FedIPR: Ownership Verification for Federated Deep Neural Network Models

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Abstract

Federated learning models must be protected against plagiarism since these models are built upon valuable training data owned by multiple institutions or people. This paper illustrates a novel federated deep neural network (FedDNN) ownership verification scheme that allows ownership signatures to be embedded and verified to claim legitimate intellectual property rights (IPR) of FedDNN models, in case that models are illegally copied, re-distributed or misused. The effectiveness of embedded ownership signatures is theoretically justified by proved conditions under which signatures can be embedded and detected by multiple clients without disclosing private signatures. Extensive experimental results on CIFAR10, CIFAR100 image datasets demonstrate that varying bit-lengths signatures can be embedded and reliably detected without affecting models classification performances. Signatures are also robust against removal attacks including fine-tuning and pruning.

1 Introduction

Federated learning (FL) is a machine learning setting in which many clients collaboratively train a model, and simultaneously, mitigate privacy risks and costs by keeping the training data decentralized\cite{15,26,14}. While preserving data privacy is of the paramount importance, it is also considered a critical issue to prevent adversaries from stealing and misusing models to search for model vulnerabilities\cite{14}. Moreover, protecting models from being stolen is motivated by the fact that FL models are built upon valuable data owned by multiple clients, and plagiarism of such models must be stopped. This paper illustrates a novel federated deep neural network (FedDNN) ownership verification scheme that can be used to claim legitimate intellectual property rights (IPR) of FedDNN models, in case that models are illegally copied, re-distributed or misused by unauthorized parties. The proposed scheme not only verifies model ownership against external plagiarisms, but also allows each client to claim contributions to the federated model as verified data owners.

DNN watermarking techniques have been proposed to protect DNN Intellectual Property Rights (IPR)\cite{22,9,10,28,12,17,29,8}, however, it remains an open question concerning whether existing methods are applicable to \textit{federated learning} settings, in which following technical challenges must
when an increasingly large number of signatures are embedded the global DNN model must be selected a subset of clients to update the global federated model and for each client only uploads a small fraction of model changes. Moreover, privacy preserving deep learning (PPDL) aims to collaboratively train a deep neural network (DNN) model among multiple clients without exposing private training data to each other. For the sake of improving security and efficiency, it is a common practice e.g. in the celebrated algorithm (FedAVG) for a FL server/aggregator to select a subset of clients to update the global federated model and for each client only uploads a small fraction of model changes. Moreover, privacy preserving techniques such as Homomorphic Encryption, differential privacy and secret sharing can be used to protect exchanged model updates as introduced in and . Whether different selection of model updates and privacy preserving techniques will affect the proposed FedIPR framework is one of open problems investigated in our work (see Sect. 5).

1.1 Related Work

Following the common theme of protecting data privacy for federated learning, privacy-preserving deep learning (PPDL) aims to collaboratively train a deep neural network (DNN) model among multiple clients without exposing private training data to each other. For the sake of improving security and efficiency, it is a common practice e.g. in the celebrated algorithm (FedAVG) for a FL server/aggregator to select a subset of clients to update the global federated model and for each client only uploads a small fraction of model changes. Moreover, privacy preserving techniques such as Homomorphic Encryption, differential privacy and secret sharing can be used to protect exchanged model updates as introduced in and . Whether different selection of model updates and privacy preserving techniques will affect the proposed FedIPR framework is one of open problems investigated in our work (see Sect. 5).

The original task for which the federated DNN model is built.
Backdoor attacks is a security threat that have been extensively studied in federated learning [6, 21, 7, 25]. Following [2], we adopt targeted backdoor samples as signatures for black-box ownership verification. By adopting latest backdoor injecting methods [21, 5], we show that robust backdoor signatures can evade existing backdoor removal methods and provide evidence of suspected plagiarism through remote API without accessing to internal parameters of models in question.

DNN ownership embedding and verification approaches can be broadly categorized into two schools: a) the feature-based methods that embed designated signatures [22, 9, 10, 12, 29], and b) the trigger-set-based methods that rely on backdoor training samples with specific labels [2, 28]. While feature-based methods allow persistent signatures to be reliably detected even under various forms of removal attacks, yet, they must access DNN internal parameters to detect signatures. The benefit of trigger-set based method is that model owners can collect evidence of suspected plagiarism through remote API without accessing to internal parameters of models in question. Table 1 reviews related work according to hyper-parameters used to embed/detect signatures and desired features of embedded signatures. Interestingly, [17] illustrated a black-box and white-box verification method for GAN instead of convolution networks. We also refer to a recent survey [8] for more existing methods.

2 Federated DNN Ownership Verification

This section first reviews existing DNN signature embedding and verification scheme, followed by illustration of the proposed Federated DNN (FedDNN) framework. In this paper we use signature and watermark interchangeably. There are broadly two categories of DNN signature embedding and verification methods: feature-based vs trigger-set-based. Feature-based signatures are embedded into network parameters and have to be verified by accessing network parameters i.e. in white-box manner. Trigger-set based signatures are embedded into network outputs or labels, and can be verified without accessing network parameters i.e. in black-box manner.

2.1 Review of DNN Signature Verification

For existing DNN feature-based signature embedding methods [22, 9, 10, 28, 12], N-bits target binary signatures $\mathbf{B} = (t_1, \ldots, t_N) \in \{0, 1\}^N$ are embedded during the learning of parameters $\mathbf{W}$ of a DNN model $\mathbb{N}[\mathbf{W}]$, by adding regularization terms $R$ to the loss of the original learning task $L = L_D + \alpha R$:  

$$R_{\mathbf{B}, \theta}(\mathbf{W}) = \text{Dist}(\mathbf{B}, \mathbf{B}_{\theta}(\mathbf{W})), \quad (1)$$

in which $\theta = \{\mathbf{S}, \mathbf{E}\}$ is a set of hyper-parameters used to extract signature vector  

$$\mathbf{B} = (\mathbf{W}^T \mathbf{E}) \in \mathbb{R}^N \quad (2)$$

whereas $\mathbf{W}^T = \mathbf{S}(\mathbf{W})) \in \mathbb{R}^M$ denotes a $M$-dimensional columnized vector of subset of DNN parameters and $\mathbf{E} \in \mathbb{R}^{M \times N}$ a pre-determined signature extraction matrix.

Regularization term $[1]$ restricts DNN model parameter $\mathbf{W}$ to be distributed within a subspace (see Proposition 3) such that binary strings extracted from DNN parameters $\hat{\mathbf{B}} = \text{sign}(\mathbf{B}) =$
Ownership verification, and they should be kept secret from unauthorized parties.

Note that parameters θ = {S, E} and target binary signatures B are key information used for DNN ownership verification, and they should be kept secret from unauthorized parties.

### 2.2 FedIPR: FedDNN Signature Embedding and Verification

A federated learning system consists of K client participants building local models with their own data D_n and send local models to a server-side aggregator for secure model aggregation [15, 26, 14].

\[ V(W_i, B, \theta) = \begin{cases} \text{TRUE,} & \text{if } H(W_i, \hat{B}) \leq \epsilon_H, \\ \text{FALSE,} & \text{otherwise.} \end{cases} \]  

(3)

For trigger-set based methods, Adi et al. [2] first proposed to embed backdoor trigger-set samples T = \{(X_1, Y_1), \cdots, (X_J, Y_J)\} by incorporating cross-entropy loss of backdoor samples namely,

\[ L_T(W) = CE(Y, \mathbb{N}(T)) = -\sum_{j=1}^{J} Y_j \log(\mathbb{N}(X_j)), \]  

in which X_j are backdoor samples, Y_j corresponding one-hot encoding vector of backdoor labels and \(\mathbb{N}(X_j)\) the network softmax output.

Note that parameters \(\theta = \{S, E\}\) and target binary signatures B are key information used for DNN ownership verification, and they should be kept secret from unauthorized parties.

An analysis of the existence of solutions to the system of constraining inequalities is given in Appendix ?. See Sect. 3.3 of [22] for three different settings of E (denoted as X^direct, X^diff and X^random therein).
It is often assumed the aggregator and other participants are honest-but-curious and thus no leakage of information from participants is allowed. For Federated DNN with ownership verification, this requires participants a) keep local model updates secret from the aggregator; and b) keep ownership verification information secret from the aggregators. While the first requirement has been studied extensively and fulfilled by using techniques like Homomorphic Encryption [13], differential privacy [11] or secret sharing [19], the second requirement is one of the open problems considered in this work. We give below a formal definition of Federated DNN ownership verification scheme, which is pictorially illustrated in Fig. 2.

**Definition 1.** A Federated Deep Neural Network (FedDNN) model ownership verification scheme for a given network \( \mathbb{N} \) is a tuple \( \mathcal{V} = (G, E, A, V_W, V_B, V_G) \) of processes, consisting of,

1. for client \( k, k \in \{1, \cdots K\} \), a client-side key generation process \( G \) which generates

\[
G() \rightarrow B_k, \theta_k, T_k
\]

...target signature \( B_k \), signature extraction parameters \( \theta_k = \{S_k, E_k\} \) and a trigger set \( T_k = \{(X_1, Y_1), \cdots, (X_j, Y_j)\} \) of backdoor samples \( X_j \) and corresponding output labels \( Y_j \);

2. a client-side FedDNN embedding process \( E \) which minimizes the combined loss of main task, and two regularization terms to embed trigger set backdoor samples \( T_k \) and signature \( B_k \) respectively,

\[
L := \frac{1}{n} \sum_{i=1}^{n} L_{D_k}(W_k^t) + \alpha_k L_{T_k}(W_k^t) + \beta_k R_{B_k, \theta_j}(W_k^t), \quad k \in \{1, \cdots K\},
\]

with \( \text{ClientUpdate}(n, W^t) = W^{t-1} - \eta \frac{\partial L}{\partial W} \) to be sent to the server for updating at iteration \( t \);

3. a server-side FedDNN aggregation process \( A \) which collects updates from \( m \) randomly selected clients and performs model aggregation using the FederatedAveraging algorithm [15] i.e.

\[
W^{t+1} \leftarrow \frac{1}{n} \sum_{k=1}^{K} n_k W_k^{t+1}, \quad \text{where } W_k^{t+1} \leftarrow \text{ClientUpdate}(k, W^t) \text{ for } m \text{ clients},
\]

4. a client-side white-box verification process \( V_W \) which checks whether signatures extracted from the federated model \( \hat{B}_k = \text{sign}(S_k(W)E_k) \) is similar to the client target signature \( B_k \),

\[
V_W(W, (B_k, \theta_k)) = \begin{cases} 
    \text{TRUE}, & \text{if } H(B_k, \hat{B}_k) \leq \epsilon_H, \\
    \text{FALSE}, & \text{otherwise};
\end{cases}
\]

5. a client-side black-box verification process \( V_B \) which checks whether the detection error of designated labels \( Y_j \) generated by trigger set backdoor samples \( X_j \) is smaller than \( \epsilon_y \),

\[
V_B(N, T_k) = \begin{cases} 
    \text{TRUE}, & \text{if } \mathbb{E}_{T_k}(I(Y_j \neq \mathbb{N}[X_j])) \leq \epsilon_y, \\
    \text{FALSE}, & \text{otherwise},
\end{cases}
\]

in which \( I() \) is the indicator and \( \mathbb{E} \) the expectation over trigger set \( T_n \);

6. optionally, in case that the server is trustworthy, a server-side aggregated verification process \( V_G \) which checks whether both combined trigger set \( T = \cup_{k=1}^{K} T_k \) and signatures \( B = \cup_{k=1}^{K} B_k, \theta = \cup_{k=1}^{K} \theta_k \) can be successfully verified i.e.

\[
V_G(N, W, T, B, \theta) = V_B(N, T) \cap V_W(W, (B, \theta)).
\]

A fundamental challenge for federated DNN signature embedding is to ensure that signatures embedded into local models can be reliably detected from the federated model. For trigger-set based signatures, this seems not an issues as backdoor samples with arbitrarily assigned labels can always be learned with over-parameterized models as demonstrated in [3] [27] (also see Figure 7(c) and (d)). For feature-based signatures, however, it remains an open question whether there is a common solution \( W \) for different clients to embed their own designated signatures. The following analysis elucidates the condition under which a feasible solution is guaranteed.

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4A client \( k \) may opt-out and not embed signatures or trigger set backdoor samples by setting \( \alpha_k = 0.0 \) or \( \beta_k = 0.0 \). Following [27], we adopt random sampling strategy in experiments to assign non-zero values to \( \alpha_k, \beta_k \) to simulate the situation that client make decisions by their own.
We adopt adversarial samples as trigger set $T$ (PGD)\cite{16}, the original data $(\sigma, \theta)$.

To evaluate the FedDNN model signature embedding quantitatively, we use a set of metrics to measure the reliability of the proposed feature-based signatures and trigger-set based signatures.

Fidelity: we use classification accuracy on the main task as the metrics for fidelity. It is expected classification accuracy should not be degraded by the embedding of signatures into the federated model.

Reliability: averaged detection rate of embedded signatures is used to quantify the reliability of a signature verification scheme. For feature-based signatures, detection rate $\eta$ is calculated as $\eta = 1 - D_{\text{hamming}} / M$ where $D_{\text{hamming}}$ measures Hamming distance between extracted binary signature string and the target signatures. For trigger-set based signatures detection rate $\eta$ is calculated as the ratio of backdoor samples that are classified as designated labels w.r.t. the total number of all trigger set samples.

3.2 Fidelity

Fidelity of the proposed model verification scheme was evaluated under different settings, including varying signature bit length, varying number of triggers per client and different datasets and model architectures.
Figure 3: Model performances in a federated learning system with 20 clients. Figure (a) and (b), respectively, illustrate CIFAR10 with AlexNet and CIFAR100 with ResNet18 classification accuracy, when $n_W = 5, 10$ clients embed varying bit-lengths signatures. Figure (c) and (d), respectively, illustrate CIFAR10 with AlexNet and CIFAR100 with ResNet18 classification accuracy for 5 or 10 clients embedding varying number of trigger-set samples.

Figure 4: In a federated learning system of 20 clients, figure (a) and (b), respectively, illustrate the case when $n_W = 5, 10$, the signature detection rate with varying bit length per client, figure (a) describes the case that AlexNet with CIFAR10 dataset, figure (b) describes the case that ResNet with CIFAR100 dataset. Figure (c), (d) illustrate the case when $n_B = 5, 10$, the trigger detection accuracy with varying trigger per client, figure (c) describes the case that AlexNet with CIFAR10 dataset, figure (d) describes the case that ResNet with CIFAR100 dataset.

**Trigger-set Signature:** varying number of clients may decide to embed different number of trigger set samples (as signatures) into the federated model, and Figure 6 (c) and (d) show that model performances of the main task remain almost constant when 20 to 600 trigger set samples are embedded by, respectively, each of 5 and 10 clients. There is a negligible accuracy drop (less than 1%) with respect to the model performance without embedding any trigger set signatures.

**Feature-based Signature:** Figure 6 (a) and (b) illustrates model performance measured with different length ($M$) of binary signatures embedded into normalization layer scale parameter ($W_\gamma$). It was observed that long bit-lengths (200 bits per client) of signatures lead to slight model performance drop up to 2% for AlexNet on CIFAR10 classification main task. Similar performance drop up to 2% was also observed for ResNet on CIFAR100 classification task, when up to 350 bits signatures were used for each client of 10 clients. The drop of classification accuracy is due to the sub-optimal solution restricted to the subspace defined by large number of binary signature constrains (see Proposition 2). Note that performance drop can actually be mitigated by assigning binary signatures across different layers of normalization scale parameters (see supplementary material for details).

### 3.3 Reliability

Reliability of the proposed model verification scheme was evaluated under different settings, including varying signature bit length, varying number of triggers per client and different datasets and model architectures.

**Trigger-set based signature:** reliability of trigger-set signatures were evaluated under two settings, i.e., 5 or 10 clients are randomly selected to embed trigger-set signatures generated by Projected Gradient Descent (PGD) adversarial attack method [16].
Figure 7(c) and (d) illustrate the trigger set detection rates on these adversarial sample \( T \), respectively, with AlexNet on CIFAR10 classification and ResNet18 on CIFAR100 classification tasks. The results show that the detection rate of trigger-set \( T \) almost keep constant even the trigger number per client increases. Moreover, detection rates of signatures embedded in the more complex ResNet18 is more stable than those signatures embedded in AlexNet. Also, the detection rate is not influenced by the varying number of clients and, thus, varying number of total trigger-set samples used. We ascribe the stable detection rate to the generalization capability of over-parameterized networks as demonstrated in [3, 27].

**Feature-based Signature:** Figure 7(a) and (b) illustrate binary signature detection rates in white-box manner, in which (a) is with AlexNet for CIFAR10 and (b) with ResNet18 for CIFAR100 classification tasks. First, note that the detection rates remain constant (100%) within the regime, whereas the total bit lengths assigned by multiple (5 or 10) clients does not exceed the capacity of network parameters used to embed signatures. This limit is, respectively, 256 and 512 convolution channels at the last layer for AlexNet and ResNet18. Therefore, binary signatures of all bits can be reliably detected, which is in accordance to the analysis disclosed in Proposition 2. When the total bit lengths exceeds the limit e.g. in Figure 7(a) when 100 bits signatures are assigned by 5 clients, the detection rate drops to about 80% due to the conflicts of overlapping signature assignments. Nevertheless, the dropped detection rate still guarantees very high confidence in claiming the ownership of verified models, since random guessing of designated signatures will lead to a exponentially small probability of detection rate (see supplementary material for detailed analysis).

The results illustrated in Figure 7 give rise to the capability of feature based signature \( B \) into FedDNN model: the bit length of signatures of total clients \( \left\{ M \right\}_{i=1}^{nW} \) can not exceed the channel number of normalization scale weights \( W^\gamma \) in selected convolutional layers. More experimental results about kernel parameters and cross-entropy loss \( W^K \) are attached in supplementary material.

### 3.4 Robustness

In federated learning, some strategies are widely used to protect privacy, increase efficiency, and so on. We choose two scenarios in common usage: implementing the differential privacy [24] and decrease the fraction frequency. Under these two scenarios, we test whether the trigger set and signature are persistent. Moreover, the attacker may try to remove the trigger set and embedded signature while inheriting the model performance in federated learning. Here, we conduct two removal attacks: fine-tuning and pruning to identify whether embedded watermark and signature are persisted.

**Robustness Against Differential Privacy:** we adopt the Gaussian noise-based method to provide differential privacy guarantee for federated learning. Specifically, We vary the standard deviation (std) of Gaussian noise on the local gradient before clients send gradients to the server. As Figure 8(a) shows, the classification error decreases severely as the std of noise increases while the detection rate of signature and trigger set drop slowly. In a concrete way, when std equals 0.003, all the classification accuracy and detection rate keep a high performance, which demonstrates the robustness of signature and trigger set under the conduction of differential privacy.

**Robustness Against Client Selection:** in FederatedAveraging algo., we decrease the fraction ratio of each client being selected in each epoch to increase the computation efficiency. Figure 8(b) shows that the signature could not be removed even the fraction ratio is very low. More specifically, when the fraction ratio is larger than 0.2, all the classification accuracy and detection rate keep unchanged. This small fraction of sampling gives a lower bound of efficient computation scheme in which ownership signatures can be effectively embedded and verified.

**Robustness Against Pruning:** we conduct the pruning of the network by randomly making the model weights to be zero, then testing whether the network after pruning could detect the trigger set or signature. Figure 8(c) shows signature detection rate as increasingly larger portion of network parameters are pruned. It was observed that the detection rate of signature embedded in normalization layer is stable all the time, while signatures embedded in convolution layer weights with \( W_k \) can be severely degraded. Specifically, main task model performance and signature embedded in \( W_\gamma \) are both persistent when the pruning rate is less than 70 percent.

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5The trigger set samples are regarded as correctly detected when the designated targeted adversarial labels are returned.
Figure 5: Figure describes the robustness of our FedIPR ownership verification scheme: In a federated learning system of 20 clients training AlexNet with CIFAR10 dataset, in which $n_W = 10$, $n_B = 10$, figure (a) illustrates feature-based and trigger-based signature detection rate under varying differential private noise sigma; figure (b) illustrates feature-based and trigger-based signature detection rate under different sample fraction ratio while federated training. figure (c) illustrates feature-based signature detection rate against model pruning attack with varying pruning rate; figure (d) illustrates feature-based signature detection rate against model finetuning attack in 50 epochs.

**Robustness Against Fine-tuning:** attacks on embedded signatures by fine-tuning were launched to train the network only in mask task (without the presence of the regularization term, i.e., $L_T$ and $R_B$). In Figure 8 (d), it was observed that the detection rate of signature embedded with normalization layer ($W_γ$) remains at 100% (blue curve). In contrast, the detection rate of signature embedded with convolution layer ($W_k$) drops significantly (purple curve). The superior robustness of signatures embedded in normalization layer is in accordance to observations reported in [12], whereas DNN models are trained in a standalone setting.

Finally, we refer reviewers to supplementary material for more experimental results of signature reliability under other attacks.

4 Discussion and Conclusion

This paper illustrated a novel ownership verification scheme to protect Intellectual Property Right (IPR) of Federated DNN models against external plagiarizers who illegally copy, re-distribute and/or misuse the models. To our best knowledge, it is the first ownership verification scheme that aims to protect IPR of federated learning models. We believe this work addresses a crucial issue remained open in federated learning research, since the protection of valuable federated learning models is as important as protecting data privacy.

On the technical side, this work demonstrated that reliable and persistent signatures can be embedded into local models without disclosing the presence and extraction parameters of these signatures. In particular, normalization scale parameters based signatures are extremely robust against removal attacks including fine-tuning and pruning. It is our wish that the formulation illustrated in this paper will lead to signature embedding and verification in various federated learning settings, and in particular, how to embed trigger-set signatures in vertical federated learning scenarios is one of future research topics.
A Notation of Parameters

Table 2: Notation description

| W   | Model weights | W<sup>k</sup> | Convolution kernel weights |
|-----|---------------|---------------|----------------------------|
|     |               | W<sup>γ</sup> | Normalization scale weights |
| O   | Model outputs | O<sup>k</sup> | Middle layer activation outputs |
|     |               | O<sup>I</sup> | Images outputs |
|     |               | O<sup>c</sup> | Classification labels outputs |

Key generation Process: G

| B   | Target signature | B       | Extracted signature from model |
|-----|------------------|--------|--------------------------------|
| ̂B  | sign(B)          | N      | Bits number of targeted signature |
| M   | Dimension of B   | θ = {S, E} | Hyper-parameters of extracting signature |
| T   | Trigger set      | K      | Number of clients |

Embedding Process: E

| L<sub>D</sub> | Main task loss | L<sub>T</sub> | trigger-set-based loss |
|---------------|----------------|---------------|------------------------|
| R<sub>Nθ</sub> | Feature-based regularization | Hinge loss | BCE() : Cross entropy loss |

Aggregation Process: A

| n<sub>k</sub> | The aggregate weights for k<sub>th</sub> clients |

Verification Process: V

| V<sub>W</sub> | white-box verification | ε<sub>W</sub> | threshold of signature detection |
| V<sub>B</sub> | black-box verification | ε<sub>B</sub> | threshold of signature detection |

B Proof of existence for feature based regularization

In this part, we give a proof of the Proposition 1, which illustrates the three conditions under which reliable and persistent signatures can be successfully embedded into the same FedDNN model by multiple clients.

**Proposition 2.** If U or ̂U as defined above satisfy any one of following conditions, then there exists W such that W<sup>T</sup> ̂U ≥ 0.

1. rank(U) = KN,
2. ∃ all elements of one row of ̂U<sup>M×KN</sup> are positive,
3. The dot product of any two columns of ̂U<sup>M×KN</sup> are positive.

**Proof.** For the condition (1), if rank(U) = K, then the column of U (U<sub>1</sub>, U<sub>2</sub>, ⋅⋅⋅ U<sub>KN</sub>) is independent, and the column of ̂U ( ̂U<sub>1</sub>, ̂U<sub>2</sub>, ⋅⋅⋅ ̂U<sub>KN</sub>) is also independent. Thus,

\[ y_1 ̂U_1 + y_2 ̂U_2 + ⋅⋅⋅ + y_{KN} ̂U_{KN} = 0 \iff y_1 = y_2 = ⋅⋅⋅ = y_{KN} = 0 \]  \hspace{3cm} (10)
Therefore the solution of $\tilde{U}\tilde{y} = \tilde{0}$ is only $\tilde{0}$, moreover, $\tilde{U}\tilde{y} = \tilde{0}$ doesn’t have non-negative solutions except $\tilde{0}$. According to Gordan’s theorem (4), Either $\tilde{U}\tilde{y} > \tilde{0}$ has a solution $\tilde{y}$, or $\tilde{U}\tilde{y} = \tilde{0}$ has a nonzero solution $\tilde{y}$ with $\tilde{y} \geq 0$. Since the latter statement is wrong, there exists $W = \tilde{y}^T$ such that $W\tilde{U} > 0$.

For the second condition, it is obvious that $\tilde{U}\tilde{y} = 0$ doesn’t have non-negative solutions except $\tilde{0}$. Therefore the conclusion is true based on Gordan’s theorem.

For the third condition, let the columns of $\tilde{U}$ be $(\tilde{U}_1, \tilde{U}_2, \ldots, \tilde{U}_{KN})$. We obtain a contradiction by considering $\tilde{U}\tilde{y} = 0$ has a nonzero solution $\tilde{y}$ with $\tilde{y} \geq 0$, then

$$0 = \tilde{U}\tilde{y}(\tilde{U}\tilde{y})^T = \sum_{i,j} \tilde{U}_i\tilde{U}_j^T y_iy_j$$

(11)

Since $y_i \geq 0$ and $\tilde{U}_i\tilde{U}_j^T > 0$, $y_i = 0$ for $i = 1, 2, \ldots, KN$. This shows $\tilde{U}\tilde{y} = \tilde{0}$ has a nonzero solution $\tilde{y}$ with $\tilde{y} \geq 0$, which infers the existence of $W^{1 \times M}$ such that $W\tilde{U} > 0$.

**Remark** The proposition only demonstrates the existence of solution for signature regularization term $R_{1,\phi}(W)$. Embedding signature does not influence the performance of the main task confirmed in experiments, because deep neural networks are typically over parameterized. Deep neural networks have many local minima, whose error very close to the global minimum $\beta$. Therefore, the embedding regularizer only needs to guide model parameters to one of a number of good local minima so that the final model parameters embed the signature well.

**C Experiment Settings**

This section illustrates the experiment settings of the empirical study on our FedIPR framework for the FedDNN models.

**DNN Model Architectures.** The deep neural network architectures we investigated include the well-known AlexNet and ResNet-18. Feature-based binary signatures are embedded into convolution kernel weights $W^k$ and normalization scale weights $W^\gamma$ of multiple convolution layers in AlexNet and ResNet-18. Table 3 and 4 shows the detailed model architectures and parameter shape of AlexNet and ResNet-18, which we employed in all the experiments.

**Dataset.** We evaluate classification tasks on standard CIFAR10 dataset and CIFAR100 dataset. The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. CIFAR-100 has 100 classes containing 600 images each, there are 500 training images and 100 testing images per class. Respectively, we conduct stand image classification tasks of CIFAR10 and CIFAR100 with AlexNet and ResNet-18. According to the way we split the dataset for clients in federated learning, the experiments are divided into iid setting and non-iid setting. The results for both IID setting and Non-IID federated learning setting are provided in the section D.

**Federated Learning Settings** We simulate a with $K = 20$ clients horizontal federated learning system in a stand-alone machine with 8 Tesla V100-SXM2 32 GB GPUs and 72 cores of Intel(R) Xeon(R) Gold 61xx CPUs.

In each communication round, the server samples clients with uniform distribution of a certain fraction ratio to participate training (the fraction ratio we explore includes 1.0, 0.8, 0.5, 0.2, 0.1 and 0.05). The clients update the weight updates, server adopts Federaedavg algorithm in to aggregate the model updates. The detailed experiment Hyper parameters we employ to conduct our federated learning are listed in the table.

**Embedding Process $E$**

**Feature-based signature:** For the feature-based signature embedding scheme, we constrain the sign of network parameters $W^\gamma$ and $W^k$ with regularization terms $R_{1,\phi}$ including Hinge Like loss, and cross-entropy loss targeted at different bit length of each client. We change the number of clients and the bit length of signature per client under diverse federated learning setting. The algorithm is shown in Algorithm 2.
**Trigger-set Signature:** The trigger-set embedding process adopts a batch-poisoning backdoor method: in each iteration of backdoor training, both normal samples and backdoor samples are used in the same data batch for model training.

We adopt adversarial samples as trigger set $T$: we train the adversarial samples with Projected Gradient Descent (PGD)\[16\], from original data $T_{source}$ in the standard benchmark data. The PGD parameters are listed in the table \[7\]. After the training process of PGD, the trigger $T$ can mislead the classifier to targeted label designated ahead.

**Verification process V**

After obtaining the model, we could extract the signature and test the trigger set from the model. Verification process of signature and trigger-set is shown Algorithm 3 and 4.

**Removal attack**

Following previous DNN watermarking methods, we report model performances under fine-tuning and pruning attacks.

For **finetuning**, we adopt the code\[6\] and follow their implementation in Algorithm 5. For **pruning**, we adopt the code\[7\] and follow their implementation in Algorithm 5. The hyper parameters are shown in table 5.

| layer name       | output size | weight shape | padding |
|------------------|-------------|--------------|---------|
| Conv1            | 32 $\times$ 32 | 64 $\times$ 3 $\times$ 5 $\times$ 5 | 2       |
| MaxPool2d        | 16 $\times$ 16 | 2 $\times$ 2 |         |
| Conv2            | 16 $\times$ 16 | 192 $\times$ 64 $\times$ 5 $\times$ 5 | 2       |
| Maxpool2d        | 8 $\times$ 8 | 2 $\times$ 2 |         |
| Conv3            | 8 $\times$ 8 | 384 $\times$ 192 $\times$ 3 $\times$ 3 | 1       |
| Conv4            | 8 $\times$ 8 | 256 $\times$ 384 $\times$ 3 $\times$ 3 | 1       |
| Sign Embedding ($W_γ$) | 8 $\times$ 8 | 256           |         |
| Conv5            | 8 $\times$ 8 | 256 $\times$ 256 $\times$ 3 $\times$ 3 | 1       |
| Sign Embedding ($W_γ$) | 8 $\times$ 8 | 256           |         |
| MaxPool2d        | 4 $\times$ 4 | 2 $\times$ 2 |         |
| Linear           | 10           | 10 $\times$ 4096 |         |

Table 3: Modified AlexNet architecture.

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[6] https://github.com/dingsheng-ong/ipr-gan
[7] https://github.com/zepx/pytorch-weight-prune/blob/develop/pruning/methods.py
| Layer Name | Output Size | Weight Shape | Padding |
|------------|-------------|--------------|---------|
| Conv1      | 32 × 32     | 64 × 3 × 3 × 3 | 1       |
| Conv2_x    | 32 × 32     | 64 × 64 × 3 × 3 | × 2 | 1 |
| Conv3_x    | 16 × 16     | 128 × 128 × 3 × 3 | × 2 | 1 |
| Conv4_x    | 8 × 8       | 256 × 256 × 3 × 3 | × 2 | 1 |
| Conv5_x    | 4 × 4       | 512 × 512 × 3 × 3 | × 2 | 1 |
| Sign Embedding (Wγ) | 4 × 48 | 512 × 1 | |
| Average pool | 1 × 1 | 4 × 4 | |
| Linear     | 10          | 10 × 512     |         |

Table 4: ResNet-18 architecture

| Hyper-parameter                          | Removal Attack                        |
|------------------------------------------|---------------------------------------|
| Pruning Rate                             | 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 |
| Finetuning Learning Rate                 | 0.0001                                |
| Finetuning Learning Loss                 | only Cross Entropy loss               |
| Batch size                               | 16                                    |
| Finetuning Epochs                        | 50                                    |
| Learning rate decay                      | 0.01 per epoch                        |
| Vanilla Classification model             | CNN with three convolution layers     |

Table 5: Training parameters for Removal Attack

**Algorithm 1** Generation $G$ of Signatures

1: procedure **SIGNATURE GENERATION**
2: for client $k$ in $K$ clients do
3: Initialize $B_k, \theta_k = \{S_k, E_k\}$
4: Encode $B_k$ into binary to be embedded into signs of $WT E$
5: Initialize $T_k = \{(X_1, Y_1), \cdots, (X_J, Y_J)\}$ Backdoor samples $X_j$ and corresponding output labels $Y_j$
6: return $\{(B_k, \theta_k, T_k)\}_{k=1}^{K}$
| Hyper-parameter                  | AlexNet | ResNet-18 |
|---------------------------------|---------|-----------|
| Activation function             | ReLU    | ReLU      |
| Optimization method             | SGD     | SGD       |
| Momentum                        | 0.9     | 0.9       |
| Learning rate                   | 0.01    | 0.01      |
| Batch size                      | 16      | 16        |
| Backdoor batch size             | 2       | 2         |
| Data Distribution               | IID and non-IID | IID and non-IID |
| Global Epochs                   | 200     | 200       |
| Local Epochs                    | 2       | 2         |
| Learning rate decay             | 0.99 at each global Epoch | 0.99 at each global Epoch |
| Federated Fraction              | [13]    | [13]      |
| Client numbers                  | 20      | 20        |
| Feature-based Signature         | 5,10    | 5,10      |
| Regularization Term             | BCE loss, Hinge-like loss | BCE loss, Hinge-like loss |
| $\alpha$ of Regularization Loss| 0.2, 0.5, 1, 5 | 0.2, 0.5, 1, 5 |
| Feature-based Signature parameters W | $W^k$ and $W^\gamma$ | $W^k$ and $W^\gamma$ |
| Trigger-based Signature         | 5,10    | 5,10      |
| Trigger-based Signature type    | Adversarial sample | Adversarial sample |

Table 6: Training parameters for Federated AlexNet and ResNet-18, respectively († the learning rate is scheduled as 0.01, 0.001 and 0.0001 between epochs [1-100], [101-150] and [151-200] respectively).

| Hyper-parameter                  | Projected Gradient Descent                  |
|----------------------------------|---------------------------------------------|
| Optimization method             | Profected Gradient Descent                  |
| Norm type                        | L2                                          |
| Norm of noise                    | 0.3                                         |
| Learning rate                    | 0.01                                        |
| PGD Batch size                   | 128                                         |
| Targeted at Specific Labels      | True                                        |
| Iterations                       | 80                                          |
| Learning rate decay              | None                                        |
| Vanilla Classification model     | CNN with three convolution layers           |

Table 7: Training parameters for Projected Gradient Descent Adversarial Training
Algorithm 2 Signature Embedding Process for FedIPR

1: Each client $k$ with its own signature tuple $(B_k, \theta_k, T_k)$
2: for $t$ in communication round $E$ do
3: Server distributes the global model parameters $W_t$ to each clients
4: Sample clients with fraction ratio $C$ into subset $s$ of $K$ clients
5: **Local Training:**
6: for $k$ in number of selected users subset $s$ do
7: Sample minibatch of $m$ samples $X \{X^{(1)}, \ldots, X^{(m)}\}$ and targets $Y \{Y^{(1)}, \ldots, Y^{(m)}\}$
8: if enable backdoor then
9: sample $t$ samples of $T_k$ and backdoor targets $Y_{T_k} \triangleq t = 2$, default by [2]
10: concatenate $X$ with $T$, $Y$ with $Y_{T_k}$
11: compute cross-entropy loss $L_c$ using $X$ and $Y$
12: for layer $l$ in targeted layers set $L$ do
13: compute Regularization term $R_l$ using $\theta_k$ and $W_l$
14: $R \leftarrow \sum_{l \in L} R_l$
15: $L = L_c + R$
16: Backpropagate using $L$ and update $W_k^t$
7: Server Update:
18: Aggregate the $\{W_k^t\}_{k=1}^K$ with FederateAvg algorithm

Algorithm 3 White-box Feature Based Signature Verification

**Input:** Model weights $W$ offered by adversaries, Embedding matrix $E$ and $B$ provided by user.

1: **procedure** SIGNATURE DETECTION
2: $B \leftarrow W^T E$
3: signature $\leftarrow$ sign($B$)
4: Convert signature into binary
5: Decode binarized signature into desired format e.g. ascii
6: Match decoded signature with target signature
7: Compute the signature detection rate $V_W(W, E)$

**Output:** $V_W(W, E)$

Algorithm 4 Black-box Trigger-set Based Signature Verification

**Input:** Model $N$ offered by adversaries, Trigger set $T$ and $Y_T$ provided by user.

1: **procedure** TRIGGER-SET DETECTION
2: Fed the Trigger-set $T$ into model ($N$) to derive the classification label $O_c$
3: Match $O_c$ with target label of target trigger-set label $Y_T$
4: Compute the trigger-set detection rate $V_B(T, Y_T, W)$

**Output:** $V_B(T, Y_T, W)$

Algorithm 5 Removal attack

**Input:** Model $N$, trigger set $T$ and $Y_T$, target signature $B$

1: **procedure** PRUNING
2: for $p$ in different pruning percentage do
3: Pruning the model $N$ in $p$ percentage.
4: Test the signature and trigger-set detection rate.
5: **procedure** FINETUNING
6: for epochs in 50 do
7: Train the model $N$ only in main task (classification task)
8: Test the signature and trigger-set detection rate.
Figure 6: Model performances in a federated learning system with 20 clients. Figure (a) and (b), respectively, illustrate CIFAR10 with AlexNet and CIFAR100 with ResNet18 classification accuracy, when $n_W = 5$, 10 clients embed varying bit-lengths signatures. Figure (c) and (d), respectively, illustrate CIFAR10 with AlexNet and CIFAR100 with ResNet18 classification accuracy for 5 or 10 clients embedding varying number of trigger-set samples.

D Main experiment results.

D.1 Evaluation Metrics

To evaluate the FedDNN model signature embedding quantitatively, we use a set of metrics to measure the **fidelity** and **reliability** of the proposed feature-based signatures and trigger-set based signatures.

**Fidelity:** we use classification accuracy on the main task as the metrics for fidelity. It is expected classification accuracy should not be degraded by the embedding of signatures into the federated model.

**Reliability:** averaged detection rate of embedded signatures is used to quantify the reliability of a signature verification scheme. For feature-based signatures, detection rate $\eta$ is calculated as $\eta = 1 - \frac{D_{\text{hamming}}}{M}$ where $D_{\text{hamming}}$ measures Hamming distance between extracted binary signature string and the target signatures. For trigger-set based signatures detection rate $\eta$ is calculated as the ratio of backdoor samples that are classified as designated labels w.r.t. the total number of all trigger set samples.

D.2 Fidelity

Fidelity of the proposed model verification scheme was evaluated under different settings, including varying signature bit length, varying number of triggers per client and different datasets and model architectures.

**Trigger-set Signature:** varying number of clients may decide to embed different number of trigger set samples (as signatures) into the federated model, and Figure 6 (c) and (d) show that model performances of the main task remain almost constant when 20 to 600 trigger set samples are embedded by, respectively, each of 5 and 10 clients. There is a negligible accuracy drop (less than 1%) with respect to the model performance without embedding any trigger set signatures.

**Feature-based Signature:** Figure 6(a) and (b) illustrates model performance measured with different length ($M$) of binary signatures embedded into normalization layer scale parameter ($W_\gamma$). It was observed that long bit-lengths (200 bits per client) of signatures lead to slight model performance drop up to 2% for AlexNet on CIFAR10 classification main task. Similar performance drop up to 2% was also observed for ResNet on CIFAR100 classification task, when up to 350 bits signatures were used for each client of 10 clients. The drop of classification accuracy is due to the sub-optimal solution restricted to the subspace defined by large number of binary signature constrains (see Proposition 2). Note that performance drop can actually be mitigated by assigning binary signatures across different layers of normalization scale parameters, see Section E.2 for details.

D.3 Reliability

Reliability of the proposed model verification scheme was evaluated under different settings, including varying signature bit length, varying number of triggers per client and different datasets and model architectures.
Figure 7: In a federated learning system of 20 clients, figure (a) and (b), respectively, illustrate the case when $n_W = 5, 10$, the signature detection rate with varying bit length per client, figure (a) describes the case that AlexNet with CIFAR10 dataset, figure (b) describes the case that ResNet with CIFAR100 dataset. Figure (c), (d) illustrate the case when $n_B = 5, 10$, the trigger detection accuracy with varying trigger per client, figure (c) describes the case that AlexNet with CIFAR10 dataset, figure (d) describes the case that ResNet with CIFAR100 dataset.

**Trigger-set based signature**: reliability of trigger-set signatures were evaluated under two settings, i.e., 5 or 10 clients are randomly selected to embed trigger-set signatures generated by Projected Gradient Descent (PGD) adversarial attack method [16]. Figure 7 (c) and (d) illustrate the trigger set detection rates on these adversarial sample $T$, respectively, with AlexNet on CIFAR10 classification and ResNet18 on CIFAR100 classification tasks. The results show that the detection rate of trigger-set $T$ almost keep constant even the trigger number per client increases. Moreover, detection rates of signatures embedded in the more complex ResNet18 is more stable than those signatures embedded in AlexNet. Also, the detection rate is not influenced by the varying number of clients and, thus, varying number of total trigger-set samples used. We ascribe the stable detection rate to the generalization capability of over-parameterized networks as demonstrated in [3, 27].

**Feature-based Signature**: Figure 7 (a) and (b) illustrate binary signature detection rates in white-box manner, in which (a) is with AlexNet for CIFAR10 and (b) with ResNet18 for CIFAR100 classification tasks. First, note that the detection rates remain constant (100%) within the regime, whereas the total bit lengths assigned by multiple (5 or 10) clients does not exceed the capacity of network parameters used to embed signatures. This limit is, respectively, 256 and 512 convolution channels at the last layer for AlexNet and ResNet18. Therefore, binary signatures of all bits can be reliably detected, which is in accordance to the analysis disclosed in Proposition 2. When the total bit lengths exceeds the limit e.g. in Figure 7 (a) when 100 bits signatures are assigned by 5 clients, the detection rate drops to about 80% due to the conflicts of overlapping signature assignments. Nevertheless, the dropped detection rate still guarantees very high confidence in claiming the ownership of verified models, since random guessing of designated signatures will lead to a exponentially small probability of detection rate.

The results illustrated in Figure 7 give rise to the capability of feature based signature $B$ into FedDNN model: the bit length of signatures of total clients $\{M\}_{i=1}^{n_W}$ can not exceed the channel number of normalization scale weights $W^\gamma$ in selected convolutional layers. More experimental results about kernel parameters and cross-entropy loss $W^K$ are attached in Section E.4 E.3.

### D.4 Robustness

In federated learning, some strategies are widely used to protect privacy, increase efficiency, and so on. We choose two scenarios in common usage: implementing the differential privacy [24] and decrease the fraction frequency. Under these two scenarios, we test whether the trigger set and signature are persistent. Moreover, the attacker may try to remove the trigger set and embedded signature while inheriting the model performance in federated learning. Here, we conduct two removal attacks: fine-tuning and pruning to identify whether embedded watermark and signature are persisted.

**Robustness Against Differential Privacy**: we adopt the Gaussian noise-based method to provide differential privacy guarantee for federated learning. Specifically, We vary the standard deviation (std)

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8The trigger set samples are regarded as correctly detected when the designated targeted adversarial labels are returned.
of Gaussian noise on the local gradient before clients send gradients to the server. As Figure 8 (a) shows, the classification error decreases severely as the std of noise increases while the detection rate of signature and trigger set drop slowly. In a concrete way, when std equals 0.003, all the classification accuracy and detection rate keep a high performance, which demonstrates the robustness of signature and trigger set under the conduction of differential privacy.

**Robustness Against Client Selection:** in FederatedAveraging algo., we decrease the fraction ratio of each client being selected in each epoch to increase the computation efficiency. Figure 8 (b) shows that the signature could not be removed even the fraction ratio is very low. More specifically, when the fraction ratio is larger than 0.2, all the classification accuracy and detection rate keep unchanged. This small fraction of sampling gives a lower bound of efficient computation scheme in which ownership signatures can be effectively embedded and verified.

**Robustness Against Pruning:** we conduct the pruning of the network by randomly making the model weights to be zero, then testing whether the network after pruning could detect the trigger set or signature. Figure 8 (c) shows signature detection rate as increasingly larger portion of network parameters are pruned. It was observed that the detection rate of signature embedded in normalization layer is stable all the time, while signatures embedded in convolution layer weights with \( W_k \) can be severely degraded. Specifically, main task model performance and signature embedded in \( W_\gamma \) are both persistent when the pruning rate is less than 70 percent.

**Robustness Against Fine-tuning:** attacks on embedded signatures by fine-tuning were launched to train the network only in mask task (without the presence of the regularization term, i.e., \( L_T \) and \( R_B \). In Figure 8 (d), it was observed that the detection rate of signature embedded with normalization layer (\( W_\gamma \)) remains at 100% (blue curve). In contrast, the detection rate of signature embedded with convolution layer (\( W_k \)) drops significantly (purple curve). The superior robustness of signatures
embedded in normalization layer is in accordance to observations reported in [12], whereas DNN models are trained in a standalone setting.

E Ablation Study

E.1 Influence of feature-based signature regularization parameter $\alpha$

In this section, we test the influence which the feature-based signature regularization parameter $\alpha$ brings. Our experiments demonstrates $\alpha$ only affect the fidelity.

The left image of Figure 9 shows the model performance drops seriously as $\alpha$ increases, especially when $\alpha$ equals 1 and 5. The right image of Figure 9 explains the reliability keeps the similar trend even the $\alpha$ changes from 0.2 to 5.

Figure 9: Results of CIFAR10 with AlexNet when embedding signature in different regularization parameter $\alpha$. Left is main task classification accuracy as the signature length number varies in different $\alpha$. Right images is signature detection rate with different number of signature length in different $\alpha$.

E.2 Diversity of embedding position of signature

We embed feature-based signatures into last two layers of AlexNet to explore the capacity of white-box embedding. As shown in the Table 3, the Conv. layer 4 and Conv. layer 5 have each 256 channels of convolution kernels, we test the fidelity, reliability of white box signature. We compare the results of the case with single Conv. layer 5 and the case with Conv.4 and Conv.5, the results is described in the Figure 10.

Figure 10 Left shows that the signature embedding into multiple layers yields no compromise of fidelity, the main task slightly decades as the bit length increases. Figure 10 Right describe the signatures into multiple layers of the neural network amplify the capacity of signatures, because the multiple layers enable more bit length of signatures into the model. Two-layer case enables twice the bit length of signature as one-layer case in the same detection signature rate.

This result also proves that: the bit length of signatures of total clients $\{M_i\}_{i=1}^n$ can not exceed the channel number of normalization scale weight $W^\gamma$ in selected convolution layers, which is consistent with Proposition 2.

E.3 Signature into Kernel Weights

The parameters $W$ chosen for embedding signatures includes convolution layer weights $S(W)$ (the columnized vector of convolution layer weights) and normalization layer scale parameters $S(W) = W_\gamma = \{\gamma_1, \cdots, \gamma_C\}$ where $C$ is the number of normalization filters.

The table 9 illustrates the main task classification accuracy (fidelity) with the increase of bit length of signature, the model performance is slightly affected only when the signature embedding conflict with each other. Figure 11 illustrate the reliability (signature detection rate) of signature detection on convolution weights $W^K$. Convolution kernel parameters naturally have more parameters for
embedding signatures, so the capacity is correspondingly larger the the case with normalization weights $W^K$.

**Remark** The blue line in Figure [11] doesn’t decrease because the total signature length $KN = 500 \times 5 = 2500$ is closed to number of embedding weights $256 \times 9 = 2294$

Table 8: Model classification accuracy with embedding in convolution layer ($W^k$) under two conditions (5 or 10 clients add signature)

| Bits Number | 30  | 60  | 90  | 120 | 150 | 180 | 210 | 240 |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Model Acc   | 0.9135 | 0.9131 | 0.9132 | 0.9129 | 0.9125 | 0.9123 | 0.912 | 0.913 |
|             | 0.9134 | 0.9127 | 0.9165 | 0.9149 | 0.9146 | 0.9134 | 0.9128 | 0.9129 |
|             | 270  | 300  | 330  | 360  | 390  | 420  | 450  | 480  |
| Model Acc   | 0.9142 | 0.914  | 0.9125 | 0.9132 | 0.9114 | 0.9121 | 0.9122 | 0.9094 |
|             | 0.9159 | 0.9119 | 0.91  | 0.9131 | 0.9146 | 0.9105 | 0.9113 | 0.9139 |

**E.4 Cross Entropy Loss**

The regularization term we employ for signature embedding include both binary cross entropy (BCE) loss and Hinge-like (HL) loss: Binary cross-entropy $\text{BCE}(B, B) = -\sum_{j=1}^{N} t_j \log(f_j) + (1 - \text{sgn}(f_j - B))$
Figure 11: Results in embedding signature in the last convolution layer ($W^k$) in AlexNet. The change of signature detection rate as signature length varies when 10 or 5 clients choose to embed signature.

\[ t_j \log(1 - f_j); \] where \( f_j = \frac{1}{1 + \exp(-t_j)} \), and Hinge loss \( \text{HL}(B, B) = \sum_{j=1}^{N} \max(\alpha - b_j t_j, 0) \), where signatures \( B = (t_1, \cdots, t_N) \in \{-1, 1\}^N \).

We conduct experiments with the same setting of 20 clients in BCE regularization and Hinge regularization, whose results show both two approaches are influenced with signature length similarly.

Specifically, when the bit length is in the capacity of signature embedding, the fidelity and reliability between BCE loss and Hinge loss are the same (shown in Table 9). Moreover, when the signature embedding conflict with each other, the reliability of BCE loss is slightly better than the HL loss.

To conclude, the HL regularization term is a stronger constrain than BCE regularization term, when the diverse signature embedding of clients conflict with each other, hinge like loss affects more fidelity and reliability.

Table 9: Model classification accuracy in BCE loss and Hinge loss under two conditions (5 or 10 clients add signature)

| Bits Len. | BCE loss  | Hinge loss |
|-----------|-----------|------------|
|           | Client5   | Client10   | Client5   | Client10   |
| 20        | 0.9152    | 0.9157     | 0.9137    | 0.9134     |
| 40        | 0.9146    | 0.91      | 0.912     | 0.9112     |
| 60        | 0.9137    | 0.9087     | 0.9116    | 0.9087     |
| 80        | 0.9136    | 0.9136     | 0.9115    | 0.9078     |
| 100       | 0.9135    | 0.9123     | 0.9113    | 0.9069     |
| 120       | 0.9123    | 0.913      | 0.9115    | 0.9052     |
| 140       | 0.912     | 0.9124     | 0.9112    | 0.904      |
| 160       | 0.9118    | 0.9139     | 0.9105    | 0.9036     |
| 180       | 0.9113    | 0.9082     | 0.9088    | 0.9035     |
| 200       | 0.9111    | 0.9121     | 0.9077    | 0.9026     |
Figure 12: Results in embedding signature into last normalization layer ($W^\gamma$) of AlexNet with two different regularization: Hinge regularization and BCE regularization. Left image is the comparison of signature detection rate between Hinge loss and BCE loss when 5 clients choose to add signature; right is similar comparison when 10 clients choose to add signature.

References

[1] M. Abadi, A. Chu, I. Goodfellow, H. B. McMahan, I. Mironov, K. Talwar, and L. Zhang, “Deep learning with differential privacy,” in Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, 2016, pp. 308–318.

[2] Y. Adi, C. Baum, M. Cisse, B. Pinkas, and J. Keshet, “Turning your weakness into a strength: Watermarking deep neural networks by backdooring,” in 27th USENIX Security Symposium (USENIX), 2018.

[3] Z. Allen-Zhu, Y. Li, and Z. Song, “A convergence theory for deep learning via over-parameterization,” CoRR, vol. abs/1811.03962, 2018.

[4] N. Alon and K. A. Berman, “Regular hypergraphs, gordon’s lemma, steinitz’ lemma and invariant theory,” Journal of Combinatorial Theory, Series A, vol. 43, no. 1, pp. 91–97, 1986.

[5] E. Bagdasaryan and V. Shmatikov, “Blind Backdoors in Deep Learning Models,” arXiv e-prints, p. arXiv:2005.03823, May 2020.

[6] E. Bagdasaryan, A. Veit, Y. Hua, D. Estrin, and V. Shmatikov, “How to backdoor federated learning,” arXiv preprint arXiv:1807.00459, 2018.

[7] A. N. Bhagoji, S. Chakraborty, P. Mittal, and S. Calo, “Analyzing federated learning through an adversarial lens,” in Proceedings of the 36th International Conference on Machine Learning, ser. Proceedings of Machine Learning Research, K. Chaudhuri and R. Salakhutdinov, Eds., vol. 97. PMLR, 09–15 Jun 2019, pp. 634–643. [Online]. Available: [http://proceedings.mlr.press/v97/bhagoji19a.html](http://proceedings.mlr.press/v97/bhagoji19a.html)

[8] F. Boenisch, “A survey on model watermarking neural networks,” 2020.

[9] H. Chen, B. Darvish Rohani, and F. Koushanfar, “DeepMarks: A Digital Fingerprinting Framework for Deep Neural Networks,” arXiv e-prints, p. arXiv:1804.03648, Apr. 2018.

[10] B. Darvish Rouhani, H. Chen, and F. Koushanfar, “DeepSigns: A Generic Watermarking Framework for IP Protection of Deep Learning Models,” arXiv e-prints, p. arXiv:1804.00750, Apr. 2018.

[11] N. Dinh and V. Jeyakumar, ‘Farkas’ lemma: three decades of generalizations for mathematical optimization,” Top, vol. 22, no. 1, pp. 1–22, 2014.

[12] L. Fan, K. W. Ng, and C. S. Chan, “Rethinking deep neural network ownership verification: Embedding passports to defeat ambiguity attacks,” in Advances in Neural Information Processing Systems. Curran Associates, Inc., 2019, pp. 4714–4723.

[13] K. He, X. Zhang, S. Ren, and J. Sun, “Delving deep into rectifiers: Surpassing human-level performance on imagenet classification,” in Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2015, pp. 1026–1034.
[14] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings, R. G. L. D’Oliveira, S. E. Rouayheb, D. Evans, J. Gardner, Z. Garrett, A. Gascón, B. Ghazi, P. B. Gibbons, M. Gruteser, Z. Harchaoui, C. He, L. He, Z. Huo, B. Hutchinson, J. Hsu, M. Jaggi, T. Javidi, G. Joshi, M. Khodak, J. Konečný, A. Korolova, F. Koushanfar, S. Koyejo, T. Lepoint, Y. Liu, P. Mittal, M. Mohri, R. Nock, A. Özgür, R. Pagh, M. Raykova, H. Qi, D. Ramage, R. Raskar, D. Song, W. Song, S. U. Stich, Z. Sun, A. T. Suresh, F. Tramèr, P. Vepakomma, J. Wang, L. Xiong, Z. Xu, Q. Yang, F. X. Yu, H. Yu, and S. Zhao, “Advances and open problems in federated learning,” Foundations and Trends® in Machine Learning, vol. abs/1912.04977, 2019. [Online]. Available: http://arxiv.org/abs/1912.04977

[15] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-Efficient Learning of Deep Networks from Decentralized Data,” in Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, ser. Proceedings of Machine Learning Research, A. Singh and J. Zhu, Eds., vol. 54. Fort Lauderdale, FL, USA: PMLR, 20–22 Apr 2017, pp. 1273–1282. [Online]. Available: http://proceedings.mlr.press/v54/mcmahan17a.html

[16] A. Nguyen, J. Yosinski, and J. Clune, “Deep neural networks are easily fooled: High confidence predictions for unrecognizable images,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 427–436.

[17] D. S. Ong, C. S. Chan, K. W. Ng, L. Fan, and Q. Yang, “Protecting intellectual property of generative adversarial networks from ambiguity attack,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2021.

[18] L. T. Phong, Y. Aono, T. Hayashi, L. Wang, and S. Moriai, “Privacy-preserving deep learning via additively homomorphic encryption,” IEEE Transactions on Information Forensics and Security, vol. 13, no. 5, pp. 1333–1345, 2018.

[19] T. Ryffel, D. Pointcheval, and F. R. Bach, “ARIANN: low-interaction privacy-preserving deep learning via function secret sharing,” CoRR, vol. abs/2006.04593, 2020. [Online]. Available: https://arxiv.org/abs/2006.04593

[20] R. Shokri and V. Shmatikov, “Privacy-preserving deep learning,” in Proceedings of the 22nd ACM SIGSAC conference on computer and communications security, 2015, pp. 1310–1321.

[21] Z. Sun, P. Kairouz, A. Theertha Suresh, and H. B. McMahan, “Can You Really Backdoor Federated Learning?” arXiv e-prints, p. arXiv:1911.07963, Nov. 2019.

[22] Y. Uchida, Y. Nagai, S. Sakazawa, and S. Satoh, “Embedding watermarks into deep neural networks,” in Proceedings of the 2017 ACM on International Conference on Multimedia Retrieval, 2017, pp. 269–277.

[23] Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600–612, 2004.

[24] K. Wei, J. Li, M. Ding, C. Ma, H. H. Yang, F. Farokhi, S. Jin, T. Q. Quek, and H. V. Poor, “Federated learning with differential privacy: Algorithms and performance analysis,” IEEE Transactions on Information Forensics and Security, vol. 15, pp. 3454–3469, 2020.

[25] C. Wu, X. Yang, S. Zhu, and P. Mitra, “Mitigating backdoor attacks in federated learning,” CoRR, vol. abs/2011.01767, 2020. [Online]. Available: https://arxiv.org/abs/2011.01767

[26] Q. Yang, Y. Liu, T. Chen, and Y. Tong, “Federated machine learning: Concept and applications,” ACM Transactions on Intelligent Systems and Technology (TIST), vol. 10, no. 2, p. 12, 2019.

[27] C. Zhang, S. Bengio, M. Hardt, B. Recht, and O. Vinyals, “Understanding deep learning requires rethinking generalization,” in ICLR. OpenReview.net, 2017.

[28] J. Zhang, Z. Gu, J. Jang, H. Wu, M. P. Stoecklin, H. Huang, and I. Molloy, “Protecting intellectual property of deep neural networks with watermarking,” in Proceedings of the 2018 on Asia Conference on Computer and Communications Security (ASIACC), 2018, pp. 159–172.

[29] J. Zhang, D. Chen, J. Liao, W. Zhang, G. Hua, and N. Yu, “Passport-aware normalization for deep model protection,” in Advances in Neural Information Processing Systems, H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin, Eds., vol. 33. Curran Associates, Inc., 2020, pp. 22 619–22 628. [Online]. Available: https://proceedings.neurips.cc/paper/2020/file/ff1418e8cc993fe8abcfe3ce2003e5c5-Paper.pdf