Blind leads Blind: A Zero-Knowledge Attack on Federated Learning

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Abstract—Attacks on Federated Learning (FL) can severely reduce the quality of the generated models and limit the usefulness of this emerging learning paradigm that enables on-premise decentralized learning. There have been various untargeted attacks on FL, but they are not widely applicable as they i) assume that the attacker knows every update of benign clients, which is indeed sent in encrypted form to the central server, or ii) assume that the attacker has a large dataset and sufficient resources to locally train updates imitating benign parties. In this paper, we design a zero-knowledge untargeted attack (ZKA), which synthesizes malicious data to craft adversarial models without eavesdropping on the transmission of benign clients at all or requiring a large quantity of task-specific training data. To inject malicious input into the FL system by synthetic data, ZKA has two variants. ZKA-R generates adversarial ambiguous data by reversing engineering from the global models. To enable stealthiness, ZKA-G trains the local model on synthetic data from the generator that aims to synthesize images different from a randomly chosen class. Furthermore, we add a novel distance-based regularization term for both attacks to further enhance stealthiness. Experimental results on Fashion-MNIST and CIFAR-10 show that the ZKA achieves similar or even higher attack success rate than the state-of-the-art untargeted attacks against various defense mechanisms, namely more than 50% for Cifar-10 for all considered defense mechanisms. As expected, ZKA-G is better at circumventing defenses, even showing a defense pass rate of close to 90% when ZKA-R only achieves 70%. Higher data heterogeneity favours ZKA-R since detection becomes harder.

Index Terms—Federated learning, zero-knowledge attack, untargeted attack, data heterogeneity

I. INTRODUCTION

Federated learning (FL) [21][32] enables distributed training of machine learning models, e.g., multi-class image classifiers, without sharing the raw data. Clients train models locally and the overall model, called the global model, is an aggregation of these local models. The training proceeds in multiple rounds: in each round, the central server provides a global model that clients use to initialize their local models. They then train on their local dataset and provide updates to the central server, who aggregates these updates to a new global model for the next round. In this manner, models requiring personal data such as information about medical or financial conditions can be obtained without explicit privacy violations. Recently, FL has been applied in domains such as fraud credit card detection for banks [33][39], security operations center collaboration in cybersecurity [11], and medical relation extraction [26].

A downside of preventing the central server from accessing local data is that it limits the ability of the central server to detect misbehavior. Adversarial clients may reduce the quality of the model by manipulating the data they train on [28] or their local model directly [7]. The attack can be untargeted, i.e., aiming for an overall accuracy degradation of the trained global model, or targeted, i.e., only supposed to affect certain input, e.g., inject backdoors that lead to wrong model output from input data with a certain chosen feature. In this paper, we focus on untargeted attacks, as they are far-reaching denial-of-service attacks and are more devastating for FL systems.

There have been a number of untargeted attacks on FL [4][7][23]. Yet, some attacks [4][23] assume that the adversary is aware of all of the updates that benign clients send. It is unclear how they can practically obtain such knowledge as clients only share the updates with the benign central server and communication can easily be encrypted even if the adversary has the ability to eavesdrop. Furthermore, clients may even be unaware of each other in practice. In contrast, one variant of Fang attack [7] requires that the attacker has a considerable amount of training data to train substitute benign updates. Although this assumption is realistic for common tasks, e.g., image classification of common pets, the possession of such data is much less likely for special-purpose tasks, e.g., classification of rare deceases based on detailed medical data [22]. Additionally, Fang attack only targets a few defenses and requires knowledge of the exact defenses applied by the central server. In summary, existing attacks can only be deployed in few scenarios with very restrictive assumptions.

In this paper, we show that attacks without such restrictions are possible and similarly effective. Concretely, we aim to design attacks that do NOT require local data or updates from benign clients. They merely require knowledge about the global model, which the central server sends to all participating clients every round. Furthermore, the attacks are supposed to be stealthy and overcome defense mechanisms without knowing the concrete deployed defenses.

We introduce a novel Zero-Knowledge Attack (ZKA) for multi-class image classification tasks. The goal of the attack is to reduce the overall accuracy of the model through the injection of malicious model updates. In each round, the attacker generates malicious images by making use of the received global model and then trains the local adversarial model using those images paired with a randomly chosen class Y. Our first attack variant, ZKA-R, generates synthetic local data by directly Reverse engineering from the training of the current global model. This data generation optimizes towards local synthetic data that is ambiguous according to the current global model, i.e., the current global model should
output each of the $L$ possible classes with equal probability. A local model corresponding to such data diverts the global model and reduces classification accuracy. Yet, its stealthiness is limited. In contrast, our second attack, ZKA-G, iteratively trains a Generator for exploring synthetic images that end up being identified as a class different from the randomly chosen label $Y$. Additionally, for both attacks, we propose to add a regularization term onto the normal loss function for training the classifier that steers the update generation such that updates are not detected as outliers and hence not removed by defenses. ZKA thus stealthily bypasses the defense by ensuring that the deviation to the global model follows similar patterns over multiple rounds.

In our evaluation, we use two datasets — Cifar-10 and Fashion-MNIST — and four defenses: $mKrum$ (short for multi-Krum) [5], TRmean [33], Bulyan [19], and Median [33]. The main metrics of interest are the attack success rate, i.e., the decrease in model accuracy caused by the attack, and the rate at which our attackers pass the defense. We evaluate different levels of data heterogeneity by assigning data to clients according to the Dirichlet distribution, which is a common model for heterogeneous real-world distributions [30]. In comparison to state-of-the-art attacks, ZKA-R and ZKA-G achieves similar results, despite having significantly weaker and more realistic assumptions. Indeed, for all defenses but Bulyan, our attacks perform slightly better than the existing attacks with stronger assumptions.

In detail, ZKA-G is more stealthy and always obtains a higher defense pass rate than ZKA-R. Indeed, for Fashion-MNIST with $mKrum$ as a defense, ZKA-G passes the defense in almost 90% of the cases whereas ZKA-R only passes in about 70%. However, the advantage at passing the defense does not directly translate into a similar advantage in terms of attack success rate. On Cifar-10 with a medium data heterogeneity, ZKA-G always performs better than ZKA-R but the difference are often not statistically significant. When we increase the data heterogeneity, ZKA-R outperforms ZKA-G as the higher diversity of updates increases the difficulty of detection.

In summary, we make the following contributions:

- We design the first ever zero-knowledge untargeted attack on Federated Learning systems, without eavesdropping on benign updates at all.
- The proposed attack combines data and model poisoning through the generation of malicious synthetic data.
- The ZKA-G and ZKA-R achieve slightly higher or similar attack success rate as the state-of-the-art attacks that rely on unrealistic assumptions.

II. FEDERATED LEARNING PREMIER

This section of our paper clarifies concepts in the area of Federated Learning systems, including local training optimization procedures and aggregation mechanisms. Then we summarize the most popular existing defense mechanisms in FL.

A. Federated Learning

As a distributed machine learning framework, Federated Learning (FL) [21, 52] systems consist of a set of $N$ clients and a central server. The global training process considers $R$ consecutive rounds. After model initialization by the server, each client $C_i$ (for $i = 1, 2, ..., N$) trains a local model based on their own real data without sharing the raw data. The server iteratively aggregates and distributes models/gradadients submitted from users until reaching global model convergence. As clients may be offline or unresponsive, it can be that only a subset of them submits updates.

In this paper, we focus on image classification problems with $L$ classes. Let $D_i$ be the local dataset of client $C_i$ and $F$ be the objective function for the classification task. $C_i$ updates its local model weights from the global model $w(t)$ by

$$w_i(t + 1) = w(t) - \eta \frac{\partial F(w(t), D_i)}{\partial w(t)},$$

where $\eta$ is the global uniformed learning rate.

For aggregating models of $K \leq N$ clients, the predominant method for attack-free scenarios is FedAvg [18], which aggregates the new global model as a weighted average of the submitted local models, i.e.,

$$w(t) = \sum_{i=1}^{K} \frac{n_i}{\sum_{k=1}^{K} n_k} w_i(t),$$

where $n_i$ is the number of training samples utilized by $C_i$.

However, the above algorithm is not robust under attacks, hence defenses for securing the aggregation against maliciously crafted updates (also called robust aggregation methods) have been developed.

B. Existing Defense Mechanism in FL

Generally, there are three categories of the defenses: i) Sybil defenses [9] aim at detecting Sybil attackers [9] controlled by one entity and submitting similar updates. For example, FoolsGold [9] identifies Sybils based on the diversity of client contributions using cosine similarity of client updates. ii) Statistic defenses [33] curate the aggregated model by computing the statistics of every parameter across multiple updates. Median [33] utilizes the median value of all updates for each parameter whereas Trimmed mean (TRmean) [33] excludes the minimum and maximum value from the average of each parameter. iii) Outlier detection [5, 19] removes updates based on the pairwise distances of returned models. Higher distance implies that data owned by a user is of low quality or unrelated to the training task. Krum and mKrum [5] select one (or more) updates sent from clients whose update’s cumulative distance to the other updates is low, taking the squared L2 Norm as a metric. Bulyan [19] first selects updates using mKrum and further computes the trimmed mean of the selected gradients. The main difference of Sybil and distance defense is that the former removes the ones of very high similarity whereas the latter does the contrary. Additionally, both outlier detection and statistic defenses can be very effective on various learning scenarios, e.g., different local data distribution.
In this section, we first introduce the threat model for our work. We then compare it to the threat models in previous works and find that they use stronger, often unrealistic assumptions.

A. Threat Model

We assume that communication between clients and the central server uses encrypted and authenticated channels, which prevent eavesdropping and manipulation of data during transmission. As a consequence, attackers are unaware of benign client updates. Benign clients always follow the protocol whereas malicious clients may arbitrarily deviate. All attackers may submit the same update during the whole training process. The central server applies a defense mechanism, which is not known to the clients. We also assume that the server does not apply a defense against Sybils. We added these assumptions for simplicity as we can easily circumvent Sybil defenses by adding small perturbation noise, as shown in the related work \[2\].

Additionally, we assume that malicious parties do not have any data so as to enhance the versatility of the adversary. In practice, the difficulty of obtaining data varies between tasks. It is reasonable to assume that there are tasks relying on rare data that an attacker cannot easily obtain. Our attacks can be applied even if the attacker has data as our evaluation shows that attacks with data do not necessarily outperform our zero-knowledge attack. We assume that all computations are executed by one adversarial party, who then sends the updates to individual malicious clients.

Objectives: The overall objective of an untargeted attack in Federated Learning is reducing the accuracy of the global model maintained by the central server. As a part of achieving this objective, clients need to craft malicious updates that bypass the applied defense.

Capabilities: First, we assume that the number of malicious users controlled by the adversary in the system does not exceed 50% of the total clients. It seems implausible that a defense can overcome a higher number of attackers as defenses typically need a reference for benign behavior. The attacker cannot break cryptographic primitives. More generally, it is computationally bounded so that it cannot solve NP-complete or NP-hard problems. Otherwise, they can arbitrarily control the communication and computation of the malicious clients but not of any other parties in the system.

Knowledge: Neither the defense algorithm nor benign updates is known to the adversary. As the attacker also does not have data, the only knowledge of the adversary is the classification task in general, i.e., the number of classes, training data size, which is accessible as the central server distributes the model.

B. Limitations in Existing Attacks

The three state-of-the-art untargeted attacks are LIE \[4\], Fang \[7\] and Min-Max attack \[23\]. LIE \[4\] calculates the mean and standard deviation of all of the benign updates and sends the following weighted sum back as a malicious update:

\[
 w_{m}(t + 1) = mean(W_{b}(t + 1)) + z * std(w_{b}(t + 1))
\]

where \(W_{b}(t + 1) = \{w_{b}(t + 1)\}\) represent the set of benign models, so as to shift the real mean of the global model. The factor \(z\) is fixed during the duration of the attack. Shejwalkar et. al \[23\] further improves LIE by adapting the scaling factor \(z\) of the weighted sum as well as extending the standard deviation to the sign and unit vector of the gradient. Note that while the authors proposed a number of attacks according to different levels of adversarial knowledge, we only compare to the Min-Max attack and is stronger than the other proposal Min-Sum, which — like our proposal — does not require knowledge of the defense. Fang et. al \[7\] deviate a global model parameter in the direction opposite to the benign updates where knowing the exact defense is necessary for stealthiness.

Table I summarizes the settings of existing untargeted attacks in three dimensions: defense, raw data and benign updates. In the table, ‘Defense-known’ lists the defenses considered in the paper. ‘Defense-unknown’ refers to whether the adversary is still able to attack without knowing exact defense applied by the central server. Furthermore, we consider whether the attacker is aware of benign updates and has raw data. Papers may contain attacks for multiple settings, which is indicated by using both ✓ and ✗ in the table.

Overall, Tab I highlights the following weaknesses of the existing attacks with regard to real-world scenarios:

- **Updates unknown.** Existing attacks fail short in cases when eavesdropping on communication between benign users and the server is not possible, e.g., LIE attack cannot work without benign updates.

- **Data unavailability.** Existing attacks may assume local data and cannot reliably operate without it, e.g., Fang and Min-Max attack.

- **Agnostic defense.** The server does not leak the exact defense mechanism to users, e.g., Fang attack does require knowledge of defenses to reliably circumvent them.

In addition to the aspects raised above, it is important that attacks can deal with heterogeneous data distributions. Generally, the data heterogeneity includes data attribute skew \[9\] and label skew \[14\] and distribution skew \[35\]. Label skew can be pure quantity \[18\] and distribution skew \[55\]. It has been verified that the label skew introduces larger impact on training FL \[37\]. Of the mentioned attacks, LIE attack has not been evaluated for a heterogeneous data distribution.
In a nutshell, none of existing attack has addressed the attack scenario under realistic conditions.

IV. A ZERO-KNOWLEDGE ATTACK

In this section, we propose our zero-knowledge attack (ZKA) with two variants: ZKA-R and ZKA-G. They address the limitations of existing untargeted attacks, which require either benign updates or real data. We first introduce the overall framework. Then, we explain the design, novel objectives functions, and training procedure for synthesizing malicious images.

A. Attacking framework

The overall framework of our proposed attack ZKA is illustrated in Fig. 1. The server first distributes the current global model (classifier) \( w(t) \) to all of the clients. The benign clients truthfully follow the protocol and send the trained model \( w_b(t+1) \) back the server. Malicious clients send the adversarial model \( w_m(t+1) \) instead. Then the server aggregates the submitted updates according to the deployed defense. As attackers do not have real data or benign updates, intuitively, the most obvious approach to attack is to directly change \( w(t) \). However, it is not obvious how to do so as the model weights of neural networks are deeply mapped features without intuitive meaning. We experimented with using random weights but the attack was detected almost always. Concretely, only 2.62% and 6.57% of all updates submitted by malicious clients truthfully follow the protocol and send the trained model \( w_b(t+1) \) back the server. Malicious clients send the adversarial model \( w_m(t+1) \) instead. Then the server aggregates the submitted updates according to the deployed defense. As attackers do not have real data or benign updates, intuitively, the most obvious approach to attack is to directly change \( w(t) \). However, it is not obvious how to do so as the model weights of neural networks are deeply mapped features without intuitive meaning. We experimented with using random weights but the attack was detected almost always. Concretely, only 2.62% and 6.57% of all updates submitted by malicious clients with random model weights bypassed the mKrum defense for Fashion-MNIST and Cifar-10, respectively. For the Bulryan defense, the attack only bypassed the defense in 3.27% of the cases for Fashion-MNIST and always failed for Cifar-10. As manipulating the model directly does not seem a promising approach, we leverage synthetic malicious data according to \( w(t) \) to train the local model every round. The attack process consists of the following two steps.

1. Malicious image generation. In this work, we randomly choose a label \( \hat{Y} \) from all classes and assign it to all of the synthetic data in order to bring bias to damage the model. We propose two methodologies to synthesize malicious images to train the local model. The first is ZKA-R, which is motivated by the fact that the quality of raw data has a significant impact on the training of the classifier. Representative data with correct label can increase the accuracy of the classifier. To mislead it, we generate synthetic ambiguous data by directly reverse engineering from the model. Training with these data results in confusing the model’s optimization objective. Our second method, ZKA-G, explores synthetic images that should be identified as a class different from this randomly chosen label \( \hat{Y} \). As such, the generated noisy images paired with incorrect labels are applied to malevolently update the current model. One thing to notice is that synthetic data does not have true labels, in order to train \( w(t) \) using synthetic data, we need to assign labels accordingly. The details on ZKA-R and ZKA-G are discussed in the following subsections.

2. Adversarial classifier training with distance-based loss. In this step, the attacker uses synthetic data as generated by step 1 to train the classifier \( w_m(t+1) \). The optimization problem of the attack then becomes \( \min_{w_m} (F(w_1, S), \text{where } S \text{ is the generated image set}. \text{ In order to enhance the stealthiness and hence pass the unknown defense, we propose to train with a distance-based loss function } \min_{w_m} (F(w_1, S) + L_d) \text{ with regularization term } L_d \text{ to enhance stealthiness (detailed illustration in Sec. IV-D)}. \text{ The size of } S, |S|, \text{ is a hyper parameter of our attack framework that depends on the task. In the evaluation, we find that using a similar number of images as benign clients produce good results. The adversary can estimate the size during training based on the aggregated results of the global model and the duration that other clients require for training.}

B. ZKA-R synthetic data generation

We construct the synthetic dataset \( S \) such that the current global model assigns probabilities to each class that are as close as possible to equal, i.e., the vector of inference probabilities
is optimally $Y_D = [\frac{1}{L}, \frac{1}{L}, ..., \frac{1}{L}]$, where $L$ is the total number of classes. Such data is bound to confuse the global model.

Fig. 2 depicts the optimization procedure to find $|S|$ malicious images iteratively via two steps: i) generating the malicious image through mapping a random image via a filter layer (i.e., a convolutional layer), ii) optimizing the filter layer through the cross-entropy loss of the global model between the predicted class probabilities and $Y_D$.

To generate a malicious image, we propose to first generate an image $A$, with each pixel being drawn from a uniform distribution, and then transform it to the synthetic image, $B$, through a filter layer \([12]\). In this manner, we train a mapping from randomness to images that have the desired properties. The size of image $B$ is the same as the real image. We let this convolutional layer have kernel size $J \times J$, i.e., the square filter layer between image $A$ and $B$ in Fig. 2. After being filtered from the convolution layer, the image $B$ is then classified by the current global model.

To optimize the convolutional layer that results of ambiguous $Y_D$, we first consider the image $A$, the filter layer, image $B$, and the global model as one big classification problem. Its training objective is to minimize the cross-entropy loss of predicted probabilities of image $B$ and $Y_D$, such that the model cannot predict classes reliably. Different from the regular training of a classification problem, we keep certain parts of the model and input constant. Specifically, the model weights of the global model are frozen. Furthermore, the image $A$ is a static input. Without static randomness, we would need to re-train whenever we change the randomness. Keeping the number of trainable parameters to a minimum, we optimize the efficiency of the attack. The only trainable parameters here are the parameters of the filter layer. It takes $E$ epochs to train this convolutional layer. Upon finishing training, the image $B$ is one data instance of $S$. To increase the diversity of the training dataset $S$, for each FL training round, we repeat the above process for $|S|$ times to construct $S$.

**C. ZKA-G synthetic data generation**

In contrast to ZKA-R, we proactively synthesize images through a generator, which is also trained in multiple epochs to mislead the global classifier. Since we assign a randomly chosen label $\hat{Y}$ for all of the synthetic data, the goal of training the generator is to adjust its synthesizing model according to the feedback of $w(t)$, i.e., the results of classification measured by cross-entropy loss \([16]\). Typically, benign training minimizes the cross-entropy of the prediction and true label so that the model can output an accurate prediction. However, as our goal is to reduce the model accuracy, we maximize the cross-entropy of the prediction and $\hat{Y}$ to train $G$, steering the generated images away from $\hat{Y}$.

The exact training procedure for the generator is shown in Fig. 3. We first draw a random noise vector $Z$ from the Gaussian distribution and input $Z$ into a generator $G$ to synthesize malicious images. We use the same random seed over multiple rounds so that the trained generator is able to consistently produce synthetic data different from class $\hat{Y}$. The network structure of the generator is a transpose convolution neural network (TCNN), which outputs task-specific image size data $S = G(Z)$. The size of real data can be obtained from $w(t)$.

Specifically, we use a lightweight TCNN of two transposed convolutional layers and one convolutional layer following the structure of the popular WGAN paper \([1]\). The model parameter of the generator $G$ is randomly initialized before training, denoted as $\theta$. As the generator aims at synthesizing images that differ from the chosen class $\hat{Y}$, the objective function of $G$ is $\max_{\theta} F(w(t), (S, \hat{Y}))$ where $S$ is generated from $\theta$. After training $G$ locally for $E$ epochs until convergence, the synthetic images are leveraged to train $w_m(t + 1)$.

**Difference between ZKA-R and ZKA-G.** In summary, differences between the two variants are \(i\) the objective functions, \(ii\) the use of $\hat{Y}$, and \(iii\) the randomness in their inputs. For \(i\), ZKA-R generates ambiguous data by minimizing the cross-entropy loss between the prediction of $w(t)$ and the vector $Y_D$. In contrast, ZKA-G synthesizes images different from a randomly chosen class, $\hat{Y}$, by maximizing the cross-entropy loss between the prediction of $w(t)$ and $\hat{Y}$. As a consequence, for \(ii\), ZKA-R aims to generate images such that the global model assigns a equal probability to all labels, including $\hat{Y}$, while ZKA-G aims to minimize the probability for generated images being inferred as class $\hat{Y}$ by the current global model. For \(iii\), the random inputs of ZKA-R are much bigger than for ZKA-G, i.e., the entire image $A$ vs. a random
vector $Z$, giving more image diversity in ZKA-R. All together, images generated by ZKA-R are more malicious and less stealthy than ZKA-G.

To give an intuition on the difference of the two image synthesizing methods, we show the empirical variance of data points generated for the Fashion-MNIST dataset in Fig. 4. The detailed experimental settings as well as the information of the dataset is in Sec. V. To visualize the $2 \times (|S| \times 1 \times 28 \times 28)$ synthetic images (here $|S| = 50$), UMAP dimension reduction \cite{6} has been applied to project the high dimension data into two X-Y dimensions. As shown in Fig. 4, ZKA-R results in higher variance on synthetic data than ZKA-G. This confirms our expectation that ZKA-R has more randomness as it randomly initializes full-size images to train the convolutional layer while ZKA-G only inputs a random vector to the generator. As a result, ZKA-R uses more diverse data to update the global classifier and the corresponding local model. It thus has a higher deviation from the latest global model. In contrast, data generated by ZKA-G has a lower variance so that training by such data introduces smaller deviation from the latest global model.

Fig. 4: UMAP projection of the synthetic data compared for ZKA-R and ZKA-G on Fashion-MNIST.

D. Distance-based Regularization

State-of-the-art defenses in a FL system are mainly based on the pairwise distances among multiple updates. In order to bypass the defense mechanisms, we introduce a distance-based regularization term when training the malicious classifier with the aim to further enhance stealthiness of the malicious updates. The concrete regularization term is

$$L_d = \| w - w(t) \|_2 - \| w(t) - w(t - 1) \|_2. \quad (3)$$

In Eq. 3, the first term refers to the weight differences of the malicious update and the current model. Analogously, the second term refers to the difference between the current model and the model of the previous round. We add this regularization after the cross-entropy loss in the objective function of the malicious classifier to avoid extremely high changes of the model weights, which can be easily detected by the defense. Thus, in both ZKA-R and ZKA-G, we guide the training such that the differences in weights are similar to the ones in previous rounds, as indicated with the two most recent global models.

E. Attack complexity

The communication complexity of ZKA-R and ZKA-G $O(M)$, i.e., the cost of sending malicious updates to $M$ attackers. We thus focus on analyzing the additional computation overhead, which is the main cost factor for our proposed algorithms. We discuss the complexity of ZKA-R and ZKA-G in FL systems.

Computation ZKA-R. We note that $|S|$ is a hyper parameter whose optimal values depend on the learning task, attack, defense, and population of benign and malicious clients. First, there is noisy input generation of complexity $O(|S|I^2)$ given image size $I \times I$. Then, if the size of the kernel in convolutional layer is $J \times J$, training the layer requires $O(|S|J^2P^2)$ where $Q$ is the complexity factor of training the classifier \cite{12}. Training the local classifier with synthetic data is $O(|S|QI^2)$. Thus, the total computation overhead is $O(|S|J^2QI^2)$.

Computation ZKA-G. Similar to ZKA-R, ZKA-G requires noisy input generation of complexity $O(|S|I^2)$ as well as classifier training of complexity $O(|S|QI^2)$. One of the additional steps for ZKA-G is generating images by TCNN, which has complexity $O(|S|P^2)$ where $P$ is the complexity factor for generating images by noises related to the structure and size of the neural network \cite{12}. And the other additional step is updating the generator by the inferred results, which is also $O(|S|P^2)$ due to the same network structure. Hence, the total computation complexity is $O(|S|(P + Q)I^2)$. Note that the overall complexity for training the generator as well as the convolutional layer of ZKA-R is multiplied by the number of epochs $E$, except for the classifier training.

Computation benign clients For comparison, computing a benign update of client $C_i$ has complexity of $O(D_i |Q|I^2)$. If $|D_i| \approx |S|$, the only difference are $J^2$ and $P$ for ZKA-R and ZKA-G, respectively. As these factors are typically small and adversarial computation power may well exceed the resources of benign clients, the attacker should be able to compute their updates within the same time as a benign client.

V. EXPERIMENTAL EVALUATION

In this section, we empirically evaluate the effectiveness of our proposed zero-knowledge untargeted attack, on two commonly used image classification benchmarks. We compare the attack success rate and defense pass rate for various settings with three state-of-the-art baseline attacks that requires full knowledge of benign updates or real data: LIE \cite{4}, Fang \cite{7} and Min-Max attacks \cite{14}. We show the impact of varying degree of data heterogeneity as well as the effectiveness of our building blocks. All of the results reported in this section are averaged over three runs to alleviate the influence brought by random factors.

A. Experiment Setup

FL system. The FL system considered in this paper contains 100 clients. In typical real-world FL systems, some of the clients could be offline or unavailable temporarily and hence not all of them might be able to participate in the whole training process.

```python
# Python code for experiment setup
```
Thus, as in previous work [2] [18] [23], 10 of the available clients are selected uniformly at random each round. Clients train the classifier locally for one epoch. We assume that the adversary is able to manipulate 20% of the clients.

Datasets and networks. In this work, we consider two datasets. Fashion-MNIST consists of a training set of 60,000 examples and a test set of 10,000 fashion-related images. Each instance is a $28 \times 28$ grayscale image, associated with a label from 10 classes. Cifar-10 contains 50,000 training images of 3-channel RGB images and 10,000 of test images. Similarly for Fashion-MNIST and Cifar-10, they have 10 classes in total and images are evenly distributed over classes. The total number of images used to train in this paper is reduced to 10%, chosen uniformly at random in order to model real-world scenario that full data may not be available during the whole training. This amount is verified to be sufficient for training on Cifar-10 and Fashion-MNIST [3]. For these two datasets, we use representative neural networks with 2 and 6 convolutional layers connected with 1 and 2 densely-connected layers respectively to map the inputs and outputs.

Defense mechanisms. Four state-of-the-art defenses are evaluated in our work: $mKrum$, $TRmean$, $Bulyan$ and $median$. We do not apply $Krum$ since $mKrum$ interpolates between $Krum$ and averaging, thereby allowing the trade-off between the resilience properties and the convergence speed [5]. Among these four, $mKrum$ and $TRmean$ are more lenient while the others are more aggressive, i.e., they are more likely to exclude updates from the averaging process.

Data heterogeneity. To emulate a heterogeneous distribution, we assign data to clients according to the commonly used Dirichlet distribution. It emulates a real-world data distribution and the degree of heterogeneity is governed by the hyper parameter $\beta$ [30], indicating the level of heterogeneity. In Subsec. V-D, we vary $\beta$ from 0.1 to 0.9 in order to demonstrate our effectiveness for different degrees of data heterogeneity. Higher $\beta$ means a lower degree of data heterogeneity. For our experiments except for Sec. V-D, we choose $\beta = 0.5$, as in the prior work [10] [50].

Hardware. Our FL emulator is based on Pytorch and we run experiments on a machine running Ubuntu 20.04, with 32 GB memory, a GeForce RTX 2080 Ti GPU and a Intel i9 CPUs with 10 cores (2 threads each).

B. Evaluation Metrics.

We utilize two main metrics to evaluate the effectiveness of our attack. i) Attack success rate (ASR) is defined by:

$$ASR = \frac{acc_{\text{drop}}}{acc_{\text{benign}}} \times 100\%,$$

where $acc_{\text{drop}}$ refers to the decrease of accuracy caused by attacks. Specifically, it is the difference $acc_{\text{natk}} - acc_{\text{max}}$ between the the global accuracy $acc_{\text{natk}}$ without attacks and defenses and the maximum accuracy $acc_{\text{max}}$ of the global model during one experiment with attacks. ASR specifies the effectiveness of an attack strategy through the decrease in accuracy.

ii) Defense pass rate ($DPR$) is a metric to measure the stealthiness of an attack. In our paper, it is defined by the proportion of attackers who have passed the defense ($num_{\text{pass} - \text{mal}}$) from all of the randomly selected attackers ($num_{\text{sel} - \text{mal}}$):

$$DPR = \frac{num_{\text{pass} - \text{mal}}}{num_{\text{sel} - \text{mal}}} \times 100\%.$$

$DPR$ as defined above requires that defenses select updates for aggregation rather than compute statistics on all updates. Thus, as detailed Sec. I-B $DPR$ can only be computed for $mKrum$ and $Bulyan$, but not on $TRmean$ and $Median$.

Baselines. We are the first to propose zero-knowledge untargeted attacks. So there is no direct baseline to compare to. To demonstrate the effectiveness, we compare our results with the three state-of-the-art attacks LIE [4], Fang [7] and Min-Max [23] that requires knowledge of benign updates or data. We make the following choices regarding the parametrization of the defenses. As defenses are unknown to the attacker in our scenario, we implement the version of the Min-Max attack that is designed for unknown defenses and achieves the best results. For the Fang attack, the original paper assumed knowledge of the defense. We here use the version of the Fang attack that assumes $TRmean$ or $Median$ as the defense, which is the only source code provided by the authors. Otherwise, we use the parameters that produced the best results in the original papers.

C. Comparison with baselines

ASR and DPR. Our main results for the attack success rate and defense pass rate are shown in Tab. II and Fig. 5. Among all of the baseline methods, Min-Max attack is the most successful attack, with high ASR even on low DPR. In general, our experimental evaluation demonstrates that the proposed zero-knowledge attack strategies, ZKA-R and ZKA-G, are able to achieve similar or even slightly higher attack success rate than the baseline attacks, which require full knowledge of benign updates or a large quantity of raw data. ZKA-G outperforms ZKA-R in terms of DPR for both datasets, which confirm its stealthiness.

Specifically, from the results of Fashion-MNIST, ZKA-R is better than ZKA-G and all baselines when $mKrum$ and $TRmean$ are used to defend. It is because $mKrum$ and $TRmean$ are more lenient than $Bulyan$ and $Median$. $Bulyan$ rejects on average more updates while $Median$ merely includes the median of each model parameter from all of the clients. Correspondingly, ZKA-R perform better under more lenient defense as it generates more diverse and ambiguous synthetic images to cause misclassification and it can be detected by other aggressive defenses. On the other hand, ZKA-G performs well for Cifar-10 due to the fact that training Cifar-10 network with more layers (parameters) results in slower convergence so that it favours attacks that continuously passing the defenses. Also, the use of 3-channel RGB data increases the diversity of benign updates. As a consequence, the level of uncertainty is generally higher during training, so that it becomes easier to pass the defense as the benign updates are not consistent enough to act
TABLE II: Attack success rate (ASR) and the maximum accuracy (acc) accordingly under attacks on Dirichlet distribution. \( \beta = 0.5 \). The accuracy without attacks and defenses \( \text{acc}_{\text{natk}} \) for Fashion-MNIST and Cifar-10 is 82 and 50 respectively, it is reasonable for our lightweight CNN [4].

| Dataset   | Defense | Fang | LIE | Min-Max | ZKA-R | ZKA-G |
|-----------|---------|------|-----|---------|-------|-------|
|           | acc (%) | ASR (%) | acc (%) | ASR (%) | acc (%) | ASR (%) | acc (%) | ASR (%) |
| Fashion-MNIST | mKrum | 73.5 | 10.37 | 72.7 | 11.34 | 67.3 | 17.93 | 52.6 | 35.85 | 64.3 | 21.59 |
|           | TRmean | 20.0 | 26.86 | 49.1 | 75.29 | 12.3 | 13.92 | 12.3 | 35.85 | 51.3 | 27.44 |
|           | Bulyan | 68.1 | 36.91 | 75.0 | 8.54 | 56.8 | 24.39 | 70.8 | 13.66 | 59.8 | 27.07 |
|           | Median | 56.1 | 25.49 | 73.4 | 10.49 | 62.0 | 24.39 | 62.0 | 24.39 | 60.9 | 25.73 |
| Cifar-10  | mKrum | 34.1 | 31.80 | 33.5 | 33.00 | 27.8 | 44.40 | 24.6 | 50.80 | 24.4 | 51.20 |
|           | TRmean | 13.9 | 72.20 | 13.1 | 73.80 | 12.6 | 44.40 | 14.4 | 71.20 | 12.5 | 75.00 |
|           | Bulyan | 28.4 | 43.30 | 31.4 | 37.20 | 21.2 | 57.60 | 22.2 | 55.60 | 21.7 | 56.60 |
|           | Median | 24.5 | 51.00 | 37.0 | 26.00 | 24.9 | 50.20 | 24.7 | 50.60 | 23.8 | 52.40 |

Fig. 5: Defense pass rate (DPR) on Dirichlet distribution. \( \beta = 0.5 \).

We now consider the baseline attacks in more detail. LIE appears to be weaker than other attacks since it applies only a minor static shift to the mean of benign updates in order to pass defenses. This results in LIE’s high DPR but it limits its attack effectiveness. In contrast, Min-Max attack trains (maximizes) the scale of the shifting from the mean of benign updates each round so as to enhance effectiveness, especially under heterogeneous data. This the reason why it achieves good ASR even with low DPR. The few times it overcomes the defense are sufficient for the carefully crafted updates to permanently damage the model. Fang attack has the least DPR, as it steers the global model parameters to the reverse direction. It is even more easily detected by the defenses than Min-Max, to the extent that the attack effectiveness is severely reduced.

**D. Data heterogeneity level**

We evaluate the impact of different levels of data heterogeneity on the ASR of attacks. Specifically, we choose \( \beta = 0.1 \) as the most heterogeneous case while \( \beta = 0.9 \) is the least heterogeneous case. Tab. III displays the results for both datasets when **Bulyan** is used as a defense, which is an aggressive and the most challenging defense for our attack, as can be seen from Tab. I. In general, the effectiveness for all attacks increases with an increased level of data heterogeneity, since more heterogeneity means that the benign updates are more diverse and hence detection of outliers is harder. The global model accuracy decreases on more heterogeneous data without attacks. This is consistent with the intuitive expectation that data of higher heterogeneity in an FL system results into poorer global accuracy within the same number of training rounds.

From Tab. III, we can observe that for the aggressive **Bulyan** defense, the Min-Max attack achieves mostly the best performance among all of the attacks. Attacks with full knowledge of benign updates as well as adaptive weights for maliciously shifting the mean are expected to work better. That is especially true under aggressive defenses because in contrast to our attacks, Min-Max has access to the information necessary to ensure their updates are less suspicious than others. Yet, thanks to the enhanced stealthiness, ZKA-G outperforms Min-Max when data is less heterogeneously distributed among clients. Accordingly, ZKA-R achieves the best results when \( \beta = 0.1 \) on Cifar-10 dataset. In this scenario, the requirement of stealthiness is the least for all of the six scenarios because Cifar-10, as discussed above, has more diverse updates and the high degree of heterogeneity further increases the diversity, making it hard to detect outliers. Additionally, the ASR of LIE and Fang attack decreases drastically with decreased heterogeneity. LIE attack adds a static minor shift to the true mean as it is designed to attack independent and identical distribution scenarios. For more heterogeneous updates, LIE attack is more likely to pass the defense and have an impact. Fang attack usually requires knowledge of the defense; in the absence of this knowledge, it fares better when its behavior is harder to be detected.

**E. Micro-benchmark analysis**

1) **Generator training epochs**: Here, we empirically investigate the convergence towards the optimal loss, where ZKA-R is minimizing its loss but ZKA-G is maximizing it. Fig. 6 shows the results for Fashion-MNIST on all four defenses.
TABLE III: ASR(%) on different data heterogeneity level. Accuracies without attacks and defenses on $\beta = 0.1, 0.5, 0.9$ are 80, 82, 83 for Fashion-MNIST, and 42, 50, 52 for Cifar-10 respectively.

| Dataset     | heterogeneity | Fung | LIE | Min-Max | ZKA-R | ZKA-G |
|-------------|---------------|------|-----|---------|-------|-------|
| Fashion-MNIST | $\beta = 0.1$ | 39.11 | 28.75 | 55.13 | 49.00 | 51.88 |
|             | $\beta = 0.5$ | 16.91 | 8.54 | 30.73 | 13.66 | 24.63 |
|             | $\beta = 0.9$ | 8.86 | 7.83 | 14.58 | 9.64 | 16.63 |
| Cifar-10    | $\beta = 0.1$ | 50.12 | 46.90 | 60.71 | 67.14 | 54.76 |
|             | $\beta = 0.5$ | 43.30 | 37.20 | 57.60 | 55.60 | 56.60 |
|             | $\beta = 0.9$ | 34.65 | 38.85 | 61.73 | 53.27 | 54.23 |

It can be clearly seen that the local training for generating malicious images converges to a local optimum. For both of our proposed attacks, ZKA-R and ZKA-G, we only need few epochs to train.

![Fig. 6: Local training process of ZKA-G on Fashion-MNIST.](image)

2) Comparison with non-training approach: Given that the training converges fast, we also investigate the impact of training in comparison to just using a randomly initialized filter layer for ZKA-R and a randomly initialized generator for ZKA-G without any updating over rounds. As explained, according to the definition, DPR is measured only on mKrum and Bulyan defenses. We hereby report the results for TRmean and Median as “NA”. The maximum accuracies without attack are the same as Tab. [I]

The results can be seen in Tab. [IV] and confirm that training according to the current global model is indeed necessary. For ZKA-R, training the single layer aims at generating images that confuse the global model. Without the training step, the injection of ZKA-R is less malicious. Thus, ASR usually decreases without training, except for Fashion-MNIST with Bulyan defense. This observation is due to the fact that training ZKA-R reduces the stealthiness of the attack by focusing on effectiveness and hence ZKA-R passes Bulyan more without training. This is consistent with our results in Fig. [V] that Bulyan significantly reduces the DPR of ZKA-R.

When it comes to ZKA-G, training helps to enhance stealthiness. The impact can be clearly seen from the results for DPR in Tab. [V] especially for Bulyan. Only for a relatively lenient defense like mKrum, the training has little additional impact as DPR is already high without training. These results also reflect the minor increase of DPR from Fashion-MNIST to Cifar-10 dataset for mKrum in Fig. [V].

3) Impact of the regularization term: In this part, we conduct an ablation study for our proposed distance-based loss which adds a regularization term to the original cross-entropy loss function. Tab. [V] shows both ASR and DPR with and without the regularization term on Fashion-MNIST. For ZKA-R, the effectiveness of the regularization term is more apparent for less aggressive defenses, but not significant for Median. However, for ZKA-G, the opposite holds, with the increase being most notable for more aggressive defenses. This is because the regularization term in the less stealthy ZKA-R is insufficient encountering aggressive defenses whereas it is what enables ZKA-G to pass these defenses frequently. In contrast, ZKA-G does not require the regularization term for weaker defenses as it already passes them.

TABLE IV: ASR and DPR for (non)-training approach where “Static” refers to non training way with only randomly initialized. “Fashion” and “Cifar” is short for Fashion-MNIST and Cifar-10 datasets.

| Attack | Defense | Static ASR(%) | Static DPR(%) | Trained ASR(%) | Trained DPR(%) |
|--------|---------|---------------|---------------|---------------|---------------|
| ZKA-R  | mKrum   | 18.17         | 87.78         | 35.85         | 70.33         |
|        | TRmean  | 37.20         | NA            | 73.29         | NA            |
|        | Bulyan  | 23.66         | 57.50         | 13.66         | 6.86          |
|        | Median  | 21.22         | NA            | 24.39         | NA            |
| ZKA-G  | mKrum   | 17.07         | 88.33         | 21.59         | 89.02         |
|        | TRmean  | 30.73         | NA            | 37.44         | NA            |
|        | Bulyan  | 24.88         | 65.26         | 27.07         | 69.33         |
|        | Median  | 22.44         | NA            | 25.73         | NA            |
| ZKA-R  | mKrum   | 50.00         | 85.20         | 50.80         | 86.04         |
|        | TRmean  | 71.14         | NA            | 71.20         | NA            |
|        | Bulyan  | 56.00         | 60.98         | 55.65         | 61.05         |
|        | Median  | 48.60         | NA            | 50.60         | NA            |
| ZKA-G  | mKrum   | 38.60         | 56.46         | 51.20         | 88.14         |
|        | TRmean  | 71.40         | NA            | 75.00         | NA            |
|        | Bulyan  | 47.80         | 37.35         | 56.60         | 63.99         |
|        | Median  | 50.60         | NA            | 52.40         | NA            |

TABLE V: ASR and DPR for ablation test of the regularization term proposed by our distance-based loss.

| Attack | Defense | without regularization ASR(%) | without regularization DPR(%) | with regularization ASR(%) | with regularization DPR(%) |
|--------|---------|-------------------------------|-------------------------------|---------------------------|---------------------------|
| ZKA-R  | mKrum   | 17.68                         | 41.92                         | 35.85                     | 70.33                     |
|        | TRmean  | 58.78                         | NA                            | 73.29                     | NA                        |
|        | Bulyan  | 10.73                         | 3.32                          | 13.66                     | 6.86                      |
|        | Median  | 23.72                         | NA                            | 24.39                     | NA                        |
| ZKA-G  | mKrum   | 20.98                         | 87.34                         | 21.59                     | 89.02                     |
|        | TRmean  | 31.71                         | NA                            | 37.44                     | NA                        |
|        | Bulyan  | 22.32                         | 60.27                         | 27.07                     | 69.33                     |
|        | Median  | 23.78                         | NA                            | 25.73                     | NA                        |
4) Effectiveness of our synthetic data: In order to demonstrate the effectiveness of our malicious synthetic data, we compare the attack success rate of our attacks to a version of the attack that uses real data rather than synthetic data, i.e., we use a set of real images instead of the synthetic image set $S$. We assign the number of real images owned by the attackers under the same Dirichlet distribution as for benign users. The results for the four defenses on both datasets are shown in Fig. 7 with stripped visualization. “Real-data” in the figure refers to the results of ASR using real data paired by the uniformly chosen label $\tilde{Y}$ to train $\tilde{w}(t)$ with distance-based loss as described in Sec. III similarly for the synthetic data. Fig. 7 shows the effectiveness of our malicious synthetic data generated by ZKA-R and ZKA-G as ASR significantly outperforms the case of using real images. That is expected because our synthetic images are specifically constructed such that the attack is very effective but at the same time stealthy.

Moreover, attacks can also be categorized by the component which attacks act upon. During the training time, the adversary may inject malicious data with dirty labels to train the local model, e.g., label flipping [28] and trigger injection [2, 31]. For example, backdooring [2] is executed by injecting trigger-based malicious samples [2, 36] into the local training dataset. DBA [31] then extends the study [2] to bypass Sybil defenses such as FoolsGold [9]. There is also clean label data poisoning such as watermarking [27]. Modeling poisoning [2, 4, 7, 23, 31] manipulates the submitted model rather than merely adopting malicious data to train, e.g., submit updates of the reversed sign of training gradient [7]. Generally, model poisoning attacks require sophisticated technical capabilities such as eavesdropping and sufficient computation resources.

For our zero-knowledge attack proposed in this paper, it is one type of untargeted attack according to the objective. Based on the way to do attack, it is a combination methodology of data poisoning and model poisoning via synthetic data.

VI. RELATED WORK

Due to the privacy-preserving benefits brought by sharing model gradients or weights rather than raw data in Federated Learning, FL systems are vulnerable to malicious behaviors. Attacks can happen during the training time [2, 4, 7, 23, 31] or inference time [20, 24, 34]. For the inference attacks, attackers aim to infer private data [20]. They may even reconstruct the private local training data [34]. In this paper, we focus on training-time attacks where attackers participate in the training. We summarize the training-time attacks from two perspectives: i) the attack objectives and ii) the attacked component of the FL system, e.g., data or model.

There are three popular attack objectives: free-rider, untargeted, and targeted attacks. Lin et. al. [13] first propose stealthy free-rider attacks in FL, which aim at obtaining the global model without contributing data and computation. Fraboni et. al [8] then provide theoretical guarantees on global model convergence for free-riders. Another category known as targeted attack aims to achieve high backdooring accuracy without impacting the global model accuracy [2, 31]. The third type is an untargeted attack, whose objective is to decrease the global model accuracy and even interfere with its convergence. There are three state-of-the-art untargeted attacks namely LIE [4], Fang [7] and Min-Max [23] attack. They attack the global model using different settings. Generally, they construct the malicious updates by shifting the mean of benign updates within a range to avoid being detected. However, they all assume adversarial knowledge of benign model, defenses or real data.

Fig. 7: Comparison of ASR (%) of real data and synthetic data by ZKA-R and ZKA-G with four defenses on Fashion-MNIST and Cifar-10.

This work focuses on the challenging scenario of untargeted attack without knowing benign updates, real data, and applied defense mechanisms in Federated Learning systems. We propose ZKA, a novel zero-knowledge attacking framework to effectively decrease global model accuracy by continuously injecting destructive updates trained on malicious synthetic data. To generate synthetic data, we propose two variants ZKA-R and ZKA-G, which differ in their stealthiness-effectiveness trade-off. Synthetic data generated by both variants is trained using our novel distance-based regularization term to enhance stealthiness. The experimental evaluation confirms the effectiveness of our proposed attack with similar or even higher attack success rate than state-of-the-art attacks with stronger assumptions. ZKA leverages both model poisoning and data poisoning and is powerful in various settings. This work shows that attacks on FL can be very effective, even for an attack with zero-knowledge and in the presence of defenses. Indeed, we find that synthetic data, generated specifically for an effective attack, can outperforms attacks that rely on real data. The results highlight that FL is in need of stronger defenses.

REFERENCES

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