Fed-EINI: An Efficient and Interpretable Inference Framework for Decision Tree Ensembles in Federated Learning

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ABSTRACT
The increasing concerns about data privacy and security drives the emergence of a new field of studying privacy-preserving machine learning from isolated data sources, i.e., federated learning. Vertical federated learning, where different parties hold different features for common users, has a great potential of driving a more variety of business cooperation among enterprises in different fields. Decision tree models especially decision tree ensembles are a class of widely applied powerful machine learning models with high interpretability and modeling efficiency. However, the interpretability are compromised in these works such as SecureBoost since the feature names are not exposed to avoid possible data breaches due to the unprotected decision path. In this paper, we shall propose Fed-EINI, an efficient and interpretable inference framework for federated decision tree models with only one round of multi-party communication. We shall compute the candidate sets of leaf nodes based on the local data at each party in parallel, followed by securely computing the weight of the only leaf node in the intersection of the candidate sets. We propose to protect the decision path by the efficient additively homomorphic encryption method, which allows the disclosure of feature names and thus makes the federated decision trees interpretable. The advantages of Fed-EINI will be demonstrated through theoretical analysis and extensive numerical results. Experiments show that the inference efficiency is improved by over 50\% in average.

KEYWORDS
Vertical federated Learning, decision tree, gradient boosting decision tree, random forest, SecureBoost

1 INTRODUCTION
Artificial intelligence (AI) has been widely used in various fields since 2014, such as semantic segmentation [16], face recognition [8], and machine translation [10]. It is anticipated that artificial intelligence technology will bring an additional 16\% increase in global GDP by 2030 [2]. Unfortunately, the data in the real world are widely existed in data silos, while the isolated data sources in different data providers become a fundamental limiting factor for AI modeling and data analytics. For example, personal credit assessing in data-driven risk management usually uses four types of data: qualification data, credit data, consumption data, and behavior data, which are often held by different enterprises and institutions. In recent years, there are more and more concerns about data security and privacy. On one hand, operators have enacted privacy protection laws and regulations to protect the privacy of data, such as the General Data Protection Regulation [19] by European Union and California Consumer Privacy Act by California, United States. On the other hand, the data assets are highly valued, which makes data owners often reluctant to reveal their data to others. It drives the emergence of a novel field, termed as federated learning [11, 22], studying privacy-preserving distributed machine learning from multiple data sources without sharing data.

According to the structure of sample space and feature space across data sources, federated learning can be categorized into three classes [21], i.e., horizontal federated learning [12, 15], vertical federated learning [7, 20], and federated transfer learning [13]. Horizontal federated learning refers to the scenarios where each participating party holds a subset of all data samples with common feature space. The vertical federated learning studies the collaborative machine learning where different parties share the same sample space but differ in feature space. The vertical federated learning is regarded as a promising approach to bridge the gap between isolated data providers for business cooperations, and thus go beyond the limits of locally available data to AI systems. There are a line of works studying the vertical federated learning of linear regression [20], gradient boosting decision tree (GBDT) [4], kernel methods [7], etc.

Decision tree models, especially decision tree ensemble models, are an important class of machine learning models [24] due to their powerful generalization capability, high modeling efficiency, and better interpretability. Bagging tree and gradient boosting decision tree (GBDT) are two critical categories of decision tree ensemble models by aggregating a number of weak base decision tree estimators. Random forest [1] is a representative bagging model, whose driving principle is to build several decision trees independently and then average their prediction results. In gradient boosting decision tree methods such as XGboost [3] and Lightgbm [9], base estimators are built sequentially, and one tries to reduce the bias of the combined estimator. These ensemble methods have been used to shine in many applications [12, 23] and win a lot of awards in competitions. There are a line of works proposing methods to build decision tree ensemble models for vertical federated learning, e.g., SecureBoost [4], SecureGBM [5], federated random forest [14].

Unfortunately, the existing federated decision tree ensemble modeling approach compromises the interpretability of the model.
In these works, a multi-interactive inference procedure is adopted and the meanings of features are hidden to avoid possible data information leakage due to the public knowledge of decision path. However, feature names are necessary to make the decision tree model interpretable. The availability of feature names enables us to evaluate whether the model is reasonable and whether the model violates the principle of social discrimination, which is critical for many areas such as credit risk management. The anonymity of features degrades the reliability of the federated models and becomes the barrier of their industrial applications. In addition, the multi-interactive inference procedure involves multiple rounds of communication to compute the prediction result for each decision tree model, which results in high communication costs across data providers.

To address these issues, in this paper, we shall propose Fed-EINI, an efficient and interpretable inference framework for decision tree ensemble models in vertical federated learning. It consists of two stages, i.e., parallel calculation stage and synchronization stage. In the parallel calculation stage, we shall compute a candidate output set of leaf nodes at each party based on their locally owned nodes and input data features in parallel. In the synchronization stage, we shall compute the intersection of the candidate sets yielded in the first stage with only one round of multi-party communications. It is worth noting that we propose a secure approach to obtain the weight of the only leaf node in the intersection set by adopting the efficient additively homomorphic encryption. This method makes the candidate decision paths at each party undistinguishable by other parties, which thus allows the disclosure of feature names without leaking data information. Therefore, Fed-EINI is more efficient and has better interpretability than the state-of-the-art multi-interactive inference approach. The advantages will also be demonstrated by numerous numerical experiments.

2 PROBLEM STATEMENT
This section first describes the decision tree ensemble models in federated learning, and then provides the problem statement of federated inference.

2.1 Vertical Federated Decision Tree Ensemble Models
Vertical federated learning refers to the federated learning system where the datasets of multiple participating parties share the same sample space but differ in feature space. Specifically, consider a vertical federated learning system with $M$ parties denoted by $P_i, i \in \{1, 2, \ldots, M\}$. Denote the datasets distributed in $M$ parties as $(X^m)_{m=1}^M$. The local dataset of party $k$, i.e., $X^m \in \mathbb{R}^{n \times d_m}$, consist of $d_m$ features and $n$ data samples. Therefore, the datasets of $M$ parties can be looked as a vertically split on the large dataset $X = [X^1, \ldots, X^M] \in \mathbb{R}^{n \times d}$ with disjoint feature space, in which $d = \sum_{m=1}^M d_m$. In vertical federated learning, the data labels are often available by only a single party, which is called the Guest party. Other participants without labels are called Host parties.

Decision tree ensembles are an important class of machine learning models [24] due to their powerful generalization capability, high modeling efficiency, and better interpretability. Bagging tree and gradient boosting decision tree (GBDT) are two of the essential categories of decision tree ensemble models by aggregating several base decision tree estimators. Random forest [1] is a representative bagging model, which driving principle is to build several decision trees independently and then average their prediction results. In gradient boosting decision tree methods such as XGBoost [3] and Lightgbm [9], base estimators are built sequentially, and one tries to reduce the bias of the combined estimator.

There are a line of works proposing methods to build decision tree ensemble models for vertical federated learning, e.g., SecureBoost [4], SecureGBM [5], Federated Random Forest [14]. In these works, the generation of a new node of a decision tree is based on interactively computing the information gain for each feature and each possible splitting rule. We take SecureBoost, a lossless extension of XGBoost [3] to the federated learning system, as a representative example to show the detailed procedure of interactive modeling. Given the training dataset $X = \{X^m\}_{m=1}^M \in \mathbb{R}^{n \times d}$ with $n$ samples and $d$ features, the target is to build $K$ regression trees $(f_k)_{k=1}^K$ to fit the data labels $y \in \mathbb{R}^{n \times 1}$ with objective function.

$$L = \sum_{i=1}^N L(y_i, \hat{y}_i(x_i)) + \sum_{k=1}^K \Omega(f_k),$$  \hspace{1cm} (1)$$

where $L(\cdot, \cdot)$ is the loss between prediction value and target label, and $\Omega$ is the regularization term controlling the model complexity.

To efficiently learn the models, we shall greedily add a tree $f_t$ in the $t$-th iteration by minimizing the loss:

$$L^{(t)} = \sum_{i=1}^N \left( L(y_i, \hat{y}_i^{(t-1)}(x_i) + g_t f_t(x_i) + \frac{1}{2} h_t f_t^2(x_i) \right) + \Omega(f_t),$$  \hspace{1cm} (2)$$

where $g_t = \partial L^{(t-1)}(y_i, \hat{y}_i^{(t-1)})$ is the gradient value, $h_t = \partial^2 L^{(t-1)}(y_i, \hat{y}_i^{(t-1)})$ is the Hessian value, $\hat{y}_i^{(t-1)} = \sum_{k=1}^{t-1} f_k(x_i) + \Omega(f_k)^2$ is the prediction result after $t - 1$ rounds of boosting, and $\Omega(f_t)$ is the regularization term with $\gamma > 0, \lambda > 0, T$ is the number of leaves and $w$ is the vector of weights on leaves.

In multi-party information interaction, the goal is to find the best split point based on the following segmenting information gain.

$$L^{\text{Split}} = \frac{1}{2} \left( \sum_{i \in L_L} g_i^2 h_i + \lambda \right) + \frac{1}{2} \sum_{i \in L_R} g_i^2 h_i + \lambda - \frac{1}{2} \sum_{i \in L_L} g_i^2 h_i + \lambda - \gamma.$$  \hspace{1cm} (3)$$

In the above equation, $L_L$ and $L_R$ are the sample spaces of the left and the right tree nodes according to the split. The weight of the leaf node $j$ in the $k$-th tree model $w_{(j,k)} = \sum_{i \in L_L} g_i h_i + \lambda$.

The private computation of the information gain without sharing original data is achieved by encrypting intermediate values with additively homomorphic encryption such as Paillier [17] and exchanging them among parties. With additively homomorphic encryption, we can compute the sum and scalar multiplication with ciphertexts. For example, we denote the encryption of a number $a$ as $[a]$ under an additively homomorphic encryption scheme. For any two numbers $u$ and $v$, we have $[u] + [v] = [u + v]$. In SecureBoost, the active party (Guest) calculates the gradient $g_i$ information and Hessian $h_i$ information of each iteration according to its own label information, and sends Pallier encryption $[g_i], [h_i]$ to each participant. Each party performs operations on the encryption result
where $G$ is the ensemble strategy of prediction values of all decision tree models. In federated learning, each participant holds a subset of all nodes in each $f_k$, and the leaf weights are typically available only by the Guest party. The inference results should be computed under security conditions without sharing feature data of each party to others.

In the following, we show the detailed formulations of two typical ensemble models, gradient boosting decision tree and random forest.

2.2.1 Gradient Boosting Decision Tree. As presented in Section 2.1, the federated GBDT algorithm approximates the true label by sequentially learning a decision tree $f_k$ to fit the residual of the prediction result of previous learned $k-1$ trees. The inference result is given by the sigmoid function of the weighted summation of the prediction values of $K$ trees, i.e.,

$$\hat{y} = \hat{f}(x) = \sigma \left( \sum_{k=1}^{K} a_k f_k(x) \right) = \sigma \left( \sum_{k=1}^{K} \sum_{j \in T_k} w_{(j,k)} I(x \in \text{Leaf}_j) \right),$$

where $\sigma(z) = \frac{1}{1 + e^{-z}}$ is the sigmoid function. $T_k$ is the leaf nodes of the $k$-th tree and $\text{Leaf}_j$ represents the $j$-th leaf node of the tree.

2.2.2 Random Forest. Random forest is a well-known bagging tree method by independently learning a large number of decision trees on a randomly sampled subset of data samples and features. The inference result is given by averaging the prediction values of $K$ trees, i.e.,

$$\hat{y} = \hat{f}(x) = \frac{1}{K} \sum_{k=1}^{K} f_k(x) = \frac{1}{K} \sum_{k=1}^{K} \sum_{j \in T_k} w_{(j,k)} I(x \in \text{Leaf}_j).$$

2.3 Multi-Interactive Inference Framework

As shown in Figure 1, existing works [4, 5] have adopted a multi-interactive inference framework to compute the inference result. In this framework, the decision path of a decision tree model is determined by sequentially finding the decision on the current node and moving to the next node. Each decision is made by evoking the party which owns the corresponding feature and sending the computation result back to the Guest. The weight on the leaf node reached by the decision path is the decision tree’s prediction value. The multi-interactive inference framework admits a serial structure of interactions shown in Figure 2, which means the inference is performed tree by tree.

In the multi-interactive inference process, sample feature information will be revealed to the Guest party due to its availability of the decision path. To address this issue, the existing works proposed to hide the feature name to avoid the leakage of private information of users. However, it isn’t easy to interpret the inference result of a data sample and perform a rational analysis of the results. Furthermore, the high communication costs and possible stragglers brought by multiple rounds of interactions hinders the real-time applications of the trained model.

To address the challenges for the existing multi-interactive inference approach, in this paper, we shall propose an efficient and interpretable inference framework which enables the disclosure of feature names and requires only one round of multi-party interactions.

3 FED-EINI: PROPOSED TWO-STAGE FRAMEWORK

Different from the existing multi-interactive inference approach, we shall propose a two-stage inference framework by firstly determining each candidate leaf nodes set based on locally owned data features at each party and then obtaining the prediction value of a decision tree by computing the intersection of all candidate sets. The proposed approach requires only one round of multi-party interactions.
interactions and allows the disclosure of feature names without revealing the decision path, which thus has better interpretability and higher efficiency.

### 3.1 Fed-EINI Algorithm

A decision tree model is a function of mapping a number of features (i.e., \((x_1, \cdots, x_d)\)) to a choice (i.e., the weight of a leaf node). A decision path is actually a combination of rules defined by the nodes on the path. Therefore, the output of a decision tree model \(f(x)\) is the weight of the leaf node whose corresponding path from the root node to the leaf node holds conditions that can be simultaneously satisfied by the input data sample \(x\).

Denote the sub-model party \(m\) held for the \(k\)-th tree \(f_k\) as \(f^m_k\).

The sub-model is defined by a combination of rules according to the two different search paths on a tree at the same time. \(x\) on the left and right path of each node of the decision tree are mutually satisfied by the input data sample \(x\) and there will be another weight \(w\) to condition the path \(w\) of the path.

The key observation is the intersection of the results of the sub-models of the trees held simultaneously in all candidate sets given by each party.

*Key Observation:* Given an input sample \(x\), the prediction value \(f(x)\) on the path. Therefore, the output of a decision tree model decision path is actually a combination of rules defined by the nodes and higher efficiency.

Based on this key observation, we propose an efficient and interpretable inference framework which only requires one round of multi-party communication and allows the disclosure of feature names by path obfuscation. The proposed framework consists of two stages: parallel calculation stage and synchronization stage. To present the framework concisely, we take two-party case as representative, in which case there are one Guest party and one Host party. It can be easily extended to multi-party case which will be demonstrated in Section 3.2.

#### 3.1.1 Stage 1: Parallel Calculation

In this stage, each participant generates possible candidate sets of leaf nodes according to the split conditions of locally owned nodes and local data features rather than adopting a serial communication structure as the multi-interactive inference approach. In multi-interactive inference, a structure of serial inference is adopted between multiple parties to collaboratively generate split paths. To avoid information leakage, confusion items will also be added to the candidate sets of leaf nodes in our framework.

**Guest:** For the leaf nodes in the candidate set of the Guest party, we encrypt the corresponding weights with additively homomorphic encryption such as Paillier. For the remaining leaf nodes, we generate the encryption of 0’s to protect the privacy of decision path. That is, we will compute a decision vector \(W^G_k \in \mathbb{R}_{T_k}^K\) for the \(k\)-th decision tree in the Guest party as

\[
W^G_k = \begin{cases} 
S(j,k) : & w(j,k) \quad \text{if } j \in \mathbb{I}^G_k (x^G_k) \\
0 & \text{otherwise}
\end{cases}
\]

where \(T_k\) is the number of leaf nodes in the \(k\)-th decision tree model. We present an illustrative example in Figure 3. In the \(k\)-th tree model, feature1, feature2 and the weights are held by Guest. The input data sample \(x\) does not satisfy the split condition of feature1 and feature2. The possible split path of sample \(x\) is the path through weight \(w(1,k)\) and weight \(w(2,k)\). Therefore, the decision set of Guest party is given by

\[
W^G_{k+1} = [w(1,k), w(2,k), 0, 1, 0, 0, 0] \quad \text{(11)}
\]

**Host:** Similar to the search process of Guest, the Host encodes the corresponding path as 0 or 1 according to whether the sample \(x\) satisfies the path of the local model. That is, we will compute a decision vector \(W^H_k \in \mathbb{R}_{T_k}^K\) for the \(k\)-th decision tree in the Host Party.
An illustrative example was presented in Figure 4, the rest feature were held by Host in the $k$-th tree model. The instance $x$ can’t satisfy the split condition of features3 and feature4. The possible split path of sample $x$ is the paths corresponding to Leaf2, Leaf3 and Leaf6. These path are encoded as 0, else 1. Therefore, the decision vector of Host party is given by:

$$W_k^{Host} = \begin{cases} 1 & \text{if } j \in J_k^{Host}(x^{Host}) \\ 0 & \text{otherwise} \end{cases},$$  \tag{12}

3.1.2 Synchronization Stage. In the synchronization stage, the Guest’s weight items are encrypted and sent to Host, and the Host completes the intersection of all candidates, aggregates all the weight items for instance $x$, and sends them to the Guest to update the predicted value.

**Guest:** The Guest first encrypts and synchronizes the result of parallel calculation $\|W_k^{Guest}\|$ to the Host. After receiving Host’s aggregated information, the Guest decrypts it with the local private key and calculates the predicted value.

**Host:** Firstly, the Host merges the received decision vector $\|W_k^{Guest}\|$ from Guest with local decision vector $W_k^{Host}$ to output the intersection of the $k$-th tree. The Host sums the results of all trees for each inference sample to obtain the encrypted weight item and sends it to the Guest, which is given by:

$$[S_k] = [\|W_k^{Guest}\|, W_k^{Host}].$$  \tag{14}

($\cdot, \cdot$) represents inner product.

For example, the Host sum all the weights from the active party if the local encoding corresponds to the weight is 1. Besides, the summation $[S_k]$ is the intersection of all parties on the tree $i$. Then passive party sum all the intersections $[S_k]$ as the synchronization result $[q] = [S_k]$. It means $[q] = \sum_{k=1}^{K} [S_k]$. And the result was sent to the active party for prediction.

The overall procedure of Fed-EINI algorithm is presented in Algorithm 1.

### Algorithm 1: Fed-EINI: an efficient and interpretable inference framework.

**Input:** $x^{Guest}, x^{Host}, \{f_k^{Guest}\}_{k=1}^K, \{f_k^{Host}\}_{k=1}^K$

**Output:** $Y$

Set $[q] = 0, [S_k] = 0$

for $k = 1, \ldots, K$

| Stage 1: Parallel Calculation(Guest and Host) |
|-----------------------------------------------|
| Load parameters of $f_k^{Guest}$ or $f_k^{Host}$; |
| Initialize and Update $W_k^{Host}$ or $W_k^{Host}$ during tree search according to equation(10)(12); |
| Guest: Encrypt and push $W_k^{Guest}$ to Host; |
| Host: Pull $W_{k-1}^{Guest}$ from Guest; |
| Host: $[S_k] = [W_k^{Guest}] \otimes W_k^{Host}$; |
| Host: Push value $[q] = \sum_{k=1}^{K} [S_k]$ to Guest; |
| Guest: Decrypt $[q]$ and Update label $Y$; |

3.2 Extension To Multi-party Scenarios

In the previous subsection, we introduced our inference framework by taking two participants as an example. In a multi-party scenario, we extend our inference algorithm and adopt the method of intersecting the candidates of the two parties in turn.

As Figure 5 shows, in the Multi-party Scenarios, the active party first generates a semi-homomorphic encrypted public key and synchronizes the public key to other passive parties. According to the local feature data, each party traverse the local tree model and encode the weight according to the rules: (1) The active party traverse the local model and find the weights corresponding to the candidate path, and encrypt the weights or 0 and then send the encryption to the passive party. (2) The passive party traverses the local model and encodes the leaf node with 0/1. Then, the party receives the previous result and retain the encryption items if the path corresponding to it is 1, else fill with $[0]$. (3) The last passive party traverses the local model and encodes the leaf node as the same as (2). This party sum all the encryption of the weights items as $S_k$, which is the intersection of all parties, if the weight corresponds to the local encode is 1. Finally, the last passive party synchronizes the summation $[q]$ of all trees to the active party for prediction.
4 ANALYSIS OF FED-EINI

Our proposed inference framework is efficient and interpretable with fewer communication rounds and feature name disclosure. Our framework achieves the same accuracy as the original inference method.

4.1 Efficiency

Compared with the multi-interactive inference algorithm, we proposed a parallel calculation inference framework. This framework decouples the interaction process between multiple parties, and multi parties can calculate in parallel with less communication rounds.

Communication: In the multi-interactive inference, to predict \( x \), it is necessary to interact at each node level to query whether the split condition is satisfied, and the path to the next node is generated. When inferring the sample \( x \) in multi-interactive inference, communication must be performed at each level of each tree, the communications complexity of multi-interactive inference is \( O(l \cdot K) \). Since \( f(x) \) can be expressed as the intersection of all participants’ candidates \( \{ f_m^m(x^m) \}_{k=1}^K \), in our framework, the inference of each tree only needs to communicate once at last layer. The total time of communications is \( O(K) \). As shown in Figure 6, it compares the interaction process between our method and SecureBoost.

Parallel Inference: As shown in Figure 7, it is the time cost comparison of SecureBoost by node splitting at the \( i \) layers. While traversing a tree according to a sample, only when the split condition of the previous node is satisfied, the condition of the latter node may be satisfied. Each party needs to wait for the completion of the other party to perform local inference. In our proposed inference algorithm, each party generates all the candidates in parallel based on its local splitting condition and local data. Besides, the passive party’s communication and the calculation of the locally generated candidate can also be performed in parallel.

4.2 Interpretability

In the federated multi-interactive inference framework, hiding feature names is adopted for protecting the privacy of the inference path among the parties. By obfuscating items, we protect the path from being leaked with the feature name public for improving the interpretability of inference. In the business of federated learning, feature names play an essential role in the interpretability of the ensemble tree models. First, in terms of feature importance, an interpretable model facilitates feature selection. This can improve the active party’s understanding of the model while reducing costs. In addition, this can also ensure the fairness of the model. For example, skin color and gender privacy cannot be included in the modeling.
features, which requires the active party to conduct investigations based on the business. Furthermore, the active party can guard against attacks by the passive party, such as data poisoning attacks, based on each feature’s importance.

The active party can check whether there are abnormal features mixed into the modeling during the modeling process through the importance of features. For example, Figure 9 shows the active party can evaluate the model’s rationality and the reasoning results based on the model features and feature importance after the feature name closed.

To protect all parties’ privacy, the multi-interactive inference framework selects hidden features and makes the path public. In the multi-interactive inference framework, each party only holds the local model because the interaction process of the two parties will synchronously reason whether the sample meets the split condition, which will leak the split path of the sample; if the feature name of the method is public, then the active party will You can know the characteristics that the sample satisfies in the passive model.

Our method conceals the path by obfuscating the weight term while exposing the feature name. In our model, the active party achieves the purpose of the confusion path by introducing confusion weight items. In this way, after the feature name is disclosed, either party cannot know the sample’s reasoning at other nodes to achieve the purpose of privacy protection.

4.3 Security

In this subsection, we would like to discuss our inference algorithm’s security under the semi-honest assumption. In this definition, all parties are honest-but-curious. Expressly, we assume that the active party does not collude with any passive party.

Proof. We take two participants as examples to prove. For the construction of the trained model, all that is revealed holds: (1) Each party knows the tree nodes held by itself; (2) Active party knows which site is responsible for the decision made at each node; (3) Active party knows the weight of all leaf node. (4) The active party knows the number of features held by each passive party. During the inference process, the active party receives the obfuscated encryption item sent by the passive party.

In the inference process, the passive party receives the obfuscated encryption item sent by the active party; according to the security proof of the encryption in the article, the passive party cannot decipher the encryption result to infer the split of the sample at the active node. Therefore, the active party doesn’t obtain the instance space for the active party’s node split. On the other side, the active party receives the sample’s weight sum after the passive party’s n tree model inference, and the active party cannot guess the split result on each tree. According to the above interactive information analysis, each party cannot infer the split result of the other party’s inference on the sample and infer the model.

When the number of participants exceeds two, the information received by each passive party is the weight item after obfuscation and encryption, and the real information of the previous node cannot be inferred. The information received by the active party is the summation of n trees, and the details of each tree cannot be obtained.

5 EXPERIMENTAL RESULTS

Since random forest and GBDT algorithms are similar in the inference process, we take SecureBoost as an example for numerical experiments. We first detail our experimental protocol and then present comparison results of Fed-EINI with SecureBoost. Finally, we present several experimental results to demonstrate the efficiency of our framework.

5.1 Experiments Setup and Metrics

Our experiments are conducted on three datasets, Credit1 [6], Credit2 [18], and JDYM, to verify the performance of Fed-EINI on classification model learning. The summary of the three datasets as follows:

(1). Credit 1: It’s a credit scoring dataset that is used to predict whether a user would repay on time. It consists of 30000 data instances, and each instance has 25 attributes;

(2). Credit 2: It’s also a credit scoring dataset to classify whether a user suffers from a financial problem. It consists of 150000 data instances, and each instance has ten attributes;

(3). JDYM: It consists of 512082 data instances, and each instance has 113 features.

To formulate the datasets for each party, we split each dataset into two parts vertically. The active party holds five features, and the passive party holds the remaining features. We randomly select 60% of the data as the training set, 20% as the validation set, and the remaining as the test set. To investigate the performance of our proposed method on different dataset scales, we also divide three datasets into five subsets with 10%, 20%, 40%, 80%, and 100% of the data. The summary of dataset statistics is shown in Table 1.

The Paillier encryption scheme is taken as our additively homomorphic scheme with a key size of 512 bits. All experiments are conducted on two machines with 128GB RAM and 32 CPU cores. We select 100 as the upper limit of the number of modeling decision trees, and the maximum tree depth is 4. The experimental party is divided into two sub-sections: accuracy and efficiency.
Table 2: SecureBoost versus Fed-EINI in terms of AUC and KS

|                      | SecureBoost | Fed-EINI |
|----------------------|-------------|----------|
|                      | AUC         | KS       | AUC         | KS       |
| **Credit1**          |             |          |             |          |
| Sub01                | 0.864234    | 57.2968  | 0.864234    | 57.2968  |
| Sub02                | 0.880256    | 60.2602  | 0.880256    | 60.2602  |
| Sub04                | 0.860931    | 55.9028  | 0.860931    | 55.9028  |
| Sub08                | 0.852931    | 54.9911  | 0.852931    | 54.9911  |
| Sub10                | 0.854866    | 54.9461  | 0.854866    | 54.9461  |
| **Credit2**          |             |          |             |          |
| Sub01                | 0.757504    | 42.9700  | 0.757504    | 42.9700  |
| Sub02                | 0.772826    | 42.9503  | 0.772826    | 42.9503  |
| Sub04                | 0.769282    | 40.4557  | 0.769282    | 40.4557  |
| Sub08                | 0.770117    | 41.0331  | 0.770117    | 41.0331  |
| Sub10                | 0.771487    | 40.9069  | 0.771487    | 40.9069  |
| **JDYM**             |             |          |             |          |
| Sub01                | 0.633865    | 19.6896  | 0.633865    | 19.6896  |
| Sub02                | 0.636065    | 19.9278  | 0.636065    | 19.9278  |
| Sub04                | 0.635450    | 19.4411  | 0.635450    | 19.4411  |
| Sub08                | 0.638514    | 19.8487  | 0.638514    | 19.8487  |
| Sub10                | 0.638411    | 19.7213  | 0.638411    | 19.7213  |

Protocols and evaluation metrics. In this paper, we select AUC (area under curve) and KS (Kolmogorov-Smirnov) to evaluate the accuracy of our framework. Besides, we use the time cost of the entire inference process to evaluate the efficiency of inference.

5.2 Accuracy Results

Based on the same training model, we use the SecureBoost inference method and our improved inference method on the above inference data sets to conduct experiments and calculate the predictions’ evaluation metrics.

As the Table 2 shows, the inference framework we proposed and applied on the SecureBoost can achieves the same accuracy as the multi-interactive SecureBoost inference. We can infer from that Our inference framework is lossless compared with multi-interactive inference.

5.3 Efficiency Results

To show the training efficiency of Fed-EINI, we conduct inference experiments on the federated tree algorithm (GBDT). First, we use the same data set for model training and then use the SecureBoost inference framework and Fed-EINI framework for inference. We count the total time of these two frameworks in the inference phase.

It can be seen from Figure 10, the efficiency of our proposed inference framework method far exceeds the SecureBoost inference method. In most cases, Fed-EINI’s time cost is only one third of that of SecureBoost in inference. The average time consumption is reduced by more than 50%. The time cost increases linearly with the number of samples.

6 CONCLUSION

In this paper, we studied the inference problem for vertical federated decision tree ensemble models. To address the interpretability and efficiency issue of the existing multi-interactive inference method, we proposed Fed-EINI by parallel calculation and synchronization with additively homomorphic encryption. The proposed Fed-EINI method computed candidate sets of leaf nodes locally at each party in the parallel calculation stage and exchange this information in the synchronization stage without revealing it to other parties. This method protected the privacy of decision path and allowed the disclosure of feature names, which thus makes the model used in an interpretable way. In addition, the calculation process of Fed-EINI was performed in parallel with much fewer communication rounds, which greatly improved the inference efficiency. Experimental results demonstrated the accuracy and efficiency of Fed-EINI.
compared with the multi-interactive inference approach adopted in SecureBoost.

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