pFedDef: Defending Grey-Box Attacks for Personalized Federated Learning

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Abstract

Personalized federated learning allows for clients in a distributed system to train a neural network tailored to their unique local data while leveraging information at other clients. However, clients’ models are vulnerable to attacks during both the training and testing phases. In this paper we address the issue of adversarial clients crafting evasion attacks at test time to deceive other clients. For example, adversaries may aim to deceive spam filters and recommendation systems trained with personalized federated learning for monetary gain. The adversarial clients have varying degrees of personalization based on the method of distributed learning, leading to a “grey-box” situation. We are the first to characterize the transferability of such internal evasion attacks for different learning methods and analyze the trade-off between model accuracy and robustness depending on the degree of personalization and similarities in client data. We introduce a defense mechanism, pFedDef, that performs personalized federated adversarial training while respecting resource limitations at clients that inhibit adversarial training. Overall, pFedDef increases relative grey-box adversarial robustness by 62% compared to federated adversarial training and performs well even under limited system resources.

1 Introduction

Modern computing devices such as smartphones and IoT (Internet of Things) sensors collect increasing amounts of data that can be used to improve user applications and services. Much of this data, however, is privacy-sensitive (e.g., health data from biological sensors or usage data from smartphones). Federated learning has emerged as a distributed training paradigm (Lim et al. [2020], Li et al. [2021]) that allows multiple users to collectively train a model, without revealing sensitive data to each other. Personalized federated learning builds on this paradigm to distributedly train unique models tuned for different clients in the system that are related but not identical (Smith et al. [2017], Marfoq et al. [2021], Dinh et al. [2021]). Since users in many federated learning applications have different data distributions (Fallah et al. [2020]), such personalized models have been shown to outperform standard federated learning that trains a single model for all users.

The growing popularity of federated learning, and machine learning in general, has allowed such algorithms to improve many applications, but it has also fueled attacks on learning algorithms. Evasion attacks (Biggio et al. [2013], Madry et al. [2017]), for example, aim to perturb inputs to trained models that are undetectable to human users but change the model output at test time. Slightly altering a stop sign, for example, might lead to it being classified as a speed limit sign instead (Cao and Gong [2017]). Such attacks can endanger users by subverting their ability to trust the outputs of trained models. Many applications for which attacks have been proposed can benefit from federated learning approaches. By itself, however, federated learning is not robust against evasion attacks generated by member clients or outside entities (Zizzo et al. [2020]). For example, email spam filters can be trained through personalized federated learning, and a malicious client may use their local spam filter model to craft messages that can bypass the filters of other clients (Kuchipudi et al. [2020]).
Product and movie recommendation systems can also be trained similarly, and an item can be recommended to a wider group of clients through evasion attacks (Christakopoulou and Banerjee [2019]).

In this work, we provide the first, to the best of our knowledge, formalization of internal evasion attacks in personalized federated learning, as well as quantitative evidence that these algorithms are vulnerable to such attacks. We suppose that attackers can access the personalized models of compromised federated learning clients (e.g., by posing as legitimate clients and training personalized models on their own data). They can then generate adversarial perturbations on their own trained models at test time and feed the perturbed data to other clients (Figure 1). Such adversaries can not be detected during training time by other clients or servers, as the attack can be computed entirely locally post-training.

In traditional federated learning, when all clients share the same model, evasion attacks as described above will likely be very successful. On the other hand, locally training models on the data at each client may reduce the transferability of these attacks, as no information is shared during the training process. Local training, however, may significantly decrease model accuracy. We thus observe a trade-off between accuracy and robustness to evasion attacks. Personalized federated learning, through sharing limited information between clients, can transcend this trade-off: clients can make use of each others’ information to improve their models, but still retain some differences between their models. Attackers, however, may still exploit similarities created by personalized learning between their (known) model and the clients’ (unknown) models to generate effective perturbations. The more similar the model decision boundaries are, the higher the potential for evasion attack success.

We empirically find that personalized federated learning remains vulnerable to evasion attacks, raising the question of how one might defend against such attacks. Existing defenses against evasion attacks in (non-personalized) federated learning focus on black-box attacks by external adversaries with no knowledge of clients’ models. They generally utilize adversarial training (Zizzo et al. [2020], Zhou et al. [2020], Zizzo et al. [2021], Chen et al. [2021]), where clients generate adversarial inputs and incorporate them into the training process, which has been shown to be an effective and reliable defense method against evasion attacks (Madry et al. [2017]). The grey-box scenario of personalized federated learning, in which attackers can exploit similarities created by personalized learning between their model and other clients’ models to generate effective perturbations, thus requires new adversarial training mechanisms. We emphasize that the internal attack we analyze occurs only during test time and differs from the Sybil and data poisoning attacks that occur at training time. We further note that the attack model in this work may have a negative societal impact, as we are the first to analyze the internal attack scenario in federated learning.

### 1.1 Challenges to Implementing Personalized Federated Adversarial Training

The differences between client models in personalized federated learning lead to challenges in quantifying internal attack transferability and implementing adversarial training. First, if the attacking client has a very distinct data distribution from others, then attacks crafted on its personalized model may not transfer well to other clients’ models. Conversely, adversarial training samples may not transfer well between clients either: adversarial samples generated at one client may fail to reflect another’s data distribution. It is thus difficult to predict the effectiveness of evasion attacks and the relationship between model transferability and accuracy: clients with distinct data distributions may train very different personalized models, which are robust to attacks transferred between each other.

This difficulty is exacerbated by our second challenge: clients may be limited in their abilities to generate adversarial training samples due to resource constraints, e.g., mobile devices often have limited battery and computation power (Lim et al. [2020]). Having limited adversarial samples, then, potentially compromises the robustness of the models of clients without resources. A natural solution is to distribute the adversarial samples across clients according to their computing abilities, but such a distribution risks compromising convergence of some models (McMahan et al. [2017]).
Moreover, the adversarial samples may then be skewed towards the data distributions of clients with more resources, compromising robustness against adversarial attacks generated on other data. Thus, ensuring robustness across clients’ personalized models may require quantifying the differences in client models and resources, and distributing adversarial training accordingly.

1.2 pFedDef: Defense for Personalized Federated Learning

In this paper, we first demonstrate an adversarial client’s ability to transfer evasion attacks to other clients in a federated learning system. We then propose the pFedDef algorithm (Defense for Personalized Federated Learning) to generate a robust defense against such attacks without a reduction in accuracy for benign data. In doing so, we make the following technical contributions:

- We are the first, to the best of our knowledge, to characterize and analyze the transferability of evasion attacks between models and the accuracy to robustness trade-off in different federated learning algorithms. We show that personalized algorithms provide a good foundation for defending against these attacks, though they still exhibit some vulnerability.
- We propose a pFedDef, a novel defense mechanism for internal grey-box evasion attacks that allows us to perform adversarial training at personalized federated learning clients with limited resources and low overhead.
- We perform extensive experiments to show that pFedDef maintains high test accuracy while significantly increasing robustness against internal grey-box attacks compared to existing federated adversarial training methods on the CIFAR-10, CIFAR-100, and CelebA data sets, with a relative robustness gain of 62%, 128%, and 100%, respectively. The pFedDef algorithm maintains strong performance under different system conditions, displays compatibility with other personalization methods, and even confers some robustness against other methods of attacks including ensemble and data poisoning attacks.
- We build upon the previous versions of this work (Kim et al. [2022]) with an in depth characterization of evasion attack transferability and further experiments regarding varying client characteristics in the system as well as intersection with other personalization methods and attacks.

The remainder of this paper is organized as follows. Section 2 contrasts pFedDef with related works. Section 3 provides background knowledge on personalized federated learning and adversarial training. Section 4 characterizes transferability of internal evasion attacks in different federated learning schemes corresponding to white-, black-, and grey-box models. We introduce pFedDef in Section 5 and experimentally validate its performance in Section 6. We conclude in Section 7.

2 Related Works

Federated adversarial training, where clients of a distributed system perform adversarial training on their local data and aggregate the results, is first introduced in (Zizzo et al. [2020]). However, limited hardware and communication resources, as well as the non-i.i.d. (independent and identically distributed) nature of clients’ data sets, impedes both model accuracy and performance during adversarial training (Shah et al. [2021], Reisizadeh et al. [2020]). Further extensions have proposed methods of incorporating the impact of non-i.i.d. data on federated adversarial training. The work in (Zhou et al. [2020]) analyzes the generalization error incurred in the aggregation process of federated learning as a combination of bias and variance, which is used to centrally generate adversarial examples sent to local nodes for training. The work in (Hong et al. [2021]) examines not only data heterogeneity, but also proposes batch normalization metrics to propagate adversarial robustness from nodes with resources to nodes without. Other approaches have attempted to improve federated adversarial robustness, including the use of randomized smoothing of models (Chen et al. [2021]). Our work in comparison addresses the issue of heterogeneous data and hardware capabilities through the use of personalized federated learning, which raises new questions on how adversarial training samples may propagate between clients with different models. Furthermore, pFedDef trains model defenses against multi-step attacks from other clients who have grey-box information of the victim models, instead of black-box attacks or single-step white-box attacks considered in prior work. The personalized setting also introduces the new accuracy vs. robustness trade-off.
Another line of work focuses on Sybil attacks and robust aggregation schemes of federated user updates, particularly as a defense against data and model poisoning attacks – such attacks include label flipping attacks and scaling attacks, while Krum, Bulyan, and trimmed-mean aggregation methods are proposed defenses (Blanchard et al. [2017], Jiang et al. [2020], Yin et al. [2018], Fung et al. [2020]). Works regarding Sybil attacks solely focus on the training phase of federated learning, while pFedDef defends against evasion attacks occurring at the test phase. However, we observe in Section 6 that pFedDef does increase robustness to label flipping attacks that occur in the training phase. The work in (Zizzo et al. [2020]) examines the impact of robust aggregation schemes on non-personalized federated adversarial training, while (Zizzo et al. [2021]) introduces a poisoning attack that spans both the training and testing phase as the attack gives the learned model apparent robustness during training but becomes a backdoor for attacks during the testing phase.

Outside the federated learning context, ensemble attacks (Hang et al. [2020]) generate evasion attacks by combining gradient information from multiple different model in order to increase transferability of attacks through generalization. The work in (Pang et al. [2019]) propose an adaptive diversity promoting (ADP) regularizer to create an ensemble of diverse classifiers to defend against black-box attacks. Both aforementioned works leverage the diversity present in ensembles of models, similar to the personalized federated learning setting. However, these works do not examine distributed learning frameworks.

3 Background Knowledge

We first give an overview of the personalized federated learning framework that we assume clients use, as well as the adversarial training procedure that has been previously proposed to defend against evasion attacks. A table of variables is presented in the appendix Section A.

3.1 Personalized Federated Learning

In personalized federated learning, clients train individual, related but heterogeneous learners to better fit local test data that are typically non-i.i.d. amongst clients. We formalize the objective of personalized federated learning by considering \( C \) different clients. Each client has a different data distribution \( D_c \), and it is desirable to fit a different hypothesis, or model, \( h_c \) for each client. Given that \( (x, y) \sim D_c \) represents the data and labels drawn from \( D_c \), letting \( L_{D_c} \) denote the loss incurred by \( h_c \) on \( D_c \), we wish to solve:

\[
\forall c \in [C], \min_{h_c \in H} E_{(x,y) \sim D_c} L_{D_c}(h_c, x, y) \tag{1}
\]

We assume that the clients solve this optimization problem by following the mixture-based personalized learning framework proposed in (Marfoq et al. [2021]), where similarities between clients’ data distributions are modeled by assuming that each client’s data is drawn from a weighted sum of a mixture of \( M \) (unknown) underlying distributions \( \tilde{D}_m, \forall m \in [M] \). This assumption encompasses most of the existing personalized federated learning approaches including multi-task learning (Smith et al. [2017]) and clustered federated learning (Sattler et al. [2021]). For each underlying data distribution, we assume there exists a hypothesis \( h_{\theta_{m}} \) that minimizes the loss for the classification task of that distribution, where \( \theta \in \mathbb{R}^d \) is a set of neural network parameters. It is shown in (Marfoq et al. [2021]) that the optimal hypothesis for a client is a linear sum of the hypotheses of each data distribution scaled according to prevalence of that distribution at the client: \( h^*_c = \sum_{m \in M} \pi^*_c m h_{\theta_m}, \forall c \in [C] \). Here, \( \pi^*_c m \) represents the weight of the prevalence of data drawn from distribution \( m \) at client \( c \); generally, the \( \pi^*_c m \) are not known before training.

To minimize the training loss under the given assumptions, an expectation-maximization algorithm, FedEM, is used where clients individually solve for the weights \( \pi^*_c m \), while jointly solving for the hypothesis for each distribution \( h_{\theta_m} \) (Marfoq et al. [2021]). During the E-step, the probability that each data point is drawn from a certain distribution is updated using fixed values of \( \pi^*_c m \) and \( h_{\theta_m} \). During the M-step, the distribution weights and hypothesis are updated using the probabilities computed in the E-step. Afterwards, the hypotheses are averaged at a central server and then returned to local clients.
3.2 Adversarial Training

We define an evasion attack as one in which an adversary generates perturbations to data inputs so as to compromise a model’s performance. Formally, any defense against such attacks can be formulated as a saddle point problem, with the goal of training a model that minimizes the empirical risk over a classification task, despite the adversary introducing input perturbations that maximize the loss at each data point (Madry et al. [2017]). Within the mixture-based personalized learning framework introduced above, the objective function of adversarial training is as follows:

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim \tilde{D}_m} \left[ \max_{\delta \in S} L_{D_m}(h_{\theta_m}, x + \delta, y) \right], \forall m \in [M]
\]  

(2)

The perturbation \( \delta \) added to the data is bounded within a budget \( S \). In words, we desire to find for every distribution present in the system a hypothesis that achieves low loss on the data classification task despite the presence of adversarial perturbations.

Adversarial training is a defense mechanism known to be reliable against black-box perturbation attacks (Shafahi et al. [2019]). Intuitively, the goal of adversarial training is to introduce perturbed inputs into the training data set of a model, thus allowing the model to learn how to correctly classify perturbed inputs that it may later encounter. In this paper, it is assumed that both adversarial training and evasion attacks are performed through the commonly used projected gradient descent (PGD) method (Madry et al. [2017]). If the adversary’s goal is to launch an untargeted attack, i.e., to induce any incorrect classification label, it iteratively updates the current input \( x^t \) as:

\[
x^{t+1} = \Pi_{x+S} \left( x^t + \alpha \text{sgn}(\nabla_x L(\theta, x, y)) \right)
\]  

(3)

The input is perturbed along the gradient of the loss function \( L \) with step size \( \alpha \) and then projected \( (\Pi_{x+S}) \) to be within the perturbation budget \( S \). This budget is most often an \( l_2 \) or \( l_\infty \) norm-ball.

4 Characterizing Evasion Attack Transferability in Federated Learning

In a federated learning setting, each client has information about the classifiers at other clients to varying degrees based on the training method: FedAvg (non-personalized federated learning) clients have white-box information as clients share a model (McMahan et al. [2016]), the personalized federated learning setting presents a grey-box scenario, and local training leads to a black-box scenario. In each of these cases, a malicious client performs transfer attacks (Demontis et al. [2019], Suciu et al. [2018]) by generating evasion attacks with its local model and sending them to other clients. The probability of success for a transfer attack increases when the decision boundary (Karimi et al. [2019], Yousefzadeh and O’Leary [2019]) of the malicious client’s model is more similar to that of the victim (Tramèr et al. [2017]). To quantitatively measure the decision boundary similarity between clients, the inter-boundary distance metric is used as presented in (Tramèr et al. [2017]) where a smaller distance value indicates higher similarity of the decision boundaries of two models. The legitimate inter-boundary distance (Leg. \( I_d \)) measures decision boundary similarity with respect to benign training points, and the adversarial version (Adv. \( I_d \)) with respect to adversarially perturbed points. An in-depth explanation of the inter-boundary distance metric is presented in the appendix Section D.

To observe the impact of different distributed training methods on both inter-boundary distance and transferability, we simulate attacks on both the CIFAR-10 and MovieLens data sets for models trained with the FedEM, FedAvg, and local training methods. The MovieLens data set has been altered such that each data point contains the ratings of a single user, and the task is to classify each user into one of 5 groups. Each group can indicate a cluster to which new movies or advertisements can be offered to based on cluster characteristics. The model for CIFAR-10 is trained with

| Data set | Method | Test. Acc. | Adv. Acc. | Leg. \( I_d \) | Adv. \( I_d \) |
|----------|--------|------------|-----------|----------------|----------------|
| (CIFAR10) | Local | 0.52 | **0.38** | 39.5 | 49.7 |
| | FedEM | **0.84** | 0.10 | 9.26 | 10.0 |
| | FedAvg | 0.81 | 0.00 | 0.00 | 0.00 |
| (MovieLens) | Local | 0.59 | **0.12** | 2.65 | 10.21 |
| | FedEM | **0.64** | 0.10 | 4.63 | 0.10 |
| | FedAvg | 0.51 | 0.00 | 0.00 | 0.00 |

Table 1: Transferability of untargeted attacks and inter-boundary distances (measured by the \( l_2 \) distance in input) given different distributed training algorithms.
the MobileNetV2 architecture \cite{sandler2018mobilenetv2} for 40 clients, and MovieLens with a model with two convolutional layers followed by a linear layer. Both data sets are split in a non-i.i.d. manner across clients. The training parameters are equivalent to those presented in Section 6.1. The test accuracy (Test Acc.) is measured by the classification accuracy of benign points, and the robustness of models is measured by the classification accuracy of untargeted attacks that are crafted from the test data of an adversarial client and sent to the victim client (Adv. Acc.).

As seen in Table 1, there is a trade-off between accuracy and robustness as the sharing of information with two convolutional layers followed by a linear layer. Both data sets are split in a non-i.i.d. manner. Some clients may not be able to generate adversarial data sets that cover \(G\) fraction of their data sets, due to local resource constraints \(R_c\) \(\in [0, 1]\). Thus, each client sets its true adversarial proportion \(F_c\) \(\leq R_c\). Clients with more resources may set \(F_c \geq G\) in order to compensate for clients with limited resources. After the adversarial data sets are generated, FedEM is performed on top of the augmented data sets.

### 5 pFedDef - Adversarial Training

Given the vulnerabilities of FedEM in Section 4, we next introduce pFedDef, a novel adversarial training algorithm for personalized federated learning. Unlike existing works \cite{zizzo2020fedavg}, pFedDef leverages the differences between client models in the personalized federated learning setting to be robust to both black-box and grey-box attacks. Furthermore, the pFedDef algorithm takes into consideration different resource availabilities at clients and propagates adversarial learning from clients of similar data sets with more resources to clients with less resources. Though similar propagation ideas are used in \cite{hong2021fedavg} for FedAvg, we allow more fine-grained and dynamic client participation in adversarial training compared to their assumption of binary participation. Furthermore, unlike propagation for FedAvg, pFedDef propagates robustness between underlying distribution hypotheses \(h_m\), allowing propagation while maintaining difference in models between clients.

**Algorithm 1 pFedDef Training**

1: **Input:** Adv. Proportion \(G\), Dataset \(c\), Update Freq. \(Q\), PGD steps \(K\), Client resource \(R_c\)
2: **for** \(t \in \text{Rounds} \) **do**
3: 
4: 
5: **for** \(c \in [C] \) **do**
6: 
7: **end**
8: **end**
9: federated_adversarial_training()
10: **end**

**Algorithm 2 Robustness Propagation (adv_prop())**

1: **Input:** Adv. Prop. \(G\), Client resource \(\{R_c\}_{c \in [C]}\)
2: **Setting:** Increment \(\Delta\), Repetitions \(I\)
3: **for** \(c \in [C] \) **do**
4: 
5: **end**
6: \(F_c' \leftarrow \text{sample_no_replacement}(\text{clients } F_c' = G)\)
7: 
8: **end**
9: **for** \(i \in [I] \) **do**
Adversarial Robustness Propagation. The pFedDef algorithm takes into consideration the limited and diverse resources across clients as it is possible for clients with more available resources to propagate their adversarial learning to clients with fewer resources due to the shared information from the aggregation process of federated learning. We formulate an optimization problem for adversarial robustness propagation, which attempts to achieve the desired adversarial data set proportion $G$ globally by inducing clients with ample resources to increase their local adversarial proportions $F_c$. Formally, given the desired proportion $G$ and client resource constraints $R_c$, we desire to solve for the local adversarial proportion $F_c$ at each client $c$ such that:

$$
\min_{F \in [0,1]} \sum_{m \in [M]} \left( \sum_{c \in [C]} (F_c | D_c | \pi_{c,m}) - G | D | \pi_{c,m} \right) 
\text{ s.t. } F_c \leq R_c, \forall c \in [C]
$$

The goal of the optimization problem is to adversarially represent each of the hypotheses for underlying distributions in the FedEM framework proportionally to the prevalence of each distribution across clients. Algorithm 2 presents a heuristic solution to problem 4. In line 11, the adversarial proportion for client $c$ is incrementally increased by value $\Delta$ until it either reaches the resource constraint or there is no reduction in problem 4 despite the increase in adversarial proportion. Note that this algorithm can guarantee that the objective in Eq. 4 monotonically decreases, and alternative algorithms with provable guarantees may be substituted. A limitation of the the propagation method is that it is built on the FedEM framework. To have adversarial propagation with another method of personalized learning, a new method of measuring similarity of data distributions between clients must be developed. The benefits of robustness propagation are shown in Section 6.3.

6 Evaluation

We experimentally evaluate pFedDef applied to the FedEM training method. Specifically we aim to show that pFedDef increases robustness against grey-box attacks despite limited system resources to perform adversarial training while maintaining high test accuracy. After describing our experimental setup, we examine the achieved robustness and model accuracy for different federated adversarial training scenarios. We further examine the performance of pFedDef given different systems where resource availability, number of clients participating in training, and data set distributions are varied. Lastly, we examine the effects of increased personalization through local tuning and ensemble attacks, as well as the effects of Sybil label flipping attacks on pFedDef. We refer to the benign versions of the training methods as FedEM and FedAvg, while referring to the adversarially trained counterparts as pFedDef and federated adversarial training (FAT), respectively. Classification accuracy against benign points are referred to as test accuracy (Test Acc.) and classification accuracy against perturbed evasion attack inputs are referred to as robustness (Adv. Acc.). The set up and analysis for the CIFAR-100 and CelebA data sets are provided in the appendix Section C and Section E.2.

6.1 Numerical Analysis Setup

We perform distributed learning on the CIFAR-10 data set. Subsets of the data set are split in a non-i.i.d. fashion amongst 40 clients. The MobileNetV2 architecture is used for each mixture hypothesis. Each of the FedEM learners assumes $M = 3$ underlying distributions. The initial training rate for FedEM and local learning is set to $lr = 0.03$, and $lr = 0.01$ for FedAvg. All models are trained with the sgd optimizer for 150 rounds. Unless otherwise specified the adversarial proportion is set to $G = 0.15$, with expected system resources for each user set at $\mathbb{E}[R_c] = 0.7$. Both adversarial training and attacks are performed with a multi-step PGD procedure that is bounded by a $\ell_2 = 4.0$ norm ball with the number of steps set at $K = 10$ with step size $\alpha = 0.05$, while the adversarial training set is updated once every $Q = 10$ rounds. Our analysis focuses on examining a subset of clients in the system that have highly non-i.i.d. data sets from one another. When splitting the data in a non-i.i.d. manner across clients, the term $\beta = 0.4$ is used (Marfoq et al. [2021]). Higher values of $\beta$ (e.g., $\beta > 1$) indicate data distributions that are more i.i.d. than lower values (e.g., $\beta < 0.6$). A detailed explanation of this parameter and data splitting is available in the appendix Section E.1.

6.2 Model Accuracy v. Robustness

We first analyze the impact of pFedDef on test accuracy and robustness against internal (grey-box and white-box) attacks compared to different variations of distributed adversarial training as shown
(a) Performance of pFedDef with adversarial propagation gains higher robustness when resources are more limited.

(b) Increasing the number of clients increases test accuracy, and pFedDef displays consistent levels of robustness despite client count.

(c) Data with higher value of $\beta$ is more i.i.d. than lower values, leading to lower robustness in FAT.

Figure 2: The pFedDef algorithm has consistently increased robustness given for varying resource availability, number of clients in learning, and different data distribution across clients.

Table 2: Performance of pFedDef algorithm on CIFAR-10 data set. The pFedDef algorithm outperforms and achieves high robustness to internal attacks compared to existing algorithms.

| Metric / Method     | Adv. Training: | Adv.        | Benign        |
|---------------------|----------------|-------------|---------------|
|                     | pFedDef FAT    | Local       | FedEM FedAvg  |
| Test. Acc           | 0.74 0.74 0.46 | 0.84 0.81   | 0.52          |
| Internal Adv. Acc   | **0.42** 0.26 0.30 | 0.10 0.00 | **0.38**      |
| Black-box Adv. Acc  | 0.60 **0.69** 0.31 | 0.23 0.15 | **0.36**      |

The performance against black-box attacks is examined as well. Such attacks are generated based on a foreign CIFAR-10 model with a different data distribution trained separately from the federated learning models in examination. Local learning still performs poorly due to poor standard generalization and low test accuracy. FedEM and FedAvg display increased robustness compared to internal attacks, while FedEM maintains higher innate robustness over FedAvg. Both pFedDef and FAT display increased robustness compared to internal grey-box attacks, with FAT displaying higher robustness to black-box attacks compared to pFedDef. Thus, the pFedDef algorithm is also effective against black-box attacks, although more effective than FAT only in the internal attack setting.

6.3 Varying Client Characteristics for Federated Learning

**Resource Availability.** The performance of pFedDef with and without robustness propagation is analyzed given varying amounts of resources in Figure 2a. The number of clients with ample resources for adversarial data set generation ($R_c = 0.7$) is gradually increased while clients with no resources ($R_c = 0$) is proportionally decreased. Test accuracy remains consistent regardless of resource availability and the presence of robustness propagation. Robustness consistently increases as the resources in the system is increased in both cases. However, robustness propagation allows models to obtain higher robustness by leveraging resource availability at resource ample clients, especially improving performance when overall system resources are low.

**Client Count.** Increasing the total number of clients participating in federated learning increases the total amount of data and resources available. As seen in Figure 2b, increasing the number of clients consistently increases the test accuracy of pFedDef and FAT as there are more data and resources
Additional local tuning increases robustness of FAT models, and has marginal effect on pFedDef models.

Ensemble attacks increases attack transferability in FedEM, but not in pFedDef.

Sybil label flipping attack is mitigated by adversarial training for both FAT and pFedDef.

Figure 3: The pFedDef algorithm maintains consistent performance subject to ensemble and label flipping attacks, while showing marginal reaction to local tuning.

for learning. The robustness of FAT has a similar increase given more clients in training, while the robustness of pFedDef achieves high levels even with fewer clients available in the system.

Data Set Distribution. When splitting data across the clients, a low value of $\beta$ leads to a more non-i.i.d. split compared to a higher value of $\beta$. In Figure 2c, the test accuracy and robustness of pFedDef and FAT are analyzed for values $\beta = 0.3$ and $2.0$. As the data split becomes more i.i.d., the test accuracy of pFedDef decreases and becomes similar to that of FAT as less personalization is needed across clients. However, internal robustness for clients trained with FAT decreases as the data becomes more i.i.d., and pFedDef maintains higher robustness than FAT in both cases.

6.4 Intersection with Other Personalization Methods and Attacks

Local Tuning. After federated learning has taken place, clients may perform local tuning by further training their model with local data sets. Updates to the model from local tuning are not shared between clients. As seen in Figure 3a, as more rounds of local tuning takes place across all clients in a distributed system, test accuracy for models initially trained with FAT initially increases as models are fine-tuned to local data sets, then decreases due to over-fitting. The robustness for FAT consistently increases as more rounds of local tuning takes place, as the models of different clients diverge. The effects of local tuning are less pronounced for pFedDef trained models, as clients already have personalized models and increased robustness. The effects of the accuracy to robustness trade-off is once again more pronounced in the FAT case than pFedDef given local tuning.

Ensemble Attacks. As shown in (Hang et al. [2020]), generating ensemble evasion attacks with gradient information from multiple models increases the success rate of attacks. We examine the transferability of ensemble attacks for FedEM and pFedDef by assuming a varying number of cooperating adversarial clients. We generate evasion attacks with different combinations of 3 adversarial clients, where each adversarial client’s model is equivalent to a single hypothesis $h_{\theta_m}$ for each underlying distribution $m \in [M = 3]$. Here, the adversarial perturbations generated for the same input from different clients are averaged to perform an ensemble attack. For FedEM, when the perturbations are generated from more clients, the attack success rate increases, as seen in Figure 3b. However, pFedDef manages to defend the entire hypothesis space, and dramatically improves robustness even against ensemble attacks with many participating adversaries.

Sybil Attacks. The performance of FedEM, FedAvg, FAT, and pFedDef are analyzed given the presence of a Sybil data poisoning attack. Here, 10 of the 40 clients in the system perform a label flipping attack by scrambling the labels in their training sets during the training phase to reduce the performance of the models of other clients (Yin et al. [2018]). As seen in Figure 3c, the label swapping attacks reduce the test accuracy for the non-adversarially trained models of FedEM and FedAvg. However, although FAT and pFedDef are designed to increase robustness against evasion attacks at test time, they also gain robustness against data poisoning attacks during train time, as adversarial training methods generally have more exposure to perturbed and abnormal data points. Furthermore, while byzantine robust aggregation methods are the traditional way to defend against such Sybil attacks for the FAT and FedAvg case (Blanchard et al. [2017]), a limitation of FedEM and pFedDef is that they are not necessarily compatible with such methods as model aggregation occurs
for multiple hypotheses. Therefore, FedEM and pFedDef are frail against scaling attacks, where adversaries upload high magnitude noise for aggregation, [Jiang et al. (2020)] without byzantine robust aggregation methods.

7 Conclusion

While the use of adversarial training in the context of federated learning has been explored in recent years, such defenses exhibit robustness against black-box transfer attacks and not against attacks crafted by adversarial clients participating in the federated learning system. Such adversarial clients possess grey-box information of the learned model and generate effective transfer attacks. In this paper, we introduce pFedDef, an adversarial training framework built upon personalized federated learning in order to reduce the model information shared between participating clients. Compared to existing federated adversarial training methods, pFedDef significantly increases robustness to internal transfer attacks while maintaining robustness against external black-box attacks. Moving forward, we can examine the use of smart local tuning methods to reduce attack transfer rates between federated clients with similar data distributions, as well as finding defenses for personalized federated learning systems against Sybil attacks. For example, adapting new byzantine robust aggregation methods may further increase pFedDef’s robustness in different federated learning settings.

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A Table of Variables

| $c \in [C]$ | Clients of distributed system. | $I_d(h, h', x)$ | Inter-boundary distance between models $h$ and $h'$ based on point $x$. |
| $m \in [M]$ | Number of underlying data distributions assumed to exist | $G$ | Desired adversarial training proportion for pFedDef |
| $(x, y) \sim D_m$ | Data drawn from underlying data set $m \in [M]$ | $F_c \leq R_c$ | Actual adversarial proportion for pFedDef for client $c$ bounded by resource $R_c$. |
| $h_m \in [H]$ | Hypothesis to fit data of underlying distribution $m \in [M]$ | $Q$ | Number of rounds between generating new adversarial training data in pFedDef |
| $\pi_{c,m}$ | Proportion of underlying distribution $m$ at client $c$ \((\forall c, \sum_{m \in [M]} \pi_{c,m} = 1)\) | $K$ | Number of steps in multi-step PGD attack |
| $d(h, x)$ | Direction between $x$ and a different label point $x'$ for model $h$ | $\delta \in S$ | Perturbation $\delta$ added to data point $x$ bounded by perturbation budget $S$. |
| $N_d(h, x)$ | Distance from $x$ to decision boundary for model $h$ | $\alpha$ | PGD step-size parameter |

Table 3: Variables and notation used for transferability characterization and the pFedDef algorithm. The data distribution parameter $\beta$ is explained in appendix Section E.1.

B Resources and Assets

The code used to run the experiments for pFedDef is provided at https://github.com/tj-kim/pFedDef_v1. The FedEM implementation is created by the authors of (Marfoq et al. [2021]), and the code used to run their experiments is found at https://github.com/omarfoq/FedEM. Our work has adjusted the work presented in FedEM with the following changes:

- We introduce the adversarial training mechanisms for different types of distributed learning, including pFedDef that utilizes adversarial robustness propagation.
- We build an transfer attack analyzer that can perform and analyze internal transfer attacks between federated clients. This includes the inter-boundary distance measurement tools between clients (Tramèr et al. [2017]).
- We add an ensemble attack mechanism and label flip attack mechanism.

C Data Sets Explanation

**CIFAR.** The CIFAR-10 and CIFAR-100 data sets are selected to analyze the trends of pFedDef for two similar classification tasks of varying sizes. The CIFAR-100 model is also trained on MobileNetV2. The training and attack parameters of CIFAR-100 are equivalent to that of CIFAR-10, except that the number of clients in the system is 50, and the adversarial proportion is set at $G = 0.5$. The data is artificially split between clients in a non-i.i.d. manner for both data sets with $\beta = 0.4$. As seen in Table 4, CIFAR-100 displays the accuracy to robustness trade-off seen in Table 1 for CIFAR-10.

| Data set | Method | Test. Acc. | Adv. Acc. | Leg. | Adv. $I_d$ | Adv. $I_d$ |
|----------|--------|------------|-----------|------|------------|------------|
| CIFAR100 | Local  | 0.29 | 0.04 | 10.3 | 6.98 |
|          | FedEM  | 0.34 | 0.03 | 4.59 | 6.70 |
|          | FedAvg | 0.31 | 0.01 | 0.00 | 0.00 |
| CelebA   | Local  | 0.57 | 0.19 | 22.8 | 8.61 |
|          | FedEM  | 0.85 | 0.13 | 6.33 | 12.8 |
|          | FedAvg | 0.80 | 0.01 | 0.00 | 0.00 |

Table 4: Transferability of untargeted attacks and inter-boundary distances for CIFAR-100 and CelebA (measured by the $\ell_2$ distance in input) given different distributed training algorithms.
CelebA. The CelebA data set is a large-scale data set with celebrity images, each with 40 binary labels, from LEAF, a benchmarking framework for federated learning (Caldas et al. [2019]). This data set is selected for analysis as the distribution of data across clients follows a more realistic pattern than artificial division of data amongst clients used for other data sets. We combine 4 binary classification tasks (Smiling, Male, Eyeglasses, Wearing Hat) to formulate a classification problem with 16 classes. The images are reshaped to 50x50 shaped tensors. The CelebA model is trained on MobileNetV2, with equal training and attack parameters to CIFAR-10 except the number of training rounds is set at 100. The results for CelebA in Table 4 display similar patterns to other data sets analyzed.

MovieLens. The MovieLens data set is a data set with user ratings for movies. This data set is often used to train models for recommending movies to users based on previous ratings data. We use this data set to demonstrate the danger of internal attacks in recommendation systems trained with federated learning, as seen in Table 1. We transform this data set such that each data point corresponds to all ratings of one user. Users are labeled based on the user category, which is decided by learning a movie recommendation system that learns user embedding and minimizes the L2 norm between the true and predicted movie ratings. Then, user embedding and clustering techniques are used to assign the class labels to individual data points. The number of class labels is set to 5. Thus, the classification task becomes classifying each user correctly into the discovered cluster based on their movie rating.

D Background Knowledge: Inter-boundary Distance

The metric of *inter-boundary distance* introduced by (Tramèr et al. [2017]) measures the distance between the decision boundaries of two models. The unit-norm direction vector between any point \( x \) that is classified correctly by the two models in comparison, and the closest point in the \( \ell_2 \) distance \( x' \) misclassified by \( h_c \) is

\[
d(h, x) := \frac{x' - x}{||x' - x||_2}
\]

Given model \( h_c \) for client \( c \), the *legitimate direction* \( d_{\text{leg}}(h_c, x) \) is defined for each data point \( x \) and the closest data point \( x' \) with a different class label from \( x \). The *adversarial direction* \( d_{\text{adv}}(h_c, x) \) is similarly defined by \( x \) and an adversarial example \( x' = x + \delta \) that is misclassified by model \( h_c \). Given a direction \( d \) (e.g., \( d_{\text{leg}} \) or \( d_{\text{adv}} \)), the minimum distance \( N_d \) between point \( x \) to the decision boundary of model \( h_c \) is:

\[
N_d(h_c, x) := \min \epsilon \quad \text{s.t.} \quad h_c(x + \epsilon \cdot d) \neq h_c(x), \epsilon > 0
\]

Given a point \( x \) and a direction \( d \) computed according to a model \( h_c \), the inter-boundary distance \( I_d \) between two different models \( h_c \) and \( h_c' \) is defined as:

\[
I_d(h_c, h_c', x) := |N_d(h_c, x) - N_d(h_c', x)|
\]

Smaller inter-boundary distances indicate more similar models, inducing high transferability of attacks from one model to another. A visual depiction of the inter-boundary distance between two models in the legitimate and adversarial directions is shown in Figure 4. We use the inter-decision boundary metric to quantify the similarity of clients’ models in the FedAvg, FedEM, and local training settings, and compare it to empirical transferability values. Small inter-boundary distances for the legitimate direction indicate similarity in classification tasks for models, while small distances for the adversarial direction indicate the potential for attack transferability between models. The inter-boundary distance metric is used to gauge the robustness to accuracy trade off of different learning methods in Table 1 and Table 4.
E.1 Extended Numerical Analysis Setup

All experiments in the main body and appendix are carried out on an AWS EC2 instance of type g4dn.xlarge. These instance types have NVIDIA GPUs using NVIDIA libraries such as CUDA.

**Non-i.i.d. Data Distribution.** The data distribution process across clients is taken from [Marfoq et al. (2021)](https://doi.org/10.1109/ICMLC.2021.9499868). When dividing data across clients during experiments, the parameter $\beta > 0$ impacts how the data is distributed. The data division process begins with an assumption $M$ underlying distributions, identical to the set up of FedEM. The underlying distributions are constructed by having each label in the data set is divided in a i.i.d. manner into one of the distributions. Afterwards, data points are mapped from each distribution to all clients using the Dirichlet distribution, which takes $\beta$ as an input parameter. When $\beta$ is a low value, data is more non-i.i.d. across clients as there is higher variance between clients for the number of data points assigned from a specific underlying distribution. When $\beta$ is a higher value, clients tend to have a similar number of data points from each underlying distribution compared to other clients, making the global data distribution more i.i.d.. For all experiments in the paper, the number of underlying distributions assumed is $M = 3$. The impact of different settings of data distribution on federated learning and pFedDef are analyzed in Section 6.3.

E.2 CIFAR-100 and CelebA pFedDef Evaluation

The performance of pFedDef compared to FAT and local adversarial training for CIFAR-100 and CelebA are shown in Table 5 and Table 6, respectively. Performance is measured against both internal grey-box evasion attacks and foreign black-box attacks.

| Metric / Method  | Adv. Training | Adv. Non-i.i.d. | Benign |
|-----------------|---------------|-----------------|-------|
| Test. Acc       | 0.35          | **0.37**        | 0.26  |
| Internal Adv. Acc| **0.16**      | 0.07            | 0.07  |
| Black-box Adv. Acc| 0.29         | **0.31**        | 0.09  |

Table 5: Performance of pFedDef algorithm on CIFAR-100 data set.

| Metric / Method  | Adv. Training | Adv. Non-i.i.d. | Benign |
|-----------------|---------------|-----------------|-------|
| Test. Acc       | 0.78          | 0.78            | 0.58  |
| Internal Adv. Acc| **0.36**      | 0.18            | 0.35  |
| Black-box Adv. Acc| 0.61         | **0.69**        | 0.37  |

Table 6: Performance of pFedDef algorithm on CelebA data set.

The results show similar patterns to that of CIFAR-10 presented in Table 2. The pFedDef algorithm maintains both high test accuracy and robustness compared to both FAT and local training, and has high robustness against black-box evasion attacks as well. For CIFAR-100, the robustness of pFedDef against internal attacks is relatively 128% higher at 0.16 compared to that of FAT at 0.07. For CelebA, the robustness of pFedDef against internal attacks is relatively 100% higher at 0.36 compared to that of FAT at 0.18. For both data sets, pFedDef and FAT against black-box attacks are more robust than against internal attacks.

E.3 Overhead of pFedDef Training Parameters

To observe the impact of pFedDef parameters on robustness and overhead, different values of parameters $G$ (desired adversarial data proportion), $Q$ (adversarial data set update frequency) and $K$ (number of PGD steps) are analyzed. Increasing each of these parameters increases overhead with respect to the adversarial training data generation. We only show results on the CIFAR-10 data set to conserve space. We note that targeted attacks are created with the intent of altering the classification...
(a) High pFedDef adversarial proportion increases robustness with diminishing returns.

(b) More PGD steps during pFedDef increases robustness with diminishing returns.

(c) More rounds between adv. data set updates overall reduces robustness.

Figure 5: Comparisons of different algorithm parameters for pFedDef implementation on CIFAR-10 regarding impact on performance and robustness. High robustness against grey-box attacks can be achieved with low overhead parameter settings.

of a data point to a specific label. Untargeted attacks are created following the method introduced in Section 3.2 and is used for analysis in the main body of the text (Adv. Acc.).

Increasing both adversarial data proportion $G$ in Figure 5a and number of PGD steps $K$ in Figure 5b has similar effects on pFedDef’s test accuracy and robustness. As both values are increased, test accuracy gradually decreases, while robustness against untargeted and targeted attacks increases. However, both the changes in test accuracy and robustness become minimal as $G$ exceeds 0.3 and $K$ exceeds 5. Thus, we can achieve high robustness with lower values of $G$ and $K$ that reduce algorithm overhead. Furthermore, robustness can be achieved when system resources $R_c$ are constrained for many clients due to resource propagation, as seen in Figure 2a.

In Figure 5c as the number of rounds between adversarial data set updates ($Q$) increases, the test accuracy increases, indicating that the negative effect of adversarial training on test accuracy is less prevalent. In contrast, robustness against targeted and untargeted attacks initially increases and subsequently decreases as $Q$ is increased. Robustness is reduced when the value of $Q$ is too small as the training set is altered too quickly compared to the neural network parameters that are trained. Overall, the pFedDef algorithm achieves relatively high robustness given lower values of $G$ and $K$ and infrequent updates $Q$ to the adversarial data set, reducing the overhead of the adversarial training procedure.

E.4 Personalized Layers Federated Learning

A brief experiment is conducted with the use of the personalized layers approach instead of FedEM (Arivazhagan et al. [2019]). Here, we use the FEMNIST data set to train a 5 layer model with 2 convolutional layers, a batch normalization function, and three linear layers. All "neck" layers are shared between clients of the federated learning process (i.e., the weights are averaged every round), while "head" layers are not shared, leading to personalization between different clients. As shown in Table 7, as less personalization occurs due to the increase in number of shared "neck" layers in a 5 layer model across 8 users, the test accuracy falls, while targeted evasion attacks have higher success rate. Thus, the trend of personalized learning achieving better test performance as well as lower attack transferability is shown beyond the results of FedEM in Table 1.

| Shared Layers | 2 | 3 | 4 |
|---------------|---|---|---|
| Test Accuracy | 0.82 | 0.71 | 0.43 |
| Targeted Attack Success | 0.82 | 0.94 | 0.90 |

Table 7: Personalized layers adversarial transferability.