DPAUC: Differentially Private AUC Computation in Federated Learning

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Abstract

Federated learning (FL) has gained significant attention recently as a privacy-enhancing tool to jointly train a machine learning model by multiple participants. The prior work on FL has mostly studied how to protect label privacy during model training. However, model evaluation in FL might also lead to potential leakage of private label information. In this work, we propose an evaluation algorithm that can accurately compute the widely used AUC (area under the curve) metric when using the label differential privacy (DP) in FL. Through extensive experiments, we show our algorithms can compute accurate AUCs compared to the ground truth. The code is available at https://github.com/bytedance/fedlearner/tree/master/example/privacy/DPAUC.

Introduction

With increasing concerns over data privacy in machine learning, regulations like CCPA\textsuperscript{1}, HIPAA\textsuperscript{2}, and GDPR\textsuperscript{3} have been introduced to regulate how data can be transmitted and used. To address privacy concerns, federated learning (McMahan et al. 2017; Hanzely et al. 2020; Yuan and Ma 2020; Ghosh et al. 2020) has become an increasingly popular tool to enhance privacy by allowing training models without directly sharing their data. Depending on how data is split across parties, FL can be mainly classified into two categories (Yang et al. 2019a): Horizontal Federated Learning (Geiping et al. 2020; Hamer, Mohri, and Suresh 2020; Karimireddy et al. 2020; Li et al. 2020) and Vertical Federated Learning (Vepakomma et al. 2018a; Gupta and Raskar 2018; Abudhba et al. 2020; Ceballos et al. 2020). In Horizontal FL (hFL), data is split by entity (e.g., a person), and data entities owned by each party are disjointed from other parties. In Vertical FL (vFL), a data entity is split into different attributes (e.g., features and labels of the same person), and each party might own the same data entities but their different attributes. In this paper, we focus on the setting of hFL which enables devices (i.e., mobile phones) to collaboratively learn a machine learning model (i.e., binary classifier) while keeping all the training and testing data on the device.

Although raw data is not shared in federated learning, sensitive information may still be leaked when gradients and/or model parameters are communicated between parties. In hFL, (Zhu, Liu, and Han 2019) showed that an honest-but-curious server can uncover the raw features and labels of a device by knowing the model architecture, parameters, and communicated gradient of the loss on the device’s data. Based on their techniques, (Zhao, Mopuri, and Bilen 2020) showed that the ground truth label of an example can be extracted by exploiting the directions of the gradients of the weights connected to the logits of different classes. Researchers have shown that vFL can still leak data information indirectly. For example, (Li et al. 2022) demonstrated that the gradient norms and directions can leak label information in the two-party vFL setting. However, the prior work on FL privacy mostly focuses on model training and there can also be privacy leaks from model evaluation. Specifically, the private label information owned by clients/devices can be leaked to the server when computing evaluation metrics in FL.

Previous work (Matthews and Harel 2013a) has shown that releasing the actual ROC curves on a private test dataset can allow an attacker with some prior knowledge of the test dataset to recover some sensitive information about the dataset. Some recent works (Chen et al. 2016; Stoddard, Chen, and Machanavajjhala 2014) proposed to provide differential privacy (DP) for plotting and releasing ROC curves. However, they have several challenges such as how to privately compute the true positive rate (TPR) and false positive rate (FPR) values and how many and what thresholds to pick (Stoddard, Chen, and Machanavajjhala 2014). And they are not designed and applicable for evaluating FL models. As the ground-truth labels often contain highly sensitive information (e.g., whether a user has purchased (in online advertising) or whether a user has a disease or not (in disease prediction)) (Vepakomma et al. 2018b; Li et al. 2022), it cannot be directly shared between clients and servers, and clients and clients. Hence preventing the label leakage from the AUC computation in the general setting of FL is challenging.

To address the challenge, we consider the area under the Receiver operating characteristic (ROC) curve as the target AUC to evaluate the accuracy of a binary classifier. Since the class label is often the most sensitive information in a predic-
tion task, our goal in this paper is to achieve label differential privacy (Ghazi et al. 2021) while plotting the ROC curve. To this end, we propose to adopt the Laplace mechanism \(^4\) to add noise to the shared intermediate information between the server and clients to plot the Receiver operating characteristic (ROC) curve and calculate the area under the ROC curve as the AUC. We conduct extensive experiments to demonstrate the effectiveness of our proposed approach.

### Preliminaries

We focus on the setting of hFL which contains one server and multi-clients (devices). The labels are distributed in multi clients and our proposed approach can compute the evaluation metric AUC with label differential privacy. We start by introducing some background knowledge of our work.

#### Label Differential Privacy

Differential privacy (DP) (Dwork et al. 2006; Dwork and Roth 2014a) is a quantifiable and rigorous privacy framework. We adopt the following definition of DP. We define Differential privacy (DP) (Dwork et al. 2006; Dwork and Roth 2014a) as the following:

**Definition 0.1 (Differential Privacy).** Let \(\varepsilon, \delta \in \mathbb{R}_{\geq 0}\), a randomized mechanism \(\mathcal{M}\) is \((\varepsilon, \delta)\)-differentially private (i.e. \((\varepsilon, \delta)\)-DP), if for any of two neighboring training datasets \(D, D'\), and for any subset \(S\) of the possible output of \(\mathcal{M}\), we have

\[
\Pr[\mathcal{M}(D) \in S] \leq e^\varepsilon \cdot \Pr[\mathcal{M}(D') \in S] + \delta.
\]

If \(\delta = 0\), then \(\mathcal{M}\) is \(\varepsilon\)-differentially private (i.e. \(\varepsilon\)-DP).

In our work, we focus on protecting the privacy of label information. Following (Ghazi et al. 2021), we define label differential privacy as the following:

**Definition 0.2 (Label Differential Privacy).** Let \(\varepsilon, \delta \in \mathbb{R}_{\geq 0}\), a randomized mechanism \(\mathcal{M}\) is \((\varepsilon, \delta)\)-label differentially private (i.e. \((\varepsilon, \delta)\)-LabelDP), if for any of two neighboring training datasets \(D, D'\) that differ in the label of a single example, and for any subset \(S\) of the possible output of \(\mathcal{M}\), we have

\[
\Pr[\mathcal{M}(D) \in S] \leq e^\varepsilon \cdot \Pr[\mathcal{M}(D') \in S] + \delta.
\]

If \(\delta = 0\), then \(\mathcal{M}\) is \(\varepsilon\)-label differentially private (i.e. \(\varepsilon\)-LabelDP).

Our proposed approach also shares the same setting with local DP (Duchi, Jordan, and Wainwright 2013; Erlingsson, Pihur, and Korolova 2014; Kasiviswanathan et al. 2008; Bebensee 2019) which assumes that the data collector (server in our paper) is untrusted. Following the same setting with local DP, in our proposed approach, each client locally perturbs their sensitive information with a DP mechanism and transfers the perturbed version to the server. After receiving all clients’ perturbed data, the server calculates the statistics and publishes the result of AUC. We define local DP as the following:

\(^4\)Other mechanisms such as the Gaussian mechanism are applicable (too)

**Definition 0.3 (Local Differential Privacy).** Let \(\varepsilon > 0\) and \(1 > \delta \geq 0\), a randomized mechanism \(\mathcal{M}\) is \((\varepsilon, \delta)\)-local differentially private (i.e. \((\varepsilon, \delta)\)-LocalDP), if and only if for any pair of input values \(v\) and \(v'\) in domain \(D\), and for any subset \(S\) of possible output of \(\mathcal{M}\), we have

\[
\Pr[\mathcal{M}(v) \in S] \leq e^\varepsilon \cdot \Pr[\mathcal{M}(v') \in S] + \delta.
\]

If \(\delta = 0\), then \(\mathcal{M}\) is \(\varepsilon\)-local differentially private (i.e. \(\varepsilon\)-LocalDP).

**Definition 0.4 (Sensitivity).** Let \(d\) be a positive integer, \(D\) be a collection of datasets, and \(f : D \rightarrow \mathbb{R}^d\) be a function. The sensitivity of a function, denoted \(\Delta f\), is defined by \(\Delta f = \max||f(D) - f(D')||_p\) where the maximum is over all pairs of datasets \(D\) and \(D'\) in \(D\) differing in at most one element and \(||\cdot||_p\) denotes the \(l_p\) norm.

**Definition 0.5 (Laplace Mechanism).** Laplace mechanism defined by (Dwork and Roth 2014b) preserves \((\varepsilon, 0)\)-differential privacy if the random noise is drawn from the Laplace distribution with parameter \(\Delta/\varepsilon\), where \(\Delta\) is the \(l_1\) sensitivity and \(\varepsilon\) is the corresponding privacy budget.

In this paper, we leverage two DP properties (Dwork and Roth 2014b; McSherry and Talwar 2007) to help us build a complex workflow that still has the DP guarantee: sequential composition and postprocessing. Let \(M_1(\cdot)\) and \(M_2(\cdot)\) be \(\varepsilon_1\) and \(\varepsilon_2\)-differentially private algorithms, sequential composition guarantees that releasing the outputs of \(M_1(D)\) and \(M_2(M_1(D))\) satisfies \((\varepsilon_1 + \varepsilon_2)\)-DP. Postprocessing an output of a DP algorithm does not incur any additional loss of privacy. For example, releasing \(M_1(D)\) and \(M_2(M_1(D))\) still satisfies \(\varepsilon_1\)-DP.

### ROC Curve and AUC

In a binary classification problem, given a threshold \(\theta\), a predicted score \(s_i\) is predicted to be 1 if \(s_i \geq \theta\). Given the ground-truth label and the predicted label (at a given threshold \(\theta\)), we can quantify the accuracy of the classifier on the dataset with True positives (TP(\(\theta\))), False positives (FP(\(\theta\))), False negatives (FN(\(\theta\))), and True negatives (TN(\(\theta\))).

- True positives, TP(\(\theta\)), are the data points in the test whose true label and predicted label equal 1. i.e. \(y_i = 1\) and \(s_i \geq \theta\)
- False positives, FP(\(\theta\)), are the data points in test whose true label is 0 but the predicted label is 1. i.e. \(y_i = 0\) and \(s_i \geq \theta\).
- False negatives, FN(\(\theta\)), are data points whose true label is 1 but the predicted label is 0. i.e. \(y_i = 1\) and \(s_i < \theta\).
- True negatives, TN(\(\theta\)), are data points whose true label is 0 and the predicted label is 0. i.e. \(y_i = 0\) and \(s_i < \theta\).

The area under the receiver operating characteristic (ROC) curves plots TPR (x-axis) vs. FPR (y-axis) over all possible thresholds \(\theta\), and AUC is the area under the ROC curve. True Positive Rate (TPR) (i.e. recall) is defined as \(TPR(\theta) = \frac{TP(\theta)}{TP(\theta) + FN(\theta)}\) and False Positive Rate (FPR) is defined as \(FPR(\theta) = \frac{FP(\theta)}{FP(\theta) + TN(\theta)}\). If the classifier is good,
the ROC curve will be close to the left and upper boundary and AUC will be close to 1.0 (a perfect classifier). On the other hand, if the classifier is poor, the ROC curve will be close to the line from (0, 0) to (1,1) with AUC around 0.5 (random prediction).

Privacy Leakage in AUC

Researchers have shown AUC computation can cause privacy leakage. Matthews and Harel (Matthews and Harel 2013b) demonstrate that by using a subset of the ground-truth data and the computed ROC curve, the data underlying the ROC curve can be reproduced accurately. Stoddard et al. (Stoddard, Chen, and Machanavajjhala 2014) show that an attacker can determine the unknown label by simply enumerating over all labels, guessing the labels, and then checking which guesses lead to the given ROC curve. They propose a differentially private ROC curve computation algorithm. They first privately choose a set of thresholds (with privacy budget ϵ). By modeling TP and FP values as one-sided range queries, they can compute noisy TPRs and FPRs values (using privacy budget ϵ2). They also leveraged a postprocessing step to enforce the monotonicity of TPRs and FPRs. However, the above method is not designed for FL settings. In this paper, we aim to provide a differentially private way to compute AUC in the FL setting.

Threat Model

In our hFL setting, there are multiple label parties (i.e. clients/devices) that own private labels (i.e. Y) and there is a central non-label party (i.e. server) that is responsible for computing global AUC. The model is trained using the normal hFL protocol.

Our work focuses on the evaluation time and the goal of the server is to compute global AUC without letting clients directly share their private test data. In other words, clients cannot directly send the test data (i.e. private labels and prediction scores) to the server for it to compute AUC. Specifically, we are interested in protecting label information and therefore it is required that the exchanged information between client and server excludes the ground-truth test labels (Y) and corresponding prediction scores.

Methods

In this section, we introduce how to compute the AUC with label differential privacy by leveraging the Laplace mechanism. Here we use the Laplace mechanism as an example. Settings for other DP mechanisms such as the Gaussian mechanism will be the same.

Overall Workflow

The workflow of this method is shown in Figure 1. The algorithm has six steps:

1. **Clients Execute.** Each client Ck computes the prediction scores sk = f(Xk) for all its own labeling data points.

2. **Clients Execute.** For each decision threshold θ ∈ Θ, client Ck computes four local statistics TPk, θ, TNk, θ, FPk, θ, and FNk, θ given the prediction scores sk.

3. **Clients Execute.** The client Ck adds perturbation with DP guarantee to each local statistics TPk, θ, TNk, θ, FPk, θ, and FNk, θ and get corresponding noisy statistics TP′k, θ, TN′k, θ, FP′k, θ, and FN′k, θ for each θ ∈ Θ. Client Ck sends all noisy statistics to the server.

4. **Server Executes.** For each θ ∈ Θ, the server aggregates the noisy statistics from all the clients: TP′ = k=1 K TP′k, θ, TN′ = k=1 K TN′k, θ, FP′ = k=1 K FP′k, θ, and FN′ = k=1 K FN′k, θ.

5. **Server Executes.** For each θ ∈ Θ, the server computes the corresponding TPR = TN′/FP′ + TN′ and FPR = FP′/FP′ + TN′.

6. **Server Executes.** The server plots TPR (x-axis) vs. FPR (y-axis) over all possible thresholds θ and computes the area under the corresponding curve as AUC.

Adding DP Noise to Local Statistics

In this section, we explain in detail on how to perturb TP, TN, FP, and FN for each θ ∈ Θ in each client. It’s worth mentioning that both Gaussian and Laplace mechanisms can be leveraged to generate the corresponding DP noise. Without loss of generality, we use Laplace as an example. Laplace mechanism preserves (ϵ, 0)-differential privacy if the random noise is drawn from the Laplace distribution Lap(2/|Δ|) with parameter Δ/ϵ where Δ is the l1 sensitivity (Dwork and Roth 2014b) and ϵ is the corresponding privacy budget. We name this method as DPAUC_{Lap}. The noise is added as the following:

1. Adding noise to TP: Each client Ck sets the corresponding sensitivity ΔTPk, θ = 1 for each θ ∈ Θ. Given a privacy budget ϵTP, client Ck draws the random noise from Lap(1/ϵTP) and add it to TPk, θ to get TP′k, θ.

2. Adding noise to FP: Each client Ck sets the corresponding sensitivity ΔFPk, θ = 1 for each θ ∈ Θ. Given a privacy budget ϵFP, client Ck draws the random noise from Lap(1/ϵFP) and add it to FPk, θ to get FP′k, θ.

3. Adding noise to TN: Each client Ck sets the corresponding sensitivity ΔTNk, θ = 1 for each θ ∈ Θ. Given a privacy budget ϵTN, client Ck draws the random noise from Lap(1/ϵTN) and add it to TNk, θ to get TN′k, θ.

4. Adding noise to FN: Each client Ck sets the corresponding sensitivity ΔFNk, θ = 1 for each θ ∈ Θ. Given a privacy budget ϵFN, client Ck draws the random noise from Lap(1/ϵFN) and add it to FNk, θ to get FN′k, θ.

Privacy Analysis. Based on the Composition Theorem of DP (Dwork and Roth 2014b), the privacy budget for each decision boundary (θ) is (ϵTP, ϵFP, ϵTN, ϵFN). Since we have |Θ| decision thresholds (θ), the total DP privacy budget is ϵ = |Θ| * (ϵTP + ϵFP + ϵTN + ϵFN). Without loss of generality, we set ϵTP = ϵFP = ϵTN = ϵFN = ϵ′ in our paper and the total DP budget is 4|Θ|ϵ′.

Experiments

In this section, we show the experimental results of evaluating our proposed approaches. We introduce the experimental
and use the corresponding mean and standard deviation of the computed AUC as our evaluation metric. A good computation method should achieve a small std of the computed AUC and the corresponding mean value of the computed AUC should be close to the ground-truth AUC.

**One Randomized Responses based Competitor: DPAUC\_RR**

We introduce another algorithm to compute AUC for evaluating FL models as one competitor. The algorithm is based on randomized response (Warner 1965) and we name it as DPAUC\_RR. We include the workflow in Figure 2. We now explain the algorithm step by step.

**Step 1: Clients Flip Their Local Labels** Randomized response (RR) is $\epsilon$-LabelDP (Ma and Wang 2021; Xiong et al. 2020) and works as follows: let $\epsilon$ be a parameter and let $y \in \{0, 1\}$ be the true label. Given a query of $y$, RR will respond with a random draw $\hat{y}$ from the following probability distribution:

$$\Pr[\hat{y} = \hat{y}] = \begin{cases} \frac{e^\epsilon}{1 + e^\epsilon} & \text{for } y = \hat{y}, \\ \frac{1}{1 + e^\epsilon} & \text{otherwise}. \end{cases} \quad (1)$$

Clients leverage randomized responses to flip their owning labels as a preprocessing step before computing the AUC. It’s worth mentioning that all labels are only flipped once and the generated noisy labels can then be used for further evaluations multi-times.

**Step 2: Server Computes AUC from Flipped Labels**

Since the corresponding AUC is computed with flipped labels, we denote this AUC as noisy AUC: $\text{AUC}^{\text{noisy}}$. It has the same six steps as DPAUC except that each client computes local statistics with flipped labels and sends the corresponding results (without adding additional noises) to the server.

**Step 3: Server Debias AUC** We leveraged (Menon et al. 2015) to debias the noisy AUC and get the final clean AUC $\text{AUC}^{\text{clean}}$ that we are interested in.

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**Figure 1: Illustration of our proposed DPAUC with Laplace mechanism as an example.**

| Client$_b$, $b \in [1, K]$ | Server |
|-----------------------------|--------|
| 1. Client$_b$ computes prediction scores $s^b = f(X_b)$ for its local data $X_b$ | Message from the server to Client$_b$ |
| 2. For each decision threshold $\theta \in \Theta$, Client$_b$ computes four local statistics $TP^b$, $TN^b$, $FP^b$, and $FN^b$ for $s^b$ | Message from Client$_b$ to the server |
| 3. Client$_b$ adds DP noise to each local statistic and get $TP^b$, $TN^b$, $FN^b$, and $FP^b$ for $\theta \in \Theta$ | 4. For each $\theta \in \Theta$, Server aggregates $TP^b$, $TN^b$, $FN^b$, and $FP^b$ to generate $TP^\theta$, $TN^\theta$, $FN^\theta$, and $FP^\theta$ |
| 5. For each $\theta \in \Theta$, Server computes the $\text{TPR}^\theta$ and $\text{FPR}^\theta$ | 6. Server computes the area under the ROC curve as the final AUC |

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**Experimental Setup**

**Dataset.** We evaluate the proposed approaches on Criteo\(^5\), which is a large-scale industrial binary classification dataset (with approximately 45 million user click records) for conversion prediction tasks. Every record of Criteo has 27 categorical input features and 14 real-valued input features. We first replace all the NA values in categorical features with a single new category (which we represent using the empty string) and replace all the NA values in real-valued features with 0. For each categorical feature, we convert each of its possible value uniquely to an integer between 0 (inclusive) and the total number of unique categories (exclusive). For each real-valued feature, we linearly normalize it into a value uniquely to an integer between 0 and 1. We then randomly sample 90% of the entire Criteo set as our training data and the remaining 10% as our test data. We computed the AUC on the test set which contains $M = 458, 407$ where $P = 117, 317$ and $N = 341, 090$ for 3 epochs.

**Model.** We modified a popular deep learning model architecture WDL (Cheng et al. 2016) for online advertising. Note that our goal is not to train the model that can beat the baseline. Instead, we modified the AUC on the test set which contains $M = 458, 407$ where $P = 117, 317$ and $N = 341, 090$ for 3 epochs.

**Evaluation Metric.** For each method, we run the same setting for 100 times (change the random seed every time)

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\(^3\)https://www.kaggle.com/c/criteo-display-ad-challenge/data

\(^4\)https://scikit-learn.org/stable/modules/generated/sklearn.metrics.auc.html

\(^5\)https://www.tensorflow.org/api_docs/python/tf/keras/metrics/AUC
Utility and Privacy Analysis The corresponding results of \( \text{DPauc}_{RR} \) can be seen in Table 1. However, \( \text{DPauc}_{RR} \) has potential privacy issues since the prediction scores can be inferred from the change of adjacent local statistics. For example, we can conclude that there are some prediction scores that fall in \( \theta_{i+1} \) if there are some differences between \( (TP_{\theta_{i+1}}, TP_{\theta_{i+1}'}, TP_{\theta_{i+1}'}, TP_{\theta_{i+1}'}) \) and \( (TP_{\theta_{i}}, TP_{\theta_{i}}, TP_{\theta_{i}}, TP_{\theta_{i}}) \) from client \( k \).

Attacks can then infer the label information based on the exposed prediction scores. We propose a simple attack method to infer the label information based on the prediction scores. The strategy of the attack is to select the samples with top-K prediction scores as positive labels. We measure the corresponding guessing performance by precision and recall. As shown in Figure 3 and Table 2, positive instances can have relatively higher prediction scores than negative ones at some density areas. For example, we can achieve a 79% precision if we select the instances with top-100 prediction scores. Hence, exposing prediction scores among all participants can increase the risk of label leakage. However, since the prediction scores \( s^k \) are shuffled before sending to the server, the server has no idea which prediction score belongs to which data sample.

To prevent label leakage from the prediction scores, we may leverage DP to add noise to the prediction scores. Since the prediction score is the output of a softmax/sigmoid function.

\[ |s^k| \geq 2 \]
We now introduce the experimental results of DPAUC in FL.

### Effects of Number of Samples per Client

| Epoch | Tensorflow | scikit-learn |
|-------|------------|--------------|
| 0     | 0.7494     | 0.7494       |
| 1     | 0.7665     | 0.7665       |
| 2     | 0.7702     | 0.7702       |

Table 3: AUC calculated with ϵ-DP for prediction scores with Laplace mechanism on Criteo dataset.

### Experimental Results of DPAUC

We now introduce the experimental results of DPAUC and demonstrate the effectiveness of DPAUC.

### IID vs. Non-IID

Based on the setting of how to assign data samples to clients, we provide two simulations to conduct the corresponding experiments.

1. IID: all data points are uniformly assigned to the clients.
2. Non-IID: all data points are assigned to the clients based on their corresponding prediction scores. Data samples with similar prediction scores will be assigned to the same client.

We divide $M$ data samples into $K$ clients based on the IID and Non-IID settings and each client has $\frac{M}{K}$ data samples on average. We set $|\Theta| = 100$ and compare the difference between IID and Non-IID settings for $K = 10$ and $K = 1,000$ in Table 4. We can observe that our method can achieve similar performance (mean and standard deviation of computed AUC) under both IID and Non-IID settings. It indicates that our proposed method is robust to Non-IID settings.

### Effects of Number of Decision Boundaries

We also conducted experiments to test the effects of the number of decision boundaries ($|\Theta|$). The corresponding experiments are performed with IID setting with $K = 10$. We tested $|\Theta| = 10, 25, 50, 100, 200$ as shown in Table 5. Given the same privacy budget $\epsilon$, with increasing $|\Theta|$, each local statistic has to be assigned a smaller privacy budget $\epsilon'$. As a result, the standard deviation of the computed AUC will be smaller for smaller $|\Theta|$. However, smaller $|\Theta|$ can have a worse effect on the computed precision of the resulted AUC. In our experiments, we found $|\Theta| = 100$ can achieve a good performance on both precision and standard deviation of the AUC.

### Related Work

**Federated Learning.** FL (McMahan et al. 2017; Yang et al. 2019b) can be mainly classified into three categories: horizontal FL, vFL, and federated transfer learning (Yang et al. 2019b).

**Information Leakage in FL.** Recently, studies show that in FL, even though the raw data (feature and label) is not shared, sensitive information can still be leaked from the gradients and intermediate embeddings communicated between parties. For example, (Vepakomma et al. 2019) and (Sun et al. 2021) showed that server’s raw features can be leaked from the forward cut layer embedding. In addition, (Li et al. 2022) studied the label leakage problem but the leakage source was the backward gradients rather than forward embeddings.
Table 4: IID vs. Non-IID and $K = 10$ vs. $K = 1,000$ with $|\Theta| = 100$. Setting a: IID, $K=10$; b: Non-IID, $K=10$; c: IID, $K = 1,000$; d: Non-IID, $K=1,000$.

Table 5: Sensitivity of number of thresholds ($|\Theta|$) with IID setting and $K = 10$.

(Zhu, Liu, and Han 2019) showed that an honest-but-curious server can uncover the raw features and labels of a device by knowing the model architecture, parameters, and communicated gradient of the loss on the device’s data. Based on their techniques, (Zhao, Mopuri, and Bilen 2020) showed that the ground truth label of an example can be extracted by exploiting the directions of the gradients of the weights connected to the logits of different classes.

**Information Protection in FL.** There are three main categories of information protection techniques in FL: 1) cryptographic methods such as secure multi-party computation (Bonawitz et al. 2017); 2) system-based methods including trusted execution environments (Subramanyan et al. 2017); and 3) perturbation methods that add noise to the communicated messages (Abadi et al. 2016; McMahan et al. 2018; Erlingsson et al. 2019; Cheu et al. 2019; Zhu, Liu, and Han 2019). In this paper, we focus on adding DP noise to protect the private label information during computing AUC in FL.

**Conclusion**

In this paper, we focus on providing label differential privacy for computing AUC during the model evaluation in the setting of hFL. We proposed an approach with label DP to compute AUC for evaluating models. We conducted extensive experiments to verify the effectiveness of our proposed methods. We use the Laplace mechanism as an example. Other DP mechanisms such as the Gaussian mechanism can be applied to our framework too. In our current design, the privacy budget of $DPAUC_{\text{Lap}}$ linear with the query times (model evaluation times on the same evaluation set).
References

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

Abuadbba, S.; Kim, K.; Kim, M.; Thapa, C.; Cantepe, S. A.; Gao, Y.; Kim, H.; and Nepal, S. 2020. Can We Use Split Learning on 1D CNN Models for Privacy Preserving Training? In Proceedings of the 15th ACM Asia Conference on Computer and Communications Security, 305–318.

Bebensee, B. 2019. Local Differential Privacy: a tutorial. CoRR, abs/1907.11908.

Bonawitz, K.; Ivanov, V.; Kreuter, B.; Marcedone, A.; McMahan, H. B.; Patel, S.; Ramage, D.; Segal, A.; and Seth, K. 2017. Practical secure aggregation for privacy-preserving machine learning. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, 1175–1191.

Ceballos, I.; Sharma, V.; Mugica, E.; Singh, A.; Roman, A.; Vepakomma, P.; and Raskar, R. 2020. SplitNN-driven Vertical Partitioning. arXiv preprint arXiv:2008.04137.

Chen, Y.; Machanavajjhala, A.; Reiter, J. P.; and Barrientos, A. F. 2016. Differentially Private Regression Diagnostics. In 2016 IEEE 16th International Conference on Data Mining (ICDM), 81–90.

Cheng, H.-T.; Koc, L.; Harmsen, J.; Shaked, T.; Chandra, T.; Aradhye, H.; Anderson, G.; Corrado, G.; Chai, W.; Ispir, M.; et al. 2016. Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems, 7–10.

Cheu, A.; Smith, A.; Ullman, J.; Zeber, D.; and Zhilyaev, M. 2019. Distributed differential privacy via shuffling. In Annual International Conference on the Theory and Applications of Cryptographic Techniques, 375–403. Springer.

Duchi, J. C.; Jordan, M. I.; and Wainwright, M. J. 2013. Local Privacy and Statistical Minimax Rates. In 2013 IEEE 54th Annual Symposium on Foundations of Computer Science, 429–438.

Dwork, C.; McSherry, F.; Nissim, K.; and Smith, A. 2006. Calibrating noise to sensitivity in private data analysis. In Theory of cryptography conference, 265–284. Springer.

Dwork, C.; and Roth, A. 2014a. The algorithmic foundations of differential privacy. Found. Trends Theor. Comput. Sci., 9(3–4): 211–407.

Dwork, C.; and Roth, A. 2014b. The Algorithmic Foundations of Differential Privacy. Found. Trends Theor. Comput. Sci., 9(3–4): 211–407.

Erlingsson, U.; Feldman, V.; Mironov, I.; Raghunathan, A.; Talwar, K.; and Thakurta, A. 2019. Amplification by shuffling: From local to central differential privacy via anonymity. In Proceedings of the Thirtieth Annual ACM-SIAM Symposium on Discrete Algorithms, 2468–2479. SIAM.

Erlingsson, U.; Phur, V.; and Korolova, A. 2014. RAPPOR: Randomized Aggregatable Privacy-Preserving Ordinal Response. In Ahn, G.; Yung, M.; and Li, N., eds., Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security, Scottsdale, AZ, USA, November 3–7, 2014, 1054–1067. ACM.

Geiping, J.; Bauermeister, H.; Dröge, H.; and Moeller, M. 2020. Inverting Gradients - How easy is it to break privacy in federated learning? In Larochelle, H.; Ranzato, M.; Hadsell, R.; Balcan, M. F.; and Lin, H., eds., Advances in Neural Information Processing Systems, volume 33, 16937–16947. Curran Associates, Inc.

Ghazi, B.; Golowich, N.; Kumar, R.; Manurangsi, P.; and Zhang, C. 2021. On Deep Learning with Label Differential Privacy. arXiv preprint arXiv:2102.06062.

Ghosh, A.; Chung, J.; Yin, D.; and Ramchandran, K. 2020. An Efficient Framework for Clustered Federated Learning. In Larochelle, H.; Ranzato, M.; Hadsell, R.; Balcan, M. F.; and Lin, H., eds., Advances in Neural Information Processing Systems, volume 33, 19586–19597. Curran Associates, Inc.

Gupta, O.; and Raskar, R. 2018. Distributed learning of deep neural network over multiple agents. Journal of Network and Computer Applications, 116: 1–8.

Hamer, J.; Mohri, M.; and Suresh, A. T. 2020. FedBoost: A Communication-Efficient Algorithm for Federated Learning. In III, H. D.; and Singh, A., eds., Proceedings of the 37th International Conference on Machine Learning, volume 119 of Proceedings of Machine Learning Research, 3973–3983. PMLR.

Hanzely, F.; Hanzely, S.; Horváth, S.; and Richtarik, P. 2020. Lower Bounds and Optimal Algorithms for Personalized Federated Learning. In Larochelle, H.; Ranzato, M.; Hadsell, R.; Balcan, M. F.; and Lin, H., eds., Advances in Neural Information Processing Systems, volume 33, 2304–2315. Curran Associates, Inc.

Karimireddy, S. P.; Kale, S.; Mohri, M.; Reddi, S.; Stich, S.; and Suresh, A. T. 2020. SCAFFOLD: Stochastic Controlled Averaging for Federated Learning. In III, H. D.; and Singh, A., eds., Proceedings of the 37th International Conference on Machine Learning, volume 119 of Proceedings of Machine Learning Research, 5132–5143. PMLR.

Kasiviswanathan, S. P.; Lee, H. K.; Nissim, K.; Raskhodnikova, S.; and Smith, A. D. 2008. What Can We Learn Privately? CoRR, abs/0803.0924.

Li, O.; Sun, J.; Yang, X.; Gao, W.; Zhang, H.; Xie, J.; Smith, V.; and Wang, C. 2022. Label Leakage and Protection in Two-party Split Learning. In The Tenth International Conference on Learning Representations (ICLR).

Li, Z.; Kuznietz, A.; and Kotlowski, W. 2019. Learning with Limited Compliance: A Tutorial. Proceedings of Machine Learning Research, 116: 1–8.

Li, Z.; Kovalev, D.; Qian, X.; and Wang, C. 2020. Averaging for Federated Learning. In III, H. D.; and Singh, A., eds., Proceedings of the 37th International Conference on Machine Learning, volume 119 of Proceedings of Machine Learning Research, 5895–5904. PMLR.

Ma, F.; and Wang, P. 2021. Randomized Response Mechanisms for Differential Privacy Data Analysis: Bounds and Applications. CoRR, abs/2112.07397.

Matthews, G.; and Harel, O. 2013a. An Examination of Data Confidentiality and Disclosure Issues Related to Publication of Empirical ROC Curves. Academic radiology, 20: 889–96.
Matthews, G. J.; and Harel, O. 2013b. An examination of data confidentiality and disclosure issues related to publication of empirical ROC curves. *Academic Radiology*, 20(7): 889–896.

McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; and y Arcas, B. A. 2017. Communication-efficient learning of deep networks from decentralized data. In *Artificial Intelligence and Statistics*, 1273–1282. PMLR.

McMahan, H. B.; Ramage, D.; Talwar, K.; and Zhang, L. 2018. Learning Differentially Private Recurrent Language Models. In *International Conference on Learning Representations*.

McSherry, F.; and Talwar, K. 2007. Mechanism Design via Differential Privacy. In *48th Annual IEEE Symposium on Foundations of Computer Science (FOCS’07)*, 94–103.

Menon, A.; Rooyen, B. V.; Ong, C. S.; and Williamson, B. 2015. Learning from Corrupted Binary Labels via Class-Probability Estimation. In Bach, F.; and Blei, D., eds., *Proceedings of the 32nd International Conference on Machine Learning*, volume 37 of *Proceedings of Machine Learning Research*, 125–134. Lille, France: PMLR.

Stoddard, B.; Chen, Y.; and Machanavajjhala, A. 2014. Differentially Private Algorithms for Empirical Machine Learning. *CoRR*, abs/1411.5428.

Subramanyan, P.; Sinha, R.; Lebedev, I.; Devadas, S.; and Seshia, S. A. 2017. A formal foundation for secure remote execution of enclaves. In *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, 2435–2450.

Sun, J.; Yao, Y.; Gao, W.; Xie, J.; and Wang, C. 2021. Defending against Reconstruction Attack in Vertical Federated Learning. *CoRR*, abs/2107.09898.

Vepakomma, P.; Gupta, O.; Dubey, A.; and Raskar, R. 2019. Reducing leakage in distributed deep learning for sensitive health data. *arXiv preprint arXiv:1812.00564*.

Vepakomma, P.; Gupta, O.; Swedish, T.; and Raskar, R. 2018a. Split learning for health: Distributed deep learning without sharing raw patient data. *arXiv preprint arXiv:1812.00564*.

Vepakomma, P.; Gupta, O.; Swedish, T.; and Raskar, R. 2018b. Split learning for health: Distributed deep learning without sharing raw patient data. *arXiv preprint arXiv:1812.00564*.

Warner, S. L. 1965. Randomized Response: A Survey Technique for Eliminating Evasive Answer Bias. *Journal of the American Statistical Association*, 60(309): 63–69.

Xiong, X.; Liu, S.; Li, D.; Cai, Z.; Niu, X.; and Del Rey, A. M. 2020. A Comprehensive Survey on Local Differential Privacy. *Sec. and Commun. Netw.*, 2020.

Yang, Q.; Liu, Y.; Chen, T.; and Tong, Y. 2019a. Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(2): 1–19.

Yang, Q.; Liu, Y.; Chen, T.; and Tong, Y. 2019b. Federated machine learning: Concept and applications. In *ACM Transactions on Intelligent Systems and Technology (TIST)*, 1–19. ACM New York, NY, USA.

Zhu, L.; Liu, Z.; and Han, S. 2019. Deep leakage from gradients. In *Advances in Neural Information Processing Systems*, 14774–14784.