FedDef: Robust Federated Learning-based Network Intrusion Detection Systems Against Gradient Leakage

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Abstract—Deep learning methods have been widely applied to anomaly-based network intrusion detection systems (NIDS) to detect malicious traffic. To expand the usage scenarios of DL-based methods, the federated learning (FL) framework allows intelligent techniques to jointly train a model by multiple individuals on the basis of respecting individual data privacy. However, it has not yet been systematically evaluated how robust FL-based NIDSs are against existing privacy attacks under existing defenses. To address this issue, in this paper we propose two privacy evaluation metrics designed for FL-based NIDSs, including leveraging two reconstruction attacks to recover the training data to obtain the privacy score for traffic features, followed by Generative Adversarial Network (GAN) based attack that generates adversarial examples with the reconstructed benign traffic to evaluate evasion rate against other NIDSs. We conduct experiments to show that existing defenses provide little protection that the corresponding adversarial traffic can even evade the SOTA NIDS Kitsune. To build a more robust FL-based NIDS, we further propose a novel optimization-based input perturbation defense strategy with theoretical guarantee that achieves both high utility by minimizing the gradient distance and strong privacy protection by maximizing the input distance. We experimentally evaluate four existing defenses on four datasets and show that our defense outperforms all the baselines with strong privacy guarantee while maintaining model accuracy loss within 3% under optimal parameter combination.

Index Terms—Federated Learning, Intrusion Detection, Gradient Privacy Leakage

I. INTRODUCTION

Deep learning-based network intrusion detection system (NIDS) have been widely used in diverse security domains to detect malicious traffic activities and intrusion attacks, they are expected to raise alarms whenever the incoming traffic carries malicious properties (e.g. scan user’s ports) or induces attacks (e.g. DDoS). Recently, researchers have been trying to adopt federated learning (FL), where multiple users collaboratively exchange information and train a global model with publicly shared gradients, to derive more accurate detection of cyberattacks without privacy leakage. For example, [1] proposes a decentralized federated architecture that collaborates with eleven Internet Exchange Points (IXPs) that operate in three different regions, which allows participant mitigation platforms to exchange information about ongoing amplification DDoS attacks, experimental results show that such collaboration can detect and mitigate up to 90% more DDoS attacks locally, which proves great success for faster and more effective detection and neutralization of attack traffic among collaborative networks. Another work [2] also proposes an autonomous federated learning-based anomaly detection system to locate compromised Internet of Things (IoT) devices with high detection rate (95.6%) and fast inference (257ms), while [3] further proposes a FL-based NIDS for industrial cyber-physical systems in real world. These new researches indicate a promising trend that combination with federated learning can improve the overall detection performance of NIDS and is receiving extensive attention.

However, recent works demonstrated that sharing model updates or gradients also makes FL vulnerable to inference attack in computer vision (CV) domain, e.g., property inference attack that infers sensitive properties of training data [4] and model inversion attack that reconstructs image training data [5]–[8]. Accordingly there has also been some defense strategies such as differential privacy for deep learning [9] and Soteria [10] that perturbs the data representation features for images. However, unlike CV domain where slight noises added to the images can induce totally different visual perception and thus have higher tolerance for privacy, the reconstruction of traffic data may be more intimidating as adversaries can train GAN model with the reconstructed benign data to generate new malicious traffic to launch black-box adversarial attack to evade the target FL model or other NIDSs. Unfortunately, no researches have systematically investigated to what extent current defenses combined with NIDS can protect user privacy, and whether there exist defense strategy that achieves both high utility and strong privacy guarantee to build a more robust FL-based NIDS.

To derive a more accurate evaluation of privacy for FL-based NIDSs, we propose two privacy metrics specifically designed for NIDS domain, i.e. privacy score and evasion rate. For the first one, we leverage reconstruction attacks, i.e. inversion and extraction attack, to recover the original training data from model gradients. Then we can calculate the similarity between raw data and the reconstructed one to evaluate privacy leakage, where we use different distance metric for continuous (e.g. traffic duration) and discrete features (e.g. protocol type). After we obtain enough reconstructed
traffic, we can evaluate evasion rate by training Generative Adversarial Network (GAN) model to generate adversarial traffic to attack other NIDSs, which presents the practical threats in real world. With the above privacy metrics, we evaluate existing defenses combined with FL-based NIDS and demonstrate that all the baselines fail to provide sufficient privacy protection and the adversarial traffic can even evade the SOTA NIDS Kitsune [11], which urges for new effective defense strategy.

To bridge this gap and build a more robust FL-based NIDS, we further propose a novel input perturbation-based defense approach with theoretical guarantee for model convergence and data privacy named FedDef, which optimizes an objective function to transform the original input such that: 1) the distance between the new input and the raw input is as far as possible to prevent privacy leakage and 2) the corresponding gradients are as similar as possible to maintain model performance. Experimental results on four datasets show that our defense can easily mitigate both reconstruction attacks and achieve high privacy score during the whole FL training phase, and the following GAN-based adversarial attack fails to evade other NIDSs, which significantly outperforms other baselines. For model performance, we show that the FL model can still converge under our defense with iid or non-iid data distribution, and that model accuracy can be guaranteed within at most 3% loss with the optimal parameter combination.

Contributions. We summarize our contributions as follows:

- We propose two privacy evaluation metrics designed for FL-based NIDS, including privacy score that evaluates the similarity between raw traffic feature and the recovered feature using reconstruction attacks, and evasion rate against NIDSs from GAN-based adversarial traffic.

- To the best of our knowledge, we are the first to propose an optimization-based input perturbation defense scheme for NIDS in federated learning to prevent privacy leakage while maintaining model performance.

- We provide theoretical analysis for model convergence and privacy guarantee for our defense.

- Experimental results on four datasets show that our defense outperforms current defense approaches and can defeat two reconstruction attacks and the following GAN-based adversarial attack while also maintaining high model accuracy.

The rest of the paper is organized as follows: In section [II] we introduce some background for FL-based NIDS and recent work with respect to reconstruction attacks and existing defenses. In section [III], we present our threat model including reconstruction attack, GAN-based adversarial attack and the corresponding privacy metrics with evaluation example. In section [IV] we introduce our defense design and detailed implementation. We provide theoretical analysis for model convergence and privacy guarantee with our defense in section [V]. In section [VI] we evaluate our defense along with other four baselines on four datasets with respect to privacy preserving and model performance. We discuss some future work in section [VII] and conclude this study in section [VIII].

II. PRELIMINARIES

In this section, we first introduce some background of FL-based NIDS (II-A), then we present two SOTA reconstruction attacks (II-B) and current defenses accordingly (II-C).

A. Federated Learning-based NIDS

FL-based NIDS is a new promising research topic that combines federated learning [12] with intrusion detection. Local users first extract features from their private traffic data and then update the global model with the derived gradients, which are aggregated at the trusted server for later distribution.

For example, [13] proposes a FL-based anomaly detection approach to proactively recognize intrusion in IoT networks using decentralized on-device data. [14] presents a communication-efficient FL-based framework for sensing time-series data with attention-based neural network in industrial IoT. Some work also consider privacy-preserving and interpretable FL to further enhance practical NIDS [15], [16].

However, although FL has achieved great success because users can collaboratively train a model by only updating gradients instead of raw data to preserve privacy, recent work, as we will show in [II-B], has demonstrated that FL is also vulnerable to gradient inversion attack which can still reconstruct the raw data and thus induce great privacy issues.

B. Reconstruction Attack

Recently, researches show that FL also faces privacy leakage, and there exist several adversarial goals to infer private information: data reconstruction, class representative inference, membership inference, and attribute inference, among which data reconstruction poses the greatest threats that aim to recover training samples used by participating clients. Current reconstruction attack can be categorized into two types, i.e. optimization-based inversion attack and accurate extraction attack.
TABLE I: A summary of existing defense approaches.

| Approach          | Category           | Setting   | Privacy | Utility | Theoretical Guarantee | Scalability | Feasibility |
|-------------------|--------------------|-----------|---------|---------|------------------------|-------------|-------------|
| MPC [17]          | Generative         |           | ●       | ●       | ●                      | ●           | ○           |
| DataLens [18]     | MPC                |           | ●       | ●       | ○                      | ●           | ○           |
| DP [9], [15], [19]| Gradient Perturbation |           | ●       | ●       | ○                      | ●           | ○           |
| GP [20]           | Gradient Perturbation |           | ●       | ●       | ○                      | ●           | ○           |
| Lossless [21]     | Gradient Perturbation |           | ●       | ●       | ○                      | ●           | ○           |
| Instahide [22]    | Input Perturbation  |           | ●       | ●       | ○                      | ●           | ○           |
| Soteria [10]      | Input Perturbation  |           | ●       | ●       | ○                      | ●           | ○           |
| ATS [23]          | Input Perturbation  |           | ●       | ●       | ○                      | ●           | ○           |
| FedDef (Ours)     | Input Perturbation  |           | ●       | ●       | ○                      | ●           | ○           |

Notes: ●, ○, ◯ mean that the approach greatly, partly, barely considers setting metric or provides certain ability (other 5 metrics), respectively.

**Inversion Attack.** [20] first presents an algorithm named DLG (i.e. Deep Leakage from Gradients) which solves an optimization problem to obtain the raw features and labels and can be formulated as:

$$\text{argmin}_{x^*, y^*} \| \nabla \theta(x^*, y^*) - \nabla \theta(x, y) \|_2$$ (1)

where $\nabla \theta(x, y) = \frac{\partial \ell(\theta, x, y)}{\partial \theta}$, $\ell$ is the local overall loss function on differentiable deep learning model (e.g. DNN), $\theta$ is the overall model parameter and $(x, y)$ is the original feature and label. Figure 1 illustrates the process of inversion attack in FL, where malicious server (or clients in decentralized mode) tries to match the publicly shared gradient with the dummy gradient. Specifically, first they randomly initialize a dummy input $x^*$ and $y^*$ and iteratively optimize the dummy gradients $\nabla \theta_i(x^*, y^*)$ close as to original by Euclidean distance which also makes the dummy data close to the real training data.

Follow-up works improve on these results by using different distance metrics such as cosine similarity [6]:

$$\text{argmin}_{x^*, y^*} 1 - \frac{\langle \nabla \theta(x^*, y^*), \nabla \theta(x, y) \rangle}{\| \nabla \theta(x^*, y^*) \| \| \nabla \theta(x, y) \|}$$ (2)

where $\langle \cdot, \cdot \rangle$ means inner product. [24] also proposes an improved DLG (iDLG) by analytically and accurately extract ground-truth label from the last fully-connected (FC) layer, and thus it performs better as objective function only has to optimize $x^*$.

Such optimization-based inversion attack proves excellent results during early training stage when the gradients are of significant magnitudes, but the results can get quite unstable during late stage where gradients are relatively small, which motivates more sophisticated attacks.

**Extraction Attack.** To overcome the drawbacks of optimization-based attack, researches [6], [25] propose an accurate extraction attack which can almost perfectly reconstruct a single training sample without any costs. This kind of attack assumes the adversary has full knowledge of the FL model architecture and that the model contains at least one layer which consists of a weight and a bias. In particular, we assume the first layer contains both weight and bias, then the direct output of the first layer $y$ is computed as $W^T x + b$, where $x$ is the raw input data and $(W, b)$ is the corresponding weight and bias with compatible dimensionality. We further let $l$ be the row of the first layer such that $\frac{\partial \ell}{\partial \theta_l} \neq 0$, then by chain rule we can obtain $x$ as $x^T = \left( \frac{\partial \ell}{\partial \theta_l} \right)^{-1} \frac{\partial \ell}{\partial \theta_l}$.

In this way, we can extract the exact data as long as there exists $\frac{\partial \ell}{\partial \theta_l} \neq 0$. [6] also proves that it can be extended to a more general expression by replacing $\frac{\partial \ell}{\partial \theta_l}$ with $\frac{\partial \ell}{\partial \theta_i}$ until there is a FC layer with both weight and bias. Interestingly, most of the neural networks leverage such FC layer as the last prediction layer and thus extraction attack is applicable. Note that we can only reconstruct the input data with extraction attack, label information can be obtained by optimization or analytically inference from the last layer [24]. In section III we present a specific solution of $x^*$ using PyTorch and give proof for its failure when batch size of input data $x$ is more than 1.

**C. Defenses**

There exist several defenses to mitigate such reconstruction attacks in FL and can be categorized into four types: secure multi-party computation, DP generative model, gradient perturbation and input perturbation, and we summarize existing representative defense approaches in table I in terms of 6 metrics, where setting describes the data distribution setting during the experiments (iid and non-iid), utility evaluates the model performance, scalability denotes whether such defense can be applied in different domains, and feasibility denotes whether it requires extra setup or data to perform such defense.

**Secure Multi-party Computation.** Secure multi-party computation (MPC) [17] allows a group of parties to synchronously compute a function and obtain accurate representations of the final value while protecting their private data from privacy leakage. For example, [26] adopts a tree topology to derive a secure aggregation protocol for machine learning, [27] proposes to let users encrypt their local updates such that the central server can only recover the aggregation of the updates. However, MPC requires special setup and can be costly to implement, and [28] shows that adversaries can still launch inference attacks against MPC for certain scenarios.

**DP Generative Model.** DP generative models leverage certain data generation algorithm with differential privacy guarantee such as bayesian network [29] to generate surrogate data for model training. For example, recent work [18] proposes DataLens that leverages a novel dimension compression and aggregation approach in GAN model framework to improve...
synthetic data’s performance. However, this technique requires large amount of data for training GAN, and may not work out in FL due to limited training samples for each user.

**Gradients Perturbation.** Gradients perturbation-based defenses modify the gradients before updating them to the server. For example, when [20] proposes the original gradient inversion attack, they also present a defense scheme named gradient pruning that sets certain percents of the derived gradients of small absolute magnitudes to zero which serves as a gradient mask to hide data information.

Another representative defense is the well-known differential privacy [19] which provides theoretical privacy guarantee and bounds the change in output distribution caused by a small input difference for a randomized algorithm. Specifically, users can add Gaussian or Laplace noise to all the gradients to disrupt adversaries’ reconstruction attacks and protect data privacy [9], [15]. A more recent work [21] also proposes to add and eliminate random noises to the global model from the server to prevent information leakage from malicious clients, yet it works only when the server is trusted and thus has limitations.

**Input Perturbation.** Input perturbation-based defenses tend to perturb or mix the original data in order to mitigate reconstruction attack from the source. For example, [22] proposes Instahide to encode the raw data with user’s private dataset. For each training data, it first picks certain amount of raw data from the rest of dataset and then adds them up by their corresponding weights to output the mixed data and the composite label. It also randomly flips certain signs of the composite data to further preserve data privacy.

[10] proposes Soteria to optimize an objective function to perturb the feature representation before the defended layer such that the new image is dissimilar from the raw image while keeping the representation input close to maintain model performance. In the meantime, [23] introduces a novel defense scheme that searches for optimal image transformation combination such as image rotation and shift to preserve privacy. However, it’s not suitable for traffic data to perform such transformation because each flow consists of certain amount of related packets that carry specific meaning, altering several properties can induce significant differences.

### III. Threat Model and Privacy Metric

In this section, we present our adversary and make several assumptions in III-A and introduce two reconstruction attacks designed for NIDS domain in III-B. GAN-based black-box adversarial attack is presented in III-C. III-D presents an example of privacy evaluation for existing defenses.

#### A. Adversary

We consider an honest-but-curious server that follows the exact federated learning protocol and is allowed to observe the updates from different users. The goal of the attacker is to reconstruct each user’s private data and further launch black-box attack using GAN model. We make several assumptions of the adversary’s power as follows: (1) The adversary is aware of the model architecture and loss function. (2) The adversary knows about the property of the training data, including value ranges, and feature numerical types (i.e. discrete or continuous). (3) The adversary is aware of each user’s local training setting, including local training epochs and batch size. In this way, the adversary can perform suitable attacks depending on different scenarios and thus evaluates defenses’ lower bound with respect to privacy preserving.

#### B. Reconstruction Attack against NIDS

**Inversion Attack.** We leverage optimization-based reconstruction attack using different distance metrics as introduced in III-B. However, there exist two challenges when it comes to traffic features:

Firstly, traffic features are usually normalized during preprocessing procedure, therefore the reconstructed data $x^*$ should satisfy $x^* \in [0, 1]^{\text{dim}}$, where dim is the dimension of data features. Secondly, there are discrete and continuous traffic features in $x^*$ which requires different techniques.

To address the first challenge, we can project the final optimized $x^*$ into legal feature space such that $x^* = \text{clamp}(x^*, \text{min} = 0, \text{max} = 1)$. Note that we don’t leverage variable change since it induces additional computation and achieves similar performance from simple projection.

To address the second challenge, we first project the normalized $x^*$ into original feature space that shares the same value ranges with raw data, and then we force the discrete features to be integer and normalize $x^*$ again for later privacy evaluation.

Note that when the batch size of the training data is more than 1, inversion attack may not converge because the reconstructed data can have different permutations according to different initialization. Therefore we reconstruct a single training sample at a time while keeping the rest the same. We incorporate label $y^*$ in the optimization process and output the index of the maximum value of $y^*$ as the final reconstructed label.

**Extraction Attack.** In section III-E, we showed that extraction attack is effective for a single training sample whenever there is a layer with both weight and bias. According to the official implementation of neural network in PyTorch, we have the following theorem:

**Theorem 1.** Assume the first layer has a bias, then $x^T = (\partial \ell / \partial W)^T (\partial y^* / \partial b)^T (\partial \ell / \partial b)^T (\partial \ell / \partial b)^{-1}$ only when batch size is 1.

Proof of Theorem 1. When batch size is 1: The output $y$ of a FC layer is computed as $y = xW + b$, where $x$ is the input with size $1 \times \text{in}_\text{feature}$, $(W, b)$ are the weight and bias with size $\text{out}_\text{feature} \times \text{in}_\text{feature}$ and $1 \times \text{out}_\text{feature}$ respectively, and we have $(\partial \ell / \partial W)^T = (\partial \ell / \partial y)^T = x^T \partial y^* = x^T \partial \ell / \partial b$, then we have:

$$x^T = (\partial \ell / \partial W)^T \partial y^* (\partial \ell / \partial b) (\partial \ell / \partial b)^{-1}$$

When batch size is more than 1: Since $b$ is broadcast into $b^* = [b, \ldots, b]$ with size batch $\times \text{out}_\text{feature}$, and we have $(\partial \ell / \partial b) (\partial \ell / \partial b)^T = \begin{bmatrix} bb^T & \ldots & bb^T \\ \ldots & \ldots & \ldots \\ bb^T & \ldots & bb^T \end{bmatrix} = b^T \begin{bmatrix} 1 & \ldots & 1 \\ \ldots & 1 & \ldots \\ 1 & \ldots & 1 \end{bmatrix}$, where the second matrix is not invertible and equation fails.
Privacy Score. Based on the reconstructed data, we introduce a metric named privacy score where we directly add up the absolute distance for continuous features, and then we project the data into their original feature space and set the distance of discrete features to 1 if they don’t match the original value.

The overall score computation can be written as:

$$score(x, x^*) = \frac{\sum_{i \in S_c} |x_i - x_i^*| + \sum_{i \in S_d} equal(X_i, X_i^*)}{|S_c| + |S_d|}$$

(4)

where $S_c$ and $S_d$ denote the continuous and discrete features, $X$ and $X^*$ are projected features with original value ranges, $equal(x_1, x_2) = 1$ if $x_1 = x_2$, and it gets 0 otherwise. In this way, we can quantitatively evaluate the privacy leakage for each defense for FL-based NIDS.

C. GAN-based Black-box Attack

As long as the adversary obtains enough reconstructed data using either inversion attack or extraction attack, black-box adversarial attack is available using GAN. Specifically, the adversary first filters out data with benign labels and then use them to train GAN to generate adversarial examples that can evade different target NIDSs. To further accelerate the convergence of GAN, we leverage Wasserstein Generative Adversarial Networks (WGAN) which is more stable and achieves better performance than the original GAN.

Evasion Rate. We use the generated adversarial traffic to attack the trained FL model and Kitsune. For more straight evasion results, we use model accuracy change for FL model and directly present the Root Mean Squared Error (RMSE) change for Kitsune, where RMSE above the threshold means successful evasion.

D. Evaluation Example

To better understand the privacy metrics, we present a reconstruction example using inversion attack (II-B) against several existing defenses (optimal parameters) on KDD99 dataset [29] and list some features in table II where $x$ and $x^*$ denote the original and reconstructed traffic feature respectively. We can find that with or without any defense, the adversary can still reconstruct the data from the raw gradient with similar continuous and discrete features, which corresponds to the privacy score that smaller score means more privacy leakage.

To further demonstrate the consequences of reconstruction attack, we manipulate the reconstructed benign traffic features to train GAN against the SOTA NIDS, Kitsune [11]. Figure 2 shows the RMSE of adversarial examples (AEs) during the training process. We can find that even differential privacy with such strong privacy guarantee can induce successful evasion against Kitsune (RMSE under the threshold), let alone other defenses. Therefore, it is critical to design a new defense approach to build a more robust FL-based NIDS that preserves traffic data privacy without damaging model performance.

### Table II: Reconstruction example on KDD99 dataset during early training stage, PS denotes privacy score, feature* means discrete features and we present the normalized value $x_{nor}$ and the corresponding original value $x_{ori}$ (i.e. the encoding of the discrete feature) as $x_{nor}/x_{ori}$.

| Data | Feature | Duration | Protocol* | Service* | Sec_bytes | Den_bytes |
|------|---------|----------|-----------|----------|-----------|-----------|
| x    | PS      | 0.00     | 1.092     | 0.1612   | 2.016e-4  | 0.00      |
| x*   | with defense | 0.6e-4   | 0.00      | 0.162    | 0.046e-4  | 0.00      |
| x    | w/. Instahide | 2.6e-4   | 0.51     | 0.0162   | 0.00      | 0.00      |
| x    | w/. Soteria | 1.2e-4   | 0.11     | 0.0162   | 0.00      | 0.00      |
| x    | w/. GP | 2.6e-4   | 0.10     | 0.162    | 0.00      | 0.00      |
| x    | w/. Instahide | 2.0e-4   | 0.00     | 0.0162   | 0.00      | 0.00      |

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IV. FedDef: Optimization-based Input Perturbation Defense

In this section, we first present our defense overview in [IV-A] and then we introduce detailed optimization design and implementation of FedDef in [IV-B]

A. Overview of FedDef

The overview of FedDef is shown in figure 3. In federated learning (left side), local users first download the latest global model from the server. During local training, users first leverage FedDef to transform their own private data into pseudo data such that the data are dissimilar to preserve privacy and the corresponding gradients are similar to preserve FL model performance. Finally the users update the pseudo gradient generated by pseudo data instead of the original gradient to the server.

The right side illustrates the adversary manipulating the reconstructed data to attack the target models. The adversary first leverages reconstruction attack to recover user’s private training data and labels from the gradients, then black-box adversarial attack is available using GAN to evade DNN model or other NIDSs such as Kitsune. While our defense ensures that the adversary can reconstruct only the pseudo data which doesn’t help GAN model converge and therefore the adversarial attack fails.

For better understanding, we list some frequently used notations in table III

B. Optimization Design & Implementation

We now present the detailed design of FedDef and introduce the optimization problem. In federated learning, privacy
preserving and model performance are two key indicators of evaluating FL performance, users collaboratively train a global robustness model to acquire better detection results on intrusion attacks while also protecting their private data from possible information leakage. Based on these two aspects, we design a novel defense scheme for NIDS named FedDef aiming to (1) preserve data privacy against reconstruction attack and the following black-box adversarial attack, and (2) maintain FL model performance with respect to convergence and accuracy.

Privacy Preserving. To address the privacy concern, we prevent privacy leakage from the source that the input training data should be dissimilar from the original data, and we have the following optimization:

$$\arg\max_{x',y'} D(x',y';x,y)$$  \hspace{1cm} (5)

where $x$ and $y$ are the original input data and labels, $x'$ and $y'$ are the pseudo pair for later pseudo gradient computation, $D(\cdot,\cdot)$ denotes the distance metric that evaluates how dissimilar $(x',y')$ is from $(x,y)$ where features and labels require different techniques.

Data Transformation. According to the inversion attack and extraction attack introduced in equation (1) and (3), the reconstructed features $x^*$ depend on the absolute numerical values of $x'$, therefore we optimize $x'$ to be as far from $x$ as possible by $L_2$ distance metrics as $\arg\max_{x'} \|x' - x\|_2$.

However, the reconstructed data $x^*$ are always projected into $[0, 1]^{\dim}$, where $\dim$ is the feature dimension of $x$ and $x^*$. Therefore it makes no difference to the reconstructed data $x^*$ when $x^* \leq 0$ or $x^* \geq 1$. Due to the consideration above, we can constrain the upper bound of the $L_2$ distance and rewrite the optimization with respect to $x'$ as

$$\arg\min_{x'} ReLU(\delta - \|x' - x\|_2)$$  \hspace{1cm} (6)

where $\delta$ is the upper bound of the distance between $x$ and $x'$, and $ReLU(x) = \max(0,x)$ which ensures the distance is as large as possible while also guaranteeing the upper bound.

Label Transformation. On the contrary, the reconstructed labels $y'^*$ do not rely on the absolute numerical values of $y'$, instead the adversary takes the index $i$ of the maximum $y^*_i$ as the final label, therefore increasing the overall distance between $y'$ and $y$ does not guarantee label privacy. For example, let $i$ be the index of $y$ where $y_i = 1$ and $y_j = 0$, $\forall j \in [1,n], j \neq i$, where $n$ is the total label classes. By leveraging $L_2$ distance metric to optimize $y'$, we may obtain $y'$ where $y'_i = 2$ and $y'_j = 1$, $\forall j \in [1,n], j \neq i$. In this way, though the overall distance between $y'$ and $y$ is quite large, the adversary may still acquire the correct label $i$ since $y'_i$ is the maximum one in $y'$ and the reconstructed label $y'^*$ may also share the same property, therefore label information is extracted by equation $i = \arg\max_i(y'^*)$.

To address this problem, we choose to minimize $y'_i$ so that it stays the minimum one in $y'$ and the adversary will probably get any indexes other than the ground-truth label $i$. Specifically, we first locate the label index $i$ in $y$, and we minimize $y'$ such that the minimum one $y'_i$ is as close to $y_i$ as possible which can be formulated as $\arg\min_{y'} |y'_i - y_i|$, where $|\cdot|$ denotes the absolute distance. In this way, we optimize $y'_i$ to be the minimum one in $y'$ so that the adversary will most probably reconstruct any indexes except $i$.

Finally, we formulate the optimization for privacy preserving as follows:

$$\arg\min_{x',y'} ReLU(\delta - \|x' - x\|_2) + |y'_i - y_i|$$  \hspace{1cm} (7)

where $i$ denotes the ground-truth label index such that $y_i = 1$, and $y'_i$ is the minimum one in $y'$.

Model Performance. To maintain FL model performance, we choose to add a constraint for the pseudo gradient $\nabla \theta(x',y')$ generated by the pseudo data and label $(x',y')$.

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**Table III: Notations**

| Notation | Description |
|----------|-------------|
| $(x, y)$ | original data and corresponding label |
| $(x', y')$ | reconstructed data and label from shared gradients |
| $(x'', y'')$ | transformed pseudo data and label using FedDef |
| $\theta$ | parameters of differentiable model |
| $F(\theta, x, y)$ | local loss function |
| $\alpha$ | tradeoff parameter for privacy and model performance in FedDef |
| $\delta$ | maximum distance between pseudo data and raw data |
| $\epsilon$ | distance constraint between pseudo gradient and raw gradient |

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**Fig. 3:** Overview of FedDef. Local user leverages FedDef to generate pseudo gradient to prevent malicious reconstruction attack and the following adversarial attack.
to be as close to the original gradient $\nabla \theta(x, y)$ as possible. In particular, we expect the $L_2$ distance between the pseudo gradient and the original gradient to be within $\epsilon$ boundary which can be written as

$$s.t. \|\nabla \theta(x', y') - \nabla \theta(x, y)\|_2 \leq \epsilon$$  \hspace{1cm} (8)

However, such constraint is highly non-linear and thus we transform the constraint into an optimization problem using $ReLU$ function as

$$\arg\min_{x', y'} \text{ReLU}(\|\nabla \theta(x', y') - \nabla \theta(x, y)\|_2 - \epsilon)$$  \hspace{1cm} (9)

Finally, we can combine the two objective functions to optimize $(x', y')$ such that the pseudo data and the original data are dissimilar to preserve data privacy and the corresponding gradients are similar to maintaining model performance. In particular, we can derive the combined optimization as follows:

$$\arg\min_{x', y'} L_{Pri} + \alpha L_{Per}$$

$$L_{Pri} = \text{ReLU}(\delta - \|x' - x\|_2) + |y'_{\text{min}} - y'_\text{gt}|$$

$$L_{Per} = \text{ReLU}(\|\nabla \theta(x', y') - \nabla \theta(x, y)\|_2 - \epsilon)$$  \hspace{1cm} (10)

where $L_{Pri}$ and $L_{Per}$ stand for optimization loss for privacy preserving and FL model performance respectively, and $\alpha$ is a parameter that evaluates the tradeoff between privacy and model performance. The overall algorithm is presented as follows:

**Algorithm 1:** Transformation of private data and label

**Input:** original data pair $(x, y)$, global differentiable model parameters $\theta$, loss function $F$, defense epochs $def\_iters$, privacy tradeoff $\alpha$, learning rate $def\_lr$, constant $g\_value$

**Output:** pseudo data pair $(x', y')$

1. $x' \leftarrow U(0, 1), y' \leftarrow U(0, 1)$; ▷ random Initialization
2. $\nabla \theta(x, y) \leftarrow \frac{\partial F(\theta, x, y)}{\partial \theta}$; ▷ original gradient
3. $gt \leftarrow \arg\max(y)$; ▷ derive ground-truth label index of $y$
4. for $i \leftarrow 1$ to $def\_iters$ do
5. $\nabla \theta(x', y') \leftarrow \frac{\partial F(\theta, x', y')}{\partial \theta}$; ▷ pseudo gradient
6. if max($|\nabla \theta(x', y')|$) $\leq g\_value$ then return $x', y'$;
7. ▷ early stop
8. $loss \leftarrow \text{ReLU}(\|\nabla \theta(x', y') - \nabla \theta(x, y)\|_2 - \epsilon) \cdot L_2$ distance
9. $y'_{\text{min}} \leftarrow \text{min}(y')$;
10. $loss \leftarrow \alpha \cdot loss + \text{ReLU}(\delta - \|x' - x\|_2) + |y'_{\text{min}} - y'_\text{gt}|$;
11. $x' \leftarrow \text{Adam}(x', \frac{\partial loss}{\partial x'}, def\_lr)$; ▷ Adam optimizer
12. $y' \leftarrow \text{Adam}(y', \frac{\partial loss}{\partial y'}, def\_lr)$;
13. end
14. return $x', y'$

**Data Initialization.** First of all, we initialize $(x', y')$ using uniform distribution $U(0, 1)$ (on line 1) instead of the original data $(x, y)$ with or without any perturbation. The reason is that we find it significantly degrades the privacy performance since such initialization still contains certain information of the original data. Therefore it may end up searching for pseudo data within certain range of the original data, which does not provide optimal tradeoff between privacy and model performance.

**Vanishing Gradient.** During our experiments, we find that sometimes the optimization converges in a local optimal point when the global model training is almost complete and the original gradient tends to get small. In this scenario, equation (10) optimizes privacy better than model performance. Specifically, the pseudo data can be quite dissimilar from the original data while the pseudo gradients tend to vanish even though the gradient distance is optimized because the absolute values of the original gradient are also small. However, updating pseudo gradient of extremely small magnitudes or even zero values provides little help in global model convergence.

To address this problem, we leverage early stop to terminate the optimization as long as the pseudo gradient tends to vanish. In particular, we first set a predetermined constant $g\_value$, the we check the maximum absolute value of each gradient in each layer of the FL model and stop the optimization whenever the maximum value is lower than $g\_value$ (on line 6). In this way, we maintain the utility of the gradient in exchange of some privacy loss, and we also show in section VI that such loss is within acceptable range since our defense still proves effective against reconstruction attack and the following black-box adversarial attack.

Specifically, we also find it effective against extraction attack because the pseudo gradients are small enough that $\frac{\partial F}{\partial \theta} \cdot (\frac{\partial F}{\partial x})^T$ tend to become 0 and thus matrix inversion in equation [5] fails, and global model can still get updated in the meantime.

**V. THEORETICAL ANALYSIS**

In this section, we first formulate the optimization problem and present the training procedure in FedAvg combined with our defense in [V-A] and then we derive theoretical analysis of model convergence and privacy guarantee in [V-B] and [V-C].

**A. Problem Formulation of FedAvg**

**Problem Statement.** We first formulate our FL training objective in FedAvg as:

$$\arg\min_\theta \{ F(\theta) = \sum_{k=1}^N p_k F_k(\theta) \}$$  \hspace{1cm} (11)

where $N$ is the total number of local users, $p_k$ is the corresponding weight of the $k$-th user participating in the global model training, and $p_k \geq 0, \sum_{k=1}^N p_k = 1$, $\theta$ is the parameter of the global differentiable model, $F_k(\cdot)$ is the overall loss function for the $k$-th user (e.g. cross entropy loss). Local users collaboratively train a global model by solving optimization (11) iteratively. Here we present one training round (e.g. $t$-th) with our defense as follows:

1. The server has learnt a global model $\theta_t$ at $t$-th round and distributes the model to all the participants.
2. Every local user (e.g. $k$-th) first initializes their model with $\theta_t$, i.e. $\theta^k_t = \theta_t$ and then performs $E \geq 1$ local updates.
Specifically, during each update, user first leverages FedDef to transform their private data and label with the latest model $\theta^k_t$ to generate pseudo data pair $(x', y')$ for pseudo gradient computation. Therefore, the local model can be updated for the $i$-th iteration as:

$$\xi^k_{t+i} = FedDef(\xi^k_{t+i})$$  \hfill (12)

$$\theta^k_{t+i+1} \leftarrow \theta^k_{t+i} - \eta_{t+i}\nabla F_k(\theta^k_{t+i}, \xi^k_{t+i}), \quad i=0,1, ..., E-1$$  \hfill (13)

where $\xi^k_{t+i}$ is a sample pair (i.e. $(x^k_{t+i}, y^k_{t+i})$) uniformly chosen from the $k$-th user’s private dataset, FedDef is our defense algorithm that outputs the pseudo data pair $\xi^k_{t+i}$, $\eta_{t+i}$ is the learning rate for the $i$-th iteration. In this way, user $k$ performs equation (12) and (13) for $E$ rounds and finally obtains the local trained model $\theta^k_{t+E}$.

(3) After local training is complete, the central server determines a set $S_t$ which contains a subset of $K$ indices randomly selected with replacement according to the sampling probabilities $p_1, ..., p_N$ from the $N$ users. Then the global model is aggregated by simply averaging as:

$$\theta_{t+E} \leftarrow \frac{1}{K} \sum_{k \in S_t} \theta^k_{t+E}$$  \hfill (14)

In this way, the global model $\theta_{t+E}$ can be updated with only partial users which can mitigate serious "straggler’s effect" where the server has to wait for the slowest (even offline) user’s update and faces great time delay.

B. Convergence Analysis

We provide theoretical analysis for FL model convergence using FedAvg combined with our defense. Our analysis follows Li’s work [30] on the convergence of FedAvg on non-iid data with partial users’ update.

We first make the five following assumptions same as [30]:

**Assumption 1.** $F_1, ..., F_N$ are all $L$-smooth, that is, for all $V$ and $W$, and any $k \in [1, N]$, $F_k(V) \leq F_k(W) + (V - W)^T \nabla F_k(W) + \frac{L}{2} ||V - W||_2^2$.

**Assumption 2.** $F_1, ..., F_N$ are all $\mu$-strongly convex, that is, for all $V$ and $W$, and any $k \in [1, N]$, $F_k(V) \geq F_k(W) + (V - W)^T \nabla F_k(W) + \frac{\mu}{2} ||V - W||_2^2$.

**Assumption 3.** Let $\xi^k_t$ be sampled from the $k$-th user’s local data uniformly at random. The variance of stochastic gradients for each user is bounded: $\mathbb{E}||\nabla F_k(\theta^k_t, \xi^k_t) - \nabla F_k(\theta^k_t)||_2^2 \leq \sigma^2_k$, for all $k = 1, ..., N$.

**Assumption 4.** The expected squared norm of stochastic gradients is uniformly bounded: $\mathbb{E}||\nabla F_k(\theta^k_t, \xi^k_t)||_2^2 \leq G^2$, for all $k = 1, ..., N$ and $t = 0, ..., T - 1$, $T$ is the total iterations of local users’ updates.

**Assumption 5.** Assume $S_t$ contains a subset of $K$ indices randomly selected with replacement according to the sampling probabilities $p_1, ..., p_N$. The aggregation step of FedAvg performs $\theta_t \leftarrow \frac{1}{K} \sum_{k \in S_t} \theta^k_t$.

**Theorem 2.** Let $F^*$ and $F^k_t$ be the minimum values of $F$ and $F_k$, respectively. We use the term $\Gamma = F^* - \sum_{k=1}^N p_k F^k_t$ to quantify the degree of non-iid. Recall that $E$ denotes the local updates for each user and $T$ denotes the total iterations. Let assumptions 1-5 hold and $L, \mu, \mu_k, G$ be defined therein. Choose $\gamma = \max \{8\epsilon, \mu\}$, and learning rate $\eta = \frac{\mu}{2(\mu+T)}$. Then FedAvg with our defense with partial users participation for non-iid data satisfies:

$$\mathbb{E}[F(\theta_T)] - F^* \leq \frac{2\mu}{\mu+T} (\frac{B+C}{\mu} + 2L\|\theta_0 - \theta^*\|^2)$$  \hfill (15)

where

$$B = \sum_{k=1}^N p_k^2 (\epsilon + \sigma)^2_k + 6LG + 8(E-1)^2(\epsilon + G)^2$$

$$C = \frac{4}{K} E^2(\epsilon + G)^2$$

Proof of Theorem 2. We first replace assumptions 3-4 with our pseudo gradients and then derive the final conclusion.

Without the loss of generality, we consider the $k$-th user’s pseudo gradients’ property. We first present the following lemmas:

**Lemma 1.** Let $\| \cdot \|_2$ be a sub-multiplicative norm, for all $A$ and $B$, we have $\|A\|_2 - \|B\|_2 \leq \|A + B\|_2 \leq \|A\|_2 + \|B\|_2$.

**Lemma 2.** Let $\| \cdot \|_2$ be a sub-multiplicative norm, for all $A$ and $B$, we have $\mathbb{E}^2\|A\|_2 \|B\|_2 \leq \mathbb{E}\|A\|_2^2 \mathbb{E}\|B\|_2^2$. The proof of lemma 1 and 2 can be naturally obtained with norm triangle inequality and Cauchy–Schwarz inequality.

**Lemma 3.** Let $\| \cdot \|_2$ be a sub-multiplicative norm, for all $A$ and $B$, we have $\mathbb{E}\|A + B\|_2^2 \leq (\sqrt{\mathbb{E}\|A\|_2^2} + \sqrt{\mathbb{E}\|B\|_2^2})^2$.

Proof of Lemma 3.

$$\mathbb{E}\|A + B\|_2^2 \leq \mathbb{E}\|A\|_2^2 + \mathbb{E}\|B\|_2^2 + 2\mathbb{E}\|A\|_2 \mathbb{E}\|B\|_2$$

$$\leq \left(\sqrt{\mathbb{E}\|A\|_2^2} + \sqrt{\mathbb{E}\|B\|_2^2}\right)^2$$

**Replace Assumption 3.** According to our optimization (10), the pseudo gradients’ $L_2$ distance from the original gradients are constrained within $\epsilon$. Therefore we have the following equation:

$$\mathbb{E}||\nabla F_k(\theta^k_t, \xi^k_t) - \nabla F_k(\theta^k, \xi^k)||_2^2 \leq \epsilon^2$$  \hfill (18)

Therefore the variance of the pseudo stochastic gradients for each user is bounded with lemma 3:

$$\mathbb{E}||\nabla F_k(\theta^k_t, \xi^k_t) - \nabla F_k(\theta^k, \xi^k)||^2$$

$$\leq \left(\sqrt{\mathbb{E}||\nabla F_k(\theta^k_t, \xi^k_t) - \nabla F_k(\theta^k, \xi^k)||^2} + \sqrt{\mathbb{E}||\nabla F_k(\theta^k_t, \xi^k) - \nabla F_k(\theta^k_t)||^2}\right)^2$$

$$\leq (\epsilon + \sigma^2)^2$$  \hfill (19)

**Replace Assumption 4.** We adapt similar method to replace assumption 4 with our pseudo gradient, the expected squared norm of pseudo stochastic gradients is uniformly bounded:
\[ |\| F_k(\theta_0^k, \xi_0^k) \| |^2 \leq \mathbb{E}[|\| F_k(\theta_0^k, \xi_0^k) - \nabla F_k(\theta_0^k, \xi_0^k) + \nabla F_k(\theta_0^k, \xi_0^k) \| |^2] \]
\[ 
\leq (\sqrt{\mathbb{E}[|\| F_k(\theta_0^k, \xi_0^k) - \nabla F_k(\theta_0^k, \xi_0^k) \| |^2] + \sqrt{\mathbb{E}[|\| F_k(\theta_0^k, \xi_0^k) \| |^2]})^2 
\leq (\epsilon + G)^2 
\] (20)

In this way, we can replace the bound of the original gradients in assumptions 3-4 with our pseudo gradients. Therefore assumptions 1-5 hold with our defense. By applying our new bounds in Li’ work [30], we can derive theorem 2 aforementioned.

C. Privacy Analysis

We provide theoretical analysis for data privacy with our defense. Specifically, we derive a possible lower bound for the deviation of pseudo data \( x' \) from the original \( x \) using the derivatives of the first layer. We first make the following assumption:

Assumption 6. Assume there exist both weight \( W \) and bias \( b \) in the first layer of the model, and that the norm of the gradient with respect to the bias is bounded for some \( M > 0 \) : \( |\| W \| ||_2 \leq M \).

Theorem 3. Let assumption 6 hold, \( (x, y) \) be the original data pair after normalization, \( (x', y') \) be the transformed data pair with our defense, \( \nabla b = \frac{\partial F(\theta, x, y)}{\partial b}, \nabla W = \frac{\partial F(\theta, x, y)}{\partial W}, \nabla b' = \frac{\partial F(\theta, x', y')}{\partial b}, \nabla W' = \frac{\partial F(\theta, x', y')}{\partial W} \) and we have the following theorem to guarantee data privacy.

\[ |\| x' - x \| | \geq \frac{2(|\| \nabla W' - \nabla W \| |_2 - |\| \nabla b' - \nabla b \| |_2) \}}{2M + |\| \nabla b' - \nabla b \| |_2} \] (21)

Proof of Theorem 3. We can derive the following equations:

\[ \nabla W^T = x^T \nabla b \]
\[ \nabla W'^T = x'^T \nabla b' \]

therefore we have the following transformation:

\[ 2(\nabla W - \nabla W')^T = (x - x')^T (\nabla b + \nabla b') + (x + x')^T (\nabla b - \nabla b') \] (22)

With Lemma 1, we can derive the inequality on the one hand:

\[ |\| (x - x')^T (\nabla b + \nabla b') \| |_2 \leq |\| x - x' \| |_2 |\| \nabla b + \nabla b' \| |_2 \]
\[ \leq |\| x - x' \| |_2 |\| \nabla b \| |_2 + |\| \nabla b' \| |_2 \]
\[ \leq 2M |\| x - x' \| |_2 \]

Note that \( |\| x \| |_2 \leq 1 \) since \( x \) is normalized. Therefore, on the other hand, we also have:

\[ |\| (x - x')^T (\nabla b + \nabla b') \| |_2 \]
\[ \geq 2 |\| \nabla W' - \nabla W \| |_2 - |\| \nabla b - \nabla b' \| |_2 \]

Therefore by combining the above inequalities, we have:

\[ 2M |\| x' - x \| | \geq 2(|\| \nabla W' - \nabla W \| |_2 - |\| \nabla b' - \nabla b \| |_2) \]

VI. Evaluation

In this section, we conduct several experiments to evaluate our defenses with respect to model performance and privacy preserving. We first introduce our experiment setup in VI-A including our parameters setting, datasets, and several baselines. In VI-B we present model convergence and accuracy results with our defense. In VI-C we present the privacy leakage with our new metric and then perform adversarial attack using the reconstructed data under different defenses. Finally, we conduct ablation study to derive appropriate parameters combination in VI-D.

| Dataset | Property | Feature Dimension | Attack Type | Training Samples | Testing Samples |
|--------|----------|------------------|-------------|------------------|-----------------|
| KDDCUP | 41       | 2                | 2000        | 500000           |                 |
| Mirai  | 100      | 2                | 2           | 2000000          | 500000          |
| CIC-IDS | 96       | 2                | 2           | 1500000          | 67711           |
| UNSW-NB15 | 42     | 10               | 2           | 16000             | 77301           |

A. Experimental Setup

We conduct our experiments using PyTorch with 8-core, 64GB CPU and one Nvidia-P100 (16GB) GPU. The basic experiments setting as follows:

Datasets. We choose four network intrusion attack datasets to evaluate our defense including KDDCUP’99 [29], Mirai botnet [11], CIC-IDS2017 [31], and UNSW-NB15 [32] where Mirai botnet contains only one type of malicious traffic named Botnet Malware and the other three datasets contain multiple attack types. To further balance the datasets, we select only DDoS attack traffic from CIC-IDS2017 so that we evaluate on two 2-class dataset (i.e. Mirai Botnet and CIC-IDS2017) and two multi-class datasets (i.e. KDDCUP’99 and UNSW-NB15). We present more details of the dataset in in table IV.

Baselines and Parameters Configuration. We choose five baselines mentioned in [11-C to compare with our work including no defense, Soteria, gradient pruning (GP), differential privacy (DP), and Instahide.
For our defense, we set the pseudo gradient deviation distance constraint $\epsilon = 0$ for all the experiments to acquire the best model performance guarantee. We set upper bound of pseudo data distance from raw data as $\delta = 1$ due to the normalized value. We also set constant $g_{value} = 1e-15$, and in ablation study, we will derive the best parameter combination with respect to tradeoff $\alpha$, optimization learning rate $def_{lr}$ and optimization steps $def_{iter}$.

For other defenses, we optimize the parameters to achieve the best tradeoff between performance and privacy. Specifically, we set the gradient compression rate to 99% for GP, and we leverage laplace noise and set the mean and variance of the noise distribution as 0.1 and 0.1 for DP, while following the default setting for Soteria and Instahide.

**FL model.** We simulate the federated learning procedure by initializing 10 local users to collaboratively train a global DNN model under iid or non-iid data setting. We will present detailed experiment setup in VI-B.

**Reconstruction Attack.** We leverage optimization-based inversion attack with $L_2$ and cosine distance and accurate extraction attack to reconstruct local user’s private data and label.

**GAN adversarial attack.** We leverage WGAN model to accelerate the convergence and achieve better evasion performance. We evaluate black-box adversarial attack on two NIDSs, i.e. the exact global DNN model after federated learning and a SOTA NIDS Kitsune.

### B. Model Performance Results
We consider 10 local users training a DNN model under FedAvg framework and Adam optimizer with learning decay to evaluate utility metric **accuracy**. We first divide the original datasets to acquire the corresponding training dataset and testing dataset by $7:3$, and each user can get certain amount of the training dataset under iid or non-iid setting.

We design a new non-iid data generation algorithm in algorithm 2. Specifically, we ensure that each user randomly gets the same percent of the benign traffic (line 3), and then we randomly select $p$ attack types (lines 4-5) and distribute the same percent of that specific malicious traffic (line 7).

To provide a more practical result, we consider non-iid data distribution for KDD99 dataset and ensures each user can get benign traffic and at least one type of malicious traffic. For the rest of the three datasets, we consider iid data distribution where each user gets the same percent of the whole training dataset. After dataset distribution, local users normalizes their own datasets with maximum/minimum values.

We set the overall training rounds $T = 300$, and each user updates the global model only once $local_{ep} = 1$ with batch size $local_{bs} = 1000$. For our defense, we follow the same parameter setting introduced in VI-A and we set privacy tradeoff $\alpha = 0.25, 0.5, 1$ accordingly to observe the impact, we also set default optimization learning rate $def_{lr} = 2e-1$ and steps $def_{iter} = 40$. We optimize the local training learning rate for different defenses where no defense is around $1e-2$ and strong defense like DP requires higher learning rate as $3e-2$, otherwise such great noises to the gradients can hardly optimize the model. Note that we only study the impact of $\alpha$ currently, we will derive the optimal parameter combination with optimization learning rate and steps in ablation study VI-D.

We run the training for five times and we choose the best results for baselines and present the average accuracy for our defense in table VI-D. We can see that our defense with $\alpha = 1$ achieves similar performance from the baseline with at most 2.6% accuracy loss and the least deviation under iid or non-iid setting. In the meantime, as $\alpha$ tends to get smaller, equation $[10]$ tends to optimize pseudo data’s privacy more than pseudo gradients’ utility, which is why FedDef with $\alpha = 0.25$ achieves lower accuracy with greater deviation.

Meanwhile, we also compare our defense with other baselines and find that Soteria achieves the highest accuracy with only 1% loss at most while Instahide generally performs the worst. We suspect that the reason for Instahide’s poor performance is that it randomly flips certain signs of the mixed data to provide additional security protection in exchange of model performance.

In general, the FL model can still converge and reach high accuracy combined with our defense which demonstrates our model performance guarantee. Next we will present our privacy protection ability with different tradeoff $\alpha$ and then derive the optimal parameter.

### C. Privacy Results
In this section, we evaluate the ability of privacy preserving against two reconstruction attacks (i.e. optimization-based and

| Dataset   | Baseline | FedDef | Instahide | SOEC | Soteria | FL | DP | Instahide |
|-----------|----------|--------|-----------|------|---------|----|----|-----------|
| KDD99     | 0.970    | 0.985  | 0.970     | 0.985| 0.985   | 0.985| 0.985| 0.985     |
| ICIC-IDS2017 | 0.970| 0.985  | 0.970     | 0.985| 0.985   | 0.985| 0.985| 0.985     |
| UNSW     | 0.970    | 0.985  | 0.970     | 0.985| 0.985   | 0.985| 0.985| 0.985     |

**Algorithm 2: Non-iid data generation**

**Input:** full dataset $D$, number of users $n$, number of total attack types $m$

**Output:** non-iid data $D^k$ for each user $k$

1. **for** $k ← 1$ to $n$ **do**
2. **set initialization**
3. $D^k ← D^k ∪ \frac{1}{n} shuffle(D_{benign})$; **randomly add** the same percent of benign traffic
4. $p ← rand(min = 1, max = m)$; **random number** of attack types
5. $p_{mal} ← choice(all\_classes = m, size = p)$; **randomly select** $p$ types of attacks without replacement
6. **for** each $i$ in $p_{mal}$ **do**
7. $D^k ← D^k ∪ \frac{1}{n} shuffle(D_{mal−i})$; **randomly add** the same percent of the $i^{th}$ malicious traffic
8. **end**
9. **return** $D^k$, for $k = 1, 2, ..., n$
Early+Inversion Early+Extraction Late+Inversion Late+Extraction
0.0
0.2
0.4
0.6
0.8
1.0 Score

Fig. 4: Reconstruction privacy score comparison on KDD99 and Mirai datasets, higher is better.

TABLE VI: Label reconstruction accuracy comparison on four datasets, lower is better.

| Data       | Stage | No Defense | Early  | Late  | Soteria | GP | DP | Instahide |
|------------|-------|------------|--------|-------|---------|----|----|-----------|
| KDD99      | Early | 0.61       | 0.49   | 0.36  | 0.06    | 1.00| 1.00| 0.91      |
|            | Late  | 0.59       | 0.50   | 0.46  | 0.26    | 0.99| 0.99| 0.71      |
| Mirai      | Early | 0.81       | 0.81   | 0.61  | 0.01    | 1.00| 1.00| 0.90      |
|            | Late  | 0.81       | 0.80   | 0.61  | 0.01    | 1.00| 1.00| 0.90      |
| CIC-IDS2017| Early | 0.72       | 0.72   | 0.55  | 0.01    | 1.00| 1.00| 0.81      |
|            | Late  | 0.72       | 0.72   | 0.55  | 0.01    | 1.00| 1.00| 0.81      |
| UNSW-NB15  | Early | 0.71       | 0.71   | 0.54  | 0.01    | 1.00| 1.00| 0.77      |
|            | Late  | 0.71       | 0.71   | 0.54  | 0.01    | 1.00| 1.00| 0.77      |

Note: None FedDef alpha 1 FedDef alpha 0.5 FedDef alpha 0.25 Soteria GP DP Instahide

extraction attack) and the following adversarial attack. We also consider different local training batches that require different attack setting.

A. Single Sample Reconstruction. We first consider local users updating model only once with only one training sample. In this scenario, the adversary can launch both inversion attack and extraction attack.

In particular, we optimize the inversion attack using appropriate distance metric due to the gradient magnitude, i.e. we use cosine distance for KDD99 and CIC-IDS2017 datasets during late training stage and L2 for the rest of the cases. Note that extraction attack may fail due to the precision of computation when gradients are small, and we will fall back to inversion attack when the inversion in equation 3 fails.

As introduced in II-B we can only derive accurate data from extraction attack, therefore we only adapt optimization-based attack to acquire labels.

We follow the same parameter setting as in VI-B for our defense, and we set the overall iteration $T = 100$, local batch size local bs = 1, local step localtep = 1 for both early stage and late stage. Note that we use the randomly initialized model for early stage and trained model in VI-B for late training stage, we do not actually update the model to constantly evaluate the reconstruction score. The full results for privacy score and reconstructed label accuracy using inversion attack over the $T$ samples is in figure 4 and table VI.

Early Stage Reconstruction Result Analysis. During early training stage, the reconstruction attacks prove excellent performance against the model with no defense, the reconstructed data score can reach almost 0 which means the reconstruction is almost perfect, and that labels are also accurately extracted among four datasets.

On the contrary, our defense outperforms other baselines and significantly mitigates such attacks in a way that the score is around 0.6 with $\alpha = 1$, and it tends to get even higher with smaller $\alpha$ which means user’s privacy is well protected with little information leakage, and our defense also prevents the label leakage especially for multi-class datasets with almost 0 inversion accuracy.

Another interesting spot is that Soteria almost proves no privacy protection against either attack, we suspect it’s because we don’t leverage CNN as our feature extractor and that Soteria only perturbs the gradients of the defended layer while the rest still carry much private information of the raw data $x$.

Late Stage Reconstruction Result Analysis. During the late training stage, the shared gradients tend to get smaller, and such optimization-based attack performs worse because it’s more difficult to optimize the dummy gradient to fit the original one. As shown in figure 4 and table VI the reconstruction score using inversion attack vary from 0.2 to 0.5 even for gradients without defenses, and the label accuracy also drops from 1 to even 0.52 for CIC-IDS2017 dataset.

Nonetheless, our defense still generally outperforms other baselines where extraction attack still performs with similar privacy score from early stage because matrix inversion is always accurate. We also notice that smaller $\alpha$ may induce even lower score because the gradients are of small magnitude and thus may trigger falling back from extraction to inversion.
attack, which makes the reconstruction results more unstable.

**Adversarial Attack Result Analysis.** To better understand the threats of the reconstruction attack, we manipulate the reconstructed benign data to train WGAN model to launch adversarial attack against two NIDSs. For Kitsune setup, we first train Kitsune with the four datasets and then determine a threshold respectively, test data will be classified as malicious if its RMSE is higher than the threshold.

Specifically, we first leverage extraction attack to acquire user’s data and labels until there are 100 traffic data with benign labels, then we filter out those benign traffic features and feed them to the discriminator. After regular GAN training process, we use the adversarial features (default number is 100) from the generator to attack the target NIDSs. We present the results for early training phase with extraction attack in figure 5 and late stage with inversion attack in figure 6 (since extraction attack for late stage is similar to early stage).

For early stage, we can find that almost all baselines fail to prevent such adversarial attack except for Mirai dataset, where threshold is more strict and DP may be sufficient with strong privacy guarantee, while our defense consistently outperforms baselines that the curve under FedDef doesn’t converge with higher RMSE and the corresponding adversarial example fails to evade Kitsune. However, we also notice that it’s easier to evade the target DNN model even with our defense for CIC-IDS2017 dataset. We suspect it’s because we also leverage DNN model to train GAN, therefore evading discriminator also means evasion on DNN model with great chances.

While in early training stage, inversion attack can be quite unstable thus the recovered data approaches random guess, which is why RMSE is similar to that of randomly initialized data, and accuracy is around 0.5.

**B. Batch Samples Reconstruction.** To study a more practical scenario with multi-sample reconstruction, we leverage inversion attack to reconstruct data and labels because we proved in section III that extraction attack is only effective when batch size is 1.

Note that we don’t consider the specific privacy score because the reconstructed data may have different permutations and it’s hard to correspond them to the ground-truth data and label. Instead, we directly apply the data with benign labels to train the GAN model.

The representative results for KDD99 dataset with batch size 5 and 10 are in figure 7. We can observe that with larger batch size, the accuracy of the adversarial attack against Kitsune decreases significantly.
TABLE VII: Accuracy comparison on KDD99 datasets for different parameters with baseline 0.996, higher is better.

| \( \text{def}_lr \) | \( \text{def}_\text{iters} \) | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|-----------------|-----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| \( 2e^{-2} \)   | \( 0.442 \pm 0.186 \) | 0.534 \pm 0.087 | 0.91 \pm 0.049 | 0.982 \pm 0.015 | 0.97 \pm 0.003 | 0.982 \pm 0.002 | 0.985 \pm 0.001 | 0.987 \pm 0.001 | 0.987 \pm 0.001 |
| \( 8e^{-2} \)   | \( 0.491 \pm 0.192 \) | 0.98 \pm 0.003 | 0.98 \pm 0.001 | 0.98 \pm 0.002 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 |
| \( 2e^{-1} \)   | \( 0.986 \pm 0.006 \) | 0.98 \pm 0.002 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 | 0.98 \pm 0.001 |

Fig. 8: Ablation study on \( \text{def}_lr \) during early training stage on KDD99 dataset with inversion attack for single sample reconstruction.

Fig. 9: Running Time Comparison.

size, the inversion attack may perform worse and therefore may slightly degrade our defense (more like random guess reconstruction), yet the overall results are similar to that of single sample reconstruction, which further demonstrates the threats in practical training.

Conclusion. We briefly conclude our privacy analysis that our defense generally outperforms all current defenses with high reconstruction privacy score and low evasion rate even with strong model performance guarantee in both training stages against either privacy attack for single or multiple samples.

D. Ablation Study

So far, we have demonstrated our defenses model performance and privacy preserving guarantees. Next we will study some parameter impact on the overall performance of FedDef.

Specifically, we try to study the optimal parameter combination with respect to \( \alpha \), \( \text{def}_lr \) and \( \text{def}_\text{iters} \) with determined \( \epsilon \) and \( \delta \).

Firstly, we choose our optimal \( \alpha = 1 \) because it induces the best accuracy performance with more stable guarantee. Moreover, such \( \alpha \) is already sufficient against reconstruction attack and the following adversarial attack.

We conduct ablation study on \( \text{def}_lr \) and derive the optimal value using KDD99 dataset. We follow the same experiment setting for model performance and privacy evaluation as introduced in section VI-B and VI-C. The average accuracy results over five training times can be found in table VII and we mainly consider the early training stage and present the privacy score using inversion attack as an example and label accuracy change in figure 8.

We can find that higher learning rate generally reduces the steps needed to fully optimize pseudo data to preserve privacy while maintaining model performance and mitigating deviation, which accelerates our algorithm. However, when \( \text{def}_lr = 0.2 \), more optimization steps can induce privacy protection loss during early stage (see figure 8) which means pseudo data is over-optimized.

Due to the above consideration, we recommend predetermined constants \( g_{\text{value}} = 1e-15 \), and key parameter \( \alpha = 1 \), \( \text{def}_lr = 0.2 \) and \( \text{def}_\text{iters} = 40 \) as our optimal parameter combination where the model accuracy is maintained and privacy score is high enough to mitigate any reconstruction attack and the following adversarial attack.

E. Running Time

Finally, we conduct experiments to present different defenses’ computation overhead. For fair comparison, we only consider 1 local user training a global DNN model on KDD99 dataset with full training dataset. We also run the training process for five times and report the average result. Note that for Instahide, directly mixing the whole dataset before training costs too much time, instead for each local update, we first randomly select local bs samples from the whole training dataset, and then mix the batched samples according to certain algorithm for final gradient computation. We set the average time with no defense as our baseline. The running time under our optimal parameters is in figure 9.

We can find that our defense induces additional \( \times 0.35 \) time for such pseudo data transformation in exchange for model performance and privacy protection guarantee. Such computation overhead is reasonable because optimization-based defense iteratively searches for optimal pseudo data while other defenses such as differential privacy directly injects noises and does not induce additional computation.

VII. DISCUSSION

We present some limitations and future work in this section.

Additional Computation Overhead. The main reason for additional training time is that our defense transforms the data for every local update. Our future work can try transforming private data only once while satisfying both performance and privacy requirements.
Traffic Space Attack. So far we have only leveraged GAN to generate adversarial features instead of real traffic data to attack the NIDSs. However, generating more practical traffic attack is beyond the scope of our work, and we may adopt current approaches like GAN+PSO algorithm to further improve the attacks and thus better evaluate the defenses.

VIII. CONCLUSIONS
In this work, we first propose two privacy metrics specifically designed for FL-based NIDS, i.e. privacy score from reconstruction attacks and evasion rate from GAN-based adversarial attack, to derive a accurate evaluation of privacy protection and demonstrate the insufficiency of existing defenses. To build a more robust FL-based NIDS, we further propose a novel and practical defense strategy named FedDef. Specifically, we solve an optimization problem to generate pseudo data that satisfies both convergence and privacy requirements, i.e., we solve an optimization problem to generate pseudo data to both training stages against both attacks while also maintaining privacy guarantee with our defense.

The experimental results show that our defense outperforms existing baselines and proves great privacy protection during both training stages against both attacks while also maintaining model accuracy loss within 3%.

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