PerDoor: Persistent Non-Uniform Backdoors in Federated Learning using Adversarial Perturbations

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Abstract

Federated Learning (FL) enables numerous participants to train deep learning models collaboratively without exposing their personal, potentially sensitive data, making it a promising solution for data privacy in collaborative training. The distributed nature of FL and unvetted data, however, makes it inherently vulnerable to backdoor attacks: In this scenario, an adversary injects backdoor functionality into the centralized model during training, which can be triggered to cause the desired misclassification for a specific adversary-chosen input. A range of prior work establishes successful backdoor injection in an FL system; however, these backdoors are not demonstrated to be long-lasting. The backdoor functionality does not remain in the system if the adversary is removed from the training process since the centralized model parameters continuously mutate during successive FL training rounds. Therefore, in this work, we propose PerDoor, a persistent-by-construction backdoor injection technique for FL, driven by adversarial perturbation and targeting parameters of the centralized model that deviate less in successive FL rounds and contribute the least to the main task accuracy. An exhaustive evaluation considering an image classification scenario portrays on average 10.5× persistence over multiple FL rounds compared to traditional backdoor attacks. Through experiments, we further exhibit the potency of PerDoor in the presence of state-of-the-art backdoor prevention techniques in an FL system. Additionally, the operation of adversarial perturbation also assists PerDoor in developing non-uniform trigger patterns for backdoor inputs compared to uniform triggers (with fixed patterns and locations) of existing backdoor techniques, which are prone to be easily mitigated.

1 Introduction

Federated Learning (FL) [11][16], a decentralized deep learning framework, enables massively distributed collaborative training with thousands or even millions of participants [3][10]. FL is an iterative protocol where a central server broadcasts the current global model to a random subset of participants. The participants then update the received model locally using their own data and transmit the updated model back to the central server, which aggregates the updates into a new global
model. FL provides a promising framework where participants need not share private information with the service provider or other participants, promising for settings where data privacy is desired.

Most FL settings assume that the central server can not verify the training data of participating clients and can not control their training process. Hence, despite its benefits, FL is shown to be vulnerable to so-called backdoor attacks where an adversary can manipulate local models of a subset of participants and inject backdoor functionalities into the aggregated global model, producing target incorrect predictions for inputs chosen by the adversary. \cite{1,27,29}. Though the existing attacks deliver very high backdoor accuracy immediately after the iteration when the backdoor is injected into the global model, they are not designed to maintain the persistence of the backdoor functionality, which largely depends on the poisoned parameters of the global model. The central server aggregates global model using local updates of other benign participants in successive training iterations, resulting in continuous mutation of global model parameters. As a result, if the adversary is removed from training iterations, the global model will gradually unlearn backdoor task, and the backdoor functionality will diminish as FL training continues. In this work, we uncover a new vulnerability that ensures an adversarial impact on FL setting, even after an active adversary is removed. We propose PerDoor, a persistent-by-construction backdoor injection methodology for FL, which aims to address the challenge of backdoor persistence in existing works. PerDoor targets parameters of the global model that deviate less in successive FL rounds to implant the backdoor functionality for better persistence. In addition, PerDoor does not tamper with parameters that contribute most to the main task accuracy of the global model and has no distinguishable impact to other benign model updates.

PerDoor uses the principle of adversarial attacks to generate backdoor triggers because of their ability to misclassify human-imperceptible perturbed examples to the desired class with high efficiency. Adversarial attacks have previously been used to generate efficient backdoor triggers for traditional deep learning systems; however, the efficacy of such a method in a massively distributed FL framework has not been explored previously. The application of adversarial attacks also aids PerDoor in generating non-uniform trigger patterns for different inputs compared to the fixed uniform trigger patterns of existing backdoor attacks in FL; \cite{1,20,29}, which are prone to be easily mitigated. A brief illustration of PerDoor is shown in Figure 1b compared to the traditional backdoor attacks in FL shown in Figure 1a.

Existing defenses against backdoor attacks in FL primarily aim to prevent it instead of detecting it, as it has been shown that detecting backdoors is challenging without breaking the privacy of participants \cite{1,17,18}. Moreover, detecting backdoors in a model is proven to be an NP-Hard problem. We consider two state-of-the-art backdoor prevention methods in FL, Krum \cite{2} and FoolsGold \cite{8}, which use byzantine-tolerant aggregation methods and evaluate the effectiveness of PerDoor in presence of such defenses. Experimental evaluation considering an image classification

\footnote{Parameters of neural network consist of ‘weights’ and ‘biases’. In this paper, we treat these two identically.}

\footnote{A secret pattern that helps misclassify altered inputs to an incorrect, targeted label.}
scenario demonstrates that PerDoor can achieve, on average, 10.5× persistence over successive iterations of FL training compared to traditional backdoor injection methods when the backdoor is injected at the same round. We also show that PerDoor can achieve high persistence even in the presence of state-of-the-art defenses.

Our Contribution: We summarize our main contributions as follows: (1) We propose PerDoor, a backdoor injection method in FL, which is persistent-by-construction. PerDoor targets parameters of the centralized global model that deviate less in successive FL rounds and contribute the least to the main task accuracy. Targeting such parameters for injecting backdoors instead of affecting all parameters makes PerDoor more persistent than traditional backdoor injection methods in FL. (2) We use the principle of adversarial attacks to generate backdoor triggers for PerDoor, which to the best of our knowledge, has not been explored in an FL framework. The non-uniform triggers generated from adversarial perturbation provide high backdoor accuracy and make it challenging to patch compared to fixed uniform triggers of traditional backdoor injection methods.

2 Problem Formulation and Objectives

Brief Overview of Federated Learning: Let us consider an FL framework having \( n \) participants \( \{p_1, \ldots, p_n\} \) and a central aggregation server that collaboratively train a global model \( G \). In a training round \( r \in \{1, \ldots, R\} \), the central server randomly selects a (typically small) subset of \( m \) participants \( S_m \) and broadcasts the current global model \( G^r \). Starting from \( G^r \), each selected participant \( p_i \in S_m \) trains respective local models \( L_{p_i}^r \) using its private data \( D_{p_i} \) by running a standard optimization algorithm, and transmits the difference \( L_{p_i}^r - G^r \) back to the central server, which aggregates the received updates into the global model \( G^{r+1} \). In this work, without loss of generality, we assume that the central server employs Federated Averaging (FedAvg) \[16\] aggregation method as it is commonly applied in FL \[4\, 7\, 16\, 26\] and related work on backdoor attacks in FL \[1\, 8\, 19\, 28\]. Under FedAvg, the global model is updated by performing a weighted average on the received updates as:

\[
G^{r+1} = G^r + \sum_{p_i \in S_m} \frac{n_{p_i}}{n_{S_m}} (L_{p_i}^{r+1} - G^r)
\]

(1)

where \( n_{p_i} = |D_{p_i}| \) and \( n_{S_m} = \sum_{p_i \in S_m} n_{p_i} \) is the total number of training data used at the selected round. Learning does not stop even after the model converges. Participants, throughout their deployment, continuously update the global model. A malicious participant thus always has an opportunity to be selected and influence the global model.

Threat Model: Following recent studies \[27\, 28\], we consider a scenario where a fixed pool of malicious participants can only conduct the attack in certain FL rounds when the central server randomly selects them. This participating pattern of adversaries is also known as the random sampling strategy.\[3\] Multiple adversaries may participate in a single FL round in such a scenario. While we only consider an independent adversary in this work, collusion can further strengthen the attack as demonstrated in \[29\].

Capability of the Adversary: Following existing work on backdoor attacks in FL \[1\, 2\, 19\], we consider that an adversary \( A \) has full control over the malicious participants. However, \( A \) has no control over other benign participants nor has access to their data or local updates. We assume that \( A \) has complete knowledge of the central aggregation server and deployed defense, if any. More precisely, \( A \) knows the algorithms used in the central server along with all configuration parameters but can not tamper with them.

Goal of the Adversary: The objectives of \( A \) are four-fold: (1) Impact: \( A \) utilizes the broadcasted global model at round \( r \), i.e., \( G^r \), to construct a malicious local model \( \hat{L}_{A}^{r+1} \) using a set of trigger inputs \( \mathcal{T} \) targeting an incorrect chosen label. \( A \) aims to obtain desired incorrect outputs for the set \( \mathcal{T} \) from \( \hat{G}^{r+1} \) at the subsequent round, even after the central server aggregates \( \hat{L}_{A}^{r+1} \) with local updates of other benign participants. (2) Stealthiness: \( A \) aims to construct \( \hat{L}_{A}^{r+1} \) as indistinguishable

\[3\]We also consider Krum and FoolsGold for attack evaluation in Section 4.

\[4\]The authors in \[27\, 28\] also proposed a fixed-frequency strategy where a participant is selected at every \( f \) round, \( f \) being a fixed value. The random sampling strategy is considered to be more practical in a realistic robust FL framework. However, the proposed approach is independent of the participating strategy of the attackers.
where \( \hat{\mathcal{L}}_{\mathcal{A}}^{r+1} \) with other benign models greater than a threshold that can be estimated by comparing \( \hat{\mathcal{L}}_{\mathcal{A}}^{r+1} \) to \( \mathcal{G}^r \) as \( \mathcal{A} \) does not have access to the local updates of other benign participants. (3) Persistence: \( \mathcal{A} \) aims to create \( \mathcal{T} \) and construct \( \hat{\mathcal{L}}_{\mathcal{A}}^{r+1} \) so that \( \mathcal{A} \) can obtain desired incorrect outputs for the set \( \mathcal{T} \) from \( \hat{\mathcal{G}}^{r+1} \) over multiple subsequent rounds, even after numerous aggregations with local updates of other benign participants. (4) Non-Uniformity: \( \mathcal{A} \) aims to create the trigger inputs in \( \mathcal{T} \) so that the trigger patterns and locations are different for different inputs compared to the fixed uniform nature of existing triggers, making it difficult for the central server to patch global models based on the knowledge of trigger patterns.

**Poisoning Method:** Following existing works on backdoor attacks in FL [1, 27, 28], we consider that \( \mathcal{A} \) carries out single-shot model replacement attack to inject backdoors in \( \hat{\mathcal{G}}^{r+1} \) by transmitting back non-uniform triggers for different inputs. A brief overview of adversarial perturbations is provided in Appendix A. However, the adversarial examples alone perturbation also generates non-uniform backdoor triggers for different inputs. A higher value of \( \Delta \) can impact more parameters and thus has a higher chance of affecting main task accuracy. On the contrary, a lower value of \( \Delta \) impacts fewer parameters but may not inject backdoors efficiently with a high backdoor accuracy.

Let us define \( \mathcal{I}_l^r \) be the contribution of each parameters in the \( l \)-th layer of \( \mathcal{G}^r \) on main task accuracy. Let us also consider \( \mathcal{X} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_d, y_d)\} \) as the set of benign inputs to which \( \mathcal{A} \) has access. The \( \mathcal{I}_l^r \) can be computed as:

\[
\mathcal{I}_l^r = \frac{1}{|\mathcal{X}|} \sum_{(x,y) \in \mathcal{X}} \nabla \theta_{\mathcal{G}^r}(x)[y]
\]

(3)

where \( \nabla \theta_{\mathcal{G}^r}(x)[y] \) denote the gradient of \( \mathcal{G}^r \) on input \( x \) considering the label \( y \) with respect to the parameters in the \( l \)-th layer of \( \mathcal{G}^r \). Let us denote \( \theta_{\sigma_l}^r \) be the set of parameters on the \( l \)-th layer and \( \sigma_l^r \) be the set of all parameters of \( \mathcal{G}^r \), respectively, that contribute the least to the main task accuracy, which can be computed as:

\[
\theta_{\sigma_l}^r = \mathbb{1}_{\mathcal{I}_l^r \leq \text{mean}(\mathcal{I}_l^r)}
\]

(4)

\[
\theta_{\sigma}^r = \bigcup_{l} \theta_{\sigma_l}^r
\]

(5)

where \( \text{mean}(\cdot) \) is the estimated mean. The backdoor parameters \( \theta_B \) that \( \mathcal{A} \) intends to target for injecting backdoor on \( \mathcal{G}^{r+1} \) can be computed as: \( \theta_B = \theta_\Delta \cap \theta_{\sigma}^r \).

**PerDoor** uses adversarial perturbations on \( \mathcal{G}^r \) to generate backdoor triggers because of its ability to misclassify perturbed examples to the desired class with high efficiency [3]. The adversarial perturbation also generates non-uniform backdoor triggers for different inputs. A brief overview of adversarial example generation is provided in Appendix A. However, the adversarial examples alone fail to provide desired persistence over successive FL rounds as the efficacy of such attacks depends on the decision boundary (i.e., parameters) of the target model, which continuously mutates over consecutive FL rounds. Hence, \( \mathcal{A} \) adjusts the backdoor parameters \( \theta_B \) of the local model to construct

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1. We also consider continuous poisoning method to evaluate **PerDoor** against traditional backdoor injection methods in FL later in Section 4.

2. Note that the variance is computed inter rounds for each parameter. It is not an intra-round variance.
We use VGG-11 [25] with 9,756,426 parameters as the classifier.

Random sampling

\[ \hat{\mathcal{A}}^{r+1} \] for implanting the effect of adversarial examples for better persistence. Let us consider the set of adversarial backdoor images be \( \hat{\mathcal{X}} = \{(\hat{x}_1, \hat{y}_1), (\hat{x}_2, \hat{y}_2), \ldots, (\hat{x}_f, \hat{y}_f)\} \), generated using a small subset of benign examples \( \{(x_1, y_1), (x_2, y_2), \ldots, (x_f, y_f)\} \) in \( \mathcal{X} \) for the target label \( \hat{y} \). The goal of \( \mathcal{A} \) is to construct \( \hat{\mathcal{A}}^{r+1} \) by only adjusting \( \theta_B \) so that its loss is minimized for the examples in \( \hat{\mathcal{X}} \). The parameter modification is performed iteratively over \( K \) local iterations as:

\[
[\hat{\mathcal{L}}^{(r+1)}_{\mathcal{A}}]_{\theta_B}^{k+1} = [\hat{\mathcal{L}}^{(r+1)}_{\mathcal{A}}]_{\theta_B}^{k} - \text{clip}_\delta \left( \frac{1}{|\mathcal{X}|} \sum_{(x,y) \in \mathcal{X}} \nabla_{\theta_B} J(\hat{\mathcal{L}}^{(r+1)}_{\mathcal{A}}, x, y) \right)
\]

where \([\hat{\mathcal{L}}^{(r+1)}_{\mathcal{A}}]_{\theta_B}^{k} \) denotes the values of backdoor parameters \( \theta_B \) at \( k \)-th local iteration, initial value of \( \hat{\mathcal{L}}^{r+1}_{\mathcal{A}} \) is \( \mathcal{G}^{r} \), \( J(\hat{\mathcal{L}}^{(r+1)}_{\mathcal{A}}, x, y) \) denotes the loss for \( \hat{\mathcal{L}}^{r+1}_{\mathcal{A}} \) considering input \( x \) and corresponding label \( y \), \( \nabla_{\theta_B} \) denotes the gradient with respect to the backdoor parameters \( \theta_B \), and \( \delta \) (termed as backdoor strength) works as a parameter controlling both stealthiness through the impact on main task accuracy and efficiency through the impact on backdoor accuracy, \( \text{clip}_\delta(\cdot) \) denotes the function regulating parameter modification within \( \delta \)-ball of the original parameters. A higher value of \( \delta \) introduces large modifications in \( \hat{\mathcal{L}}^{r+1}_{\mathcal{A}} \), which may affect main task accuracy. On the contrary, a lower value of \( \delta \) may not inject backdoors efficiently with a high backdoor accuracy. As discussed in Section 2, an optimum value of \( \delta \) can be estimated by comparing \( \hat{\mathcal{L}}^{r+1}_{\mathcal{A}} \) to \( \mathcal{G}^{r} \).

4 Experimental Evaluation

4.1 Experimental Setup

Experimental Platform: We conduct all experiments on a server with a 24-core AMD Ryzen 3900X CPU, NVIDIA GeForce RTX 2080 Ti GPU (8GB memory), and 256GB RAM. We used the Python-based Deep Learning framework PyTorch [22] for all implementations.

Dataset and Training Configurations: We consider an image classification task to evaluate the effectiveness of PerDoor in FL. Following recent studies on FL [1, 2, 8, 28], we use CIFAR-10 [13] as benchmark dataset. We consider an FL framework where the participants collectively train the global model using training data that is independent and identically distributed among the participants. We use VGG-11 [25] with 9,756,426 parameters as the classifier.

Following the FL training configuration discussed in [1], we train the global model with \( n = 100 \) total participants, 10 of whom are selected randomly in each FL round, i.e., \( |S_m| = 10 \). Each chosen participant in a round trains individual local model for 2 epochs with the learning rate of 0.1, as described in [1]. The local training is performed using the stochastic gradient descent optimization and the negative log-likelihood loss. As discussed in Section 2 the central server uses the widely used standard FedAvg aggregation method as baseline implementation. We also consider two state-of-the-art backdoor preventing aggregations in FL, Krum [2] and FoolsGold [8], and reimplement them for CIFAR-10 and VGG-11 to evaluate the effectiveness of PerDoor in presence of such defenses.

Attack Strategy: We consider 1\% of the total participants to be malicious for our evaluation. As mentioned in Section 2, malicious participants are selected using the random sampling strategy following a uniform distribution. We consider two analysis windows for the malicious participants before injecting backdoors: (1) stable point (\(|V| = 30\)) - where the global model is close to generalizing the training data, and (2) volatile point (\(|V| = 20\)) - where the global model still produces large differences in generalization errors. We considered these two points for evaluating the impact of backdoors when injected at different stages during FL training. The values of \( V \) are empirically selected considering the classifier architecture and the training dataset, which may differ from other architecture and/or datasets. We use the Basic Iterative Method (BIM) [14] with \( L_\infty \)-norm to generate adversarial perturbations for backdoor triggers. A brief overview of BIM is provided in Appendix A. We use the CleverHans v2.1.0 library [21] for implementing BIM. We evaluate the backdoor impact using three different attack strengths (\( \epsilon = 0.05, 0.075, 0.1 \)) for BIM. We primarily use \( \epsilon = 0.1 \) for generating the adversarial perturbations unless mentioned otherwise. Without loss

\[^7\] An increased number of malicious participants will boost the attack effectiveness, as shown in recent studies on backdoor attacks in FL [1, 8, 19, 27, 29].
of generality, we select two labels randomly as the source (‘airplane’) and target label (‘frog’). The
method is equally applicable for other combinations of source and target labels.

**Evaluation Metrics:** We consider the following two metrics to evaluate the effectiveness of PerDoor:
(1) $\text{Acc}_B$ (Backdoor Accuracy) indicating the accuracy of a model in the backdoor task, i.e., it is the
fraction of trigger images for which the model provides target outputs as chosen by the adversary and
(2) $\text{Acc}_M$ (Main Task Accuracy) indicating the accuracy of a model in its main task, i.e., it denotes
the fraction of benign images for which the model provides correct predictions. The adversary aims
to maximize $\text{Acc}_B$ and minimize the effect on $\text{Acc}_M$.

4.2 Research Questions

We construct subsequent experiments to answer the following research questions (RQ) considering
the objectives of an adversary as discussed in Section 2:

[RQ1] *What is the attack performance of PerDoor?* In this RQ, we investigate the effectiveness
of PerDoor in terms of $\text{Acc}_B$ and $\text{Acc}_M$. A higher value of $\text{Acc}_B$ indicates a successful
backdoor injection which should not drop the value of $\text{Acc}_M$. We also investigate the
stealthiness of such backdoor injection by monitoring similarity of the malicious local model
with the broadcasted global model.

[RQ2] *How persistent are the backdoors over FL rounds?* In this RQ, we investigate the persistence
of PerDoor in terms of $\text{Acc}_B$ after the adversary stops uploading poisoned updates. A
higher value of $\text{Acc}_B$ over subsequent FL rounds indicates a persistent backdoor injection.

[RQ3] *How does PerDoor perform against state-of-the-art backdoor defenses?* In this RQ, we
investigate the performance of PerDoor against two state-of-the-art defense methods in
terms of $\text{Acc}_B$. A higher value of $\text{Acc}_B$ over multiple FL rounds indicates a successful
evasion of backdoor defenses.

[RQ4] *How diverse are the backdoor trigger patterns for different inputs?* In this RQ, we investigate
the non-uniformity of backdoor trigger patterns in PerDoor for different input images of
the same source label and target label compared to traditional uniform backdoor triggers.

4.3 Experimental Results

We first identify the set of backdoor parameters $\theta_B$ in the global model. Without loss of generality,
we assume that the adversary analyzes the broadcasted global model parameters until the stable point
of FL rounds for this analysis. For simplicity, we present the variance of each parameter in the second
convolution layer of the global model over successive FL rounds till the stable point in Figure 2a. In
Figure 2b, we present the contribution of each parameter in the second convolution layer with respect
to main task accuracy on the global model at the stable point of FL rounds.

![Figure 2](image)

Figure 2: (a) Variance of parameters in second convolution layer over successive FL rounds till the
stable point. (b) Contribution of parameters in second convolution layer towards main task accuracy.
The total number of parameters in $\theta_B$ are shown in Table 1 for different values of $t_\Delta$. We can intuitively observe that as the value of $t_\Delta$ decreases, fewer parameters are selected for the backdoor injection. As discussed in Section 3, affecting a higher number of parameters poses a possibility of becoming distinguishable from other benign model updates, whereas affecting a lower number of parameters may fail to create the desired backdoor impact. In our further analysis, we have selected $t_\Delta = 0.001$, which provides the best performance considering both stealthiness and backdoor impact. The average cumulative variance of $\theta_B$ and the non-backdoor parameters over successive FL rounds after the backdoor injection is shown in Figure 3. Even after the malicious modification through $\theta_B$, we can observe that their average variance is always significantly lower than the average variance of non-backdoor parameters, aiding the persistence of backdoors which we will discuss later.

**[RQ1] Attack performance of PerDoor:** We inject backdoors in the global model with different values of backdoor strength $\delta$ for this analysis. To analyze the similarity of the malicious backdoor model with the broadcasted global model, we use linear *Central Kernel Alignment* (CKA) analysis 12. The CKA metric, which lies between $[0, 1]$, measures the similarity between a pair of neural network models, where a higher CKA value indicates substantial similarity. We compute the CKA similarity between $\mathcal{L}_A^{t+1}$ and $\mathcal{G}^r$ for different values of $\delta$ and present the result in Figure 4. We can observe that with an increase in the value of $\delta$, the CKA value reduces, indicating a significant drop in the similarity between $\mathcal{L}_A^{t+1}$ and $\mathcal{G}^r$. Figure 4 also presents $\text{Acc}_M$ of the global model $\mathcal{G}^{r+1}$ immediately after backdoor injection for corresponding values of $\delta$. We can likewise observe that with an increase in the value of $\delta$, $\text{Acc}_M$ also reduces, indicating a substantial influence on the main task accuracy due to backdoor injections. As discussed previously, an appropriate value of $\delta$ can be estimated by comparing the CKA values of $\mathcal{L}_A^{t+1}$ to the broadcasted $\mathcal{G}^r$ in successive FL rounds. In our further analysis, we have estimated $\delta = 0.00001$, which provides the best performance considering both stealthiness and backdoor impact.

**[RQ2] Persistence of PerDoor:** We consider both the stable point and the volatile point, as discussed previously, during FL training for evaluating the persistence of injected backdoors. Figure 5a shows $\text{Acc}_M$ for 5000 successive rounds where two separate instances of backdoors are injected at the volatile point and stable point. We can observe that the backdoor injection does not influence $\text{Acc}_M$ (main task accuracy stays almost equivalent to when backdoors are not injected). We consider two scenarios to evaluate the persistence and effectiveness of PerDoor: (1) adversary injects backdoors only using adversarial examples but not restricting the effects on backdoor parameters, i.e., adversary does not employ Equation 6 for the local model modifications, and (2) adversary injects backdoors...
Figure 5: (a) Global main task accuracy $A_{cM}$ in successive FL rounds and two instances of separate backdoor injection at volatile point and stable point. (b) Backdoor accuracy $A_{cB}$ in successive FL rounds after backdoor injection considering multiple scenarios.

Figure 6: (a) Backdoor images generated using adversarial perturbation with three different attack strengths $\epsilon$ along with $L_2$-norm of the added perturbation. (b) Backdoor accuracy $A_{cB}$ in successive FL rounds after backdoor injection for different attack strengths using PerDoor. Figure 6b shows $A_{cB}$ over successive FL rounds after the backdoor injection for both scenarios. Also, the adversary does not participate in further FL rounds once the backdoor is injected. We can observe that backdoors show higher persistence if they are injected at the stable point compared to the volatile point. We can also observe that only adversarial examples show reasonable persistence over successive FL rounds because of their high transferability property. However, integrated with PerDoor, backdoors display more prominent and persistent backdoor accuracy.

We consider three different attack strengths $\epsilon$ for generating adversarial perturbations to evaluate the effectiveness of PerDoor against different values of $\epsilon$. Figure 6a shows two benign images and corresponding adversarial images for attack strength $\epsilon = 0.05$, $\epsilon = 0.075$, and $\epsilon = 0.1$. The figure also shows the $L_2$-norms of the noise added to benign images to generate adversarial counterparts, which act as triggers in the backdoor attack. As the attack strength increases, we can observe that images get more perturbed by strong noise patterns. Figure 6b shows $A_{cB}$ over successive FL rounds after the backdoor injection for different values of attack strength $\epsilon$, where the backdoor is injected at the stable point. We can observe that the backdoor persists for all these epsilon values; however, the backdoor accuracy is lower for weaker attacks.

To compare the persistence of PerDoor against other traditional backdoor injection techniques, we follow the methodology discussed in [1]. We consider a pre-defined set of backdoor images with

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8Transferability represents the ability of an attacker against a deep learning model to be effective against a different, potentially unknown model [6].
a fixed ‘cross’ trigger pattern at the top left corner of the inputs. When selected, the adversary updates the broadcasted global model using backdoor images for 6 local epochs with an initial learning rate of 0.05 that decreases by a factor of 10 after every 2 epochs and uploads the poisoned model for global aggregation. All these parameter values are chosen following the method discussed in [1]. We consider two scenarios for the evaluation: (1) single-shot poisoning - adversary injects backdoored at stable point, same as PerDoor and (2) continuous poisoning - adversary injects backdoor continuously whenever it is selected during FL training from the beginning and stops uploading the poisoned updates after the stable point. Figure 7 shows AccB over successive FL rounds after the backdoor injection for both scenarios along with PerDoor. We can observe that single-shot poisoning obtains very high AccB immediately after that round. However, that decreases significantly as FL training continues. The continuous poisoning maintains high AccB at initial rounds when selected. However, the backdoor impact diminishes whenever the adversary stops uploading poisoned updates. On contrary, PerDoor maintains high AccB throughout the training rounds, demonstrating its efficacy in preserving AccB. PerDoor, on average, achieves 10.5× more AccB than single-shot poisoning over 5000 rounds and 6.4× considering continuous poisoning.

[RQ3] Performance of PerDoor against state-of-the-art Defenses: We evaluate the effectiveness of PerDoor against two existing state-of-the-art defenses, Krum and FoolsGold. Figure 8a shows AccM for 5000 successive rounds considering both these defenses and unprotected FedAvg. We consider that the adversary injects backdoors at the stable point. We can observe that while FoolsGold performs almost identical to unprotected FedAvg in terms of AccM, the main task accuracy of Krum drops below 80% (i.e., almost a drop of 10%). It may be noted that the accuracy drop is not because of backdoor injection but due to the internal anomaly detection mechanism of Krum consistently producing global models representing data from the majority of clients. The result also aligns with the observations discussed in [1, 8]. Figure 8b shows AccB over successive FL rounds after the backdoor injection considering all three aggregation methods. We can observe that PerDoor can efficiently inject impactful backdoors into the global model even in the presence of defense methods.
Figure 9: (a) Backdoor images generated using uniform and adversarial trigger patterns. (b) Distribution of sum squared differences between each pair of 50 adversarial triggers.

[RQ4] Analysis of Trigger Patterns: We analyze the backdoor triggers generated using adversarial perturbation by PerDoor against the uniform trigger used in existing backdoor techniques [1, 20, 29]. Figure 9a shows two instances of clean images belonging to the label ‘airplane’, uniform trigger images with a fixed ‘cross’ trigger pattern at the top left corner, and adversarial trigger images generated by PerDoor. The target label for both uniform and adversarial triggers is ‘frog’. Figure 9b shows the distribution of pixel-wise sum squared differences between each pair of 50 adversarial triggers. We can observe that the adversarial triggers generate a non-uniform distribution of patterns compared to one fixed value for the uniform counterpart considering the same source and target labels. The non-uniform patterns of adversarial triggers make it difficult for the central server to patch global models based on the knowledge of trigger patterns.

5 Discussion

Limitations and Future Works: In this work, we consider: (1) an FL framework where the participants collectively train the global model using training data that is independent and identically distributed (IID) among the participants and (2) backdoor triggers that modify pixels of the input image. We keep the evaluation of PerDoor under a non-IID setting and more challenging-to-construct semantic backdoors (backdoors that do not tamper with input pixels) for future research exploration. We evaluated PerDoor in an image classification scenario using the CIFAR-10 dataset and VGG-11 architecture. However, we will also explore the same evaluation on different datasets, architectures, and application scenarios in our future research direction.

Societal Impacts: FL is specifically used in healthcare [23] and its results may directly have financial impact (insurance) or societal stigma related to it. Persistent backdoor attacks in FL may enable an adversary exploit these consequences over a long period of time.

6 Conclusion

In this paper, we propose PerDoor, a persistent-by-construction backdoor injection method in FL targeting parameters of the global model that deviate less in successive FL rounds and contribute the least to the main task accuracy for injecting backdoors. PerDoor uses adversarial attacks to generate backdoor triggers from the global model, which not only helps to achieve good backdoor accuracy but also aids in generating non-uniform backdoor triggers for different inputs of the same class targeting the same label, compared to the uniform fixed triggers in existing backdoor methods in FL that are prone to be easily mitigated. Experimental evaluation considering an image classification scenario demonstrates that PerDoor can achieve, on average, $10.5 \times$ persistence over successive iterations of FL compared to traditional backdoor injection methods when the backdoor is injected at the same round. PerDoor can also achieve high persistence even in the presence of state-of-the-art defenses.
Resources

The implementation will be available at: https://github.com/momalab/PerDoor after the paper is published.

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A Brief Overview of Adversarial Example Generation

Let us consider a benign data point \( x \in \mathbb{R}^d \), classified into class \( C_i \) by a classifier \( M \). A targeted adversarial attack tries to add visually imperceptible perturbation \( \eta \in \mathbb{R}^d \) to \( x \) and creates a new data point \( x_{\text{adv}} = x + \eta \) such that \( M \) misclassifies \( x_{\text{adv}} \) into a target class \( C_j \). The imperceptibility is enforced by restricting the \( l_p \)-norm of the perturbation \( \eta \) to be below a threshold \( \epsilon \), i.e., \( \| \eta \|_p \leq \epsilon \) [9, 15]. We term \( \epsilon \) as the attack strength.

An adversary can craft adversarial examples by considering the loss function of a model, assuming that the adversary has full access to the model parameters. Let \( J(\theta, x, y) \) denote the loss function of the model, where \( \theta \), \( x \), and \( y \) represent the model parameters, benign input, and corresponding label, respectively. The goal of the adversary is to generate adversarial example \( x_{\text{adv}} \) such that the loss of the model is minimized for the target class \( \hat{y} \) while ensuring that the magnitude of the perturbation is upper bounded by \( \epsilon \). Hence, \( J(\theta, x_{\text{adv}}, \hat{y}) < J(\theta, x, y) \) adhering to the constraint \( \| x_{\text{adv}} - x \|_p \leq \epsilon \).

Several methods have been proposed in the literature to solve this constrained optimization problem. We discuss the method used in the evaluation of our proposed approach.

**Basic Iterative Method (BIM):** This attack is proposed in [14]. The adversarial example is crafted iteratively using the following equation

\[
x^{(k+1)} = x^{(k)} - \text{clip}_\epsilon(\alpha \cdot \text{sign}(\nabla_x J(\theta, x^{(k)}, \hat{y})))
\]

where \( x^{(0)} \) is the benign example. If \( r \) is the total number of attack iteration, \( x_{\text{adv}} = x^{(r)} \). The parameter \( \alpha \) is a small step size usually chosen as \( \epsilon / r \). The function \( \text{clip}_\epsilon(\cdot) \) is used to generate adversarial examples within \( \epsilon \)-ball of the original image \( x^{(0)} \).