clipping threshold, while smaller updates (end of training when the model converges) are more tightly clipped [1, 5]. Dynamic clipping can lead to a better convergence performance and utilizes the data more effectively, enhancing the overall performance of the federated learning process [10, 13, 16]. We will also go over current iterations of/research on dynamic clipping in Section 2.1.

2.0.2 Noising. In federated learning, noise is often introduced during the aggregation of model updates from different participants. This prevents an attacker from discerning specific information about any single participant's data by analyzing the aggregated updates. Noise can be added using techniques like noise injection or noise perturbation, which blur the actual update values without significantly affecting the overall learning process [8, 10, 13]. By adding noise, the central aggregator hopes to strike a balance between respecting client privacy while still retaining the ability to extract valuable insights from the privatized client models.

2.1 Related Works

Some other works on improving existing dynamic clipping defenses attempt a multitude of methods such as clipping to the mean or median of previous client update L1/L2 Norms [1], a percentile of users [2, 6, 14], or by some multiple coefficient of a mean, median, or calculated value [5, 10, 13, 16].

While all these methods produced successful results, it should be noted that many of them depended on some arbitrary and often complicated calculation to determine the clipping factor. For example, a scaling factor of 1.1 times the mean [13] or to the 35^{th} percentile [6]. While the introduction of scaling factors improves their performance, there must be careful consideration and statistical analysis to prove that the increased complexity upholds the integrity of the experiment's findings. More paramount is that with the variety of real world applications and model interactions, it would be best for federated defenses to be simple and not depend on an additional confounding variable for its success.

In our paper we will be focusing specifically on dynamic clipping because maintaining the model's integrity is easier to do with clipping rather than noising. Additionally, our research focuses on developing an innovative method for dynamic clipping where we have a core group of "trusted users" that we assume will always be benign and will always give us accurate results to update our central model with. We will then use the L2-Norm update values given by t number of trusted clients (1-5) as a standard to perform our difference clipping. To our knowledge, this is a novel method and we show its effectiveness in reducing backdoor threats (BA) while maintaining main task accuracy (MTA).

3 EXPERIMENTS

For our research, we used a modified version of the GitHub repository that Eugune Bagdasaryan graciously provided with his publication on "How to Backdoor Federated Learning" [3]. Our research is focused specifically on the image classification task using the CIFAR-10 data set with the pixel pattern attack. We won't be using noising in our experiments to isolate and exclusively determine the effects of clipping. The end goal that we are aiming for is to prove that our defense is able to maintain overall task accuracy (MTA), while diminishing the backdoor accuracy (BA).

3.0.1 Setup. We implemented the federated learning algorithms using TensorFlow on a Anaconda virtual environment running Python 3.7. All experiments were done on two Dell Precision 5470s with an Intel i7-12800H CPU, Nvidia RTX A1000 GPU, 32 GB Ram each on Ubuntu 22.04.

3.0.2 Parameters. For each experiment there are 100 clients that each train an individual model. In each round of training, the central aggregator selects 10 users to combine their models for an update to the central model. From these 100 clients, we set aside 5 as the trusted users group that can never be selected as backdoor clients. Then from the remaining 95, we select 10 malicious users to insert our pixel pattern backdoor. Finally, within the selection portion, we can choose between 1 to 5 trusted users to be selected within the 10 users with the other 5 being randomly selected from our pool of 95 "unknown" users (85 good, 10 malicious).

3.0.3 Scenarios. In each round, the central aggregator selects 10 clients who are then trained and clipped separately and in sequential order before being aggregated into a global update. The only modifications made to the default settings during our model training were changing the learning rate (0.05), the number of epochs (100), and then for attacks the number of adversaries and their attack weight scale. We made changes to the learning rate and number of epochs to reduce the training time of models so we could quickly prove the effectiveness of our method. Despite these changes, the overall MTA of the model did not drop and still converged between 80% and 82% (with 350 epochs and a learning rate of 0.10, the MTA was also around 80%).

3.0.4 Procedure. Our research can be categorized into four scenarios that we then add varying additional parameters to to show the effectiveness of our method. All of these scenarios started with a 10% poisioning rate (10 compromised clients out of 100) and a backdoor weight scale of 2. We chose these values as the poisoning rate is pretty standard within backdoor attack environment and if the scaling rate is too high then it becomes trivial for the defense to clip the longer backdoored models.

(1) **Baseline:** (No Clipping, No Attack) - This first scenario represents the baseline performance, where the model operates without any attacker and without applying clipping. This graph establishes a reference point for what the normal MTA and BA of the model are without any adversarial influences.
(2) **Attack with No Clipping:** (No Clipping, Has Attack) - The second scenario displays the model's performance when subjected to our backdoor attack without any defense mechanisms such as clipping or noise. This scenario allows us to get MTA and BA results of a backdoored model to prove the potency of the backdoor that we will be defending against. We satisfy the conditions of a successful backdoor as it maintains the MTA, remaining stealthy, while achieving a perfect success rate on the backdoor performance, BA.
(3) **Attack with Static Clipping:** (Static Clipping, Has Attack) - The third scenario explores the model's behavior with various parameters of static clipping. As we will show later, utilizing a static parameter is difficult and more importantly, unviable. Finding a balance between maintaining MTA and and reducing BA is extremely difficult and time costly. We will use these results to show the effectiveness and simplicity of our dynamic approach during training.
(4) **Attack with Dynamic Clipping:** (Dynamic Clipping, Has Attack) - Our fourth scenario investigates the model's performance when equipped with our new dynamic clip which is designed to adapt to the converging behavior of our model updates. This dynamic clip aims to provide a more robust and flexible protection against backdoor attacks as we show by outperforming traditional static clipping methods.

Through these four scenarios, our research aims to offer a comprehensive assessment of the model's resilience against backdoor attacks and the impact of static vs. dynamic clipping. The results for all scenarios will be shown on the figures included in the next section.

4 RESULTS

We have taken to liberty to split our Results section into four subsections in the order of our previously mentioned scenarios. All graphs included will fall into two categories: the first will display the MTA of our model and the the second will show the BA. For ease of viewing and comparison, all graphs will have axes that go from 0 to 100 by intervals of 20 (x-axis: number of rounds trained, y-axis: accuracy rate as a percentage).

4.0.1 Baseline - (No Defense, No Attack). In this scenario we ran multiple tests with the parameters mentioned above to get an idea of what results we should be expecting. Below we will show a graph containing the results of 5 of the models trained.

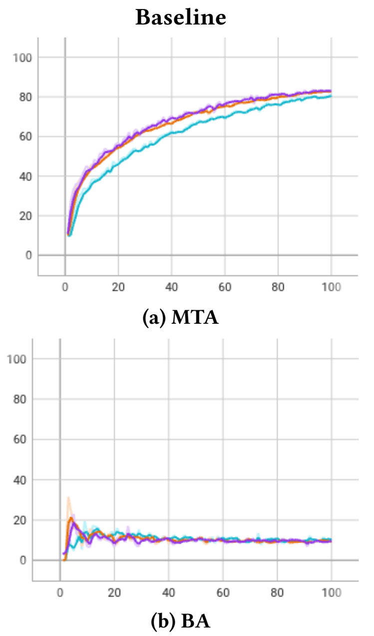


Figure 2: For this specific scenario, the different models/colors don't need to be distinguished as they are trained on identical parameters.

We saw that MTA hovers between 80% and 85% while BA is around 10%. This is expected as the BA is determined by whether the backdoored images are classified correctly into the correct category. Thus, if the backdoor has not been introduced in the round, then the model randomly classifies the backdoored images and because there are 10 categories, it has a one in 10 chance (10% MA) to get it right. If it is partially introduced then the accuracy will be grow until the backdoor has fully been inserted into the central model which results in the model correctly misclassifying the backdoored images into their respective categories (100% MA)

We will now use this 80% MTA and 10% BA as a comparison to judge the success of our other scenarios.

4.0.2 Attack with No Clipping. From this point on we will show one model for each set of different parameters as to not clutter our graphs and confuse readers. In this test, we simply introduce an attacker to see the effect of a backdoor attack.

In judging the potency of a backdoor, a successful one should maintain the MTA (demonstrating its stealthiness) while also injecting the backdoor into the model. Our attack accomplishes both of those tasks as its MTA has a negligible difference and its BA is 100%. In fact, it was able to achieve that BA of a 100% within the first 20 rounds as shown by **Fig. 3b**.

4.0.3 Attack with Static Clipping. We will include the baseline (pink) and attacker (cyan) models in our graphs to act as references for the effectiveness of static clipping. In our testing, we clipped with L-2 Norm values ranging from 5 to 1000. We chose to clip at intervals between 5 to 1000 because those were the size of the updates we saw when printing out the update sizes during training. From 5 to 50 we clipped by intervals of 5 and then after that at 100,

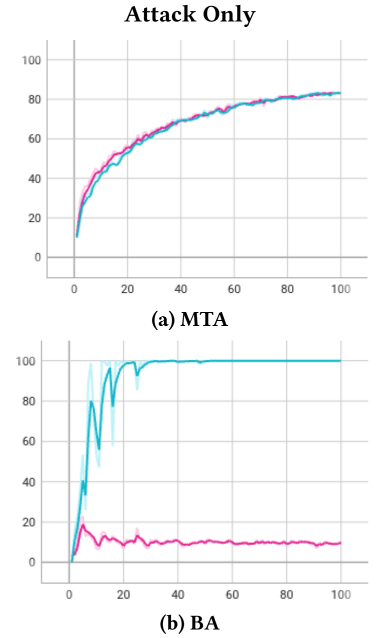


Figure 3: Pink represents our baseline; Cyan is for our attacker scenario.

250, 500, and finally 1000. The following figure will explain why we chose such intervals.

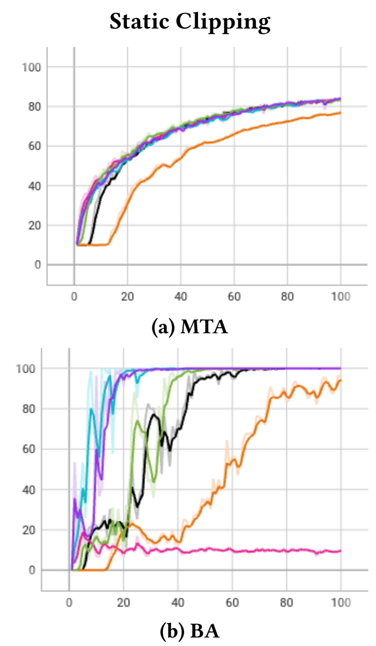
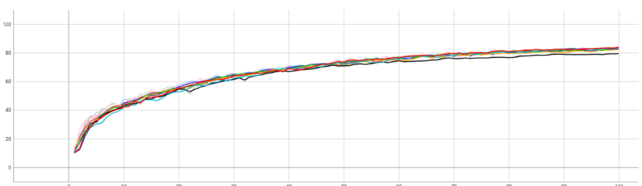


Figure 4: Orange is clipping at 5; Black is at 10; Green at 20; Purple at 50

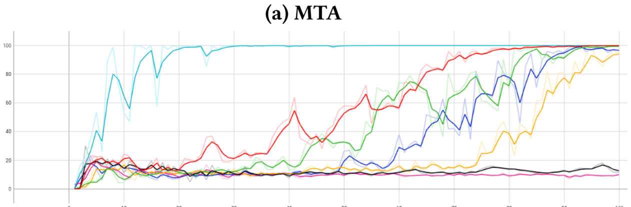
As we notice in **Fig. 3b**, the static clipping value does not affect the overall performance of the backdoor after 100 rounds of training. We have chosen not to include results after the parameter of 50 because as shown by the graph, the performance of our model at 50 (purple) is already virtually the same as having no static parameter (pink) at all. Also as pointed out by others, we see that clipping too tightly (parameter of 5) deteriorates the overall performance of the model as it over clips the helpful benign updates (**Fig. 3a**).

4.0.4 Attack with Dynamic Clipping. For our method, we tried a variety of tests involved with varying the number of trusted users, t, selected during each round ($t/10$). We again will display the baseline (pink) and attack (cyan) models to act as judgement standards to our method. For sake of viewing, we have made these graphs bigger, however we are still presenting all models shown in an identical parameter to allow for fair comparison.

Varying the Number, t, of Trusted Users



(a) MTA



(b) BA

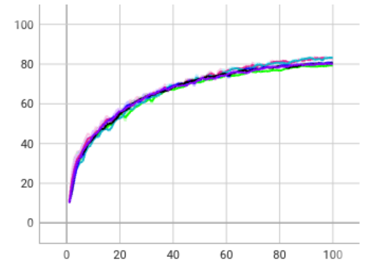
Figure 5: Red: t = 1; Green: t = 2; Blue: t = 3; Orange: t = 4; Black: t = 5

There are a few important things to note with our method. While using only 1 through 4 trusted users doesn't succeed in reducing the backdoor effectiveness, we see that we initially do mitigate the effect of the backdoor while maintaining MTA (unlike in static clipping). More importantly we see that using the median of 5 trusted users virtually eliminates the effect of the backdoor. In our testing the critical value of t to eliminate the backdoor fell between 3 and 5 depending on our model parameters.

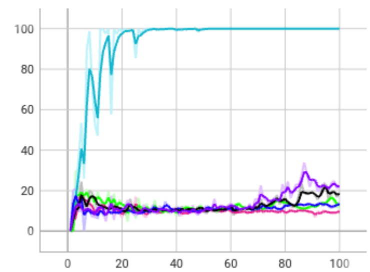
For example, increasing the backdoor weight scale (values of 5 and 10 instead of 2) meant that the backdoor L2-norm updates would be larger, thus making it easier for the median of $t = 3, 4$ trusted users (less representative of all 100 clients as compared to using 5) to clip the backdoor's update size. This also means that if we failed to catch the backdoor that it would proliferate within the central model and quickly increase the BA due to it being a larger update than a backdoor client with a scale of 2. However, we were able to repeatedly get low BA results even with only 3 trusted users (20% was the highest we saw with a weight clip of 5) to calculate a dynamic clipping parameter.

After comparing our results across these four scenarios we are able to conclude that our method is viable and is able to achieve significant results in maintaining overall model accuracy while eliminating backdoors.

Dynamic Clipping with Varied Backdoor Weights



(a) MTA



(b) BA

Figure 6: Purple: t = 3 and weight of 5; Black: t = 3 and weight of 10; Blue: t = 4 and weight of 5; Green: t = 4 and weight of 10

5 LIMITATIONS AND FUTURE WORK

In this section, we want to discuss limitations to our method that we were able to discover and make recommendations based on those results that we would implement in the future.

5.0.1 More Backdoor Clients. We wanted to test the effectiveness of our defense if more malicious users (20% and 30% poisoning rate were tested) were included in the 100 clients under the assumption that they could successfully coordinate a pixel pattern attack on our model.

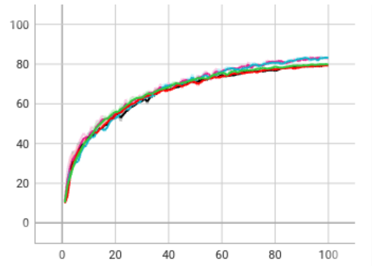
Unfortunately as we show in **Fig. 7**, our defense suffers when tasked with too many attackers. However again, we are assuming that these attackers are all able to sneak into our client pool as well as properly coordinate an attack. We believe that in the real world, this is difficult to accomplish and should not be perceived as a major threat to our method.

5.0.2 Malicious Client within Trusted Users. Finally, we wanted to test to see if our method would work if a malicious client was able to slip into the trusted user pool that our central aggregator calculates a dynamic clipping parameter from.

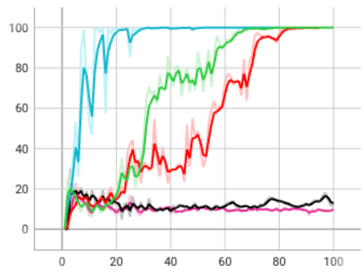
Again, unfortunately as shown if a malicious client is able to slip into the trusted user pool, it is quiet trivial for them to successfully introduce a backdoor. However, we believe that a central aggregator can easily prevent this from happening by screening its trusted users or even by using the client models that it individually trains. If the aggregator is unable to guarantee such terms, then we would advise them to use another defense method as ours depends on the assumption that the trusted users are trustworthy.

With these drawbacks in mind, we want to restate that while our method has been shown to be successful, it is not an end all be

Varying Amounts of Attackers



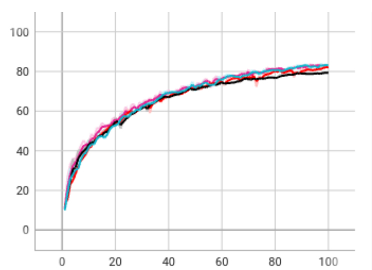
(a) MTA



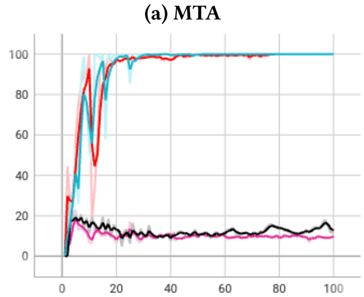
(b) BA

Figure 7: Red is 20 attackers; Green is 30 attackers; Pink is baseline; Cyan is Attacker Only; Black is the model with 5 trusted users

Introducing a Sneaky Attacker



(a) MTA



(b) BA

Figure 8: Red is the malicious client; Pink is baseline; Cyan is Attacker Only; Black is the model with 5 trusted users

all solution to preventing backdoor attacks in federated learning. Users should employ the method appropriate to their circumstances as to better their accuracy or chance of success. We would also like to remind readers that malicious users will continue to evolve and create new attackers and as a result we in the cybersecurity community must continue to adapt to these constant advances.

6 CONCLUSION

In this paper, we proposed a new technique for calculating dynamic clip parameters by introducing the concept of trusted users. We presented that by using this trusted pool of users, we can successfully determine a parameter value to dynamically clip the update norms of clients during the aggregation portion of federated learning. With our method, we found that we were able to uphold the overall accuracy of our image classification model while simultaneously reducing the success of the backdoor. While our test environment is not an ideal representation of the variety of real time scenarios that federated learning defenses can be applied, our results provide a clear path for the introduction of trusted users during client model aggregation.

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