Gradient Inversion Attack: Leaking Private Labels in Two-Party Split Learning

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Abstract

Split learning is a popular technique used to perform vertical federated learning, where the goal is to jointly train a model on the private input and label data held by two parties. To preserve privacy of the input and label data, this technique uses a split model and only requires the exchange of intermediate representations (IR) of the inputs and gradients of the IR between the two parties during the learning process. In this paper, we propose Gradient Inversion Attack (GIA), a label leakage attack that allows an adversarial input owner to learn the label owner’s private labels by exploiting the gradient information obtained during split learning. GIA frames the label leakage attack as a supervised learning problem by developing a novel loss function using certain key properties of the dataset and models. Our attack can uncover the private label data on several multi-class image classification problems and a binary conversion prediction task with near-perfect accuracy ($97.01\% - 99.96\%$), demonstrating that split learning provides negligible privacy benefits to the label owner. Furthermore, we evaluate the use of gradient noise to defend against GIA. While this technique is effective for simpler datasets, it significantly degrades utility for datasets with higher input dimensionality. Our findings underscore the need for better privacy-preserving training techniques for vertically split data.

1. Introduction

The plethora of apps and services we use for our everyday needs, such as online shopping, social media, communication, healthcare, finance, etc., have created distributed silos of data. While aggregating this distributed data would improve the performance of machine learning models, doing so is not always feasible due to privacy constraints. For instance, in healthcare, laws like HIPAA require hospitals to keep medical records private. For finance and internet companies, user agreements and privacy laws might prevent them from sharing data. These challenges have led to the development of several techniques for federated learning, which allow models to be trained without the data owner having to share their data explicitly. Split learning [9, 23] is one such technique that allows federated learning to be performed when the inputs and the corresponding labels are held by two different parties. Split learning uses a composition model $g \circ f$ that is split between the input and label owners as shown in Figure 1. The network is trained end-to-end with the input owner transmitting the embedding $z_i$ (intermediate representation) to the label owner in the forward pass and the label owner returning the gradient $\nabla_z L_i$ to the input owner during the backward pass. This allows the split model to be trained on the distributed data while keeping the sensitive data with their respective owners.

Unfortunately, split learning does not have formal privacy guarantees, and it is not clear if it allows the input and label owners to hide their private data from each other. We set out to answer this question by considering an adversarial input owner who wants to break label privacy by leaking the private labels in two-party split learning. To this end, we propose a label leakage attack called Gradient Inversion Attack (GIA). GIA frames the attack as a supervised learning problem by leveraging the gradient information ($\nabla_z L_i$) obtained during split learning. GIA “replays” split learning by replacing the label owner’s model $g$ and labels $\{y_i\}$ with a randomly initialized surrogate model $g'$ (with parameters $\theta_{g'}$) and surrogate labels $\{y'_i\}$ respectively. We leverage key properties of the model and dataset to develop a loss function using the following objectives:

- **Gradient Objective**: The gradient computed using the surrogate model and labels during replay split learning should match the gradients received from the label owner during the original split learning process.

- **Label Prior Objective**: The distribution of surrogate labels must match the expected label prior distribution. For instance, if the classification problem in consideration has a uniform label prior, the surrogate labels must also have a uniform distribution.

- **Label Entropy Objective**: Since we consider datasets...
with hard labels, each individual surrogate label must have low entropy.

- **Accuracy Objective:** The surrogate model should achieve high accuracy i.e., the predictions made by the surrogate model must be close to the surrogate labels.

Using the above objectives, we formulate a loss function that can be used to train the surrogate parameters and labels. By minimizing this loss function over all the embedding, gradient pairs \{zi, \nabla_{zi} L'_i\} received during split learning, the surrogate labels \{yi\} can be trained to match the private labels of the label owner \{yi\}, allowing an adversarial input owner to carry out a label leakage attack with high accuracy. Our paper makes the following key contributions:

**Contribution 1:** We propose Gradient Inversion attack, a label leakage attack for two-party split learning. Our proposal replaces the label owner’s private labels and model with surrogate parameters and exploits the gradient data obtained during split learning to perform supervised learning. We develop a novel loss function using the properties of the model and dataset to train the surrogate parameters and uncover the private labels of the label owner. To the best of our knowledge, GIA is the first attack that breaks label privacy for split learning with multi-class classification problems.

**Contribution 2:** We carry out extensive evaluations on the Criteo conversion prediction [21] task and several image classification datasets, including MNIST, FashionMNIST, CIFAR-10, and CIFAR-100, to show that GIA can leak private labels with near-perfect accuracy (97.01% - 99.96%).

**Contribution 3:** We evaluate perturbing the gradient with noise as a defense against Gradient Inversion Attack. Our results show that gradient noise allows the label owner to trade off model accuracy (lower utility) for improved privacy against GIA (better label privacy). While this technique works well for simpler datasets like MNIST, it leads to significant degradation in accuracy for datasets like CIFAR-10 and CIFAR-100, making it unsuitable for more complex datasets.

Our findings in this work demonstrate that split learning does not protect the privacy of labels, emphasizing the need for better techniques to learn on vertically split data.

2. Related Work

Label leakage attack on split learning is a relatively new research topic and has not received much attention. We are aware of only one prior work [14] that proposes a label leakage attack and defense for split learning, specifically for the conversion prediction problem. In this section, we discuss this prior work and its limitations. We also provide an overview of other techniques besides split learning that can be used to learn on vertically partitioned data and discuss their limitations.

2.1. Label leakage Attack and Defense for Split Learning

Recently Li et al. [14] proposed a label leakage attack on two-party split learning, specifically for the conversion prediction problem. We provide background on the conversion prediction problem, describe the prior work (Norm-based attack) and discuss its limitations.

**Conversion Prediction:** Conversion prediction is an important user behavior modeling problem in online advertising. Given the attributes of a user and an ad, conversion prediction tries to estimate the likelihood of a user purchasing the product. Conversion modeling is an essential component of ad-ranking algorithms, as ads with a high likelihood of conversion are more relevant to the user and need to be ranked higher. The data required to train the model are split between the advertising and product websites, as depicted in Figure 2. The user attributes, which serve as the inputs, are stored with the advertising company, while the purchase data, which serve as the labels, are held with the product company. The companies are interested in training a model to predict the conversion likelihood while keeping their respective datasets private.

**Norm-based Attack:** Norm-based attack [14] was pro-
The goal of conversion prediction is to estimate the likelihood of a purchase when a user clicks on an ad. The training data is vertically partitioned, with the user attributes (inputs) held by the advertising company and the purchase data (outputs) held by the product company (Figure adapted from [15]).

posed to leak private labels, specifically for the conversion prediction problem. This work leverages the observation that only a small fraction of ad clicks result in a purchase. Consequently, there is a high class imbalance in the training dataset of the conversion prediction task. This imbalance results in the magnitude of the gradients being higher when the infrequent class is encountered. Thus, by considering the norm of the gradients, an adversarial input owner can infer the private class labels. Note that a critical limitation of this attack is that it only works on binary classification problems with high class imbalances. In contrast, our proposed Gradient Inversion Attack does not require a class imbalance and is designed to work in a more general setting of multi-class classification problems.

Defense against Norm-based attack: The authors of the Norm-based attack [14] also propose a defense against their label leakage attack by adding noise to the gradients to trade-off utility for protection against label leakage attack. The noise is specifically crafted to minimize the disparity in the gradient norms between the two classes, which deters the attack. However, this defense is tailored to protect against the Norm-based attack, and it is unclear how this defense can be extended to the more general setting of a multi-class classification problem. Our paper evaluates perturbing the gradients using Gaussian noise to defend against our proposed Gradient Inversion Attack.

2.2. Other Privacy-Preserving Training Techniques

In addition to split learning, several methods have been proposed to train a model on vertically partitioned private data. These methods can broadly be classified into three categories: 1. Differential Privacy (DP) 2. Multi-Party Compute (MPC) and 3. Trusted Execution Environment (TEE). We discuss solutions in each category and describe their limitations.

Label Differential Privacy: Differential privacy [7] is a principled system for training on a private database that restricts the influence of any single entry of the database on the outcome by adding noise to a query’s response. A recent work [8] proposed Label Differential Privacy (LDP) to train a model on vertically partitioned data with sensitive labels. LDP relies on a randomized response algorithm to provide a noisy version of the labels to the input owner by defining a probability distribution over class labels as follows:

\[
\Pr[\hat{y} = \hat{y}] = \begin{cases} \\
\frac{e^{\varepsilon}}{e^{\varepsilon} + K^{-1}} & \text{for } \hat{y} = y \\
\frac{K^{-1}}{e^{\varepsilon} + K^{-1}} & \text{otherwise}
\end{cases}
\]

The label owner uses the noisy labels sampled from this distribution and the input data to train a model. To prevent the model from overfitting on the incorrect labels, the authors propose using the Mixup technique [28] to train the model, which provides resilience to label noise. One drawback of this technique is that it allows the input owner to have complete ownership of the model. In contrast, split learning enables the input and label owners to jointly own the model, which might be desirable if the label owner wants to exercise control over the usage of the model.

Multi-Party Compute (MPC): Several works [16, 18, 25] have proposed using cryptographic techniques to enable private computations over distributed data held by multiple parties. These works use a combination of cryptographic primitives such as oblivious transfer [2, 12, 20], garbled circuits [27], secret sharing [6] and homomorphic encryption [19] to train the model. Unfortunately, these methods have significant computational overheads and require multiple rounds of communication between the parties involved. Consequently, even training a simple 2-layer network incurs a 30× overhead [16] compared to training without privacy, making it impractical for training larger networks.

Trusted Execution Environment (TEE): Trusted Execution Environments use hardware enclaves to enable remote computations with confidentiality and integrity. A centrally hosted TEE can be used to train a model on distributed data. The data owners can communicate data securely over an encrypted channel to the trusted enclave. Training is performed while ensuring data confidentiality, and the resulting model is transmitted securely to the data owners. Unfortunately, TEEs have slow memory due to the overheads associated with encryption and integrity checks [10, 17]. Moreover, commercially available TEEs such as Intel SGX [15] and Arm Trustzone [24] are CPU-based and offer less parallelism compared to GPUs. The combination of these two factors results in orders of magnitude [3] increase in training times of models. Additionally, this solution requires specialized hardware, which adds to the cost of implementation.

3. Preliminaries

In this section, we provide background on the two-party split learning framework and formally state the objectives of the label leakage attack and defense.
3.1. Two-Party Split Learning

Two-party split learning involves a dataset that is vertically partitioned between two parties. In our work, we consider an input owner who owns the inputs \( D_{\text{inp}} = \{x_i\} \) and a label owner who owns the labels \( D_{\text{label}} = \{y_i\} \) in the dataset. The goal of split learning is to train a composition model \( g \circ f \) that is distributed between the two parties. Training with supervised learning requires mapping examples in the input set to the corresponding example in the label set. If this mapping is not known, private set intersection algorithms [5] can be used to link the corresponding examples in the two datasets. A single training iteration involves a forward and a backward pass (as shown in Figure 1), which proceeds as follows:

- **Forward pass:** The input owner samples a batch of inputs \( \{x_i\}_{\text{batch}} \sim D_{\text{inp}} \) and performs forward propagation through \( f \) and produces the corresponding embeddings \( \{z_i\}_{\text{batch}} \). These embeddings, along with the corresponding inputIDs are sent to the label owner. The label owner feeds the embeddings to \( g \) to produce the final predictions \( \{p\}_{\text{batch}} \). The labels \( \{y\}_{\text{batch}} \) corresponding to the inputs are used to compute the model’s loss \( L = \mathbb{E}[H(y, p)] \).

- **Backward pass:** The label owner initiates backpropagation and returns \( \{\nabla z L\}_{\text{batch}} \) to the input owner. Both the label and input owner compute the gradient of the loss with respect to the model parameters and update model parameters using gradient descent as shown below:

\[
\theta_{g}^{t+1} = \theta_{g}^{t} - \eta \nabla_{\theta_{g}} L; \tag{2}
\]

\[
\theta_{f}^{t+1} = \theta_{f}^{t} - \eta \nabla_{\theta_{f}} L. \tag{3}
\]

**Privacy Objectives:** There are two key privacy objectives that split learning aims to achieve:

- **Input privacy:** The label owner should not be able to infer the input owner’s private inputs \( \{x_i\} \).

- **Label privacy:** The input owner should not be able to infer the label owner’s private labels \( \{y_i\} \).

3.2. Label Leakage Attack Objective

In this work, we propose a label leakage attack, where an adversarial input owner tries to learn the label owner’s private labels \( D_{\text{label}} = \{y_i\} \). We consider an honest-but-curious adversary, where the input owner tries to infer the private labels while honestly following the split learning protocol. During the training process of split learning, for each input \( x_i \), the adversarial input owner transmits the embeddings \( z_i \) and receives the gradient \( \nabla_{z} L_i \) from the label owner. The adversary uses an algorithm \( A \) to estimate the private labels \( y'_i \) for each input using these \( \{z_i, \nabla_{z} L_i\} \) pairs obtained during split learning as shown below:

\[
A(D_{\text{grad}}) \rightarrow D_{y'} \tag{4}
\]

where, \( D_{\text{grad}} = \{z_i, \nabla_{z} L_i\}; \ D_{y'} = \{y'_i\} \)

The attack objective is thus to maximize the accuracy of estimated labels as shown below:

\[
\max_{y_i \sim D_{\text{label}}} \mathbb{E} [\text{Acc}(y_i, y'_i)] \tag{6}
\]

Since the private labels \( \{y_i\} \) are unavailable to the input owner, evaluating Eqn. 6 is not possible. Instead, our proposed attack uses a surrogate objective that can be optimized to uncover the private labels with high accuracy.

3.3. Label Leakage Defense Objective

A label owner trying to defend against label leakage attacks needs to balance two objectives:

**Utility Objective:** The composition model \( g \circ f \) trained with split learning needs to have high classification accuracy on an unseen validation set (Eqn. 7).

\[
\max_{x_i,y_i \sim D_{\text{val}}} \mathbb{E} [\text{Acc}(y_i, g(f(x_i)))] \tag{7}
\]

**Privacy Objective:** The accuracy of the estimated labels \( \{y'_i\} \) that the adversarial input owner can recover from the gradient information should be minimized (Eqn. 8).

\[
\min_{y_i \sim D_{\text{label}}} \mathbb{E} [\text{Acc}(y_i, y'_i)] \tag{8}
\]

4. Gradient Inversion Attack

We propose the Gradient Inversion Attack to leak the private labels in two-party split learning. Our key insight is that the attack can be framed as a supervised learning problem by replacing the unknown parameters of the label owner with learnable surrogate variables. This allows the adversarial input owner to “replay” the split learning process with surrogate variables. We develop a novel loss function that matches the gradients collected during replay split learning with the gradients obtained during the original split learning. By minimizing this loss function, we can recover the label owner’s private labels with high accuracy. The rest of this section describes our proposed attack in greater detail.

4.1. Surrogate Variables Substitution

From the input owner’s point of view, the split learning process has two key unknowns: the label owner’s model \( g \) and the private labels \( \{y_i\} \) (see Figure 3a). Our goal is to uncover these unknown values by treating them as learnable parameters. To do so, we start by substituting these
unknowns with randomly initialized surrogate parameters, as shown in Figure 3b. We replace $g$ with a surrogate model $g'$ (with parameters $\theta_{g'}$), and $\{y_i\}$ with a set of surrogate labels $\{y'_i\}$. We want $y'_i$ to be a point on an $n-1$ dimensional probability simplex for an n-class classification problem. To enforce this property, we set $y'_i = \text{Softmax}(\hat{y}_i)$, where $\hat{y}_i \in \mathbb{R}^n$. With the surrogate parameters in place, the goal of our attack is to learn the surrogate labels $\{y'_i\}$ (or equivalently to learn $\{\hat{y}_i\}$).

4.2. Replay Split Learning

To train the surrogate parameters, we “replay” the split learning process using the surrogate variables (Figure 3b). First, in the forward pass, the embedding $z_i$ (collected during split learning) is fed into $g'$ to get the prediction $p'_i$, which along with the surrogate labels $y'_i$ can be used to compute the loss $L'_i = H(y'_i, p'_i)$. Next, we perform backpropagation through $g'$ and compute the gradient of the loss with respect to the embedding $\nabla_z L'_i$. To learn the surrogate parameters, we develop a loss function that tries to match the loss gradient $\nabla_z L'_i$ obtained during replay split learning with the gradient $\nabla_z L_i$ obtained during the original split learning process.

4.3. GIA Loss

To train the surrogate parameters $\theta_{g'}$ and $\hat{y}_i$, we formulate a loss function using four key objectives:

1. **Gradient Objective**: The loss gradient $\nabla_z L'_i$, obtained during replay split learning, must match the original gradients $\nabla_z L_i$, obtained during the original split learning process. This can be achieved by minimizing the $l^2$ distance between $\nabla_z L'_i$ and $\nabla_z L_i$, as shown below:

$$\min_{\theta_{g'},\{\hat{y}_i\}} \mathbb{E}\left\|\nabla_z L'_i - \nabla_z L_i\right\|_2$$ (9)

2. **Label Prior Objective**: The distribution of surrogate labels must match the label prior of the dataset. We assume that the input owner knows the label prior distribution $P_y$ for the dataset\(^1\). The probability distribution of the surrogate labels can be computed by taking the expectation of the surrogate labels $P_{y'} = \mathbb{E}(y'_i)^2$. We perform the following optimization to match the distributions of the original and surrogate labels:

$$\min_{\theta_{g'},\{y'_i\}} \mathcal{D}_{KL}(P_y \parallel P_{y'})$$ (10)

3. **Label Entropy Objective**: Each of the individual surrogate labels $y'_i$ must have low entropy. This is because the classification problems we consider have zero entropy one-hot labels.

4. **Accuracy Objective**: The surrogate model must have high prediction accuracy with respect to the surrogate labels. In other words, the predictions of the surrogate model $p'_i$ must be close to the surrogate labels $y'_i$.

To achieve the label entropy and accuracy objectives, we can minimize the normalized cross-entropy loss between the surrogate predictions ($p'_i$) and labels ($y'_i$) as shown in the following equation:

$$\min_{\theta_{g'},\{y'_i\}} \frac{\mathbb{E}[H(y'_i, p'_i)]}{H(P_y)}$$ (11)

Note that the cross-entropy term $H(y'_i, p'_i)$ in Eqn. 11 can be expressed as a sum of the label entropy and KL divergence between the surrogate label and prediction: $H(y'_i, p'_i) = H(y'_i) + \mathcal{D}_{KL}(y'_i \parallel p'_i)$. Thus, by minimizing cross-entropy, we can minimize the entropy of surrogate labels (label entropy objective) and match the model’s predictions with the

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\(^1\)See Appendix B for a discussion on this assumption.

\(^2\)Each surrogate label $y'_i$ represents a discrete probability distribution over the output classes.
surrogate labels (accuracy objective). We normalize cross-entropy with the entropy of the label prior \( H(P_y) \) to ensure that the metric is insensitive to the number of label classes and the label priors [11].

We combine all the learning objectives described above to derive the final loss function as shown below:

\[
L_{GIA} = E\left[ \| \nabla_z L_i - \nabla_z L'_i \|_2 \right] + \lambda_{ce} \cdot E\left[ H(y_i, p'_i) / H(P_y) \right] + \lambda_p \cdot D_{KL}(P_y || P_{y'})
\]

(12)

Here, \( \lambda_{ce} \) and \( \lambda_p \) dictate the relative importance of the cross-entropy and label prior terms compared to the gradient loss term (first term in Eqn. 12). By optimizing the surrogate model and label parameters using this loss function, we can recover the private labels of the label owner with high accuracy. We consider the gradient loss term to be the primary optimization objective of our loss function. The cross-entropy and label prior terms act as regularizers and help us achieve a better label leakage accuracy (see Appendix D for an ablation study).

### 4.4. Putting It All Together

The individual components described thus far can be combined to carry out our label leakage attack. Our attack starts with the input owner performing split learning process with the label owner, as shown in Figure 3a. During this process, the input owner collects the embedding \( z_i \) and the corresponding loss gradient \( \nabla_z L_i \) produced for each input. Using this data, the input owner can use the Gradient Inversion Attack to leak the private labels. Our attack is described in Algorithm 1. In the outer loop, we pick values for hyperparameters \( \lambda_p, \lambda_{ce} \) and the learning rates \( \eta_g, \eta_y \) using a Bayesian hyperparameter optimization algorithm. The surrogate parameters \( \{\hat{y}_i\} \) and \( \theta_{g'} \) are randomly initialized, and each inner loop of the attack proceeds as follows:

1. **Replay split learning with surrogate parameters.** This involves the following steps:
   a. Sample a batch of embeddings, gradients and surrogate labels \( \{z, \nabla_z L, \hat{y}\}_{\text{batch}} \).
   b. Perform forward pass to produce predictions \( \{p'\} \) and compute the loss \( \{L'_i\} \) with labels \( \{y'\} \).
   c. Perform backpropagation to compute the loss gradients \( \{\nabla_z L'_i\} \).
2. **Compute the GIA loss:** \( L_{GIA} \) (Eqn. 12).
3. **Update surrogate parameters \( \theta_{g'} \) and \( \{\hat{y}_i\} \) using gradient descent to minimize \( L_{GIA} \).

We repeat the above steps for multiple iterations until the surrogate parameters converge.

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**Algorithm 1:** Gradient Inversion Attack

**Input:** \( \{z_i\}, \{\nabla_z L_i\}, P_y, N_{iter} \)

**Output:** \( \{y_i^*\} \)

\( D_{\text{train}} = \{z_i, \nabla_z L_i, y_i\} \)

for \( i \leftarrow 0 \) to \( N_{iter} \) do

\[
\lambda_p, \lambda_{ce}, \eta_g, \eta_y \leftarrow \text{BayesOpt}()
\]

Initialize \( \{\hat{y}_i\}, g'(:; \theta_{g'}) \)

repeat

for \( \{z, \nabla_z L, \hat{y}\}_{\text{batch in D_{train}}} \) do

\[
\{y'_i\} = \{\text{Softmax}(\hat{y}_i)\}
\]

\( P_{y'} = E(y'_i) \)

// 1. Replay Split Learning

for \( \{z, \nabla_z L, \hat{y}\}_{\text{batch}} \) do

\[
p'_i = g'(z_i; \theta_{g'})\]

\( L'_i = D_{KL}(y'_i || p'_i) \)

Compute \( \nabla_z L'_i \)

// 2. Compute GIA loss (Eqn. 12)

\[
L_{GIA} = E\left[ \| \nabla_z L'_i - \nabla_z L_i \|_2 \right] + \lambda_{ce} \cdot E\left[ H(y'_i, p'_i) / H(P_y) \right] + \lambda_p \cdot D_{KL}(P_y || P_{y'})
\]

// 3. Update surrogate model, label parameters

\[
\theta_{g'} \leftarrow \theta_{g'} - \eta_{g'} \cdot \nabla_{\theta_{g'}} L_{GIA}
\]

\( \hat{y} \leftarrow \hat{y} - \eta_y \cdot \nabla_{\hat{y}} L_{GIA} \)

end

until Convergence;

\( \text{NewBest} = \text{UpdateBayesOpt}(E[\| \nabla_z L'_i - \nabla_z L_i \|_2]) \)

if \( \text{NewBest} \) then

\( \{y_i^*\} \leftarrow \{\text{Softmax}(\hat{y}_i)\} \)

end

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**Hyperparameter Optimization:** We learn a set of surrogate labels \( \{y'_i\} \) in each outer loop for different selections of the hyperparameters. Unfortunately, evaluating the accuracy of the surrogate labels produced in each iteration is not possible since the input owner is unaware of any of the true labels. Consequently, we cannot use accuracy to guide the hyperparameter search. Instead, we evaluate the gradient loss term: \( E[\| \nabla_z L'_i - \nabla_z L_i \|_2] \) after completing each outer iteration and use this as our objective function to be minimized by tuning the hyperparameters. We report the accuracy of the surrogate labels obtained for the best set of hyperparameters that minimizes this objective.
5. Experiments

We evaluate our attack by performing split learning with multiple datasets and show that GIA can leak the private labels of the label owner with high accuracy. We describe our experimental setup and discuss the results.

Table 1. Datasets and the corresponding split-models used in our experiments to evaluate gradient inversion attack.

| Dataset     | f            | g              |
|-------------|--------------|----------------|
| MNIST       | Conv3        | FC[32-10]      |
| FashionMNIST| Conv3        | FC[32-32-10]   |
| CIFAR-10    | Resnet-18 (conv) | FC[64-10] |
| CIFAR-100   | Resnet-18 (conv) | FC[64-10] |
| Criteo      | EMB-FC[32-32] | FC[32-32-2]    |

5.1. Setup

Dataset and Models: The datasets and the corresponding split-models \((f \circ g)\) used in our evaluations are shown in Table 1. MNIST, FashionMNIST, CIFAR-10, and CIFAR-100 datasets are used for multi-class image classification tasks. The Criteo dataset is used for the conversion rate (CVR) prediction task. This is a binary classification problem with a large class imbalance (roughly 90% of the labels are 0’s, and the rest are 1’s). Each input in this dataset has 3 continuous features and 17 categorical features corresponding to an ad-click and a binary label that indicates if the ad-click resulted in a purchase (conversion). For the image classification tasks, the input owner’s models \(f\) comprise convolutional layers, and the label owner’s model \(g\) consists of fully connected layers. For the Criteo CVR task, the input owner’s model consists of a learnable embedding layer (to handle categorical features) followed by fully connected layers. The label owner’s models consist of fully connected layers. For all the tasks, we train the models with Adam optimizer with a learning rate of 0.001. We train the image classification tasks for 10 epochs and the conversion prediction task for 5 epochs.

Attack parameters: We assume that the architecture of the label owner’s model \(g\) is not known to the input owner. Thus, we use a 3 layer fully connected DNN \(\text{FC}[128-64-10]\) for image classification and \(\text{FC}[32-32-10]\) for Criteo as the surrogate model \(g'\). We set the number of outer loop iterations \(N_{\text{iter}} = 500\), and the learning rate range to \([1^{-5}, 1^{-3}]\) for \(\eta_g\) and \([10^{-5}, 10^{-1}]\) for \(\eta_g\). The range for \(\lambda_{cc}\) and \(\lambda_p\) is set to \([0.1, 3]\). We carry out GIA for each training epoch of split learning.

Evaluation Metric: Our attack groups inputs that belong to the same class by assigning them the same label. The true class label corresponding to each group remains unknown. We report the clustering accuracy [26] obtained with the best hyperparameters (corresponding to the lowest gradient loss) for each dataset.

5.2. Results

The label leakage accuracy of GIA and the corresponding test accuracy/normalized cross entropy\(^3\) of the split model for each epoch is shown in Figure 4. We find that the efficacy of our attack improves for the later epochs of training (seen most clearly in the case of CIFAR-100). This is because our attack approximates the label owner’s model \(g\) using a fixed surrogate model \(g'\). However, in reality, \(g\) is not fixed, and changes as training progresses. The rate of this change is smaller for the latter epochs. Consequently, our ability to approximate \(g\) with a fixed surrogate model improves for the later epochs, improving our attack’s efficacy and resulting in better label leakage accuracy.

Overall, our results show that GIA can carry out label leakage with an accuracy of up to 99.96% (for CIFAR-10) and over 97% for all datasets. Our attack also achieves a higher label leakage accuracy compared to the Norm-based attack [14] (NBA) for the Criteo dataset (see Appendix A for evaluation details of NBA). NBA is specifically designed for binary classification problems with an imbalanced class distribution (like Criteo) and is not applicable.

\(^3\)We use normalized cross-entropy (NCE) instead of test accuracy to measure the model performance for the Criteo dataset as it has a high class imbalance. A lower value of NCE indicates better performance.
to the multi-class datasets in our experiments. In contrast, our attack achieves near-perfect label leakage accuracy for several multi-class classification problems in the image domain, regardless of class distributions. The efficacy of our attack demonstrates that split learning offers negligible privacy benefits for the label owner.

6. Gradient Noise Defense

GIA uses the gradient information obtained from the label owner during split learning to leak the private labels. One way to defend against GIA is by perturbing the loss gradients $\nabla z L_i$ with noise as shown in Eqn. 13.

$$\nabla z \hat{L}_i = \nabla z L_i + \eta$$  \hspace{1cm} (13)

where, $\eta \sim N(0, \sigma)$  \hspace{1cm} (14)

The label owner can transmit these noisy gradients $\nabla z \hat{L}_i$ to the input owner to perform split learning. Adding noise to the gradients prevents the input owner from having reliable access to the true gradients. This reduces the efficacy of GIA, providing better privacy to the label owner. On the other hand, adding noise to the gradients is detrimental to training the split model and results in lower accuracy, thus impacting utility. To evaluate the utility-privacy trade-off offered by this defense, we perform split learning with different amounts of gradient noise by sweeping $\sigma$ in Eqn. 13. For each value of $\sigma$, we train the split-model till convergence and report the test accuracy and the label leakage accuracy with GIA\textsuperscript{4}. Since the gradients obtained during split learning are noisy, optimizing the hyperparameters of our attack using the gradient loss objective is not optimal. Instead we tune the hyperparameters using $L_{GIA}(\lambda_{ce} = 1, \lambda_p = 1)$ as the optimization objective.

6.1. Results for Gradient Noise Defense

The results of the gradient noise defense are shown in Figure 5. As the amount of gradient noise is increased, the gradient leakage accuracy obtained from GIA reduces, improving privacy against our label leakage attack. However, gradient noise also negatively impacts the split learning process and yields a split model with lower test accuracy. Thus, gradient noise allows the label owner to trade-off the accuracy of the split model (utility) for better protection against our label leakage attack. We also note that this defense provides a much better utility-privacy trade-off for low dimensional datasets like Criteo, MNIST and FashionMNIST compared to CIFAR-10 and CIFAR-100. For instance, gradient noise degrades the label leakage accuracy for MNIST by 77\% with only a 4\% reduction of test accuracy. In contrast, for CIFAR-10, a 79\% reduction in label leakage accuracy incurs a 38\% reduction in test accuracy. This discrepancy is because adding gradient noise hampers the quality of the input owner’s model, which impacts different models differently. Simpler datasets are more resilient to this degradation in the quality of $f$, whereas more complex datasets like CIFAR-10 and CIFAR-100 are impacted more if the initial convolutional layers are not trained properly. Thus, while gradient noise might be suitable for simpler datasets, it may not be practical for more complex datasets as it causes significant degradation in accuracy.

7. Conclusion

Split learning has been proposed as a method to train a model on vertically split data while keeping the data private. This paper investigates the privacy properties of two-party split learning, where the input and label data are held by two parties. We develop a Gradient Inversion Attack to show that an adversarial input owner can learn the label owner’s private labels during two-party split learning. Our key insight is that the attack can be framed as a learning problem by substituting the unknown parameters of the label owner with learnable surrogate parameters. We use the gradient data collected during split learning and a novel loss function to train the surrogate parameters. Our evaluations on several multi-class image classification tasks and a binary conversion prediction task show that GIA can leak the private labels with near-perfect accuracy (97.01% – 99.96%), prov-
ing that split learning provides a negligible amount of label privacy. We also evaluate using gradient noise to improve label privacy at the cost of reduced test accuracy. While this provides a reasonable defense for simpler datasets, we find that the utility-privacy tradeoff of this technique is unfavorable for more complex datasets. Our findings in this work underscore the need for better techniques to perform vertical federated learning.

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A. Evaluation of Norm-based Attack

The norm-based attack was proposed for the conversion prediction task, which is a binary classification problem with highly imbalanced classes. Since only a small fraction of ad-clicks result in a conversion (purchase), the negative class is far more likely compared to the positive class, with roughly 90% of the labels being negative (0-labels). This imbalance results in the magnitude of the gradients being higher for the infrequent positive class and lower for the frequent negative class. This can be seen clearly from Figure 6, which shows the distribution of gradient norms $\|\nabla_z L\|_2$ obtained during split learning for different epochs. The norm-based attack exploits this observation and uses it to infer the private labels in split learning. This attack uses a threshold $T$ to classify the examples into positive and negative classes as follows:

$$y' = \begin{cases} 1 & \|\nabla L_x\|_2 > T \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

We sweep the value of $T$ and pick a threshold that gives the best accuracy value to report the Norm-based attack results in Section 5.2. Note that in a real attack setting, the adversary does not have the ability to check the accuracy for different values of $T$. Our goal in doing so is to understand the best possible accuracy that can be obtained with the Norm-based attack.

B. Limitations

Our proposed Gradient Inversion Attack uses the gradient information obtained during split learning to leak the private labels. We assume that the input owner has knowledge of the number of classes and the distribution of the labels over these classes (prior information) to develop our loss function (Eqn. 12). If the attacker is completely unaware of the downstream classification task, this information could be hard to estimate, making our attack less effective (see Appendix D). However, we argue that it is rare for the input owner (attacker) to be completely unaware of the downstream classification task. Even if the label prior is unknown, knowledge of the task itself might be sufficient to make an educated guess about the label prior. For instance, in the case of conversion prediction, the average conversion rate for online advertising is publicly available [4]. In the case of disease prediction, the prevalence rate of a disease is often known and can be used as the label prior. Developing attacks that do not require label prior information is an interesting avenue of exploration for future work.

C. Input Privacy Attacks and Defenses in Split Learning

Recent works have proposed attacks to break input privacy in split learning. The goal of these attacks (a.k.a model inversion attack) is for an adversarial label owner to recover the private inputs $\{x_i\}$ of the input owner using the embedding information $\{z_i\}$ obtained during split learning. A recent work [1] showed that, for simple 1-d time-series signals, the embedding data obtained in split learning might not preserve privacy as it has a high distance correlation with the original input data. Model inversion attacks have also been demonstrated on split learning with more complex datasets in the image domain [22]. To carry out the attack, the adversary uses examples from the input data distribution $\{x_i'\}$ to query the input owner’s model and generate embeddings $z_i' = f(x_i')$. The input and embedding data can be used to train an inversion model $f_{inv}$ that maps the embedding to the input: $\mathcal{Z} \rightarrow \mathcal{X}$. This inversion model can be used to reconstruct the input data using the embeddings during the attack. Note that such attacks require access to the examples from the input data distribution and black-box query access to the input owner’s model. In contrast, our label leakage attack does not require black-box access to the label owner’s model or access to the ground truth label data. [1] also proposes using additive noise to perturb the embedding to defend against such attacks. This is similar in spirit to our work, which uses gradient noise to deter label leakage attacks.

D. Ablation Study

Our attack replaces the unknown labels and model of the label owner with surrogate labels and uses the gradient information obtained during split learning to train these parameters. In addition to matching the surrogate gradients obtained during “replay” split learning with the original gradients, our loss function consists of two regularization terms as shown in Eqn. 16.

$$L_{GIA} = \mathbb{E}\left[\|\nabla z L_i - \nabla z L_i'\|_2\right] + \lambda_{ce} \cdot \mathbb{E}\left[H(y_i', p_i')/H(P_y)\right] + \lambda_P \cdot D_{KL}(P_{y'}|P_y) \quad (16)$$

The cross-entropy regularization (CER) term $\mathbb{E}\left[H(y_i', p_i')/H(P_y)\right]$ achieves the dual objective of minimizing the entropy of the individual surrogate labels and improving the accuracy of the surrogate model ($y'$). The label prior regularization (LPR) term $D_{KL}(P_{y'}|P_y)$ tries to match the distribution of the surrogate labels with the label prior. We conduct an ablation study to understand the importance of the two regularization terms by carrying out GIA without using LPR, without using CER, and
Figure 6. Distribution of gradient norms $\|\nabla_z L\|_2$ for the conversion prediction task with Criteo dataset. Positive classes are infrequent and typically produce higher gradient norms.

Table 2. Ablation Study showing the label leakage accuracy of GIA when the two regularization terms: Label Prior Regularization (LPR) and Cross Entropy Regularization (CER), are not used.

| Dataset    | Original (%) | No LPR (%) | No CER (%) | No LPR, CER (%) |
|------------|--------------|------------|------------|-----------------|
| MNIST      | 99.88        | 68.29      | 31.43      | 17.95           |
| FMNIST     | 99.84        | 69.78      | 59.31      | 27.83           |
| CIFAR-10   | 99.96        | 99.28      | 99.35      | 99.84           |
| CIFAR-100  | 97.01        | 60.78      | 17.04      | 20.38           |
| Criteo     | 99.90        | 99.65      | 99.87      | 97.75           |

without using both LPR and CER. The results of this study are shown in Table 2. As expected, we find that there is a degradation in accuracy when regularization terms are not used. CER seems to be more important compared to LPR as the degradation is higher when CER is not used. For CIFAR-10 and Criteo, the regularization terms seem to matter less as the accuracy is high even when we disable both regularization terms.