FederBoost: Private Federated Learning for GBDT

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Abstract—Federated Learning (FL) has been an emerging trend in machine learning and artificial intelligence. It allows multiple participants to collaboratively train a better global model and offers a privacy-aware paradigm for model training since it does not require participants to release their original training data. However, existing FL solutions for vertically partitioned data or decision trees require heavy cryptographic operations.

In this paper, we propose a framework named FederBoost for private federated learning of gradient boosting decision trees (GBDT). It supports running GBDT over both vertically and horizontally partitioned data. Vertical FederBoost does not require any cryptographic operation and horizontal FederBoost only requires lightweight secure aggregation. The key observation is that the whole training process of GBDT relies on the ordering of the data instead of the values.

We fully implement FederBoost and evaluate its utility and efficiency through extensive experiments performed on three public datasets. Our experimental results show that both vertical and horizontal FederBoost achieve the same level of accuracy with centralized training where all data are collected in a central server; and they are 4-5 orders of magnitude faster than the state-of-the-art solutions for federated decision tree training; hence offering practical solutions for industrial applications.

Index Terms—Federated Learning, GBDT, Decision Trees, Privacy

1 INTRODUCTION

It is commonly known that big data plays an essential role in machine learning. Such big data are typically pooled together from multiple data sources and processed by a central server (i.e., centralized learning). Now, it becomes troublesome to conduct such activities as governments are increasingly concerned with the unlawful use and exploitation of users’ personal data. For example, the European Union has recently enacted General Data Protection Regulation (GDPR), which was designed to give users more control over their data and impose stiff fines on enterprises for non-compliance. Consequently, service providers become unwilling to take the risk of potential data breaches, and centralized learning becomes undesirable.

Federated learning (FL) [1] addresses this challenge by following the idea of transferring intermediate results of the training algorithm instead of the data itself. More specifically, it offers a privacy-aware paradigm of model training that does not require data sharing but allows participants to collaboratively train a more accurate global model. Since 2017 when it was first proposed by Google [1], significant efforts have been put by both researchers and practitioners to improve FL [2], [3], [4], [5], [6], [7], [8]. Nevertheless, there are still two problems that remain unsolved in the community: (1) unable to efficiently handle vertically partitioned data, and (2) unable to efficiently support decision trees.

![Fig. 1. Data partitions for federated learning.](image)

Horizontal and Vertical FL. Based on how data is partitioned, FL can be roughly classified into two categories: horizontal FL and vertical FL [9]. Horizontal FL, also known as sample-wise FL, targets the scenarios where participants’ data have the same feature space but differ in samples (cf. Figure 1(a)). For example, two regional banks might have the same feature space as they are running the same business; whereas the intersection of their samples is likely to be small since they serve different customers in their respective regions. Vertical FL or feature-wise FL targets the scenarios where participants’ data have the same sample space but differ in features (cf. Figure 1(b)). For example, consider two participants; one is a bank, and the other is an e-commerce company. They can find a large intersection between their respective sample spaces because a customer needs a bank account to use the e-commerce service. Their feature spaces are certainly different as they are running different businesses: the bank records users’ revenue, expenditure behavior, and credit rating, and the e-commerce company retains users’ browsing and purchasing history.
Unlike horizontal FL, which has been extensively studied by the research committee, less attention has been paid to vertical FL. Existing vertical FL schemes rely on heavy cryptographic technologies such as homomorphic encryption and secure multiparty computation to combine the feature space of multiple participants [9], [10], [11], [12].

Decision trees. The FL community focuses on neural networks and pays less attention to other machine learning models, such as decision trees. Even though neural networks are the most prevailing models in academia, they are notorious for lack of interpretability, which hinders their adoption in some real-world scenarios like finance and medical imaging. In contrast, the decision tree method is regarded as a gold standard for accuracy and interpretability.

A decision tree outputs a sequence of decisions leading to the final prediction, and these intermediate decisions can be verified and challenged separately. Furthermore, gradient boosting decision trees (GBDT) such as XGBoost [13] and LightGBM [14] is regarded as a standard recipe for winning ML competitions[1] and has been widely used in real-world settings for diverse applications, such as aiding explainability challenges in the financial domain [15], preventing fraudulent activities [16], and facilitating business decision-making [17]. Additionally, the Bank of England survey found that tree-based methods remain the most prevalent techniques in financial institutions in England [18]. Unfortunately, decision trees have not received enough attention in FL research. To the best of our knowledge, most privacy-preserving FL frameworks for decision trees are fully based on cryptographic operations [19], [20], [21], [22], and they are expensive to be deployed in practice. For example, the state-of-the-art solution [21] takes ~28 hours to train a GBDT in LAN from a dataset that consists of 8192 samples and 11 features.

Our contribution. In this paper, we propose a novel framework named FederBoost for private federated learning of decision trees. It supports running GBDT over both horizontally and vertically partitioned data.

The key observation for designing FederBoost is that the whole training process of GBDT relies on the ordering of the samples in terms of their relative magnitudes. Therefore, in vertical FederBoost, it is enough to have the participant holding the labels collect the ordering of samples from other participants; then it can run the GBDT training algorithm in exactly the same way as centralized learning. We further utilize bucketization and differential privacy (DP) to protect the ordering of samples: participants partition the sorted samples of a feature into buckets, which only reveals the ordering of the buckets; we also add differentially private noise to each bucket. Consequently, vertical FederBoost achieves privacy without using any cryptographic operations.

The case for horizontally partitioned data is tricky since the samples and labels are distributed among all participants: no one knows the ordering of samples for a feature. To conquer this, we propose a novel method for distributed bucket construction so that participants can construct the same global buckets as vertical FederBoost even though the samples are distributed. We also use secure aggregation [23] to compute the gradients for each bucket, given that no single party holds the labels. Both the bucket construction method and secure aggregation are lightweight; hence horizontal FederBoost is as efficient as the vertical one.

We summarize our main contribution as follows:

- We propose FederBoost: a private federated learning framework for GBDT. It supports both horizontally and vertically partitioned data.
- In vertical FederBoost, we define a new variant of DP, which is more friendly for high-dimensional data and saves much privacy budget in a vertical setting.
- In horizontal FederBoost, we propose a novel method for distributed bucket construction.
- We evaluate the utility of FederBoost on three public datasets. The results show that it achieves the same level of accuracy with centralized learning.
- We provide a full implementation of FederBoost and deploy it on a cluster of up to 32 nodes. The benchmark results show that both vertical and horizontal FederBoost are 4-5 orders of magnitude faster than the state-of-the-art solutions [21], [22] for federated decision tree training.

2 Preliminaries

This section provides the necessary background and preliminaries for understanding this paper.

2.1 Gradient boosting decision tree (GBDT)

A decision tree is a tree-like model for machine learning predictions. It consists of nodes and edges: each internal node represents a “test” on a feature; each edge represents the outcome of the test; and each leaf node represents the prediction result. The path from root to leaf represents a prediction rule.

Fig. 2. An example of GBDT.

Gradient boosting decision tree (GBDT) is a boosting-based machine learning algorithm that ensembles a set of decision trees [13]. Figure 2 shows an example of GBDT: in each tree, the input $x$ is classified to one leaf node that predicts the input with a weight; then it sums the predictions of all trees and gets the final prediction:

$$\hat{y} = \sum_{t=1}^{T} f_t(x)$$  (1)

1. https://github.com/dmlc/xgboost/blob/master/demo/README

2. In fact, it is a regression tree; we abuse the notion here.
where $T$ denotes the number of trained decision trees and $f_t(x)$ denotes the prediction result of the $t$th tree. For classification, it calculates $p = \text{sigmoid}(\hat{y})$ and determines its predicted class based on $p$.

Next, we explain how a GBDT training algorithm works given a dataset $X \in \mathbb{R}^{n \times m}$ that consists of $n$ samples and $m$ features. It first initializes the prediction result $\hat{y}_i$ for each sample with random values. Then, it trains the first decision tree as follows:

1) For each sample, calculate the first- and second-order gradient:

$$
\begin{align*}
    g_i &= \partial_{\hat{y}_i(t-1)}L(y_i, \hat{y}_i(t-1)), \\
    h_i &= \partial^2_{\hat{y}_i(t-1)}L(y_i, \hat{y}_i(t-1))
\end{align*}
$$

(2)

where $\hat{y}_i(t-1)$ is the prediction result aggregated from previous trees, $y_i$ is the real label, and $L(y_i, \hat{y}_i(t-1))$ is the loss function. The binary cross entropy loss function is typically used as a loss function.

2) Run the following steps for each node of the tree from root to leaf:

   a) For each feature, find the best split of the samples that maximize the following function:

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

   (3)

   where $\lambda$ is a hyper-parameter, $I_L$ denotes the samples divided into the left child node, $I_R$ denotes the samples divided into the right child node, and $I$ denotes all samples in the current node. The samples in $I_L$, $I_R$, and $I$ are in sorted order of their corresponding feature values.

   b) Choose the feature with the maximal $L_{\text{split}}$ for the current node and split the samples accordingly.

   3) The weight of each leaf is computed by the following function:

   $$
   w = \frac{-\sum_{i \in I} g_i}{\sum_{i \in I} h_i + \lambda}
   $$

   (4)

   This is the prediction result for the samples falling into this leaf.

Most GBDT frameworks accelerate the training process by building a gradient histogram for each feature to summarize the gradient statistics; the best split can be found based on the histograms. More specifically, for each feature, the training algorithm sorts the samples based on their feature values as before. Then, it partitions the samples and puts them into $q$ buckets. For each bucket, it calculates $G = \sum_{i \in \text{bucket}} g_i$ and $H = \sum_{i \in \text{bucket}} h_i$. The gradient histogram for a feature consists of these $G$s and $H$s of all buckets. Then, the best split for a feature can be found by maximizing:

$$
L_{\text{split}} = \frac{1}{2} \left( \frac{(\sum_{i \in I_L} G_i)^2}{\sum_{i \in I_L} H_i + \lambda} + \frac{(\sum_{i \in I_R} G_i)^2}{\sum_{i \in I_R} H_i + \lambda} + \sum_{i \in I} H_i + \lambda \right)
$$

(5)

Empirically, 20 buckets are used in popular GBDT frameworks [24], [25]. The split finding algorithm is depicted in Algorithm 1.

### Algorithm 1: Split Finding

**Input:** $\{G_1, ..., G_q\}, \{H_1, ..., H_q\}$

**Output:** split with max score

1. $G \leftarrow \sum_{i=1}^q G_i, H \leftarrow \sum_{i=1}^q H_i$
2. $G_L \leftarrow 0, G_R \leftarrow 0$
3. for $i = 1 \rightarrow q$ do
   4. $G_L \leftarrow G_L + G_i, H_L \leftarrow H_L + H_i$
   5. $G_R \leftarrow G - G_L, H_R \leftarrow H - H_L$
6. $\text{score} \leftarrow \max(\text{score}, \frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} + \frac{G^2}{H + \lambda})$
7. end

**Prediction.** To generate the prediction of a new sample $x$ requires running $x$ on all decision trees and aggregating the output of each tree (cf. equation 1). Running a sample on a decision tree includes a sequence of comparison operations. Starting at the root node, the sample is compared to the threshold value of the node to determine whether to move it to the left or right child node. Then compare the sample with the threshold value of the chosen child node to determine whether to move it to the left or right child of the current node. This process repeats until the sample arrives at a leaf node, where the output of the tree is the weight of the leaf. The threshold value acts as a divider that splits the buckets into two parts. For example, if three buckets $\{\text{bucket}_1, \text{bucket}_2, \text{bucket}_3\}$ was split into two parts: $\{\text{bucket}_1, \text{bucket}_2\}$ and $\{\text{bucket}_3\}$ on a node, the threshold value could be chosen from any value between the maximal value in $\text{bucket}_2$ and the minimal value in $\text{bucket}_3$ during training.

### 2.2 Federated learning

The goal of federated learning (FL) is to enable multiple participants to contribute various training data to train a better model. It can be roughly classified into two categories: horizontal FL and vertical FL.

One horizontal FL method [1] proposed by Google is to distribute the model training process of a deep neural network across multiple participants by iteratively aggregating the locally trained models into a joint global one. There are two types of roles in this protocol: a parameter server and $l$ participants $P_1$. In the beginning, the parameter server initializes a model with random values and sends it to all $P$s. In each iteration, each $P_j$ $(j \in \{1, ..., l\})$ trains the received model with its local data and sends the parameter server its gradients. The parameter server aggregates the received gradients and updates the global model.

This elegant paradigm cannot be directly applied to vertical FL, where participants have different feature spaces so that they cannot train models locally. Furthermore, the FL research committee is focusing on neural networks, and less attention has been paid to decision trees.
2.3 Secure aggregation

Bonawitz, et al. [23] propose a secure aggregation protocol to protect the local gradients in Google’s horizontal FL. Specifically, they use pairwise additive masking to protect participants’ local gradients, and have the parameter server aggregate the masked inputs. The masks are generated by a pseudorandom generator (PRG) using pairwise shared seeds and will get canceled after aggregation. The seeds are shared via threshold secret sharing so that dropped-out participants can be handled. A malicious server can lie about whether a $P_i$ has dropped out, thereby asking all other participants to reveal their shares of $P_i$’s masks. To solve this issue, they introduce a double masking scheme requiring each participant to add another mask to its input and share this mask as well. The server can request either a share of the pairwise mask (which will get canceled if no one drops) or a share of the new mask; an honest participant will never reveal both shares for the same participant to the server. In this paper, we assume the participants are large organizations, and they will not drop out in the middle of the protocol. Thereby, we significantly simplify the secure aggregation protocol.

2.4 Differential privacy

Given a set of input data and an analysis task to perform, the goal of differential privacy [26] is to permit statistical analysis while protecting each individual’s data. It aims to “hide” some input data from the output: by looking at the statistical results calculated from the input data, one cannot tell whether the input data contains a certain record or not.

Definition 2.1 ($\epsilon$-Differential Privacy [26]). A randomized algorithm $M$ with domain $\mathbb{N}^{[X]}$ is $\epsilon$-differentially private if for all $S \subseteq \text{Range (} M \text{)}$ and for any neighboring datasets $D$ and $D'$:

$$\Pr[M(D) \in S] \leq e^\epsilon \Pr[M(D') \in S].$$

It guarantees that, by examining the outputs $M(D)$ and $M(D')$, one cannot reveal the difference between $D$ and $D'$. Clearly, the closer $\epsilon$ is to 0, the more indistinguishable $M(D)$ and $M(D')$ are, and hence the better the privacy guarantee. This nice property provides plausible deniability to the data owner as the data is processed behind a veil of uncertainty.

3 Problem Statement

We consider the setting of $l$ participants $P_1, \ldots, P_i$, holding datasets $X_1, \ldots, X_i$ respectively, want to jointly train a model. We consider both vertically (Section 4) and horizontally (Section 5) partitioned data. We assume there is a secure channel between any two participants, hence it is private against outsiders. The participants are incentivized to train a good model (they will not drop out in the middle of the protocol), but they want to snoop on others’ data. We do not assume any threshold on the number of compromised participants, i.e., from a single participant’s point of view, all other participants can be compromised.

Poisoning attacks and information leakage from the trained model are not considered in this work. We remark that information leakage from the trained model should be prevented when we consider publishing the model. This requires differentially private training [27], [28], which guarantees that one cannot infer any membership about the training data from the trained model. However, this line of research is orthogonal to federated learning (which aims to achieve collaborative learning while keeping the training data local), and we leave it as future work to include it in our protocol.

Given the above setting, we aim to propose FL schemes with the following design goals:

- The efficiency should be close to the traditional distributed ML [13], [14], [24], [25], i.e., the number of cryptographic operations should be minimized.
- The accuracy should be close to the centralized learning, which is to pool all data into a centralized server.
- The privacy should be close to the local training, i.e., each participant trains with its local data only. To achieve this, all data being transferred should be protected either by cryptographic technology or differential privacy.

Frequently used notations are summarized in Table 1.

| Notation | Description |
|----------|-------------|
| $P$ | participant |
| $l$ | number of participants |
| $\tau$ | number of compromised participants |
| $n$ | number of samples |
| $m$ | number of features |
| $q$ | number of buckets |
| $T$ | number of decision trees |
| $X$ | dataset |
| $x_i^j$ | $i$th feature |
| $x^j$ | $j$th sample |
| $x'^j$ | value of $j$th feature $j$th sample |
| $y$ | label |
| $\hat{y}$ | prediction result |
| $g_i, h_i$ | first and second order gradient |
| $Q$ | quantile |
| $\epsilon$ | level of differential privacy |

4 Vertical FederBoost

In vertical FL, $l$ participants $P_1, \ldots, P_i$, holding feature sets $X_1, \ldots, X_i$ respectively, want to jointly train a model. Only a single participant (e.g., $P_i$) holds the labels $y$. Each feature set $X_i$ consists of a set of features: $X_i = [x^1, \ldots, x^k]$ and there are $m$ features in total. Each $x^i$ consists all $n$ samples: $x^i = [x^i_1, x^i_2, \ldots, x^i_n]$; similarly, $y = [y_1, y_2, \ldots, y_n]$. We assume that the secure record linkage procedure has been done already, i.e., all $l$ participants know that their commonly held samples are $x_1, \ldots, x_n$. We remark that this procedure can be done privately via multi-party private set intersection [29], which is orthogonal to our paper.

4.1 Training

Vertical FederBoost is based on the observation that the whole training process of GBDT does not involves feature values (cf. Section 2.1). Recall that the crucial step for building a decision tree is to find the best split of samples for a feature, which only requires the knowledge of the first- and second- order gradients $g_i, h_i$, as well as the order of samples (Equation 3). Furthermore, $g_i, h_i$ are...
Protocol 2: Vertical FederBoost

Input: each $P_i$, inputs feature $x_i = \{x_i^1, \ldots, x_i^n\}$ for simplicity, we assume each $P_i$ holds a single feature, hence $m = l$

Output: $T$ decision trees

1. for $i = 1 \rightarrow l$ do
2. $P_i$ sorts $x_i$ and partitions it into $q$ buckets
3. for $j = 1 \rightarrow n$ do
4. $P_i$ moves $x_j$ to another bucket with probability
5. add DP noise
6. $P_i$ sorts the samples based on their feature values, partitions the samples, and puts them into $q$ buckets. In this way, $P_i$ only knows the order of the buckets but learns nothing about the order of the samples inside a bucket. We note that this partitioning process is uniform for both continuous and categorical data, preventing an adversary from deciphering the feature distribution through an analysis of the number of samples in each bucket. To further protect the order of two samples in different buckets, we add differentially private noise to each bucket. That is, for a sample that was originally assigned to the $i$th bucket:
   - with probability $p = \frac{e^\epsilon}{e^\epsilon + q - 1}$, it stays in the $i$th bucket;
   - with probability $p' = \frac{1}{e^\epsilon + q - 1}$, it moves to the $j$th bucket that is picked uniformly at random.

This mechanism is similar to random response [30], which achieves $\epsilon$-LDP. Let $\text{bucketize}(x)$ denote the bucketization mechanism mentioned above and its output is the bucket ID. Then, for any two samples $x_1, x_2$ and a bucket $B$, we have $\forall k \in \{1, \ldots, q\}$:

$$
Pr[\text{bucketize}(x_1) = k] \leq p \leq \frac{e^\epsilon/(e^\epsilon + q - 1)}{1/(e^\epsilon + q - 1)} = e^\epsilon,
$$

where $Pr[\text{bucketize}(x) = k]$ denotes the probability that a sample $x$ is placed in bucket $B_k$. We present the security analysis of the mechanism in Section 4.2.

Our experimental results (cf. Section 6.1) show that when $\epsilon = 4$ and $q = 16$, the accuracy achieved by vertical FederBoost is very close to that without DP. On the other hand, with this configuration, each sample has a probability of approximately $22\%$ being placed in the wrong bucket. The whole training process for vertical FederBoost is depicted in Protocol 2 and we separately detail the security analysis from the perspective of $P_1$ and $P_i$ in Section 4.3.

Prediction. Recall that the active participant $P_1$ only knows the sample IDs in each bucket; it knows nothing about their values. However, each $P_i$ holding the values is able to find the threshold value after knowing how to split its buckets (line 21 of Protocol 2). As a result, the threshold values are distributed among all participants, and they need to run the prediction phase in a distributed way. In more detail, we assume each participant knows some features of $x$ that correspond to the features it holds during prediction. Starting from the root, $P_1$ contacts the participant $P_i$ who holds the corresponding feature; $P_i$ compares the feature value of $x$ with the threshold value, and tells $P_1$ the result, based on which $P_1$ decides whether to move left or right. By repeating the process, $P_1$ could get the output of all trees and aggregate the results to make a final prediction.

| Protocol 2: Vertical FederBoost |
|--------------------------------|
| **Input:** each $P_i$, inputs feature $x_i = \{x_i^1, \ldots, x_i^n\}$ for simplicity, we assume each $P_i$ holds a single feature, hence $m = l$ |
| **Output:** $T$ decision trees |
| 1. for $i = 1 \rightarrow l$ do |
| 2. $P_i$ sorts $x_i$ and partitions it into $q$ buckets |
| 3. for $j = 1 \rightarrow n$ do |
| 4. $P_i$ moves $x_j$ to another bucket with probability |
| 5. add DP noise |
| 6. $P_i$ sorts the samples based on their feature values, partitions the samples, and puts them into $q$ buckets. In this way, $P_i$ only knows the order of the buckets but learns nothing about the order of the samples inside a bucket. We note that this partitioning process is uniform for both continuous and categorical data, preventing an adversary from deciphering the feature distribution through an analysis of the number of samples in each bucket. To further protect the order of two samples in different buckets, we add differentially private noise to each bucket. That is, for a sample that was originally assigned to the $i$th bucket: |
| - with probability $p = \frac{e^\epsilon}{e^\epsilon + q - 1}$, it stays in the $i$th bucket; |
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| This mechanism is similar to random response [30], which achieves $\epsilon$-LDP. Let $\text{bucketize}(x)$ denote the bucketization mechanism mentioned above and its output is the bucket ID. Then, for any two samples $x_1, x_2$ and a bucket $B$, we have $\forall k \in \{1, \ldots, q\}$: |
| $Pr[\text{bucketize}(x_1) = k] \leq p \leq \frac{e^\epsilon/(e^\epsilon + q - 1)}{1/(e^\epsilon + q - 1)} = e^\epsilon$, |
| where $Pr[\text{bucketize}(x) = k]$ denotes the probability that a sample $x$ is placed in bucket $B_k$. We present the security analysis of the mechanism in Section 4.2. |
| Our experimental results (cf. Section 6.1) show that when $\epsilon = 4$ and $q = 16$, the accuracy achieved by vertical FederBoost is very close to that without DP. On the other hand, with this configuration, each sample has a probability of approximately $22\%$ being placed in the wrong bucket. The whole training process for vertical FederBoost is depicted in Protocol 2 and we separately detail the security analysis from the perspective of $P_1$ and $P_i$ in Section 4.3. |
| **Prediction.** Recall that the active participant $P_1$ only knows the sample IDs in each bucket; it knows nothing about their values. However, each $P_i$ holding the values is able to find the threshold value after knowing how to split its buckets (line 21 of Protocol 2). As a result, the threshold values are distributed among all participants, and they need to run the prediction phase in a distributed way. In more detail, we assume each participant knows some features of $x$ that correspond to the features it holds during prediction. Starting from the root, $P_1$ contacts the participant $P_i$ who holds the corresponding feature; $P_i$ compares the feature value of $x$ with the threshold value, and tells $P_1$ the result, based on which $P_1$ decides whether to move left or right. By repeating the process, $P_1$ could get the output of all trees and aggregate the results to make a final prediction. |
the user has bought. To achieve this goal, more nuanced trade-offs can arise if we wish to prevent an attacker from knowing, for example, whether a user has ever bought a dress.

Here, we focus on local differential privacy. For any different inputs \( x, x' \in \mathcal{X} \) in the definition of local DP, the word "different" implies that the Hamming distance between \( x, x' \) is 1, i.e., \( d_{Hamming}(x, x') := 1 \{ x \neq x' \} \). This definition makes learning challenging in some scenarios where individual users contribute multiple data items rather than a single item. Thus, a more fine-grained distance notion is needed to keep utility while providing sufficient privacy.

We consider the scenario where data are processed by each individual and propose element-Level Local DP. We denote the distance between two users’ local data \( x = [x_1, \ldots, x_k]^T \) and \( x' = [x'_1, \ldots, x'_k]^T \) is the number of different elements of them, that is,

\[
d_{\text{element}}(x, x') = d([x_1, \ldots, x_k]^T, [x'_1, \ldots, x'_k]^T) =: \sum_{k=1}^{K} 1\{ x_i \neq x'_i \}.
\]

Then two users’ data \( x, x' \) are element-different if the distance between them \( d_{\text{element}}(x, x') \leq 1 \). The definition of local element-level differential privacy is now immediate as follows.

**Definition 4.1 (\( \epsilon \)-Local Element-Level DP).** An algorithm \( \mathcal{M} \) satisfies \( \epsilon \)-local element-level differential privacy if for all \( y \in \text{Range}(\mathcal{M}) \) and for any inputs \( x, x' \) satisfying \( d_{\text{element}}(x, x') \leq 1 \):

\[
\Pr[\mathcal{M}(x) = y] \leq e^\epsilon \Pr[\mathcal{M}(x') = y].
\]

Element-level local differential privacy guarantees that the release of a user’s data perturbed by a mechanism does not leak any particular “element” the user has. Next, we prove that our bucketize mechanism satisfies element-level local differential privacy, hence providing a sufficient privacy guarantee in our vertical FederBoost.

**Corollary 1.** Our bucketization mechanism satisfies \( \epsilon \)-element-level local differential privacy.

**Proof.** For any inputs \( x, x' \in \mathcal{X} \) satisfying \( d_{\text{element}}(x, x') \leq 1 \) and for any \( y \in \text{Range}(...), ... \), we have

\[
\frac{\Pr[\text{bucketize}(x) = y]}{\Pr[\text{bucketize}(x') = y]} = \prod_{i} \frac{\Pr[\text{bucketize}(x_i) = k_i]}{\Pr[\text{bucketize}(x'_i) = y_i]}
\]

As \( x, x' \) satisfy \( d_{\text{element}}(x, x') \leq 1 \), which implies that \( x \) and \( x' \) differ in only one element (e.g., \( x_j \neq x'_j \)), we get

\[
\prod_{i} \frac{\Pr[\text{bucketize}(x_i) = y_i]}{\Pr[\text{bucketize}(x'_i) = y_i]} = \frac{\Pr[\text{bucketize}(x_j) = y_j]}{\Pr[\text{bucketize}(x'_j) = y_j]} \leq e^\epsilon
\]

**4.3 Security analysis**

\( \mathcal{P}_i \)'s security. The active participant \( \mathcal{P}_i \) only learns the order of buckets for each feature behind a veil of uncertainty: each sample has a probability of \( p = \frac{q-1}{q^2} \) to be placed in a wrong bucket. When \( \epsilon = 4 \) and \( q = 16 \), \( p \) is approximately 22%.

\( \mathcal{P}_i \)'s security. The only information a passive party \( \mathcal{P}_i \) learns is the split information sent by \( \mathcal{P}_i \) (line 21 of protocol 2), which indicates how the buckets are split into left and right, leading to the maximal \( L_{\text{split}} \) in equation 2.5. Note that the split information of each node made up the final trained decision tree, and information leakage from it is not considered in this work.

Suppose \( \mathcal{P}_i \) also holds a feature \( x_i \). If \( \mathcal{P}_i \)'s feature \( x_i \) was selected by a tree node, the holders of child-node learn that the samples assigned to left is smaller than the samples assigned to right. Nevertheless, such information is also protected by differential privacy.

**5 Horizontal FederBoost**

In horizontal FL, the dataset is partitioned horizontally: \( l \) participants \( \mathcal{P}_1, \ldots, \mathcal{P}_l \) hold sample sets \( X_1, \ldots, X_l \) respectively. Each sample set \( X_i \) consists of a set of samples: \( X_i = [x_{i,1}, \ldots, x_{i,k}] \), and each sample \( x_i \) has all features and the label: \( x_i = [x_{i,1}, \ldots, x_{i,k}, y_i] \).

In this setting, it is natural to have participants train their models locally and aggregate the locally trained models into a joint global model (e.g., Google’s FL framework [1] we mentioned in Section 2.2). This idea applies to decision trees as well: each participant locally trains a decision tree and all decision trees are integrated into a random forest via bagging [31]. However, to train a random forest, each participant is required to hold at least 63.2% of the total samples [32], which contradicts the setting of FL.

We follow the idea of vertical FederBoost to have participants jointly run the GBDT training algorithm. However, there are two challenges we need to conquer in the setting of horizontal FL. Firstly, the samples are distributed among \( l \) participants, thereby no single participant knows the order of samples for any feature. To address this, we propose a novel method for distributed bucket construction. Secondly, each participant only holds part of the labels, hence the histogram for each bucket is difficult to compute without information leakage. We have participants calculate \( g_s \) and \( h_s \) locally and aggregate them using secure aggregation (cf. Section 2.3) to build the histograms. We provide all details in the rest of this section.

**5.1 Distributed bucket construction**

The commonest way for distributed bucket construction in traditional distributed GBDT [13], [14], [24], [25] is named quantile sketch [33], [34], which requires each participant to send representations of its local data so that the distribution of each feature can be approximated. This approach will inevitably reveal information about participants’ local data. Therefore, we propose a new method for distributed bucket construction so that privacy can be protected.

The basic idea for our distributed bucket construction method is to find the splits (named quantiles) that divide \( n \) sample values of a feature into \( q \) buckets; then, participants put their samples into the corresponding buckets based on these quantiles. The pseudo-code for finding all \( q - 1 \) quantiles of a feature is shown in Protocol 5. We use \( \mathcal{P}_i \) as
the active participant to coordinate the protocol, but any participant can be the active participant.

For the first quantile, we use binary search to find a value that is larger than \( \frac{n}{q} \) sample values and smaller than the rest. In more detail, \( P_1 \) initializes two values: \( Q_{\min} \) and \( Q_{\max} \), which are the smallest and largest possible values of the feature (line 2). Then, it initializes \( Q_1 \) as the mean of \( Q_{\min} \) and \( Q_{\max} \) (line 5). \( P_1 \) needs to count the number of sample values (\( n' \)) that are smaller than \( Q_1 \). By comparing \( n' \) to \( \frac{n}{q} \), \( P_1 \) could decide whether to increase \( Q_1 \) or decrease it for the next round of binary search (line 10-14).

However, \( P_1 \) is not able to count \( n' \), as the samples are distributed among \( l \) participants. A naive solution is to have participants count locally, and \( P_1 \) aggregates the results. Unfortunately, this will reveal information about a participant’s local dataset. To this end, we have all participants aggregate their counts via secure aggregation (line 9). After finding \( Q_1 \), participants locally remove their sample values that are smaller than \( Q_1 \) (line 17). Then, they find the second quantile \( Q_2 \) in exactly the same way as for finding \( Q_1 \). After finding all quantiles, each \( P_i \) knows how to put these samples into the corresponding buckets for this feature, and they can find the quantiles for other features in the same way. We remark that multiple instances of Protocol 3 could run in parallel so that the quantiles of multiple features could be found at the same time.

The method described above only applies to continuous features. For discrete features, the number of classes may be less than the number of buckets, and lines 4-15 could be an endless loop. In this case, we simply build a bucket for each class. Then, we can directly move to the training phase.

The pseudo-code of which is shown in Protocol 4. The key difference is that instead of sending the buckets of sample IDs to the pseudo-code of which is shown in Protocol 4. The key difference is that instead of sending the buckets of vertical FederBoost, bucket construction in horizontal FederBoost also only needs to be done once: participants can run the training phase multiple times to fine-tune the model without further bucket construction as long as the data remains unchanged.

Similar to vertical FederBoost, after finding all quantiles, each participant can locally put their sample IDs into the corresponding buckets; \( P_i \) can collect the buckets and aggregate them. Then, the setting becomes similar to vertical FederBoost. However, \( P_i \) does not hold all labels; hence it cannot train the decision trees as vertical FederBoost. To this end, we take another approach, the pseudo-code of which is shown in Protocol 4. The key difference is that instead of sending the buckets of sample IDs to \( P_i \), each \( P_i \) locally computes \( g_1 \) and \( h_1 \) for each sample (line 9), computes \( G_1 \) and \( H_1 \) for each bucket (line 18) and all participants aggregates \( G_1 \) and \( H_1 \) for the corresponding buckets using secure aggregation (line 20). We remark that all \( m \cdot q \) instances of secure aggregation can run in parallel. Another difference is that \( P_i \) needs to send the split information to all the other participants (line 24).

Naively, we can use the secure aggregation (cf. Section 23) protocol 23 by having \( P_i \) play the role of the parameter server. However, we simplify the protocol based on the assumption that the participants will not drop out
During quantile lookup, $P_i$ inputs $n'_i$ to secure aggregation (line 9 of Protocol 3). During tree construction, $P_i$ inputs $G_{i,k}$ and $H_{i,k}$ to secure aggregation (line 20 of Protocol 3).

Both inputs are protected by secure aggregation. Although $P_i$ can collude with $\tau - 1$ passive participants, it still cannot learn anything beyond the sum of $l - \tau$ participants’ inputs.

$P_i$’s security. There are again two places for potential information leakage:

- During quantile lookup, $P_i$ sends $Q_j$ to other $P_i$s (line 5 of Protocol 3).
- During tree construction, $P_i$ sends $split_j$ to other $P_i$s (line 24 of Protocol 3).

Notice that $Q_j$ is calculated based on $n'$ and $split_j$ is calculated based on $G_i$ and $H_j$. Therefore, the information leakage of $P_i$ will not be larger than $P_i$ ($P_i$’s security was proved above).

6. IMPLEMENTATION AND EXPERIMENTS

In this section, we evaluate FederBoost by conducting experiments on three public datasets:

- **Credit** It is a credit-scoring dataset used to predict the probability that somebody will experience financial distress in the next two years. It consists of a total of 150,000 samples and 10 features, and about 6.68% samples are positive.
- **Credit** It is another credit-scoring dataset correlated to the task of predicting whether a user will make a payment on time. It consists of a total of 30,000 samples and 23 features, and 22.12% samples are positive.
- **SUSY** It is a dataset about high-energy physics, used to distinguish between a process where new supersymmetric particles are produced leading to a final state in which some particles are detectable, and others are invisible to the experimental apparatus. The original dataset consists of 3,000,000 samples, and we choose 290,000 samples randomly from the dataset. Each sample has 18 features, and about 45.7% samples are positive.

For each dataset, we divide it into two parts for training and testing, respectively. The training part contains two-thirds of the samples, and the testing part has the remaining one-third. We use the commonly used Area under the ROC curve (AUC) as the evaluation metric since the negative samples accounted for most of the samples in the Credit 1 dataset.

Our evaluation consists of two parts: utility and efficiency. Recall that all participants jointly run the GBDT training algorithm in both vertical and horizontal FederBoost, hence varying the number of participants will not affect the utility of FederBoost. When evaluating utility, we only consider different numbers of buckets and different levels of DP. We consider different numbers of participants when evaluating efficiency. For “Credit 1” and “Credit 2”, we set the number of trees as $T = 20$ and each tree has 3 layers; for “SUSY”, we set the number of trees as $T = 60$ and each tree has 4 layers. All experiments were repeated 5 times and the averages are reported.

6.1 Utility

We first evaluate the utility of FederBoost with different numbers of buckets. Then, we fix the number of buckets with an optimal value and run vertical FederBoost with different levels of DP (recall that DP is not needed for horizontal FederBoost).

We also run XGBoost centrally with the same datasets and use the results as baselines. As shown in Figure 8

4. https://www.kaggle.com/c/GiveMeSomeCredit/overview
5. https://www.kaggle.com/uicml/default-of-credit-card-clients-dataset
6. https://www.csie.ntu.edu.tw/~cjlin/libsvm/
**FederBoost** achieves almost the same accuracy with XGBoost. For “Credit 1”, the AUC achieved by XGBoost is 86.10% ; the best AUC achieved by vertical FederBoost is 85.85% with 16 buckets; and the best AUC achieved by horizontal FederBoost is 86.25% with 26 buckets. For “Credit 2”, the AUC achieved by XGBoost is 78.04% ; the best AUC achieved by vertical FederBoost is 77.65% with 16 buckets; and the AUC achieved by horizontal FederBoost is 78.25% with 24 buckets.

For “SUSY”, the AUC achieved by XGBoost is 87.26% with 24 buckets. For “SUSY”, vertical FederBoost achieves almost the same accuracy with XGBoost. For “Credit 2”, vertical FederBoost achieves 85.70% accuracy when \( \epsilon = 4 \) and 85.85% when no DP added. For “Credit 1”, vertical FederBoost achieves 77.65% accuracy when \( \epsilon = 4 \) and 77.65% when no DP added. For “SUSY”, vertical FederBoost achieves 86.69% accuracy when \( \epsilon = 4 \) and 87.10% when no DP added.

### 6.2 Efficiency

We fully implement FederBoost in C++ using GMP\(^7\) for cryptographic operations. We deploy our implementation on a machine that contains 40 2.20GHz CPUs and 251 GB memory; we spawn up to 32 processes, and each process runs as a single participant. We utilize the traffic control \( \mathcal{37} \) integrated within the Linux kernel to set the traffic conditions among processes to simulate the authentic network communication among participants. By configuring the bandwidth, latency, and other parameters, we strive to recreate the real network environment between participants. Such an approach has been extensively utilized in previous research works \( \mathcal{21}, \mathcal{22}, \mathcal{38} \) and experiments show that it can effectively reflect the communication overhead comparison of different protocols in real environments. Specifically, we consider both the local area network (LAN) and the wide area network (WAN) in our experiments. We constrain each process to a network bandwidth of 1000 Mbit/s and introduce a 0.1 ms latency to each link connection to simulate LAN. To simulate WAN, we limit the network bandwidth of each process to 20 Mbit/s and add 100 ms latency to each link connection. In order to facilitate comparison with other methodologies, we adjust our network environment settings to match those reported in those methods.

Figure 4(a) shows the training time of vertical FederBoost in LAN with different number of participants. The results show that vertical FederBoost is very efficient: even for the challenging “SUSY” dataset, it only takes at most 33 seconds to train a GBDT model.

Figure 4(b) shows the training time of horizontal FederBoost in LAN. Both the bucket construction phase and the training phase require secure aggregation for each quantile lookup and each tree node split, respectively. Recall that the efficiency of secure aggregation depends on the number of participants. Hence the time usage of horizontal FederBoost increases linearly with the number of participants. For the “SUSY” dataset, it takes 23.75 seconds for 2 participants and 86 seconds for 8 participants. The results for “Credit1” and “Credit2” are similar: around 10 seconds for 2 participants and 130 seconds for 32 participants.

Figure 4(c) shows the training time of vertical FederBoost in WAN. In “SUSY”, it takes at most 691.77 seconds to train a GBDT model. Compared to LAN, the training time increases significantly because passive participants need to transfer buckets of IDs to the active participant, which is expensive in WAN. Figure 4(d) shows the training time of horizontal FederBoost in WAN. It takes at most 3103.24 seconds to finish training.

Notice that the bucket construction phase only needs to be done once in either vertical FederBoost or horizontal FederBoost. It occupies more than half of the total time usage. If we remove bucket construction from the results, it will show a significant speedup.

We also compare FederBoost with Abspoel et al. \( \mathcal{21} \) and Wu et al. \( \mathcal{22} \), which are the state-of-the-art solutions for federated decision tree training. Abspoel et al. \( \mathcal{21} \) is based on a federated boosting algorithm that uses secure aggregation techniques to train decision trees in a secure and private manner. Wu et al. \( \mathcal{22} \) proposed a distributed boosting algorithm that uses secure aggregation techniques to train decision trees in a distributed setting.

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7. https://gmplib.org/
on three party honest-majority replicated secret sharing; in
particular, they use oblivious sorting to sort the samples
for each feature. This scheme supports both vertically and
horizontally partitioned data, but can only support three
participants. They simulated each participant using a 2.5
GHz CPU. Moreover, their benchmarks were conducted in
LAN with a dataset consisting of 8 192 samples and 11
features; they train 200 trees and each tree has 4 layers.
We tailor our SUSY dataset to the same dimension and
evaluate vertical and horizontal FederBoost in the same
setting. Table 2 shows our time usage compared with the
results reported in Table 1 of [21]. Vertical FederBoost
achieves 83 099 times speedup and horizontal FederBoost
achieves 4 668 times speedup.

| Method            | Time usage       |
|-------------------|------------------|
| Vertical FederBoost| 1.213 s          |
| Horizontal FederBoost | 21.59 s         |
| Abspoel et al. [21] | ~28 hours       |

Wu et al. [22] combine threshold partially homomorphic
encryption (TPHE) with MPC. This scheme only supports
vertically partitioned data. They simulated each participant
using a 3.5 GHz CPU. Their benchmarks were conducted in
LAN with a dataset consisting of 50 000 samples and 15
features; they train up to 32 trees and each tree has 4 layers.
We also tailor our SUSY dataset to the same dimension and
evaluate vertical FederBoost in the same setting. Table 3
shows our time usage compared with the results reported
in Figure 4(f) of [22]. FederBoost achieves 1 111 times
speedup.

| Method               | Time usage |
|----------------------|------------|
| Vertical FederBoost  | 32.4 s     |
| Wu et al. [22]       | ~10 hours  |

7 RELATED WORK

In addition to the solutions proposed by Abspoel et al. [21]
and Wu et al. [22] (cf. Section 6.2), there are some other
works that solve the problem of federated decision tree
training. Even though not specifically mentioned, the first
federated decision tree learning algorithm was proposed
by Lindell and Pinkas in 2000 [20]. They came up with a
protocol allowing two participants to privately compute the
ID3 algorithm over horizontally partitioned data. Recently,
Cheng et al. [19] propose SecureBoost, a federated GBDT
framework for vertically partitioned data. This protocol
requires cryptographic computation and communication for
each possible split, hence is expensive. As a comparison,
our vertical FederBoost does not require any cryptographic
operation. Chen et al. [39] incorporates several engineering
optimizations into SecureBoost. Experiments on the Credit2
dataset show that it requires at least 30 seconds to train a
single tree, while we only require 2 seconds to train 20 trees.

Another recent work [40] for federated GBDT was
achieved using trusted execution environments (TEEs) [41],
[42]. It introduces a central server that is equipped with a
TEE. All participants send their data, no matter whether
vertically or horizontally partitioned, to the TEE via secure
channels. However, TEEs are known to be vulnerable to
hardware-based side-channel attacks [43]. Alternatively, Li
et al. [44] apply locality-sensitive hashing (LSH) to feder-
ated GBDT. However, their solution only supports horizon-
tally partitioned data, and the security of LSH is difficult
to quantify. Zhu et al. [45] considers a setting where the
data is vertically partitioned, but the labels are distributed
among multiple clients, whereas we assume the labels are
stored only on one client. Furthermore, they only protect the
privacy of labels, whereas we protect both data and labels.

8 DISCUSSION

Generalization of FederBoost. The direct application of
FederBoost to other machine learning-based methods may
pose significant challenges. Nevertheless, certain aspects of
our approach have the potential to be extended to other
methods. Notably, our utilization of secure aggregation to
come from gradients from passive participants in horizontal
FederBoost can serve as a helpful tool for federated training
of neural network models, where each client sends their
local gradients to a centralized server to get the global
gradients. Such an idea has already been applied in previous
research efforts [46], [47]. Additionally, our method of verti-
cal FederBoost can be applied to other approaches that rely
on knowledge of data order during training. For example,
transformer-based language models [48] that encode the
position of each token may benefit from our approach.
9 Conclusion

In response to the growing demand for a federated GBDT framework, we propose FederBoost that supports running GBDT privately over vertically and horizontally partitioned data. Vertical FederBoost does not require any cryptographic operation, and horizontal FederBoost only requires lightweight secure aggregation. Our experimental results show that both vertical and horizontal FederBoost achieves the same level of accuracy with centralized training, and they are 4-5 orders of magnitude faster than the state-of-the-art solution for federated decision tree training.

In future work, we will further improve the performance of FederBoost by improving communication among participants through structured networks [49] and addressing potential poisoning attacks. Additionally, we will attempt to deploy FederBoost in real industrial scenarios to test its effectiveness on realistic data.

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References

[1] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-efficient learning of deep networks from decentralized data,” in Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, 2017.

[2] S. U. Stich, “Local SGD converges fast and communicates little,” 2018.

[3] J. Konečný, H. B. McMahan, F. X. Yu, P. Richtárik, A. T. Suresh, and D. Bacon, “Federated learning: Strategies for improving communication efficiency,” arXiv preprint arXiv:1610.05492, 2016.

[4] M. Assran, N. Loizou, N. Ballas, and M. Rabbat, “Stochastic gradient push for distributed deep learning,” in International Conference on Machine Learning. PMLR, 2019, pp. 344–353.

[5] C. Xie, S. Koyejo, and I. Gupta, “Asynchronous federated optimization,” arXiv preprint arXiv:1903.03934, 2019.

[6] T. Chen, G. B. Giannakis, T. Sun, and W. Yin, “Lag: Lazily aggregated gradient for communication-efficient distributed learning,” 2018.

[7] M. Mohri, C. Sivek, and A. T. Suresh, “Agnostic federated learning,” in International Conference on Machine Learning. PMLR, 2019, pp. 4615–4625.

[8] L. Lyu, H. Yu, X. Ma, L. Sun, J. Zhao, Q. Yang, and P. S. Yu, “Privacy and robustness in federated learning: Attacks and defenses,” arXiv preprint arXiv:2012.06337, 2020.

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

[10] S. Hardy, W. Heneka, H. Ivey-Law, R. Nock, G. Patrini, G. Smith, and B. Thorne, “Private federated learning on vertically partitioned data via entity resolution and additively homomorphic encryption,” ArXiv, vol. abs/1711.10677, 2017.

[11] FATE, “An industrial grade federated learning framework,” 2019, https://fate.fedai.org/.

[12] F. Fu, Y. Shao, L. Yu, J. Jiang, H. Xue, Y. Tao, and B. Cui, “VF-boost: Very fast vertical federated gradient boosting for cross-enterprise learning,” in SIGMOD ’21: International Conference on Management of Data, Virtual Event, China, June 20-25, 2021, 2021.

[13] T. Chen and C. Guestrin, “Xgboost: A scalable tree boosting system,” in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016.

[14] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu, “Lightgbm: A highly efficient gradient boosting decision tree,” Advances in neural information processing systems, vol. 30, 2017.

[15] C. J. Philippe Bracke, Anupam Datta and S. Sen., “Bank of england: Machine learning explainability in finance: an application to default risk analysis,” 2019, https://www.bankofengland.co.uk/working-paper/2019/machine-learning-explainability-in-finance-an-application-to-default-risk-analysis/

[16] KPMC, “Fighting fraud with a model of models,” 2020, https://www.nets.eu/solutions/fraud-and-dispute-services/Documents/Nets-KPMG-Fighting-Fraud-with-a-model-of-models-white-paper-2020.pdf

[17] D. L. Shadraman., “Understanding the differentiating capabilities and unique features of salesforce einstein discovery within the machine learning space,” 2022.

[18] B. of England, “Machine learning in uk financial services,” 2019, https://www.bankofengland.co.uk/report/2019/machine-learning-in-uk-financial-services.

[19] K. Cheng, T. Fan, Y. Jin, Y. Liu, T. Chen, and Q. Yang, “SecureBoost: A lossless federated learning framework,” CoRR, vol. abs/1901.08755, 2019. [Online]. Available: http://arxiv.org/abs/1901.08755.

[20] Y. Lindell and B. Pinkas, “Privacy preserving data mining,” in Advances in Cryptology — CRYPTO 2000, M. Bellare, Ed. Berlin, Heidelberg: Springer Berlin Heidelberg, 2000, pp. 36–54.

[21] M. Abspoel, D. Escudero, and N. Volgushev, “Secure training from decentralized data,” in Proceedings of the 27th ACM SIGSAC Conference on Computer and Communications Security, 2020, pp. 1583–1596.

[22] Y. Wu, S. Cai, X. Xiao, G. Chen, and B. C. Ooi, “Privacy preserving vertical federated learning for tree-based models,” Proc. VLDB Endow., vol. 13, no. 11, pp. 2090–2103, 2020. [Online]. Available: http://www.vldb.org/pvldb/vol13/p2090-wu.pdf.

[23] K. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, and K. Seth, “Practical secure aggregation for privacy-preserving machine learning,” in proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, 2017, pp. 1175–1191.

[24] J. Jiang, B. Cui, C. Zhang, and F. Fu, “Dimboost: Boosting gradient boosting decision tree to higher dimensions,” in Proceedings of the 2018 International Conference on Management of Data, ser. SIGMOD ’18, Association for Computing Machinery, 2018, p. 1363–1376.

[25] F. Fu, J. Jiang, Y. Shao, and B. Cui, “An experimental evaluation of large scale gbdt systems,” Proc. VLDB Endow., vol. 12, no. 11, p. 1357–1370, Jul. 2019. [Online]. Available: https://doi.org/10.14778/3342263.3342273.

[26] C. Dwork, “Differential privacy: A survey of results,” in Theory and Applications of Models of Computation: 5th International Conference, TAMC 2008, Xi’an, China, April 25-29, 2008. Proceedings 5. Springer, 2008, pp. 1–19.

[27] M. Abadi, A. Chu, I. Goodfellow, H. B. McMahan, I. Mironov, K. Talwar, and L. Zhang, “Deep learning with differential privacy,” in Proceedings of the 2016 ACM SIGSAC conference on computer and communications security, 2016, pp. 308–318.

[28] Q. Li, Z. Wu, Z. Wen, and B. He, “Privacy-preserving gradient boosting decision trees,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 01, 2020, pp. 784–791.

[29] V. Kolesnikov, N. Matania, B. Pinkas, M. Rosulek, and N. Trieu, “Practical multi-party private set intersection from symmetric-key techniques,” in Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, 2017, pp. 1257–1272.

[30] S. Wang, L. Huang, P. Wang, H. Dong, H. Xu, and W. Yang, “Private weighted histogram aggregation in crowdsourcing,” in Wireless Algorithms, Systems, and Applications: 11th International Conference, WASA 2016, Bozeman, MT, USA, August 8-10, 2016. Proceedings 11. Springer, 2016, pp. 250–261.

[31] Tin Kam Ho, “Random decision forests,” in Proceedings of 3rd International Conference on Document Analysis and Recognition, vol. 1, 1995, pp. 278–282 vol.1.

[32] L. Breiman, “Bagging predictors,” Machine Learning, vol. 24, no. 2, pp. 123–140, 1996.

[33] E. Gan, J. Ding, K. S. Tai, V. Sharan, and P. Bailis, “Moment-based quantile sketches for efficient high cardinality aggregation queries,” arXiv preprint arXiv:1803.01969, 2018.

[34] Z. Karnin, K. Lang, and E. Liberty, “Optimal quantile approximation in streams,” in Proceedings of the 24th ACM SIGMOD International Conference on Management of Data, 2015, pp. 123–134.

[35] P. Mohassel and Y. Zhang, “Secureml: A system for scalable private machine learning,” in 2017 IEEE Symposium on Security and Privacy (SP), May 2017, pp. 19–38.
[36] Z. Huang, W.-j. Lu, C. Hong, and J. Ding, “Cheetah: Lean and Wikipedia, “tc (linux),” 2023, https://en.wikipedia.org/wiki/Tc Linux.
[37] J. Liu, M. Juuti, Y. Lu, and N. Asokan, “Oblivious neural network predictions via minionn transformations,” in Proceedings of the 2017 ACM SIGSAC conference on computer and communications security, 2017, pp. 619–631.
[38] Wikipedia, “tc (linux),” 2023, https://en.wikipedia.org/wiki/Tc Linux.
[39] Z. Huang, W.-j. Lu, C. Hong, and J. Ding, “Cheetah: Lean and fast secure (Two-Party) deep neural network inference,” in 31st USENIX Security Symposium (USENIX Security 22), 2022, pp. 809–826.
[40] W. Chen, G. Ma, T. Fan, Y. Kang, Q. Xu, and Q. Yang, “Secureboost+: A high performance gradient boosting tree framework for large scale vertical federated learning,” arXiv preprint arXiv:2110.10927, 2021.
[41] Andrew Law, Chester Leung, Rishabh Poddar, Raluca Ada Popa, Chenyu Shi, Octavian Sima, Chaofan Yu, Xingmeng Zhang, and Wenting Zheng, “Secure collaborative training and inference for xgboost,” in Workshop on Privacy-Preserving Machine Learning in Practice (PPMLP’20), 2020.
[42] “AMD Secure Processor,” http://www.amd.com/en-us/innovations/software-technologies/security
[43] Intel, “Software Guard Extensions (Intel SGX) Programming Reference,” 2013, https://software.intel.com/sites/default/files/m anuals/64/85/329266-002.pdf
[44] J. Van Bulck, M. Minkin, O. Weiss, D. Genkin, B. Kasikci, F. Piessens, M. Silberstein, T. F. Wenisch, Y. Yarom, and R. Strackx, “Foreshadow: Extracting the keys to the intel sgx kingdom with transient out-of-order execution,” in Proceedings fo the 27th USENIX Security Symposium. USENIX Association, 2018.
[45] Q. Li, Z. Wen, and B. He, “Practical federated gradient boosting decision trees,” in Proceedings of the AAAI conference on artificial intelligence, vol. 34, no. 04, 2020, pp. 4642–4649.
[46] H. Zhu, R. Wang, Y. Jin, and K. Liang, “Pivodl: Privacy-preserving vertical federated learning over distributed labels,” IEEE Transactions on Artificial Intelligence, 2021.
[47] K. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, and K. Seth, “Practical secure aggregation for federated learning on user-held data,” 2016.
[48] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-efficient learning of deep networks from decentralized data,” 2023.
[49] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” 2017.
[50] J. H. Bell, K. A. Bonawitz, A. Gascón, T. Lepoint, and M. Raykova, “Secure single-server aggregation with (poly) logarithmic overhead,” in Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security, 2020, pp. 1253–1269.

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