Privacy Leakage of Real-World Vertical Federated Learning

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Abstract—Federated learning enables mutually distrustful participants to collaboratively learn a distributed machine learning model without revealing anything but the model’s output. Generic federated learning has been studied extensively, and several learning protocols, as well as open-source frameworks, have been developed. Yet, their over pursuit of computing efficiency and fast implementation might diminish the security and privacy guarantees of participant’s training data, about which little is known thus far.

In this paper, we consider an honest-but-curious adversary who participates in training a distributed ML model, does not deviate from the defined learning protocol, but attempts to infer private training data from the legitimately received information. In this setting, we design and implement two practical attacks, reverse sum attack and reverse multiplication attack, neither of which will affect the accuracy of the learned model. By empirically studying the privacy leakage of two learning protocols, we show that our attacks are (i) effective - the adversary successfully steal the private training data, even when the intermediate outputs are encrypted to protect data privacy; (ii) evasive - the adversary’s malicious behavior does not deviate from the protocol specification and deteriorate any accuracy of the target model; and (iii) easy - the adversary needs little prior knowledge about the data distribution of the target participant.

We also experimentally show that the leaked information is as effective as the raw training data through training an alternative classifier on the leaked information. We further discuss potential countermeasures and their challenges, which we hope may lead to several promising research directions.

Index Terms—Federated machine learning; Privacy leakage.

I. INTRODUCTION

Federated learning provides a promising way for different participants to train models on their private data without revealing any information beyond the outcome [27], [47], [19], [3]. The main goal of federated learning is to protect the privacy of the participants’ training data and to effectively and efficiently learning a joint machine learning model from participants’ training data. Compelling applications include using data from multiple hospitals to train predictive models for patient survival [24] and using data from user’s smartphones to train next word prediction models [21].

In order to deal with the practical application, recent years have witnessed a great number of delicate open-source frameworks for training a distributed model in federated learning. For sample, many industry leaders develop and open source frameworks for secure and private machine learning, including PySyft [33], FATE [13], TF Federated [14], TF Encrypted [11] and CrypTen [9]. These are all designed to provide the fast development of privacy-preserving models for non-experts, who want to choose an efficient protocol for training distributed machine learning models. With the advance of open-source frameworks, federated learning now has become a mainstream choice when different data holders want to train a distributed model on their private data collaboratively.

Vertical Federated Learning. Based on the characteristics of data distribution, the general federated learning can be categorized into horizontal federated learning [2], [3], where the distributed datasets share the same feature space but different samples, and vertical federated learning [47], [19], where the distributed datasets share the same samples but differ in feature space. Vertical federated learning can also be considered as privacy-preserving machine learning, which is tightly related to multi-party computation. Compared with the horizontal setting, vertical federated learning is more complicated as it needs to design a specific learning protocol for each machine learning algorithm. In our work, we mainly focus on vertical federated learning since it has a wider scope of applications and is more suitable for joint model training between large enterprises. For example, consider two different companies in the same city, one is a bank, and the other is an e-commerce company. They share a large percentage of user sets and differs in user attributes. In this case, vertical federated learning is the right mean for these two company to train a distributed model like the risk management model collaboratively [47].

Nevertheless, many learning protocols of vertical federated learning sacrifice data security and user privacy for computing efficiency. We observe that such sacrifice for efficiency makes the practical joint model training vulnerable to the adversary, resulting in the leakage of privacy data. For the privacy-preserving version of logistic regression [19], [47] as an example, it employs a third-party coordinator to coordinator the model training procedure as well as to accelerate the training speed. In this learning protocol, the third-party coordinator holds an RSA private key and sends the public key to the computing participants for encrypting their intermediate outputs. Then, the coordinator combines the encrypted outputs, use its private key for decrypting, and sends the decrypted result back to the computing participants. Obviously, such a training procedure leaks much too private information to the

*work in progress
coordinator. Even worse, in practice, we can hardly see an honest third-party coordinator which never deviates from the protocol specification nor gathers private information from the limited outputs. On the contrast, there will probably exist a malicious adversary who mildly controls part of the distributed training process to infer participant’s private training data from the limited intermediate outputs.

**Our Work.** In this paper, we provide the first systematic study on the potential privacy risk of practical learning protocols in vertical federated learning. Specially, our work seeks to answer the crucial research question: How much is the privacy risks of the practical learning protocols for computing participates whose data is used as part of the training set? In other words, how much is the privacy leakage of the learning protocol about the participants’ training data?

Although previous works have shown the possibility of inferring private data in the scenario privacy-preserving machine learning [25], [29], [20], [45], they neither focus on the vertical setting of federated learning nor only performing membership protocols about the participants’ training data.

In summary, we make the following contributions:

- We discover the potential privacy risks in practical learning protocols of vertical federated learning by showing, a semi-honest with access to the learning process can infer privacy about the target participant’s data.
- We design two simple yet effective attacks for measuring data leakage in vertical federated learning and implement them on the practical privacy-preserving frameworks.
- We present a first systematic measurement study on the privacy risks of two commonly used learning protocols in vertical federated learning, logistic regression and SecureBoost (i.e., the private preserving version of XGBoost), with an in-depth analysis on the factors that influence the privacy.

This paper is organized as follows. In §II, we introduce the background knowledge of our work, including the formal definition of federated learning, the commonly used learning protocols and the real-world frameworks for privacy preserving machine learning. In §III, we formalize the problem and our threat model. In §IV, we describe the reverse multiplication attack, and our implementation and experimental evaluations. In §V we describe the reverse sum attack, and our implementation and experimental evaluations. We present possible countermeasure in §VI, review the related work in §VII and give our discussions in §VIII and finally conclude this paper in §IX.

### II. Preliminaries

In this section, we first introduce the basic definition of vertical and horizontal federated learning. Then, briefly review the two commonly used machine learning algorithms: logistic regression [16] and XGBoost [6], followed by their privacy-preserving versions in vertical federated learning. In the end, we review several popular real-world frameworks for vertical federated learning, including TF Federated, FATE, PySyft, TF Encrypted and CrypTen.
A. Federated Learning

a) Federated Learning: Federated learning aims to build machine learning models on datasets that are held by multiple participants without revealing anything but the model’s output. Based on the characteristics of data distribution, the general federated learning can be categorized into horizontal federated learning [2, 3] and vertical federated learning [47, 19].

In horizontal federated learning, the distributed datasets share the same feature space but different samples. In contrast, in vertical federated learning, the distributed datasets share the same samples but differ in feature space. Figure 1 visualizes the characteristics of data distribution of the horizontal and vertical federated learning. Our work mainly evaluates the privacy leakage of learning a distributed machine learning model in vertical federated learning.

b) Notations: We give the mathematical notations that are frequently used across this paper. For simplicity, we assume two participants, A and B, are collaboratively training a distributed machine learning model in the vertical setting. Let $X \in \mathbb{R}^{n \times d}$ denote the complete dataset containing $n$ samples, $Y \in \mathbb{R}^{n \times 1}$ denote the label set, and $I \in \mathbb{R}^{n \times 1}$ denote the sample IDs.

In vertical federated learning, this dataset does not exist in one place but is composed of the columns of the datasets held by A and B, giving the vertical partition: $X = [X_A | X_B]$. The label set $Y$ is held by A. We also call A activate participant as it has the vital information of class labels, while calling B passive participant as it only has the data feature.

Now, let $x_i$ be the $i$-th row of $X$. Define $x_i^A$ as the partial data of $x_i$ held by A, and $x_i^B$ as the partial data of $x_i$ held by B. In other words, $x_i$ is decomposed as: $x_i = [x_i^A | x_i^B]$.

c) Security Primitives: Next, we review the primary privacy techniques adopted by vertical federated learning for providing privacy guarantees. Vertical federated learning usually utilizes additively homomorphic encryption like Paillier [30] to encrypt the intermediated output.

Additively homomorphic encryption is a public key system that allows participants to encrypt their data with a known public key and perform computation with data encrypted by the others with the same public key. For extracting the plaintext, the encrypted result needs to be sent to the private key holder for decryption. Let the encryption of a number $u$ be $[u]$. For any plaintext $u$ and $v$, we have the following add operation, $[u + v] = [u] + [v]$. We can also multiply a ciphertext with a plaintext by repeated addition, $[v \cdot u] = v \cdot [u]$, where $v$ is not encrypted. These operations can be extended to work with vectors and matrices component-wise. For example, we denote the inner product of two vectors of plaintexts $u$ and $v$ by $v^T \cdot [u] = [v^T \cdot u]$.

B. Learning Protocols

Logistic regression [16] and XGBoost [6] are two highly effective and widely used machine learning methods. Many winner teams of machine learning competitions like Kaggle[1] challenges use a combination of logistic regression and XGBoost to build their best performance classifiers [37]. Similarly, these two algorithms are frequently used by giant institutions and the e-commerce company use linear regression to collaboratively train a scorecard model on their own private training data. Below, we briefly introduce the main ideas of linear regression and XGBoost, followed by their privacy-preserving versions in vertical federated learning.

a) Logistic Regression: Given $n$ training samples $x_i$ with $d$ features, and $n$ corresponding output labels $y_i$, linear regression is a statistical process to learn a function such that $f(x_i) = y_i$. $f$ is assumed to be linear and can be represented as the inner product of $x_i$ with the coefficient vector $\theta$: $f(x_i) = \sum_{j=1}^{d} \theta_j x_{ij}$.

To learn the coefficient $\theta$, minimize the loss between $f(x_i)$ and $y_i$ on all the training data, defined as

$$L(\theta) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{2} (\theta x_i - y_i)^2.$$  \hspace{1cm} (3)

Usually in centralized linear regression, SGD [34] is an effective approximation algorithm for approaching a local minimum of a function, step by step.

b) Loss decomposition: Different from centralized learning, each $x_i$ in vertical federated learning is partitioned as $[x_i^A | x_i^B]$ and the coefficient $\theta$ is also partially held by the two participants as $[\theta^A | \theta^B]$. The loss function of Eq. (3) is then simplified and decomposed as

$$L(\theta) \approx \frac{1}{n} \sum_{i=1}^{n} \left( \frac{1}{4} \theta^A x_i^A + \frac{1}{4} \theta^B x_i^B - \frac{1}{2} y_i \right) \cdot [x_i^A | x_i^B]$$ \hspace{1cm} (4)

$$= \frac{1}{4} \left( \frac{1}{n} \theta^A X^A + \frac{1}{n} \theta^B X^B - \frac{1}{2} Y \right) \cdot [X^A | X^B]$$  \hspace{1cm} (5)

Participants A and B jointly compute the decomposed loss function of Eq. (5) using their private training data. Then, they exchange the intermediate outputs with or without a third-party coordinator to form the final result. In [19], [47], they does require a third-party coordinator. In the following, we show the detailed steps for computing the above equation in vertical federated learning.

### TABLE I: Detailed steps for logistic regression in vertical federated learning.

| Participant A | Participant B | Coordinator C |
|---------------|---------------|---------------|
| 1. init $\theta^A$; | 2. init $\theta^B$; | send the public key to A and B; |
| 2. compute $[x] = \left[ \frac{1}{2} \theta^A X^A - \frac{1}{2} Y \right]$ and send to C; | 3. compute $\left[ v \right] X^B$ and send to C; | decrypt $\left[ v \right] X^A$ and $\left[ v \right] X^B$ to get the gradient $g^A$, $g^B$, and send them to A and B; |
| 3. compute $[v] X^B$ and sent to C; | 4. | |

[https://www.kaggle.com/competitions](https://www.kaggle.com/competitions)
c) **Secure logistic regression**: To compute Eq. (5) without revealing anything about data privacy, most of the secure protocols adopt additively homomorphic encryption like Paillier to encrypt the intermediate outputs and operate on ciphertext [27], [47], [19]. The encrypted distributed loss of Eq. (5) is

\[
[L(\theta)] \approx \frac{1}{n} \left[ \frac{1}{4} \theta^A X^A + \frac{1}{2} \theta^B X^B - \frac{1}{2} Y \right] \cdot X^A \cdot X^B
\]  

(6)

In vertical federated learning, we also employ the SGD algorithm for gradually approaching a local minimum of the distributed loss. Table I gives the detailed training steps of logistic regression in vertical federated setting. With SGD, the secure computing protocol of logistic regression works as the following.

First, participants \(A\) and \(B\) initialize \(\theta^A\) and \(\theta^B\) as vectors of random values or all 0s. Coordinator \(C\) creates an encryption key pair and sends the public key to \(A\) and \(B\). Second, in each iteration, participant \(A\) randomly selected a small mini-batch of indices \(S\) and update the distributed coefficient by averaging partial derivatives of all samples on the current coefficient. Steps 2–4 shows how \(A\) and \(B\) collaboratively compute the gradient of the encrypted distributed loss function and update the distributed coefficient. In general, using an additively homomorphic encryption scheme, participants \(A\) and \(B\) compute on the encrypted intermediate outputs, generating an encrypted derivative which, when decrypted, matches to the derivative as if it had been calculated on the plaintext. Refer [27], [47], [19] for more details about secure logistic regression.

d) **XGBoost**: Given \(n\) training samples \(x_i\) with \(d\) features, XGBoost learns a function consisting of \(k\) regression trees such that \(f(x_i) = \sum_{t=1}^{k} f_t(x_i)\) [6]. To learn such \(k\) regression trees, XGBoost adds a tree \(f_t\) at the \(t\)-th iteration to minimize the following loss,

\[
L(t) = \frac{1}{n} \sum_{i=1}^{n} \left[ (g_i - \hat{g}(t-1)) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t), \quad (7)
\]

where \(g_i\) and \(h_i\) are first and second order gradient statistics on the loss function calculated by \(f_{t-1}\), and \(\Omega\) penalizes the complexity of the model.

For constructing \(t\)-th regression tree, XGBoost starts from a leaf node and iteratively adds optimal branches to the tree until researching the terminating condition. Below is the loss reduction after the split,

\[
L_{\text{split}} = \frac{1}{2} \left[ \left( \sum_{i \in I_L} g_i \right)^2 + \left( \sum_{i \in I_R} g_i \right)^2 \right] + \lambda \left( \sum_{i \in I_L} h_i + \sum_{i \in I_R} h_i \right) \quad (8)
\]

where \(I_L\) and \(I_R\) are the instance space of the left and right nodes after split. In practice, XGBoost chooses an optimal split that can maximize the above reduction loss. That is to say, in each iteration, XGBoost enumerates all the possible split feature and value and find the one that can maximize the reduction loss. Refer [6] for more details about XGBoost.

e) **Secure XGBoost**: Secure XGBoost [7], also known as SecureBoost, is the privacy-preserving tree-boost algorithm in vertical federated learning. SecureBoost allows the learning process of \(k\) regression trees to be jointly conducted over two participants with common user samples but different features. To learn a privacy-preserving regression tree, SecureBoost also starts from a single leaf node and coordinates two computing participants to find the optimal split.

Different from logistic regression, SecureBoost does not rely on a third-party coordinator to coordinate the learning process. In SecureBoost, the participant who holds the label information serves as a coordinator. We also call the participant who hold the labels as the active participant and the other as the passive participant.

In SecureBoost, the active and passive participants collaboratively calculate the reduction loss of Eq. (8) and search for the best split. In each iteration, they search the best split and construct a regression tree as follows. First, the active participant calculates first and second order gradients for all the training samples, and then encrypts and sends them to the passive participant. Second, the passive participant receives the encrypted gradients and calculates the reduction loss for all the possible split features and values. For efficiency and privacy, instead of computing on \(\left[ g_i \right]\) and \(\left[ h_i \right]\) directly, the passive participant maps the features into data bins and then aggregates the encrypted gradient statistics based on the bins. Third, the active participant receives and decrypts the encrypted reduction loss, and then finds an optimal split dimension and feature with the maximum reduction. Refer [7] for more details about SecureBoost.
C. Real-world Secure Computing Frameworks for Vertical Federated Learning

| Framework | Developer | Vertical | Horizontal | Arch |
|-----------|-----------|----------|------------|------|
| FATE      | WeBank    | ✔️       | ✔️         | HE   |
| PySyft    | OpenAI    | ✔️       | ✔️         | SS   |
| TF Federated | Google     | ✔️   | ✔️         | SS   |
| TF Encrypted | Dropout    | ✔️       | ✔️         | HE   |
| CrypTen   | Facebook  | ✔️       | ✔️         | HE, SS |

As discussed, many industry leaders develop and open-source frameworks for secure and private machine learning, including PySyft [33], FATE [13], TF Federated [14], TF Encrypted [11] and CrypTen [9]. All of these frameworks directly or indirectly provide machine learning protocols in vertical federated learning setting. For example, FATE supports both vertical federated learning of various machine learning algorithms, including logistic regression, deep learning and tree-based learning; PySyft provides basic modules (e.g., communication and encrypted computation modules) for the fast implementation of vertical federated learning. Table II shows the functionalities and basic encryption techniques supported by these frameworks.

Of the five evaluated frameworks, Fate, PySyft, TF Encrypted and CrypTen support participants to train a joint model when their training data is vertically aligned or horizontally aligned. The remaining one TF Federated only supports to training a model when the data are horizontally aligned. For the encryption techniques, these five frameworks mainly utilize two mainstream methods, homomorphic encryption [12] and secret sharing [36].

In this paper, we study the data leakage of privacy-preserving machine learning algorithms in the vertical federated learning setting. We propose two simple yet effective attacks and evaluate them against the real-world implementations of vertical federated learning provided by these popular open-source frameworks.

III. General Privacy Risks in Vertical Federated Learning

Although secure learning protocols and open-source frameworks provide the possibility for different organizations to collaboratively train a machine learning model, we find that those protocols’ over pursuit for learning efficiency, however, lead to the privacy risk of participants’ training data. By constructing two novel attacks, reverse multiplication attack and reverse sum attack, we show there indeed exists vulnerabilities against vertical federated learning, and an adversary can steal the plaintext of participants’ private data. In this section, we present the threat model and privacy risks faced by vertical federated learning.

Figure 2 shows a typical federated learning scenario. The complete dataset \( X \) is vertically split into \( X_A \) and \( X_B \) held by participants \( A \) and \( B \) respectively. Then, \( A \) and \( B \) maintain partial models locally and exchange the encrypted partial gradient and other essential information to learn a joint model on the complete dataset \( X \).

A. Threat Model

We investigate if an adversarial participant can steal the privacy about other participant’s training data, even when the learning protocol is privacy-preserving. As shown in Figure 2, participants \( A \) and \( B \) keep their private data locally, and according to a particular secure learning protocol, they jointly train a model without revealing anything but the model’s output. In some learning protocols like logistics regression, \( A \) and \( B \) require a third-party coordinator to handle the encrypted partial gradients and update the global model. In contrast, other protocols like SecureBoost, the two participants, can independently learn a joint model without any third-parties. In both types of learning protocols, we assume that the adversarial participant is semi-honest that does not deviate from the protocol specification, but try to gather as much private information out of the learning protocol as possible.

a) Adversary: We assume that one of the participants in the vertical federated learning scenario, as shown in Figure 2, is controlled by the adversary. The adversary can send or receive the encrypted information corresponding to the statistics (e.g., gradient or the multiplication result between gradient and data) of the other participant’s training data. In general, the adversary maliciously controls the local training process. However, in our work, we assume a semi-honest adversary who does not deviate from the protocol specification, but merely operates to gather as much private information out of the learning protocol as possible. For example, in reverse sum attack (refer [IV] for more details), the adversary may construct specific strings and insert them into the least significant bits of gradients while keeping the learning protocol intact. In reverse multiplication attack (refer [IV] for more details), the adversary may also corrupt the third-party coordinator to gather much more privacy out of the protocol.

b) Adversary’s objectives: The adversary’s main objective is to infer as much as the participant’s private training dataset as possible. (i) In the reverse multiplication attack, the adversary aims to infer the target participant’s raw training data. (ii) In the reverse sum attack, the adversary attempts to infer the partial orders of the target participant’s training data.
c) **Assumption about the third-party coordinator.** In our reverse multiplication attack, we assume that the adversary could corrupt the third-party coordinator. This assumption is reasonable since finding a trusted third-party coordinator is almost impossible in practice. Even if the coordinator is protected by TEEs (Trusted Execution Environments) \(^{[39]}\) like SGX \(^{[35]}\), it still could be comprised by various state-of-the-art attacks, e.g., SGX has been proven to be vulnerable to side-channel attacks \(^{[42]}\).

Like the controlled participant, we assume that the semi-honest adversary does not destroy the third-party’s protocol specification. This semi-honest adversary only exploits the limited statistics that the corrupted third-party received or other utilities held by this third-party. Usually, in vertical federated learning, the third-party coordinator concatenates the encrypted intermediate outputs received from the two participants and forms the final gradient updates. Thus, the adversary could use such gradient updates to infer the target participant’s training data. In \(^{[11]}\) we will illustrate how the adversary reverse-engineers the multiplication terms of the training data leveraging the third-party coordinator.

### IV. Reverse Multiplication Attack

In the reverse multiplication attack, the adversary’s goal is to reverse-engineer each multiplication term of the matrix product. Matrix multiplication is the typical operator commonly used in many federated learning protocols, which may raise potential privacy leakage of participants’ private training data. Thus, we focus on logistic regression in a vertical federated setting and propose a simple yet effective reverse multiplication attack against it for inferring the target participant’s raw training data.

Below, we illustrate the attack pipeline of our proposed reverse multiplication attack. Then, we implement the reverse multiplication attack on the popular practical framework, FATE, and experimental measure the privacy leakage raised by matrix multiplication through performing the reverse multiplication attack.

#### A. Attack Pipeline

As shown in Table \(^{[8]}\) logistic regression in vertical federated learning involves both computing participants and a third-party coordinator. In our work, we focus on the simple scenario where only two data holders, \(A\) and \(B\), participate in the model training process.

Logistics regression relies on a series of multiplications between coefficients and participants’ private training data to deduce the gradient, as listed in Eq. \((6)\). Moreover, participants \(A\) and \(B\) are required to exchange the intermediate multiplication results for calculating the gradient. Though the multiplication result is encrypted by the public and contains no information about the training data, we still can collude with the private key owner to get the multiplication result’s plaintext. Further, leveraging linear algebra and scientific computation, we can reverse-engineer each multiplication terms (i.e., raw training data) from the multiplication result.

We design a reverse multiplication attack against logistic regression. We assume the adversary fully controls participant \(A\) and coordinator \(C\) to steal the private information of features from the remaining participant \(B\). In this attack, the adversary utilizes 1) the intermediate output that \(A\) receives from \(B\) and 2) the partial gradient that \(C\) sends back to \(B\). The intermediate output is the linear product of \(B\)’s partial gradient and features. Regarding the \(B\)’s features as unknown parameters, performing the reverse multiplication attack equals to solve a set of linear functions.

Below, we illustrate the detailed steps for the reverse multiplication attack. We consider that the data samples held by \(A\) and \(B\) are already aligned.

- **Step 1.** The adversary stealthily stores the intermediate encrypted multiplication result during the collaborative training on each mini-batch. To be specific, for each mini-batch \(S\), the adversary stealthily stores \((i)\) the multiplication result between \(B\)’s partial data and coefficient, \(\frac{1}{4}\theta^B_t X^B_S\), and \((ii)\) the coefficient update of gradient, \(g^B_t\). Note that this encrypted product is sent from \(B\) for jointly calculating the encrypted gradient on the mini-batch.

- **Step 2.** The adversary decrypts \(\frac{1}{4}\theta^B_t X^B_S\) calculated on each mini-batch. Note that \(A\) and \(B\) use the same public key for encryption and \(C\) uses the corresponding private key for decryption. Hence, the adversary can use \(C\)’s private key to decrypt the ciphertext.

- **Step 3.** The adversary reverses the multiplication terms to obtain \(B\)’s training data. For a specific mini-batch \(X^B_S\), the adversary have the following equation on two successive training epoch: \(\frac{1}{4}\theta^B_t X^B_S - \frac{1}{4}\theta^B_{t-1} X^B_S = g^B_t X^B_S\), where only \(X^B_S\) is the unknown parameter. The adversary can compute out the unknown \(X^B_S\) if he gets sufficient equations. The adversary needs at least \(|B|\) equations solve the unknown parameter, where \(|B|\) denotes the number of features in \(B\)’s private data.

The above steps illustrate how the adversary utilizes the intermediate output \(\frac{1}{4}\theta^B_t X^B_S\), and partial gradient \(g^B\) to steal \(B\)’s private training data. In some real-world federated learning frameworks, the coordinator directly updates the coefficient and send it back to participants. In such case, the adversary can solve out the unknown parameter \(X^B_S\) simply using several multiplication results \(\theta^B_t X^B_S\) and the partial gradients \(\theta^B_t g^B\).

The success of the reverse multiplication attack depends on the rank \(^2\) of the coefficient matrixes of the equations. The adversary can successfully compute out the private data if the coefficient matrix is fully ranked otherwise not. Hence, in our experimental evaluation, we first explore the influence of training parameters on the rank of the coefficient matrix. Then, we perform our reverse multiplication attack against Logistic Regression in a vertical federated learning setting.

#### B. Experimental Setup

- **a) Datasets:** We use three classical classification datasets in our experiments: Credit \(^{[8]}\), Breast \(^{[4]}\), and Vehicle \(^{[5]}\).

\(^2\)The rank of a matrix is defined as the maximum number of linearly independent column vectors or row vectors in the matrix.
• Credit contains the payment records of 30,000 customers from a bank, where 5,000 customers are malicious, and the remaining are benign. Each record has a total of 23 integer or real value features. The Credit dataset is a popular benchmark dataset used to evaluate binary classification tasks \cite{credit}.
• Breast is also a binary classification dataset. It contains 699 medical diagnosis records of breast cancer, of which 357 are benign, and 212 are malignant. Each record has 30 features extracted from a digitized image of a fine needle aspirate of a breast mass.
• Vehicle is a multi-classification dataset extracted from example silhouettes of objects. It contains 946 examples belonging to four vehicle categories. Each example has a set of 18 features extracted from the silhouette of the original object.

b) Implementation of Logistic Regression in Vertical Federated Learning: We implement the learning protocol of logistic regression on two real-world secure and private learning frameworks, FATE and PySyft. Then, we perform the reverse multiplication attack against these two implementations.

For the setting of training scenario, we consider two participants $A$ and $B$ with a third-party coordinator $C$ collaboratively train a logistic regression model. Below, we detail the two implementations of privacy preserving logistic regression.

• FATE provides many default implementations of machine learning algorithms, including logistic regression and tree-based algorithms. In our experiment, we use FATE’s default implementation of privacy-preserving logistic regression \cite{fate}. This implementation employs a third-party arbiter to coordinate the process of gradient computation and sends back the decrypted gradient to the participants. For protecting data privacy, this implementation uses an RSA private key to encrypt the intermediate output exchanged among the two participants, which can only be decrypted by the public key owner.

• PySyft is a library for secure and private machine learning. Based on its communication and encrypted computation modules, we implement the learning protocol of privacy-preserving logistic learning proposed in \cite{pysyft}, similar to FATE’s default implementation. Except for \cite{fate}, there exist many other similar learning protocols for privacy-preserving logistic regression \cite{fate, pysyft}. We choose to implement the protocol provided in \cite{fate} since it provides a satisfying training accuracy and learning efficiency.

• PySyft also provides many default implementations of machine learning algorithms, including logistic regression and tree-based algorithms. In our experiment, we use PySyft’s default implementation of privacy-preserving logistic regression \cite{pysyft}. This implementation employs a third-party arbiter to coordinate the process of gradient computation and sends back the decrypted gradient to the participants. For protecting data privacy, this implementation uses an RSA private key to encrypt the intermediate output exchanged among the two participants, which can only be decrypted by the public key owner.

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c) Attack Setting: We vertically partition each of the training datasets into two parts and distribute them to participants $A$ and $B$. Table \ref{table1} shows the partition details. The labels of the three datasets are all placed in $A$. In other words, $A$ is the active participant, and $B$ is the passive participant.

| Dataset  | #examples | #features for $A$ | #features for $B$ |
|----------|-----------|------------------|------------------|
| Credit   | 30,000    | 13               | 10               |
| Breast   | 699       | 10               | 20               |
| Vehicle  | 946       | 9                | 9                |

C. Results & Analysis

We set the adversary control participant $A$ and the third-party coordinator $C$. The adversary aims to steal $B$’s private data using the limited information he received from the $A$ and $B$. During the training process, the adversary stealthily stores the coefficients (or gradients) and the encrypted multiplication results. In this experiment, the adversary only gathers information out of the training process, not destroying the training process.

Fig. 3: Rank of the coefficient matrix under different settings of batch size.

Fig. 4: Rank of the coefficient matrix under different settings of learning rate.

a) Impact of Training Parameters: As stated in \ref{IV-A}, the success of reverse multiplication attack depends on the coefficient matrix rank of the equations, which is influenced by the training parameters. To understand such influence, we perform our attack under different settings of two critical training parameters, learning rate, and batch size.

Figure 3 reports the coefficient matrix rank after 100 training epochs under different settings of batch size. From this figure, we can see that the learning rate significantly affects the coefficient matrix’s rank. A small batch size makes the coefficient matrix full rank, while a large batch size cannot. In other words, with small batch size, the adversary can accurately all the private data of the target participant.

Figure 4 reports the coefficient matrix rank after 100 training epochs under different settings of the learning rate. We can see from this figure that learning rate may potentially affect the success rate of our reverse sum attack. For the Credit dataset as an example, when the learning rate is set to 0.01, the parameter matrices’ ranks are 9 in all the tested values of batch size. In other words, these matrices are not fully ranked and the adversary cannot use them to compute out $B$’s private training data. While the learning rate is set to 0.05, all the cumulated gradient matrixes under are fully ranked, resulting in the success of the collusion attack.
V. REVERSE SUM ATTACK

In the reverse sum attack, the adversary attempts to reverse each addition terms from the sum. The sum is a common statistical factor, widely used in many machine learning algorithms, including nearest neighbor-based and tree-based algorithms [16]. We focus on XGB in vertical federated learning (i.e., SecureBoost) and propose a reverse sum attack against SecureBoost to stealing private information about target participant’s training data.

Below, we describe our design of the reverse sum attack and then report our major experimental evaluation of this attack.

A. Attack Pipeline

II-B briefly outlines the learning protocol of SecureBoost. There exist two participants in SecureBoost: the active participant $A$ and the passive participant $B$. As illustrated in II-B, participant $A$ does receive the first and second gradient sums of each bin’s examples defined by participant $B$. Moreover, to compute the split loss jointly, these gradient sums are sent one by one according to bin order. Obviously, it is possible for $A$ to encode information about the training data in the gradients and further reverse the addition terms of the gradient sums received from $B$ using the encoded information. These addition terms imply the partial orders of the target participant’s private training data.

We design a reverse sum attack against SecureBoost. In our attack, we assume the adversary fully controls participant $A$. The two major steps of our attack are listed below.

- **Step 1.** The adversary controls $A$ to encode *magic number* [23] into the ciphertext of the first and second order gradients. Here, the term magic number refers to distinctive unique values that are unlikely to be mistaken for the other meanings (i.e., global unique identifiers).

- **Step 2.** The adversary stores both the first and second gradient sums received from $B$. Then, the adversary reverse engineers all the addition terms from the gradient sums leveraging the encoded magic numbers. These reversed terms revel the partial orders of $B$’s training data.

In the following, we will detail the above steps.

**Fig. 5:** Architecture of the magic number. The first few bits are random values and the remaining bits are group identifier that allows the adversary to locate the specific group the example belongs

A few bits of random values  
A few bits of group identifier

**a) Magic Number:** Aforementioned above, we encode magic numbers in the ciphertext of the first and second gradients. In practice, the public encryption ecosystem encrypts on the 1024-bit number. For the 64-bit float number of the gradient, the ecosystem usually pads it with 960 zeros to get a 1024-bit number for encryption. The 960 zeros do not deteriorate the float number precision as they are padded in the least significant position. In our attack, instead of padding 960 zeros, we design to pad the 64-bit number with a 960-bit magic number.

A magic number is a unique identifier used by the attacker to identify the specific gradient value encoded with this magic number. For this purpose, we design such a generation schema that could generate as many magic numbers as possible for identifying gradients of the training data. Figure 5 visualizes the architecture of our magic number.

As shown in Figure 5, the magic number has two parts: group identifier and random values. The group identifier is a one-hot vector under $n$-base positional numeral system, and is used to identify the specific group examples that the encoded example belongs. For example in base-10 system, 0...01 implies that the example belongs to group 1. Random values are used to note different examples from the same group. With the group identifier and random values, examples from the same group have the same group identifier while the different random values.

Below, we give an example of generating group identifiers using a base-16 positional numerical system. For simplicity, we only utilize 20 of 960 bits to encode the magic number. We set the first 4 bits as random value bits, and set the remaining 16 bits as the group identifier bits, identifying a maximum of $4 (=\log_{16}2^{16})$ unique groups of examples. Given 60 data samples, we first divide them into 4 groups, each with 60/4 samples. The 1-th to 15-th samples are placed in the first group, the 16-th to 30-th samples are in the second group, the 31-th to 45-th samples are third group, and the 46-th to 60-th samples are in the fourth group. For the data sample in the first group, we generate the first 4 bits as random values and the group identifier of the remaining 16 bits as 00001. Similar, for the data sample in the second group, the first 4 bits of the magic number are random values and the group identifier is 00010.

**b) Gradient Encoding:** Algorithm I shows how to encode magic numbers into the least significant bits of the first and second gradients.

Algorithm II shows how to encode magic numbers into the least significant bits of the first and second gradients.

First, we set the number of supergroups to $k$ and the positional numerical system base to $b$. In this setting, the group identifier’s maximum length is $\log_b2^{(960−30×k)}$, shown in Line 5. The maximum number of samples groups is $2×k×l$, and the maximum number of encoded samples is $q × b$, as shown in Lines 6&7, respectively. Second, we sequentially select $n'$ examples to encode magic numbers in their first and second gradients. Also, we can use any other elaborate selection strategy like a distribution-based strategy. Third, for each selected example, we construct a magic number and post-process its first or second gradients by setting the lower $b$ bits of each to a bit string of the magic number. Lines 9–13
Algorithm 1 Gradient Encoding

1: **Input:** the first order gradients $g_1, g_2, \ldots, g_n$, the second order gradients $h_1, h_2, \ldots, h_n$.
2: **Output:** the first and second gradients encoded with magic numbers.
3: $k \leftarrow$ number of super groups
4: $b \leftarrow$ base of the positional numerical system
5: $l = \log_{2b} 2^{(960-30 \times k)}$ \footnote{length of the group identifier}
6: $g \leftarrow 2 \times k \times l$ \footnote{number of the total groups}
7: $n' \leftarrow g \times b$ \footnote{number of the encoded samples}
8: for $i = 1; i < n'; i + i$ do
9: $s \leftarrow \text{round}(i/l)$
10: $id \leftarrow \text{round}((i\%l)/(b-1))$
11: random values $\leftarrow$ the $s$ to $s + 29$ bits are set to random values and the remaining of the first $30 \times k$ bits are set to 0
12: group identifier $\leftarrow$ the one-hot vector under $b$-base positional numerical system with the id-th number set to 1
13: magic number $\leftarrow$ concatenate(random values, group identifier)

describe the detailed steps of constructing a magic number, and Figure 5 shows the architecture of the magic number.

Third, for each selected example, we construct a magic number and post-process its first or second gradients by setting the lower $b$ bits of each to a bit string of the magic number. Lines 9–13 describe the detailed steps of constructing a magic number, and Figure 5 shows the architecture of the magic number.

c) **Gradient Sum Reversion:** Leveraging the encoded magic number, the adversary could effectively reverse engineer all the addition terms from the gradient sum.

Let $B$ denote the bin. Then, let $G_B = \sum_{x_i \in B} g_i$ and $H_B = \sum_{x_i \in B} h_i$ be the first and second order gradient sum of $B$'s samples. During the collaborative training of each boost tree, participant $A$ continually receives $G_B$ and $H_B$ from participant $B$. The adversary’s goal is to reverse all the additions items of $G_B$ and $H_B$, all of which can be further integrated to form the partial orders.

Given a $G_B$ or $H_B$, we first decode it into 1024-bit strings and then extract the lower 960 bits, denoted as $s$. In each $G_B$ or $H_B$, $s$ equals to the sum of magic numbers of $B$’s samples encoded by the adversary. Then, leveraging $s$, the adversary greedily searches out an optimal combination of samples that might be the addition terms of $G_B$ or $H_B$. Below, we give a sample to illustrate how the adversary reverse engineers all the addition items leveraging $s$.

In the example, we utilize 20 of 960 bits to encode the magic number, set the first 4 bits as random value bits, and set the base of positional numerical system to 4. We assume a data bin $B$ containing five samples: $x_2, x_{17}, x_{317}, x_{520}, x_{2400}$, where only $x_2$ and $x_{17}$ are selected to encode magic numbers. The magic number of $x_2$ is $0X30001$ and the magic number of $x_{14}$ is $0X20010$. In this example, the magic number sum of $G_B$ is $0X50011 = (0X30001 + 0X20010)$. Once extracting the magic sum of $0X50011$, the adversary can know $B$ must contains one sample from group 1 and one sample from group 2. With the additional information that sum of random values of the two magic number is $0X5$, the adversary can easily figure out that $x_2$ and $x_{17}$ are in $B$.

B. **Experimental Setup**

a) **Datasets:** We conduct experiments on two public datasets: Credit and Student [38]. The Credit dataset is the same as that used in [IV-B]. The Student dataset is a regression dataset, containing education records of 395 students collected from a mathematics class. The data attributes include student grades, demographic, social, and school-related features. This dataset is often used to train a regression model that predicts student performance in the final examination.

b) **Implementation of SecureBoost in Vertical Federated Learning:** We perform the reverse sum attack against the real-world implementation of SecureBoost, provided by FATE. Similar to § IV-B, we use FATE’s default implementation of the learning protocol of SecureBoost. For protecting data privacy, this implementation uses Paillier to encrypt the first and second order gradients and the intermediate outputs.

c) **Attack Setting:** We vertically partition each of the training datasets into two parts and distribute them to participants $A$ and $B$. Table IV shows the partition details. $A$ is the activate participant, and the labels of the two datasets are all placed in $A$.

| Dataset | #samples | #features for $A$ | #features for $B$ |
|---------|----------|------------------|------------------|
| Credit  | 30,000   | 13               | 10               |
| Student | 395      | 6                | 7                |

In this experiment, we set the adversary control $A$ and aim to steal the partial orders of $B$’s private training data. During the training process, the adversary encodes magic numbers into the least significant bits of the gradients and stores the gradient sums from participant $B$. Although the adversary slightly modifies the gradients, it does not destroy the training process at all since the least significant bits cannot affect the selection of the best split dimension and feature.

C. **Results & Analysis**

a) **Attack Performance:** In this experiment, we investigate the performance of the reverse sum attack against SecureBoost in vertical federated learning. Specifically, we experimentally analyze the factors that influence the performance of the attack, including the distribution of the data, the bin size, and the attack parameters.

| Dataset | #samples | distribution      |
|---------|----------|-------------------|
| $D_1$   | 30,000   | Normal distribution: $\mathcal{N}(0, 1)$ |
| $D_2$   | 30,000   | Bernoulli distribution: $\mathcal{B}(\frac{1}{2})$ |
| $D_3$   | 30,000   | Exponential distribution: $\mathcal{E}(1)$ |
| $D_4$   | 30,000   | Uniform distribution: $\mathcal{U}(0, 50)$ |

Impact of Data Distribution. To understand the impact of the data distribution, we perform the attack separately on four 1D synthetic datasets with four different data distribution,
including Normal distribution, Bernoulli distribution, Exponential distribution, and uniform distribution. Table VI gives detailed statistics of the four synthetic datasets.

Figure 6 shows the attack success rate for various data distribution of the target training datasets. Of the four tested datasets, the attack is performed under different settings of attack parameters. As can be seen from Figure 6, the success rate for different distributed datasets is almost the same under all attack settings.

![Figure 6: The success rate for the four synthetic datasets with different data distribution.](image)

**Impact of Bin Size.** Next, we explore the impact of bin size on the attack success rate. In this experiment, we set two participants to jointly learn an XGBoost model on $D_1$. Figure 7 shows the attack success rate when the target participant split the training data into different numbers of bins.

As the figure shows, the attack success rate increases with the number of data bins on the target’s training data increases. The reason behind this is straightforward. A large number of data bins result in fewer samples in a single bin, making it easier for the adversary to accurately figure out all the addition terms of the gradient sum of this bin. We can also observe from the figure that a small number (close to 30) of data bins leads to a 0.5+ attack success rate.

**Impact of Attack Parameters.** Finally, we demonstrate that the two attack parameters, the base of positional numerical systems and the number of supergroups, are highly correlated with the size of cracked partial orders, as they decide the maximum number of samples that can be encoded with magic numbers. In this experiment, we run the attack on the credit dataset using different settings of the two attack parameters.

Table VII shows the success rate as well as the number of successfully cracked samples of the attack by varying numerical bases and supergroup size. As the table shows, using a small base and group size results in the highest attack success rate, while using a large base and group size results in more cracked samples. The reason behind this is twofold. By using a large base and a supergroup size, the capacity of the encoded samples ramps up, which leads the adversary to encode magic numbers in more samples, and therefore the adversary can obtain more information about the addition terms of the gradient sum. However, the large capacity also results in a large search space of the samples from the same group, which makes it more difficult for the adversary to figure out all the right addition terms.

To clearly show performance change raised by the attack parameters, we plot the attack success rate under different settings of two attack parameters in Figure 8 and plot the number of cracked samples under attack parameters in Figure 9. As we can see from Figure 9, SecureBoost leaks more partial order information when the base of the numerical system and number of supergroups increase. Comparing Figure 9 with Figure 8, we find that although a large base or a large number of supergroups makes SecureBoost leak more information, it slightly reduces the effectiveness of a single magic number as the ratio of the successfully stolen samples encoded with magic numbers decreases.

From Table VII we can see that the adversary can successfully infer the right and right bounds of each bin if he knows the whole features of a few samples.

**b) Applications of the Leaked Information:** Finally, we measure the effectiveness of the leaked information through training an alternative classifier on these leaked information. For evaluating the alternative classifier, we propose a simple approach that uses a small auxiliary dataset to learn the map from target participant’s raw feature into the bin value.

In the following, we first introduce and evaluate our mapping approach. Then, we train an alternative classifier on the leaked information.

**Bin Mapping.** Let $B_j^k$ be the $j$-th bin on the $k$-th feature, and let $L(B_j^k) = \{x_i | x_i is partitioned into \ B_j^k and such partition is leaked\}$ denote the leaked partition. Here, we seek to infer the left and right bounds $B_j^k$ from the leaked partition $L(B_j^k)$ and other auxiliary data.

We assume the adversary could obtain all the features of a few samples, including the features held by the target participant, called auxiliary data. Let $Aux = \{x_i | x_i’s entire features are already known to the adversary\}$ denote as the auxiliary dataset. Given $Aux$ and $L(B_j^k)$, the
TABLE VI: Success rate for different setting of the attack parameters. FID = feature ID.

| Dataset | #Super groups | FID | Base of the positional numerical system |
|---------|---------------|-----|----------------------------------------|
|         |               | 2   |                                        |
|         |               | 3   |                                        |
|         |               | 4   |                                        |
|         |               | 5   |                                        |
|         |               | 6   |                                        |
|         |               | 7   |                                        |
|         |               | 8   |                                        |
|         |               | 9   |                                        |

Credit

(a) #super groups=2
(b) #super groups=4

Fig. 8: The success rate for the Credit dataset with different number of data bins and numerical base.

Table VII: The accuracy of the inferred data bins on Credit dataset. FID denotes the feature ID of the target participant’s training data; and #bins denotes the number of data bins on the given feature.

| FID/#bins | 5 | 10 | 20 | 40 | 80 | 160 | 320 |
|-----------|---|----|----|----|----|-----|-----|
| 0/33      |   |    |    |    |    |     |     |
| 1/2       |   |    |    |    |    |     |     |
| 2/4       |   |    |    |    |    |     |     |
| 3/3       |   |    |    |    |    |     |     |
| 4/31      |   |    |    |    |    |     |     |
| 5/6       |   |    |    |    |    |     |     |
| 6/5       |   |    |    |    |    |     |     |
| 7/5       |   |    |    |    |    |     |     |
| 8/5       |   |    |    |    |    |     |     |
| 9/5       |   |    |    |    |    |     |     |

adversary could roughly guess the left and right bounds of $B_j^k$ as $\min_{x_i \in L(B_j^k)} x_i$ and $\max_{x_i \in L(B_j^k)} x_i$.

We then experimentally evaluate the above mapping approach to learn the left and right bound of all the bins on the Credit dataset. In this experiment, we use the default segmentation to get bins on all the features of the tested dataset. Table VIII shows the accuracy of the inferred bin’s left and right bounds with different size of the auxiliary dataset. As the table shows, for a feature space, the number of known data samples that required to infer the bin values depends on the number of data bins in this feature. The more data bins existing in a feature space, the more number of known samples required for inferring bin values with a satisfied accuracy.

**Alternative Classifier.** Then, we train an alternative classifier on the Credit dataset using the leaked information. For the training, we simulate the data participant and settings of vertical federated learning, and train a distributed model classifier using a combination of participant A’s raw training data and participant B’s partial order of bin information. For the data bin values of the target participant’s features, we simple use the inferred bin values from a few known data samples.
TABLE VIII: Performance of the alternative classifiers. \# denotes the number of known samples used to estimate bin values.

| Classifier | \#samples | Accuracy |
|------------|-----------|----------|
| $C_0$      | –         | 81.23%   |
| $C_1$      | 10        | 81.23%   |
| $C_2$      | 20        | 81.23%   |
| $C_3$      | 40        | 81.23%   |
| $C_4$      | 80        | 81.23%   |
| $C_5$      | 160       | 81.23%   |
| $C_6$      | 320       | 81.23%   |

Table VIII compares the performance of the alternative classifier with the one trained on the raw data. $C_0$ represents the original distributed classifier trained on the raw data, and $C_1$ to $C_6$ are six alternative classifiers, with bin values estimated using different number of known samples. We can observe from the table that these alternative classifiers achieve the same classification accuracy as the original one. The experimental result also demonstrates that the leaked information has potential commercial values and can be further used to train an effective machine learning model.

VI. POSSIBLE DEFENSES

VII. DISCUSSION

VIII. MORE RELATED WORK

Privacy preserving machine learning. Vertical federated machine learning can be considered as privacy-preserving decentralized machine learning, which is tightly related to multi-party computation. Many research efforts have been devoted to improve both the efficiency and effectiveness of privacy-preserving machine learning [10, 43, 40, 41, 42, 49, 11, 18, 32, 28]. They either use secure multiparty or homomorphic encryption and Yao's garbled circuits for privacy guarantees. For computation efficiency, most of them sacrifice part of data security and user privacy. Our work provides the first systematic study on the potential privacy risk of privacy-preserving learning protocols in vertical federated learning.

Privacy leakage in federated learning. Recent years, privacy leakage of federated learning has aroused emerging research interests [25, 29, 20, 45, 46, 22, 31, 17, 26]. Such privacy leakage can be further categorized as membership, data properties, and data leakage.

In membership leakage, an adversarial participant desires to learn whether a given sample is part of the other participant’s training data. Nasr et al. has conducted a comprehensive analysis of the membership inference attack in federated learning, showing part of the training data membership is leaked when collaboratively training a model [29].

In data properties leakage, the adversarial participant tries to infer data properties that are independent of the main task, e.g., in an age prediction task, inferring whether people wearing a glass. Melis et al. has shown that the gradient updates leak unintended information about participant’s training data and developed passive and activate property inference attack to exploit this leakage [25].

In data leakage, the adversary reconstruct representatives of model’s training data [20, 50, 45, 17]. Several works [20, 45] trains a Generative Adversary Network (GAN) that generates prototypical samples of the target participant’s training data during the training process. The others directly reconstruct the training data from the gradient updates. Zhu et al. presents an optimization algorithm that can obtain both training samples and the labels from gradient updates [50]. Geiping et al. shows it is easy to reconstruct images at high resolution from the gradient update [17].

Although existing works have shown that federated learning does not protect the data privacy of honest participants [25, 29, 20, 43], they all focus on the horizontal setting of federated learning and does not make an in-depth privacy analysis in the vertical setting. Compared with horizontal federated learning, federated learning in vertical setting poses even more challenges due to the significantly higher complexity of the learning protocol.

IX. CONCLUSION

In this paper, we design two attacks, i.e., reverse multiplication attack and reverse sum attack, to demonstrate the possibility of stealing private information in the setting of vertical federated learning. We conduct an extensive experimental evaluation on two learning protocols implemented on the real-world framework to empirically validate the existence of these privacy threats. To shed light on future research directions, we also discuss potential countermeasures of obfuscating the exchanged intermediate outputs and their challenges. Our work is the first to show the over pursuit of computation efficiency leads to the privacy leakage of training data in vertical federated learning.

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