SECURING FEDERATED LEARNING AGAINST NOVEL AND CLASSIC BACKDOOR THREATS DURING FOUNDATION MODEL INTEGRATION

Xiaohuan Bi

Department of Statistics
Renmin University of China

Xi Li

Department of Computer Science
The University of Alabama at Birmingham

ABSTRACT

Federated learning (FL) enables decentralized model training while preserving privacy. Recently, integrating Foundation Models (FMs) into FL has boosted performance but also introduced a novel backdoor attack mechanism. Attackers can exploit the FM's capabilities to embed backdoors into synthetic data generated by FMs used for model fusion, subsequently infecting *all* client models through knowledge sharing without involvement in the long-lasting FL process. These novel attacks render existing FL backdoor defenses ineffective, as they primarily detect anomalies among client updates, which may appear uniformly malicious under this attack. Our work proposes a novel data-free defense strategy by constraining abnormal activations in the hidden feature space during model aggregation on the server. The activation constraints, optimized using synthetic data alongside FL training, mitigate the attack while barely affecting model performance, as the parameters remain untouched. Extensive experiments demonstrate its effectiveness against both novel and classic backdoor attacks, outperforming existing defenses while maintaining model performance.

***Index Terms*—** Backdoor Defense, Federated Learning, Foundation Models, Adversarial Machine Learning

1. INTRODUCTION

Federated learning (FL) enables collaborative model training across decentralized institutes or devices, enhancing data privacy and security with applications in healthcare [1, 2], finance [3], and IoT [4]. Recently, integrating Foundation Models (FMs), such as GPT series, LLaMA series, and Stable Diffusion, introduces new dynamics to FL. Pre-trained on large datasets, FMs excel in tasks from natural language processing to vision data generation and recognition, augmenting FL by improving performance through knowledge distillation [5, 6] or enabling client knowledge sharing with synthetic data generation [7, 8].

However, incorporating FMs into FL systems also introduces new complexities and exacerbates existing threats. The inherent vulnerabilities of FMs create additional attack vectors through their interaction with FL. Recent studies [9, 10] show that FMs' in-context learning (ICL) capabilities enable attackers to exploit novel attacks against FL. Specifically, an attacker can operate externally to the FL process without maintaining its presence throughout its duration. For instance, in a typical FM-integrated FL framework, a large language model (LLM) generates synthetic data for aggregating client model parameters. An attacker can embed a backdoor into the LLM-generated synthetic dataset using malicious prompts during inference. This backdoor is subsequently transmitted to *all* FL clients during knowledge sharing, thereby undermining their integrity.

Existing FL backdoor defense methods, which typically detect *anomalies* among clients during client model aggregation, are ineffective against the novel attacking mechanism [11, 12, 13, 14, 15]. Since all client updates appear *uniformly malicious* due to compromised synthetic data, no detectable anomalies arise. Moreover, many general machine learning (ML) backdoor defenses are unsuitable for FL. Some require access to clean, real datasets [16, 17], conflicting with FL's data isolation principle, while others are time-intensive [18], making them impractical for continuous FL training cycles.

Given the novel threats from ML advances, it is critical to develop an effective defense strategy that addresses these challenges within the FL framework. Since malicious updates could potentially originate from the majority of clients rather than being limited to outliers, a feasible method is to periodically constrain potential malicious updates from all clients on the server. Studies [19, 20, 17] show that backdoor attacks often cause abnormally large activations in the hidden layers of the compromised model. To mitigate this, one could impose upper bounds on the internal activations following the aggregation of client updates. These constraints aim to keep activations within reasonable limits, effectively mitigating the risk of novel backdoor attacks. The optimal upper bounds can be adjusted to balance model performance on certain datasets, *e.g.*, the synthetic dataset. Moreover, the proposed approach suits FL better than general ML backdoor defenses. It uses synthetic data for constraint optimization, preserving local data independence, and periodic adjustment of bounds is more efficient than parameter tuning or trigger estimation strategies.

In summary, this paper presents the following contributions: (1) We introduce the first data-free defense strategy against the novel backdoor attacks arising from the integration of FMs into FL. (2) Extensive experiments in diverse FL scenarios validate the effectiveness of our defense against both novel and classic backdoor attacks, which are unified within the proposed defense framework.

2. RELATED WORK

Vulnerabilities Introduced by FM integrated FL: The interaction between FMs and FL enhances both domains [21] but also introduces new attack vectors [22]. A common use of FM-integrated FL is generating synthetic data for model pre-training [23], knowledge transfer [6], and model aggregation [7]. However, FMs, especially LLMs with ICL ability, are vulnerable to inference-time poisoning [24, 25, 26]. Recent studies [9, 10] reveal a novel attack mechanism exploiting this capability. The attacker uses malicious prompts to embed a backdoor in LLM-generated synthetic data, which is then transmitted to all FL clients during model aggregation, compromising their integrity.

FL Defenses: The existing FL defenses[11, 27, 12, 13, 14, 15] primarily target client-originated threats and offer limited protection against this attack approach. [11] applies a fixed norm threshold to client updates in FL. [27] combines norm thresholding of client updates with the injection of Gaussian noise into the aggregated global model at the server end. [12, 13, 14, 15] selects the most reliable gradient update from all participants to counter adversarial or faulty updates. [28] employs federated aggregation of neuron activation values to prune the least active neurons.

3. METHODOLOGY

3.1. FM integration in FL

Our work follows existing FM-integrated FL frameworks, such as [21, 23]. An LLM on the server generates synthetic data for model aggregation, including text data and prompts guiding other FMs to produce data in formats like images. Combined with classic frameworks like [7], the FM-integrated FL cycle involves *local client training, update uploads, "Ensemble Distillation" based model fusion using the synthetic data, and aggregated parameters distribution*.

3.2. Threat Model and Assumptions on Defender

Our threat model aligns with the use of cutting-edge FMs accessed via APIs and focuses on classification tasks, which is commonly studied in both backdoor and FL research.

Attacker's knowledge: The attacker lacks access to the local training set and process, distinguishing it from traditional backdoor attacks. Instead, they exploit access to the server's LLM queries to insert malicious instructions, specifying the trigger, target class, and demonstrations that show how the attack is activated.

Attacker's goals: The attacker aims to (1) direct the LLM and other FMs to generate synthetic datasets with a percentage of backdoor poisoned samples, and (2) leveraging (1), propagate the backdoor to all client models in FL, causing the final model to misclassify triggered inputs to the target class while maintaining high performance on clean samples.

Attack scenario: Given the diversity of LLMs and the goal of improving outputs, users may rely on third-party services for API integration and prompt engineering. In this case, the attacker could be the service provider, thereby accessing the user's queries.

Defender's knowledge: Like most FL defenses, this method is server-side, with no access to clean local training sets or processes. It assumes no knowledge of an attack, trigger type, or target class, relying solely on local updates and the server's synthetic dataset.

Defender's goals: The defender aims to counteract backdoor attacks during FL training, ensuring the final model matches clean model performance. Specifically, it should classify backdoor-embedded inputs correctly while maintaining high accuracy on clean samples.

3.3. Method

Existing defenses face challenges with the novel attack: (1) Most FL defenses [11, 12, 14, 15, 13] detect *anomalies* in client updates but are ineffective against novel attacks where malicious updates may come from the *majority* of clients. (2) General ML defenses need clean, real datasets, which contradicts the decentralized nature of FL [16, 17]; (3) The ongoing nature of FL makes repeated use of *time-consuming* ML defenses like trigger estimation [18] impractical.

Given the unique attack mechanism and limitations of current defenses, a feasible strategy is to periodically constrain all client (malicious) updates on the server. Studies[19, 20, 17] show backdoor attacks often cause abnormally large activations in hidden layers. Hence, malicious updates can be mitigated by setting upper bounds on internal activations after client update aggregation, with the bounds optimized to maintain model performance on certain datasets. To address challenge 2, upper bounds optimization can be performed using the (possibly poisoned) synthetic dataset, preserving the independence of local data and training in FL. This method minimizes impact on the model's classification ability without altering underlying parameters. Additionally, periodically adjusting these bounds is more efficient and practical than the extensive parameter tuning or trigger estimation used in other contexts, addressing challenge 3.

Now we elaborate on the server-side defense in FL. It is implemented *after the "Ensemble Distillation" based model fusion using the synthetic data* D_{syn}[1]. Let $g(\cdot|\theta)$ denote the L-layer model with parameters θ, derived from the model fusion at FL round t[2]. We define the set $\mathcal{K} \subseteq \{1, \cdots, L\}$ to include all layers where bounds are applied, and the set $\mathcal{Z} = \{\mathbf{z}_k \in \mathbb{R}^{n_k} | k \in \mathcal{K}\}$ to encompass all vectors used to

[1] The processes of client local training and "Ensemble Distillation" based model fusion, which remain unaltered, are not covered here. For details, refer to [7]

[2] For clarity, we omit t in our notation.

constrain activations at layer k within $\mathcal{K}$. Then the logit function for any class $c \in \mathcal{C}$ and any input $\mathbf{x} \in \mathbb{R}^{n_0}$ with activation bounds $\mathcal{Z}$ can be written as

$$\overline{g}_c(\mathbf{x}; \mathcal{Z}) = \mathbf{w}_c^T(\tau_L \circ \sigma_L \circ \cdots \circ \tau_1 \circ \sigma_1(\mathbf{x})),$$

where $\sigma_l : \mathbb{R}^{n_{l-1}} \to \mathbb{R}^{n_l}$ is the composition of the weight and activation function at the l-th layer of the model, $\mathbf{w}_c^T \in \mathbb{R}^{n_L}$ is the weight vector associated with class c, and $\tau_l(\cdot)$ applies upper bounds. For layer $l \in \mathcal{K}$, $\tau_l(\mathbf{v}) = \min\{\mathbf{v}, \mathbf{z}_l\}$, applied element-wise to the vectors; otherwise, $\tau_l(\mathbf{v}) = \mathbf{v}$.

To ensure effective defense, activation upper bounds are minimized to allow only legitimate activations through while filtering out malicious ones. Since the defender lacks knowledge of attack triggers and target classes, the optimization relies solely on clean samples. Hence, one can minimize the upper bounds so that the classification accuracy on clean samples exceeds a certain threshold.

However, in the defense scenario considered here, the defender lacks access to clean, real data. Consequently, we adjust the optimization problem to align the logits of synthetic data - with bounds applied - with those of the original model. This approach helps preserve the effectiveness of the defense and the model's functionality as much as possible by: (1) optimizing the bounds based on the model's relative performance on the synthetic data, thus avoiding reliance on absolute (possibly poor) classification accuracy on the synthetic data; and (2) keeping the model parameters unchanged. Motivated by the above, we optimize the upper bounds by minimizing the following Lagrangian function:

$$H(\mathcal{Z}, \lambda) = \sum_{\mathbf{x} \in D_{\text{syn}}, c \in C} [\overline{g}_c(\mathbf{x}; \mathcal{Z}) - g_c(\mathbf{x})]^2 + \lambda \sum_{l \in \mathcal{K}} \|\mathbf{z}_l\|_2$$

For an effective defense, we dynamically adjust the Lagrangian multiplier λ during FL. Let the threshold $\Delta\pi$ represent the allowable drop in classification accuracy on synthetic data. A lower threshold preserves performance but may miss constraining misclassifications, while a higher threshold may overly constrain. If the accuracy drop is below $\Delta\pi$, we increase λ by α to tighten bounds; if it exceeds $\Delta\pi$, we decrease λ to relax the constraints.

Note that the classic backdoor attack is a special case of the novel attack in our defense framework. Activation bounds also suppress malicious updates from few compromised clients. Moreover, after model fusion and activation bounds optimization, only the model parameters are distributed to clients. Separating bounds from local training prevents compromised clients from adapting to the bounds and thus evading the defense. Additionally, only a few optimization iterations are needed to ensure effective defense, efficiently securing the FL training process.

4. EXPERIMENT

4.1. Experimental Setup

Datasets and models: We use two benchmark datasets, **CIFAR-10** and **CIFAR-100**, for image classification [29]. CIFAR-10 has 60k 32×32 color images across 10 classes, with 5k images per class for training and 1k per class for testing, while CIFAR-100 includes the same number of images across 100 classes, with 500 images per class for training and 100 for testing. For the foundation models, we employ **GPT-4** to produce prompts guiding **Dall-E** to produce 10,000 synthetic data for each dataset, with an equal distribution across all classes. For downstream models in FL systems, we use **ResNet-18** [30] with added linear layers to simulate heterogeneous FL models.

FL settings: We consider both homogeneous (**homo-FL**) and heterogeneous (**hete-FL**) federated learning settings, along with **cross-device** and **cross-silo** scenarios. In the cross-device scenario, 100 clients are available, with 10% randomly selected for each global round. In the cross-silo scenario, 10 clients participate in every round. In all FL settings, we consider both **IID** (independent and identically distributed) and **non-IID** local data, where non-IID is simulated using a Dirichlet distribution with β (the parameter deciding the degree of data heterogeneity) set to 0.1.

Training settings: FL global rounds are set to 50, with 5 iterations for local training, ensemble distillation, and bound optimization. A learning rate of 1×10^{-3} is used for local training and 5×10^{-4} for distillation and bound optimization.

Attack settings: For the novel attack mechanism, we focus on the classic backdoor attack **BadNet**[31]. For the classic attack strategy, we also consider **Blend**[32], and **SIG**[33]. For all datasets, class 0 is chosen as the target class, and all trigger-embedded instances are mislabeled as class 0. The poisoning ratio for synthetic datasets is set to 20%, *i.e.*, 20% of instances per non-target class are embedded with triggers.

Defense settings: ResNet-18 consists of four stages of residual blocks, each composed of a series of convolutional layers. To ensure the effectiveness and efficiency of the defense method, we define $\mathcal{K}$ as the set of final layers from the four stages of ResNet-18. The initial value of the Lagrangian multiplier λ is set to 1, and α is set to 1.1.

Evaluation metrics: We define accuracy (**ACC**) as the fraction of clean test samples correctly classified, and Attack Success Rate (**ASR**) as the fraction of backdoor-triggered samples misclassified to the target class. The defense effectiveness is evaluated by (i) the average ACC of client models on their local test sets and (ii) the average ASR on trigger-embedded test sets. A lower ASR indicates better defense, while ACC should remain as close as possible to the model's original performance without defense.

Performance Evaluation: To demonstrate the effectiveness of our defense, we compare its performance with other FL defense methods, including **NormThr**[11], **DP**[27], **Krum**[12], **Clipcluster**[13], **SignGuard**[14], **RFOUT**[15], and **Pruning**[28]. For all defense methods, including ours, we adjust the hyperparameters so that the drop in ACC is within $\Delta\pi = 10\%$.

Data		Vanilla		NormThr		DP		Krum		ClipCluster		SignGuard		RFOUT		Pruning		Ours	
		ACC	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR
Cross-Silo																			
D_1	**IID**	81.56	92.67	3.14	72.42	15.28	80.24	1.72	93.36	0.50	92.83	0.21	92.77	0.02	92.84	0.56	84.79	3.14	**4.68**
	non-IID	94.33	90.43	0.74	71.13	18.45	69.27	44.44	83.70	0.28	89.40	0.20	89.80	0.29	90.43	0.67	62.98	0.16	**19.15**
D_2	**IID**	37.90	88.99	3.46	70.13	15.90	67.18	1.14	87.09	0.08	89.00	0.00	88.99	0.12	88.98	1.22	77.84	4.70	**8.34**
	non-IID	60.65	81.61	3.75	45.51	3.99	43.74	12.74	79.17	0.45	79.99	0.19	81.12	0.02	81.50	1.89	64.85	4.60	**2.47**
Cross-Device																			
D_1	**IID**	63.92	96.31	4.41	95.53	6.41	96.29	0.30	96.32	0.12	96.37	0.02	96.39	0.24	96.35	0.56	84.79	4.08	**11.81**
	non-IID	88.26	92.90	12.90	89.50	16.93	90.16	17.05	92.74	10.07	95.92	0.38	92.92	0.06	92.72	1.48	71.60	1.75	**19.67**
D_2	**IID**	20.30	90.96	2.55	82.18	11.40	82.20	1.30	89.57	0.52	90.94	0.36	90.98	0.44	90.94	0.70	83.79	2.66	**13.98**
	non-IID	53.06	89.24	3.39	55.29	3.66	53.90	11.68	79.59	0.29	89.13	0.08	89.20	0.09	89.17	0.15	64.78	2.45	**8.91**

Table 1. Defenses against the novel backdoor attack in homo-FL. D1: CIFAR-10, D2: CIFAR-100

Data		Vanilla		NormThr		DP		Krum		ClipCluster		SignGuard		RFOUT		Pruning		Ours	
		ACC	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR	ACC↓	ASR
Cross-Silo																			
D_1	**IID**	79.52	93.36	3.28	77.39	16.22	87.35	0.52	93.74	1.22	93.47	0.34	93.75	0.40	93.74	2.90	72.55	2.46	**5.98**
	non-IID	94.31	91.56	1.48	87.54	3.64	87.60	31.58	89.02	0.36	89.30	0.32	90.98	0.21	91.03	0.69	64.73	0.00	**20.17**
D_2	**IID**	36.52	89.31	3.76	69.82	14.70	64.65	0.10	87.96	1.58	89.35	0.80	89.22	0.48	89.26	1.14	81.05	3.80	**9.92**
	non-IID	61.83	84.19	3.92	55.04	4.15	51.78	6.04	85.92	1.52	84.24	0.27	84.76	0.14	64.77	1.12	71.01	4.18	**3.36**
Cross-Device																			
D_1	**IID**	63.48	96.44	4.00	95.55	7.20	95.95	5.20	96.40	4.48	95.37	0.10	96.46	0.10	96.38	1.72	87.19	2.06	**16.57**
	non-IID	87.17	92.22	6.78	88.86	5.23	89.42	22.84	91.55	14.73	95.66	0.38	92.33	0.34	92.41	2.21	72.91	1.41	**23.13**
D_2	**IID**	21.24	90.90	3.70	80.34	9.60	81.95	0.75	89.04	0.10	90.93	0.02	90.95	4.24	92.81	0.74	84.06	3.38	**14.17**
	non-IID	52.76	89.02	3.95	58.92	4.57	58.96	8.94	83.28	0.12	89.16	0.34	93.00	0.24	89.12	0.44	62.22	1.45	**9.69**

Table 2. Defenses against the novel backdoor attack in hete-FL. D1: CIFAR-10, D2: CIFAR-100

Attack	Vanilla				Ours			
	IID		non-IID		IID		non-IID	
	ACC	ASR	ACC	ASR	ACC↓	ASR	ACC↓	ASR
No Attack	81.36	-	94.53	-	1.48	-	0.24	-
BadNet	82.54	96.50	94.57	60.38	3.50	29.25	0.69	30.08
Blend	82.04	90.04	95.07	92.36	6.80	41.27	1.43	37.36
SIG	81.46	85.42	93.97	73.52	6.36	22.43	2.14	36.34

Table 3. Proposed defense against classic backdoor attacks on CIFAR-10 in cross-silo homo-FL.

4.2. Experimental results

Against Novel Backdoor Attack. The vanilla FM-FL system is highly vulnerable to the novel backdoor attack across all FL settings and datasets. As shown under "Vanilla" in Table 1 and Table 2, the ASRs exceed 90% in all settings, while the ACCs remain at reasonable levels. As expected, existing defense methods, including **NormThr**, **DP**, **Krum**, **ClipCluster**, **SignGuard**, **RFOUT**, and **Pruning**, show limited effectiveness against this threat. While they slightly reduce ACC on clean samples, they fail to significantly mitigate the attack, as ASRs remain high, often close to those of the vanilla models. In contrast, our method offers an effective defense against the novel attack. Under the proposed defense for homo-FL (shown in Table 1), the drop in ACC (denoted as ACC↓) is less than 5% in all cases. We reduce the ASR to below 15% for IID datasets and below 20% for non-IID datasets, indicating that neither the number of clients nor the degree of data heterogeneity significantly impacts defense performance. Our method achieves similarly strong results in hete-FL (as shown in Table 2), demonstrating that it generalizes well across various FL settings and data distributions.

Against Classic Backdoor Attack. Table 3 demonstrates the effectiveness of our defense method against classic backdoor attacks, including BadNet, Blend, and SIG, in the homo-FL cross-silo setting on CIFAR-10. To ensure the attacks remain potent, we compromise two clients and adjust the attack hyperparameters, resulting in most ASRs above 85% for vanilla models. In most cases, our method reduces the ASR by more than 50%, while keeping the ACC drop below 10%. The method demonstrates robustness across various attack strategies and FL settings, highlighting its applicability in defending against a wide range of backdoor threats in FL systems.

Applied in non-attack setting. Since our defense method does not assume the presence of an attack, we also evaluate its performance in clean (attack-free) settings, as shown under "No Attack" in Table 3. The drop in ACC is within 2% in the homogeneous cross-silo FL setting, demonstrating that our method minimally impacts model performance in the absence of an attack.

5. CONCLUSION

This paper introduces the first data-free defense strategy to address emerging backdoor threats resulting from the integration of FMs into FL. Within the proposed defense framework, novel and classic FL backdoor attacks are unified. Extensive experiments conducted across diverse FL scenarios validate the effectiveness of our defense method, demonstrating its robustness and applicability in various contexts.

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