# Client-Wise Targeted Backdoor in Federated Learning

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March 17, 2022

#### Abstract

Federated Learning (FL) emerges from the privacy concerns traditional machine learning raised. FL trains decentralized models by averaging them without compromising clients' datasets. Ongoing research has found that FL is also prone to security and privacy violations. Recent studies established that FL leaks information by exploiting inference attacks, reconstructing a data piece used during training, or extracting information. Additionally, poisoning attacks and backdoors corrupt FL security by inserting poisoned data into clients' datasets or directly modifying the model, degrading every client's model performance.

Our proposal utilizes these attacks in combination for performing a client-wise targeted backdoor, where a single victim client is backdoored while the rest remains unaffected. Our results establish the viability of the presented attack, achieving a 100% attack success rate downgrading the target label accuracy up to 0%. Our code will be publicly available after acceptance.

Keywords— Federated Learning, Backdoor attacks, Client-wise attack

# 1 Introduction

Machine Learning (ML) has revolutionized the industry and academia by its broad applicability and performance [20]. ML popularity growth under security and privacy assessments, e.g., EU data privacy regulations [18]. Researchers found that the ML centralized scheme caused essential privacy issues, leaking private information, for example [13]. As an improvement, a privacy-driven decentralized ML architecture arose in 2016 — Federated Learning (FL) [7]. Clients make the FL network, where each train an ML model locally under their private dataset and share the trained model with a server, i.e., the aggregator, which joins every model. FL keeps data records private, preventing privacy leakage. Unfortunately, recent investigations found that FL is still prone to security and privacy violations [9]. Despite defensive mechanisms development, there exist plenty of security and privacy issues to be solved [6].

Two of the most popular attacks in FL are inference attacks, where the aim is to cause privacy leakage, and poisoning attacks, where the goal is to lower the classification accuracy of the target model [6]. Current state-of-the-art poisoning attacks, especially backdoors [1], focus on downgrading every client's model performance. Backdoors are widely developed under different scenarios and assumptions. However, in an FL network with many clients, an attacker may want only to target a single one or a subset of them. The client-targeted scenario has not been contemplated for backdoors yet; however, it has for inference attacks [3, 15].

This research determines if a client model could be poisoned while the rest are not under some assumptions, contrary to state-of-the-art poisoning attacks. First, we leverage and refine state-of-the-art inference attacks for gaining information. We then replace the client model with a backdoored one, reducing the accuracy on the target class while the rest are not affected.

#### 1.1 Related Work

FL has recently gained attention as a learning alternative to centralized ML, focusing on privacy. FL security and privacy have been evaluated since its release [9, 6]. Assessments concluded that FL could be attacked by causing misclassification of the models, i.e., poisoning attacks [12, 1], or causing privacy leakages, i.e., inference attacks [10]. During the training phase, poisoning attacks inject poisoned samples on the training dataset or alter the model directly targeting the performance. During the training phase, poisoning attacks can be performed targeting the performance of every model in the network [1]. Depending on whether the attack's goal is to downgrade the model's overall accuracy or just some target class, the attack is classified as untargeted and targeted [9]. Even more, there is a particular type of attack, called backdoor [1], where the goal is to misclassify a sample just under a presence of a property or a characteristic, e.g., a pixel pattern [21].

Inference attacks, on the contrary, focus on causing privacy leakage. Depending on the attacker's capabilities, the attacker may have oracle access to the model, its inner computation, or clients' updates [10]. Depending on the target information, inference attacks are classified as membership inference, property inference, or model inversion. Membership inference [10] goal is to establish if a data record has been used during training. In property inference [8], the goal is to find whether a model was trained over some property data. Lastly, model inversion attacks [4] reconstruct a data piece similar to the one used during training. Inference attacks could also be client-targeted, focusing on a victim client rather than the joined model for extracting information.

#### 1.2 Our Contributions

Research to date has not yet determined the viability of backdoor attacks for a target client without poisoning the rest. This study examines the practicality of client-wise backdoors as discussed in the threat model. Our contributions are:

- We develop an inference attack that identifies clients' anonymous updates by creating synthetic data per client with a Generative Adversarial Network (GAN), fed into a shadow network for training. From there, we train a Siamese Neural Network (SNN) that identifies client updates over epochs.
- We introduce triplet-loss usage for inference attacks, yielding outstanding results with complex data.

 We extend and analyze backdoor attacks' capabilities focusing on a target client, drastically reducing the source class accuracy while maintaining high accuracy in the rest.

# 2 Background

# 2.1 Federated Learning

FL is a privacy-driven decentralized scheme for training ML models. Introduced by Google, they proposed creating a network of clients that own their distinct dataset to train their data, instead of joining every dataset in a single place, causing a privacy issue [7]. The network is composed of an aggregator and N clients. Every participant of the network, upon consensus, decides to train the same model M under the same conditions, e.g., learning rate (LR) and the number of epochs. After local training, clients upload their models to the aggregator, who joins them by averaging, and sends the new model back to each client. The FL procedure is repeated during t epochs until convergence is met. FL improves privacy and training speed, achieving a better quality of the model [7].

# 2.2 Generative Adversarial Networks (GANs)

A GAN is an ML framework developed by Goodfellow et al. [5], which from noise  $z \sim p_Z$  generates data samples. The procedure simultaneously trains two networks, a generator (G) and a discriminator (D). G takes z as input and creates actual data samples, while D distinguishes fake samples from real ones. Both train simultaneously until achieving the Nash equilibrium, where G can generate real-enough data samples that D cannot differentiate. Namely, the distribution of the generated fake samples  $p_{G(Z)}$  converges towards the distribution of real data samples.

### 2.3 Siamese Neural Networks (SNNs)

SNN is a type of architecture constructed by two identical networks with the same parameters, weights, and structure [2]. Its task is to find similarities from inputs by comparing their feature vectors' latent space. Since SNN involves pairwise data for training, the loss function has to optimize the model to minimize the distance, i.e., Euclidean distance, between similar inputs and maximize it between different inputs. Triplet loss [11] is usually used to improve SNN performance during training, consisting of three types of samples: anchor, positive, and negative. Since anchor and positive samples have the same label, triplet loss optimizes the model so that the distance between the anchor and the negative samples is more significant than between the anchor and the positive.

SNN has already been used for inference attacks, e.g., [15]. During the training of the Siamese network, the authors used two representatives of different models as input. The SNN seeks similarities between them and outputs a value between "0" and "1", where zero means very similar. For improving SNN utility, we adapt triplet networks for inference attacks. Triplet networks evolved from SNN and gained popularity with the development of FaceNet [11]. Since then, triplet networks have been used in diverse domains, e.g., side-channel analysis [17] or image similarity [16].

Three types of triplets can be constructed for training:

- 1. **Easy triplets:** The negative sample is sufficiently distant from the anchor compared to the positive sample to the anchor.
- 2. **Hard triplets:** The distance between the negative sample and the anchor is closer than the positive to the anchor.
- 3. **Semi-Hard triplets:** The distance between the negative and the anchor is larger than the positive to the anchor but is not bigger than a margin  $\alpha$ .

#### 2.4 Inference & Backdoor Attacks

Inference attacks extract private information from clients. Such attacks are classified as passive or active depending on the attacker's capabilities [10]. Additionally, depending on whether the training or the inference phase is threatened, the attacker could have oracle access to the model, its inner computations, or updated information, e.g., membership inference [10], property inference [8], or model inversion [4]. By mangling the dataset or the model, backdoor attacks directly inject an adversarial effect on the model triggered by some information. For example, Bagdasaryan et al. constructed a backdoor model that triggers the adversarial effect under the presence of white striped green cars while adequately working with the rest of the cars [1].

# 3 Threat Model

## 3.1 Assumptions

Other works consider each client to use unique labels per client and share data labels they own [3]. However, we keep data labels private. For example, in the MNIST case, client 1 holds the labels "0" and "1" while client 2 holds labels "2" and "3". This assumption is more realistic since the decentralized nature of FL makes it possible for clients to own data from different sources and thus with distinct labels.

#### 3.2 Adversarial Objectives

Under our settings, the attacker aims to inject a targeted backdoor in a chosen victim's model. The backdoor would reduce the prediction accuracy in the target class while maintaining a high accuracy on the rest. We use three metrics for evaluating the attack performance: (1) **overall accuracy** for the poisoned and non-poisoned models, (2) **accuracy per class**, representing the accuracy per class for the poisoned and non-poisoned model; (3) the **attack success rate (ASR)**, representing the percentage of backdoors that were successful.

#### 3.3 Adversarial Capabilities

The adversarial actor is placed in the server. Therefore, the attacker's knowledge includes the aggregation algorithm and training information (i.e., LR, number of epochs, number of clients, FL network structure, and each client update). As some state-of-the-art defenses are based on anonymizing clients' updates [15], we also anonymize them in our approach. The attacker can modify the aggregation algorithm or the aggregated model apart from the abovementioned information. The main assets used for our attack are the information of the FL network and the ability to alter the aggregated model.

# 4 Proposed Client-wise Targeted Backdoor

#### 4.1 Attack Overview

As an overview of the inference phases (see Figure 1), the aim is to identify the anonymized updates via inference attacks based on [3, 15] and gather dataset samples from each client to perform the backdoor attack later. (1) The attack begins with standard FL training, (2) where the attacker saves anonymized clients' updates at each FL epoch (Section 4.2). Once convergence is met, the attacker selects a set of clients' models at epoch t, which influence we discuss in Section 4.3. For each model, (3) the attacker constructs a GAN where the discriminator is the client model at t (Section 4.3). One of the necessary information pieces has been fulfilled (4) by creating each client's synthetic dataset using the GAN. A structurally identical shadow FL network is constructed to identify updates (Section 4.4). (5) The attacker trains the shadow network and (6) records identified updates, (7) which are used to train an SNN (Section 4.5). The SNN is then used to identify anonymous updates recorded during the original FL network training (Section 4.6). (8) A victim client is selected, and information needed is now acquired to create the backdoor model (9) and send it to the victim client (Section 4.7).

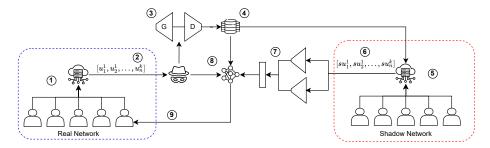


Figure 1: Attack overview.

#### 4.2 Training the Network

We compose the FL network with clients with specific labeled data that vary in size. For aggregation, the client performs local training over its dataset and submits the anonymized model weights to the server. Anonymization can be achieved by different means, e.g., using TOR as suggested in [15]. For every FL epoch t, the attacker extracts the representatives of each client uploaded model by querying a holdout data piece and getting the inner computations of the second last layer (the layer before the fully connected layer), as in [15].

Since we want to maximize the representatives' resemblance for the same client's model for every t, we fix the queried sample, so the alteration of the model over t would be slighter. Then, the server aggregates each update by FedAvg [7] and submits the joined model back to clients. This procedure is repeated until convergence is met. See Algorithm 1 as a summary.

#### Algorithm 1 FL Network Training

- 1: Input: A set of clients K. Number of clients N. Number of epochs T. Client update u.
- 2: Output: A dataset of clients' representatives D. A collection of anonymous models W.

```
3: Initialize: W_{t=0}

4: \mathbf{x} \leftarrow \text{get\_sample}() \triangleright Get the fixed sample.

5: for each epoch t = 1, 2, 3, ..., T do

6: for each client k \in K do \triangleright k is anonymous for the server.

7: u_{t+1}^k \leftarrow \text{client\_update}(k, W_t) \triangleright Local training of k.

8: D_{t+1}^k \leftarrow u_{t+1}^k(\mathbf{x}) \triangleright Representatives over input \mathbf{x}

9: W_{t+1} \leftarrow W_t + \frac{1}{N} \sum_{k=1}^N u_{t+1}^k
```

## 4.3 Creating Synthetic Data

To train the shadow network, we first need to create a dataset similar to clients', see Algorithm 2. As in [3, 15], we develop a deep convolutional GAN (DCGAN) where the discriminator is each updated client model at epoch t. We modified the client updated model by removing the last fully connected layer by another convolution and a sigmoid activation function to fit the DCGAN training procedure, as in [15]. After training, the generated samples are labeled by the last aggregated model, which has the greatest accuracy once convergence is met. Experimentally, we found that choosing the right t is vital for proper data creation. In early epochs, models are more distinct since the other models' properties have not been merged yet. As epochs progress, dataset properties merge, and models become similar. Therefore, creating data samples from dissimilar models retains the source dataset's properties, which is beneficial for better results during the SNN training and the posterior identification phase.

#### Algorithm 2 Creating Synthetic Data

```
1: Input: K set of clients. W collection of clients' models. Trained global model
    W_q. T number of epochs.
 2: Output: D collection of datasets.
 3: Initialize: t = 1
                                                                                \triangleright Set a low value of t.
 4: for each client k = 1, 2, 3, ..., K do
         Initialize: G and D.
 5:
         D \leftarrow W_t^k
 6:
         for each epoch i = 1, 2, 3, ..., T do
 7:
             z \leftarrow generate\_noise()
 8:
             train(G, D, z)
 9:
         z \leftarrow generate\_noise()
10:
         \mathbf{x} \leftarrow G(z)
                                                                                   ▷ Create fake data.
11:
         \{\mathbf{x},y\} \leftarrow W_g(\mathbf{x})
                                                                                          ▷ Label data.
12:
         D^k \leftarrow \{\mathbf{x}, y\}
13:
```

# 4.4 Shadow Training

Shadow models were firstly introduced by Shokri et al. [13] in an inference attack, determining if a data record was present in the training dataset. Shadow training is based on creating a replica of the original black-boxed training procedure, which an attacker cannot access. The attacker has white-box access to every parameter or information by shadowing the training procedure. In our proposal, inspired by [15], we shadow the entire FL network, see Algorithm 3.

As the previous section explains, each client trains the same model over the generated dataset. As in Section 4.2, the attacker calculates the clients' representatives at each epoch over now identified clients' models. In summary, the attacker has created a dataset of identified clients' representatives by shadow training.

#### Algorithm 3 Shadow Training

```
1: Input: GAN generated dataset D_{GAN}. Set of clients K. Number of epochs T. Number of clients N.

2: Output: D clients' representatives dataset.

3: \mathbf{x} \leftarrow get\_sample() \quad \triangleright Get the fixes sample for calculating clients' representatives.

4: for each epoch t = 1, 2, 3, ..., T do

5: for each client k \in K do \quad \triangleright k is not anonymous anymore.

6: u_{t+1}^k \leftarrow client\_update(k, W_t, D_{GAN}^k)

7: D_{t+1}^k \leftarrow u_{t+1}^k(\mathbf{x})

8: W_{t+1} \leftarrow W_t + \frac{1}{N} \sum_{k=1}^N u_{t+1}^k
```

#### 4.5 Triplet SNN Training

In our attack, we obtain model representatives by extracting the latent space's inner computations before each client model's last layer by querying the same sample input. Since the data provided for training is complex, we require the usage of triplet mining to create Semi-Hard triplets, improving the quality of the model [11].

#### 4.6 Updates Identification

At this point, the attacker holds a trained SNN and a collection of unidentified clients' representatives for every training epoch t. Since updates are anonymous, selecting a client as a victim requires some steps. The attacker may choose the victim based on its criteria. However, a victim-like dataset is required for creating the backdoor. As explained in previous sections, synthetic datasets are best created from models at early epochs. Thus, the attacker needs to link the victim model at an early epoch with the model at (near) convergence, mainly different. To solve this, the attacker measures the similarity of each representative in t against all the representatives in t+1. The lowest value represents the close similarity between updates, meaning the same client. Via this iterative process, we ensure a proper client identification at the last epoch, where models are more similar than in early epochs. An attacker could also simplify this identification process by comparing two representatives at different t, but the identification could not be as confident since it relies on finding similarities on two (very) dissimilar models.

#### 4.7 Backdoor Attack

Once all information is gathered, we inspect the client's dataset chosen as a victim in this last phase, see Algorithm 4. As mentioned previously, since different clients own distinct data labels, users who may employ the model for inference will commonly use it by querying samples of the same labels. Therefore, targeting those labels will maximize the misclassification effect. Since the objective is to backdoor the victim's model, the attacker averages every model and sends the non-backdoored one to non-victim clients. Then, by label-flipping target labels owned by the victim, the attacker poisons the last global model and sends it to the victim, successfully backdooring the target label. If the FL training is performed for more epochs, the victim model could be weighted by a small factor or ignored, preventing degrading the aggregated model.

#### Algorithm 4 Client identification & Backdoor

- 1: Input: Unidentified clients' representatives D. Target class  $c_t$ . Source class  $c_s$ . GAN generated datasets  $X_{GAN}$ . Poisoned data rate  $\epsilon$ .
- 2: Output: Poisoned model  $W_{poison}$ .
- 3: for each unidentified client representative pair  $x, y \in D : x \neq y$  do
- 4: SNN(x,y) ightharpoonup Similarity calculation as in Section 4.6
- 5: Define:  $u_v$

 $\triangleright$  Define a victim client

- 6:  $X_{poison} \leftarrow label\_flip(c_s, c_t, X_{GAN}^v, \epsilon)$
- 7:  $W_{poison} \leftarrow train(X_{poison}, u_v)$
- 8: Send  $W_{poison}$  to victim client v.

# 5 Experimental Results

# 5.1 Datasets

We evaluate the performance of our proposal with MNIST, EMNIST, and F-MNIST datasets. **MNIST** is a classical benchmark dataset in computer vision containing labeled grayscale images from handwritten digits. Dataset labels ranges from "0" to "9". **EMNIST** is also a grayscale dataset containing handwritten characters of the alphabet, containing 26 classes of images. **F-MNIST** is a grayscale dataset containing ten types of clothing. Every dataset contains  $70\,000\,28\times28\times1$  grayscale samples,  $60\,000$  for training, and  $10\,000$  for the test set. As most of the backdoors are performed with datasets with ten classes, our selection of datasets allows us to consider common settings but also investigate scenarios with more classes.

#### 5.2 FL Network Settings

For each dataset, the model is a DCNN with three convolutional layers and a fully connected one, with stochastic gradient descent, LeakyRelu as activation function, and batch normalization in each layer except the last. Training settings are shown in Table 1 and the architecture is shown in Figure 2.

During training, the attacker observes the computations of the second last layer of the DCNN by querying a fixed image at every epoch and per client and records the latent space. Note that clients' representatives are anonymized.

Dataset	LR	Local Epoch	FL Epoch	No. of Clients	No. of Classes
MNIST	0.1	2	50	5	10
EMNIST	0.01	2	200	13	26
F-MNIST	0.0001	1	100	5	10

Table 1: Training settings.

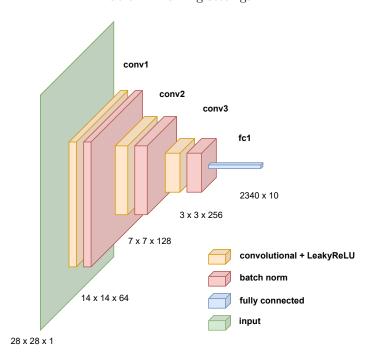


Figure 2: DCNN architecture.

After training, the network achieves 98% accuracy on MNIST (see Figure 3), 88% in EMNIST, and 80% in F-MNIST. It shows the accuracy after local training and before aggregation over the test set. Note that clients' models' accuracy is the same as servers' after aggregation. Models are trained over non-colluding labeled data and evaluated with a test dataset containing all the labels. As epochs go by, models perform better over the test set, acquiring properties from other datasets. Our research shows that the more significant the difference between the aggregated model and the clients, the more straightforward it is to perform the attack because the backdoor model is constructed by training the converged joined model with the poisoned dataset of the victim. Since datasets' properties from which models are built are more prone to stay alike, similar models will converge faster, merging other properties and making the differentiation difficult.

As mentioned previously, GANs have been used in different attacks in FL, primarily for data augmentation [19] and inference [15, 3]. These approaches used the aggregated

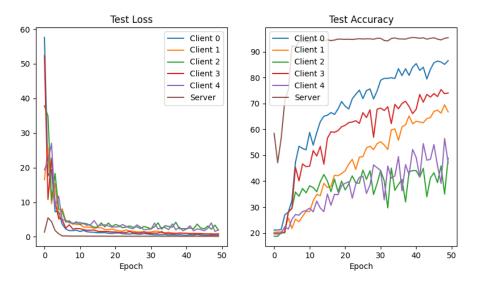


Figure 3: Accuracy and loss of the DCNN network trained with MNIST over 50 epochs with five clients.

model as the discriminator, so the generator creates data similar to the one used during the FL training. Inspired by this, we decided to use client models rather than aggregated, creating data similar to each client's distribution, improving the resemblance of the shadow network with the original, easing the following identification phase. The chosen model does not need to be near convergence, i.e., we select early FL epoch, so the client model has not already acquired the properties of the others. We train DCGAN for 200 epochs with Adam as the optimizer with LR 0.0002 those hyperparameters are selected after a tuning phase). The attacker generates and labels 70 000 images (Figure 4), and the architecture is inspired by [14].

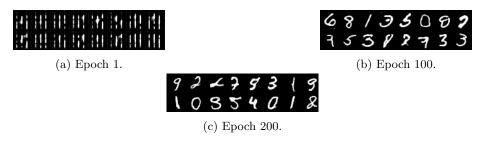


Figure 4: GAN generated MNIST images at different epochs.

### 5.3 Shadow Network Training Settings

The shadow network is a replica of the original FL network, using the training parameters presented in Section 4.2 but with the synthetic datasets. Each client owns a

synthetic dataset created using the DCGAN from their models at t=1. In the MNIST case, since the labeling is 98% accurate (the global model accuracy at convergence), errors in the dataset are introduced, lowering the shadow global model's accuracy to 90%. However, shadow network accuracy is not relevant; its only assignment is to extract identified representatives. During the FL process, the attacker extracts the latent space of the second last layer over a fixed image as input, as in Section 4.2, to create a dataset for the SNN.

## 5.4 Triplet SNN Training Settings

The SNN comprises three fully connected layers with dropout layers between them, inspired by [11]. This architecture is duplicated and concatenated. Since the dataset is not very big, we need a simple network to improve network quality with triplet mining. The dataset for training the SNN is a collection of labeled and flattened clients' representatives. The inputs are an anchor, a positive, and a negative 2 304-dimensional samples. The outputs from the last layers are embedded in five-dimensional space (experimentally set as a trade-off between network complexity and data dimensionality) and sent to a distance computing layer that calculates the Euclidean distance. After training, given two inputs, the SNN yields values close to 0 if they are similar and close to 1 otherwise. We follow the online triplet mining method, creating Semi-Hard triplets on the fly, and improving training performance [11]. Experiments show the network has an accuracy of 80% after 20 epochs,  $\alpha$  0.2, and an LR of 0.0001, with Adam as the optimizer.

# 5.5 Backdoor Attack Settings

Once the victim client is identified, the attacker uses the synthetic client dataset generated in Section 4.3. The data distribution of the generated dataset is similar to the client. The attacker uses that dataset and flips the source label to target, creating a poisoned dataset. The attacker uses the last joined model to inject the backdoor via training with poisoned data. A value  $\epsilon$  controls the amount of poisoned data in the dataset.

Our experiments yield that no matter the settings used, the attack always reduces the classification rate on the source class. However, the accuracy drop in the source class is not relevant under some settings, or the overall accuracy drop is easily noticeable. Depending on if the client has implemented a defensive mechanism, the attacker could consider fine-tuning the parameters for evading such. Overall, the ASR is 100% in most of the settings.

Table 2 shows that choosing the source and target labels influences the results. For MNIST (experiments with EMNIST and F-MNIST show similar results), we perform experiments for the common "1" to "7" attack and other randomly selected labels, "0" to "9". Without poisoning the model, its accuracy is 94%, "0" accuracy is 94%, "1" is 91%, "7" and "9" is 95%. We establish that three parameters influence the backdoor, the LR, the percentage of poisoned data  $\epsilon$ , and the number of epochs t. As the model has already achieved convergence, t has no significant influence. The most relevant parameters are the LR and  $\epsilon$ . Setting a small LR, i.e., 0.001, drastically improves the overall accuracy of the poisoned model from 76% to 82%. At the same time,  $\epsilon$  modifies the source class and target accuracy. Overall, a single-epoch is only needed to backdoor the model, while the LR and  $\epsilon$  can be tuned to adjust the adverse effect.

Table 2: Experimentation averaged results for different settings using MNIST.

			$1 \rightarrow 7$			$0 \rightarrow 9$			
LR $\epsilon$		t	A course ove	Source Class	Target Class	Accuracy	Source Class	Target Class	
	l t	Accuracy	Accuracy	Accuracy	Accuracy	Accuracy	Accuracy		
0.1	0.1	1	76%	0%	80%	73%	0%	99%	
0.1	0.01	1	77%	0%	83%	74%	0%	99%	
0.1	0.001	1	76%	0%	82%	74%	0%	99%	
0.1	0.1	10	73%	0%	75%	70%	0%	99%	
0.1	0.01	10	73%	0%	76%	70%	0%	99%	
0.1	0.001	10	73%	0%	76%	69%	0%	99%	
0.01	0.1	1	80%	0%	80%	78%	0%	98%	
0.01	0.01	1	81%	0%	82%	79%	0%	98%	
0.01	0.001	1	81%	0%	83%	79%	0%	98%	
0.01	0.1	10	79%	0%	81%	78%	0%	97%	
0.01	0.01	10	80%	0%	82%	77%	0%	98%	
0.01	0.001	10	79%	0%	81%	77%	0%	98%	
0.001	0.1	1	82%	0%	78%	80%	0%	97%	
0.001	0.01	1	83%	0%	80%	81%	3%	98%	
0.001	0.001	1	83%	15%	80%	83%	41%	98%	
0.001	0.1	10	81%	0%	80%	79%	0%	98%	
0.001	0.01	10	81%	0%	80%	80%	1%	98%	
0.001	0.001	10	82%	0%	83%	80%	2%	98%	

# 6 Conclusions & Future Work

This research investigates the viability of client-wise targeted backdoor attacks and shows the attack's success under assumptions we follow. Our findings suggest that inference attacks combined with backdoors are a powerful duple, setting directions for new, more realistic attacks. Overall, this study strengthens the idea that an attacker could cause severe degradation of the model in a targeted manner with little information. The finding will interest future work that further relaxes the considered assumptions, such as performing a client-wise targeted backdoor from a client perspective as an attacker. The generalizability of these results is subject to certain limitations. For instance, broader experimentation with different, more complex models, datasets, and a broader number of clients is a natural progression of this work.

# Acknowledgements

The European commission financially supported this work through Horizon Europe program under the IDUNN project (grant agreement number 101021911). It was also partially supported by the Ayudas Cervera para Centros Tecnológicos grant of the Spanish Centre for the Development of Industrial Technology (CDTI) under the project EGIDA (CER-20191012), and by the Basque Country Government under the ELKARTEK program, project TRUSTIND - Creating Trust in the Industrial Digital Transformation (KK2020/00054).

### References

[1] Eugene Bagdasaryan, Andreas Veit, Yiqing Hua, Deborah Estrin, and Vitaly Shmatikov. How to backdoor federated learning. In *International Conference on* 

- Artificial Intelligence and Statistics, pages 2938–2948. PMLR, 2020.
- [2] Jane Bromley, Isabelle Guyon, Yann LeCun, Eduard Säckinger, and Roopak Shah. Signature verification using a" siamese" time delay neural network. Advances in neural information processing systems, 6, 1993.
- [3] Jiale Chen, Jiale Zhang, Yanchao Zhao, Hao Han, Kun Zhu, and Bing Chen. Beyond model-level membership privacy leakage: an adversarial approach in federated learning. In 2020 29th International Conference on Computer Communications and Networks (ICCCN), pages 1–9. IEEE, 2020.
- [4] Matt Fredrikson, Somesh Jha, and Thomas Ristenpart. Model inversion attacks that exploit confidence information and basic countermeasures. In *Proceedings* of the 22nd ACM SIGSAC conference on computer and communications security, pages 1322–1333, 2015.
- [5] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. Advances in neural information processing systems, 27, 2014.
- [6] Peter Kairouz, H Brendan McMahan, Brendan Avent, Aurélien Bellet, Mehdi Bennis, Arjun Nitin Bhagoji, Kallista Bonawitz, Zachary Charles, Graham Cormode, Rachel Cummings, et al. Advances and open problems in federated learning. arXiv preprint arXiv:1912.04977, 2019.
- [7] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, pages 1273–1282. PMLR, 2017.
- [8] Luca Melis, Congzheng Song, Emiliano De Cristofaro, and Vitaly Shmatikov. Exploiting unintended feature leakage in collaborative learning. In 2019 IEEE Symposium on Security and Privacy (SP), pages 691–706. IEEE, 2019.
- [9] Viraaji Mothukuri, Reza M Parizi, Seyedamin Pouriyeh, Yan Huang, Ali Dehghantanha, and Gautam Srivastava. A survey on security and privacy of federated learning. Future Generation Computer Systems, 115:619–640, 2021.
- [10] Milad Nasr, Reza Shokri, and Amir Houmansadr. Comprehensive privacy analysis of deep learning: Passive and active white-box inference attacks against centralized and federated learning. In 2019 IEEE symposium on security and privacy (SP), pages 739–753. IEEE, 2019.
- [11] Florian Schroff, Dmitry Kalenichenko, and James Philbin. Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 815–823, 2015.
- [12] Ali Shafahi, W Ronny Huang, Mahyar Najibi, Octavian Suciu, Christoph Studer, Tudor Dumitras, and Tom Goldstein. Poison frogs! targeted clean-label poisoning attacks on neural networks. arXiv preprint arXiv:1804.00792, 2018.
- [13] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In 2017 IEEE symposium on security and privacy (SP), pages 3–18. IEEE, 2017.
- [14] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

- [15] Mengkai Song, Zhibo Wang, Zhifei Zhang, Yang Song, Qian Wang, Ju Ren, and Hairong Qi. Analyzing user-level privacy attack against federated learning. *IEEE Journal on Selected Areas in Communications*, 38(10):2430–2444, 2020.
- [16] Jiang Wang, Yang Song, Thomas Leung, Chuck Rosenberg, Jingbin Wang, James Philbin, Bo Chen, and Ying Wu. Learning fine-grained image similarity with deep ranking. In *Proceedings of the IEEE conference on computer vision and pattern* recognition, pages 1386–1393, 2014.
- [17] Lichao Wu, Guilherme Perin, and Stjepan Picek. The best of two worlds: Deep learning-assisted template attack. *Cryptology ePrint Archive*, 2021.
- [18] Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong. Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(2):1–19, 2019.
- [19] Jiale Zhang, Junjun Chen, Di Wu, Bing Chen, and Shui Yu. Poisoning attack in federated learning using generative adversarial nets. In 2019 18th IEEE International Conference On Trust, Security And Privacy In Computing And Communications/13th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE), pages 374–380. IEEE, 2019.
- [20] Lina Zhou, Shimei Pan, Jianwu Wang, and Athanasios V Vasilakos. Machine learning on big data: Opportunities and challenges. *Neurocomputing*, 237:350–361, 2017.
- [21] Xingchen Zhou, Ming Xu, Yiming Wu, and Ning Zheng. Deep model poisoning attack on federated learning. Future Internet, 13(3):73, 2021.