Federated Extra-Trees with Privacy Preserving

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Abstract

It is commonly observed that the data are scattered everywhere and difficult to be centralized. The data privacy and security also become a sensitive topic. The laws and regulations such as the European Union’s General Data Protection Regulation (GDPR) are designed to protect the public’s data privacy. However, machine learning requires a large amount of data for better performance, and the current circumstances put deploying real-life AI applications in an extremely difficult situation. To tackle these challenges, in this paper we propose a novel privacy-preserving federated machine learning model, named Federated Extra-Trees, which applies local differential privacy in the federated trees model. A secure multi-institutional machine learning system was developed to provide superior performance by processing the modeling jointly on different clients without exchanging any raw data. We have validated the accuracy of our work by conducting extensive experiments on public datasets and the efficiency and robustness were also verified by simulating the real-world scenarios. Overall, we presented an extensible, scalable and practical solution to handle the data island problem.

1 Introduction

Although we are living in the era of Big Data, we often have to face the fact that there are not enough data for modeling. Except for those data-rich companies, most organizations don’t own enough data to serve their academic research or business projects, and the necessary data are scattered across different organizations not shared. Because of the serious data island situations, secure multi-institutional collaborative modeling has many important potential applications, such as medical study, target marketing, risk management, etc. In the work of [Sheller et al., 2018], the researchers built a semantic segmentation model on multimodal brain scans. The entire modeling was conducted on a multi-institutional collaboration and no raw patient data were shared.

However, it is still challenging to unite multiple institutions modeling together. One of the biggest concerns is data privacy and protection. Not long ago, the Federal Trade Commission (FTC) of the United States imposed a record-breaking $5 billion penalty to Facebook, due to its violation of an FTC’s 2012 order about user data privacy. Companies in many other areas also face similar legal sanctions. The enactment of laws and regulations such as the European Union’s General Data Protection Regulation (GDPR) has made the cross-institutional data mining and modeling more difficult.

To meet the regulation requirements and protect data privacy, Google proposed the federated machine learning (FML) [McMahan et al., 2016; Konecný et al., 2016b; Konecný et al., 2016a]. The key concept of their work is to train models without integrating the data together in one place, and no raw data would be exposed to other parties but fully secured and under users’ own control. Different from Google, we are interested in the business situations that several similar and small size companies such as regional banks want to build joint models together to solve a common business problem, e.g., intelligent loan application approval. Inspired by this, we proposed a novel privacy-preserving federated machine learning model, entitled Federated Extra-Trees (FET). Based on it, a secure multi-institutional machine learning system was developed to support real-world applications accurately, robustly and safely. We have four major contributions:

- **Data privacy was secured** by embedding local differential privacy (LDP) into the Federated Extra-Trees, as well as establishing a third-party trusty server to coordinate and monitor the entire modeling process. And the mathematical proof is provided to illustrate that our model satisfies local differential privacy.

- **Accuracy** was guaranteed under the horizontal federated scenarios. Although LDP and randomness were introduced in several stages, our model was proved to maintain the same level of accuracy as the non-federated approach that brings the data into one place.

- **High efficiency** was achieved with the random tree building process and our model is robust to the complicated network environments. Only necessary and privacy-free modeling information was exchanged and the message size was reduced to a minimum.

- The total solution is practical, extensible, scalable and explainable to handle the data island problem and can be easily deployed for real-life applications.
2 Related Work and Preliminaries

2.1 Federated Learning

In the work of Y. Yang et al. (2019), they have provided a clear definition for the federated machine learning and how it distinguishes from other subjects, such as distributed machine learning, secure multi-party computation, etc. Generally, it can be categorized into three types, horizontal federated learning, vertical federated learning and federated transfer learning. The horizontal FML [McMahan et al., 2016; Konečný et al., 2016b; Konečný et al., 2016a; Yao et al., 2018] is focused on solving problems with data from different sample space but same feature space. The vertical FML [Hardy et al., 2017; Cheng et al., 2019; Liu et al., 2019] is the opposite, which works on problems with the same sample space but different feature space. The federated transfer learning [Liu et al., 2018] is mainly about tasks that data from different sources are overlapped in both sample and feature space, but still largely different from each other. Currently, most FML methods were developed to solve problems under horizontal scenarios. Google applied FML in applications such as on-device item ranking and next word prediction [Bonawitz et al., 2019]. In the work of [Smith et al., 2017] the researchers applied FML to solve multi-task problems and a novel federated recommender system was proposed in the work of Chen et al. (2018).

2.2 Differential Privacy

Differential Privacy (DP) [Dwork, 2008] is a commonly applied privacy-preserving method in federated learning. It aims to minimize the possibility of individual identification to ensure user-level privacy [Kairouz et al., 2014]. DP has been used extensively in machine learning tasks against privacy inference attacks. Existing work mainly focuses on adding perturbations on parameters in the gradient descent algorithms [Song et al., 2013; Abadi et al., 2016; Geyer et al., 2017]. Global differential privacy (GDP) and local differential privacy (LDP) are the two main classes of DP. The existing approaches in federated learning are mostly GDP, where a trusted curator will apply calibrated noise on the aggregated data to provide differential privacy. Conversely, LDP mechanisms, where owners will perturb their data before aggregation, provide better privacy without trusting any third party as a curator. LDP applications is on the rise due to its higher privacy and simpler implementation [Bhowmick et al., 2018; Zhao, 2018; Chamikara et al., 2019]. Formally, LDP is defined as follows [Duchi et al., 2013]:

Definition 1 ($\varepsilon$-local differential privacy). A randomized algorithm $M$ is $\varepsilon$-local differential privacy if and only if for any two input tuples $u$ and $u'$ in the domain of $M$, and for any output $w^{*}$ of $M$, $\Pr[M(u) = w^{*}] \leq e^\varepsilon \Pr[M(u') = w^{*}]$.

For a complex randomized algorithm with multiple sub-functions, two composition theorems [McSherry, 2009] were widely used.

Theorem 1 (Sequential Composition). If a series of algorithms $M = \{M_1, ..., M_P\}$, in which $M_p$ satisfies $\varepsilon_p$-local differential privacy, are sequentially on a dataset, $M$ will satisfies $\sum_{p=1}^P \varepsilon_p$-local differential privacy.

Theorem 2 (Parallel Composition). If a series of algorithms $M = \{M_1, ..., M_P\}$, in which $M_p$ satisfies $\varepsilon_p$-local differential privacy, are performed separately on disjoint datasets, $M$ will satisfies $\max_{1 \leq p \leq P} \varepsilon_p$-local differential privacy.

3 Methodology

3.1 Learning Scenario

In our work, we focused on applying Federated Extremely Randomized Trees, abbreviated to Federated Extra-Trees, to solve horizontal distributed data problems, that all data providers have the same attribute set $F$ but different sample space. Each data provider was considered as one institutional data domain and denoted as $D_i$. The overall data domain is $D = \{D_1; D_2; \cdots; D_O\}$, where $1 \leq i \leq O$ and $O$ is the number of institutional domains. On each data domain, we have $D_i = \{(x_i^1, y_i^1), (x_i^2, y_i^2), \ldots, (x_i^n, y_i^n)\}$. Here $x$ is the input sample and $y$ is the corresponding label, $(x, y) \in (X, Y)$ and $n_i$ is the total number of samples in $D_i$. We have deployed a master machine as the parameter server to coordinate the entire modeling process and assigned each institutional domain one client machine. Since we are trying to build FML models jointly on different organizations, $O$ is usually small and in our work, we only consider situations when $O <= 10$. For more parties involved, the algorithm design could be much more different.

3.2 Problem Statement

The formal statement of the problem is given as below:

- **Given:** Institutional data domain on each client.
- **Learn:** Privacy-preserved Federated Extra-Trees.
- **Constraint:** The performance (accuracy, F1-score, etc.) of the Federated Extra-Trees must be comparable to the non-federated approach.

3.3 Framework Overview

In our work, we carefully extended the Extra-Trees [Geurts et al., 2006] to suit the horizontal federated scenarios with full consideration of privacy issues by applying local differential privacy (LDP) [Duchi et al., 2013]. In Extra-Trees,
the optimal splitting under a certain feature is randomly selected instead of being calculated. With the idea of bagging \cite{Breiman.1996}, a forest can accommodate the errors caused by randomness in the single trees. Our model has provided a concise algorithm design and the computation complexity is limited to the minimum, and the training speed is greatly improved. Our model is able to solve classification problems and without applying LDP it also supports regression tasks.

As shown in Figure 1, assume we want to build an intelligent system to automatically decide if we should approve or reject the loan application. We have \( O \) clients and each of them provides information on their own loan application records. Before the modeling, we first applied LDP to transform the clients’ labels into encoded binary strings, then all clients work together to build a complete federated forest that is available for subsequent use on every client. During the training, no raw data such as Gender, Age or others would be exposed. When modeling is finished, the model will be saved locally for inference use and no communication is necessary.

### 3.4 Algorithms

In this part, we will give a detailed introduction to our model. The training process of clients and master is described in Algorithm 1 and 2. All participants, including the master and clients, share the same feature set. The key steps of building a tree are as follows.

**Algorithm 1: Federated Extra-Tree – Client**

**Input**: Training set \( D_i \) of client \( i \), feature set \( F \)

**Output**: A Federated Extra-Tree

\( S_i \leftarrow \) subsample of \( D_i \) on client \( i \);

**Function** \( \text{build} \_\text{tree}(S_i, F) \)

- if \( \text{stopping condition is true} \) then
  - Send \( \text{Sum}_i \) to master;
  - Receive leaf labels from master;
  - return leaf node;
- for each feature \( f_{i,j} \in F^* \) do
  - Pick a random split threshold \( v^*_j \) from client \( i = 1, ..., O \);
  - Send feature candidate set \( F^* \) to clients;
- right subtree \( \leftarrow \text{build} \_\text{tree}(S_{i,R,j}, F) \);
  - return tree node

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  - Send \( \text{Sum}_i \) to master;
  - Receive leaf labels from master;
  - return leaf node;
- for each feature \( f_{i,j} \in F^* \) do
  - Pick a random split threshold \( v^*_j \) from client \( i = 1, ..., O \);
  - Send feature candidate set \( F^* \) to clients;
- right subtree \( \leftarrow \text{build} \_\text{tree}(S_{i,R,j}, F) \);
  - return tree node

**Algorithm 2: Federated Extra-Tree – Master**

**Input**: Feature set \( F \)

**Output**: A Federated Extra-Tree

**Function** \( \text{build} \_\text{tree}(F) \)

- if \( \text{stopping condition is true} \) then
  - Receive \( \text{Sum}_i \) from client \( i = 1, ..., O \);
  - Send \( \text{Global Sum} \) to clients as leaf labels;
  - return leaf node;
- if \( F^* \in F \) then
  - Randomly-chosen feature labels;
  - Send feature candidate set \( F^* \) to clients;
- for each feature \( f_j \in F^* \) do
  - Gather \( v^*_j \) from client \( i = 1, ..., O \);
  - Pick a random split threshold \( v^*_j \) from client \( i = 1, ..., O \);
  - Broadcast \( v^*_j \) to all clients;
  - Gather \( \text{Sum}_i \) from client \( i = 1, ..., O \);
  - \( \text{C}_L,j, \text{C}_R,j \) \( \leftarrow \) estimated global label counts;
  - Calculate Gini Gain \( f_j \) with \( \text{C}_L,j, \text{C}_R,j \);
  - Broadcast the global best split feature \( f^* \) and the corresponding split threshold \( v^* \);
- left subtree \( \leftarrow \text{build} \_\text{tree}(F) \);
- return tree node

**Stopping criterion.** Before creating a new tree node, participants will check if the stop conditions have been satisfied. Here we adopted a CART-tree \cite{Breiman et al., 1984} like design. The stopping conditions are set by a maximum threshold for the depth of trees, a limit on the number of remaining samples in leaf nodes as well as other corner conditions.

**Random feature and threshold selection.** Master is responsible for coordinating the collection of information from clients and decide which feature to use on a node. We inherited the randomness solution in Extra-Trees and extended it to the entire process of feature selection. Experiments in Section 3 have shown that the randomization does not necessarily lead to loss of precision. To create a new tree node, the master would randomly extract a candidate feature set \( F^* \subset F \), and send it to all clients. Each client \( i \) randomly picks a value \( v^*_j \) between the local minimum and maximum value of feature \( f_j \), then send it to the master. The master collects \( v^*_j \) and arbitrarily picks a value \( v^*_j \) between \( \min(v^*_j) \) and \( \max(v^*_j) \) as the split threshold for each feature, then broadcasts the values to all clients. In this way, the true local range of features on each client will not be revealed to the master.

Clients would split local data temporarily into left and right subtrees according to the received feature threshold, then sending perturbed information of the data labels to master.
This process also increases the randomness. Receiving all the information of local subsets, the master would aggregate the data to calculate a Gini_Gain value for the feature. Feature \( f^* \) with the maximum Gini_Gain will be chosen as the best split feature for the current node. Clients should record the subsets for each feature. When the split feature \( f^* \) is finally determined, they could use the corresponding subsets directly to avoid repeated calculations.

### 3.5 Privacy Preserving Methods

In Figure 2, the dots with different colors represent different label classes. When the building process proceeds to a new node, the master needs to know the global label distribution of split data under a feature threshold, so that it can calculate the Gini_Gain value for the feature.

The algorithm should neither reveal the category of a single user nor compromise the specific distribution of categories on a client. Here we modify an aggregation algorithm, which was first proposed by Google [Erlingsson et al., 2014] for crowd-sourcing business and proven to be locally differential private. We implement a multi-layer mechanism, including one Bloom Filter layer and two separate random-response based layers. Bloom Filter [Broder and Mitzenmacher, 2004] is a randomized structure for representing a set in a space-efficient way. It adds extra uncertainty for user identification and compacts large data to reduce the communication traffic in federated scenarios.

**Step 1:** Two fixed layers are set before the tree is created. For the \( k \)-th sample in \( D_i \), its label \( y_i^k \) maps to Bloom Filter \( B_i^k \) of size \( h \) using several hash functions. The Bloom Filter strings are then encrypted as permanent random responses (Permanent RR), i.e., the second layer. Each bit in \( B_i^k \) would maintain the original value with probability \( pr \); otherwise it will be replaced by 0 or 1 with equal probability \( 1/2(1-pr) \).

**Step 2:** For each feature selection process, another layer of temporary perturbation shall be added on \( B_i^k \), i.e., an instant random response string (Instant RR) denoted as \( R_k \). Each bit \( R_{i,t}^k \) is set to 1 with a certain probability, as is shown in Equation 1

\[
Pr(R_{i,t}^k = 1) = \left\{ \begin{array}{ll}
\xi, & \text{if } B_{i,t}^k = 1 \\
\zeta, & \text{if } B_{i,t}^k = 0
\end{array} \right., t = 1, 2, \ldots, h
\]

**Step 3:** Client \( i \) adds the local values along the bit position, as shown in Equation 2.

\[
Sum_{i,t} = \sum_{k=1}^{n_i} R_{i,t}^k, t = 1, 2, \ldots, h
\]

where \( n_i \) is the number of users on client \( i \).

**Aggregation:** As is shown in Figure 3, the master will aggregate the received results into \( Sum \), with the count of each bit being:

\[
Sum_t = \sum_{i=1}^{M} Sum_{i,t}, t = 1, 2, \ldots, h
\]

With the label space mapped into \( B_1, B_2, \ldots, B_L \), master estimates the overall label counts using linear estimation methods such as Lasso Regression.

In this scheme, the Permanent RR is already fixed, and the instant perturbation is calculated at an individual level without trusting any third party as a curator. This LDP method also applies to other models that use statistics as an intermediate value. For comparisons, we also adopt GDP in Federated Extra-Trees, i.e., the clients add a disturbance to their local labeling statistics and the master sums up the received statistics directly for further calculation. In this case, the clients must be fully trusted to be responsible for ensuring the data privacy of end-users. In the experimental part, we carry out a GDP-based method using the Laplace mechanism.

### 3.6 Privacy Analysis

In this part, we will provide an analysis of the privacy level of our proposed algorithm.

**Corollary 1.** The output of \( p \)-th tree on \( i \)-th client satisfies \( \varepsilon_{ip} \)-local differential privacy.

**Proof.** After the private data is perturbed by LDP algorithm, every query that acts on the dataset satisfies \( \varepsilon_{node} \)-local differential privacy. Considering the structure of random decision trees, different nodes on every layer own disjoint datasets, which satisfies parallel composition. Thus, the maximum privacy budget will not be larger than \( \varepsilon_{ip} = \varepsilon_{node} \ast (depth + leaf) \).

**Corollary 2.** The FET satisfies \( \varepsilon \)-local differential privacy.

**Proof.** There are two views on FET, random decision trees’ view and participating clients’ views. In the previous perspective, \( P \) mutually independent random decision trees of one client act on the same data set, which satisfies sequential composition. In the latter perspective, the decision trees of \( O \) clients act on \( O \) disjoint data sets, which satisfies parallel composition. With these two composition theorems, we have

\[
Pr[M(t) = t^*] = \prod_{p=1}^{P} Pr[M_p(t) = t^*]
\]

\[
eq \prod_{p=1}^{P} \prod_{i=1}^{O} Pr[M_{ip}(t) = t^*]
\]

\[
\leq \prod_{p=1}^{P} \sum_{t' \in \mathcal{O}} e^{\max_{1 \leq i \leq O}(\varepsilon_{ip})} Pr[M_p(t') = t^*]
\]

\[
\leq e^{\sum_{p=1}^{P} \max_{1 \leq i \leq O}(\varepsilon_{ip})} \cdot \text{local differential privacy.}
\]

Therefore, we proved that our proposed FET model satisfies \( \varepsilon = \sum_{p=1}^{P} \max_{1 \leq i \leq O}(\varepsilon_{ip}) \)-local differential privacy.

### 4 Experimental Studies

#### 4.1 Experimental Setup

To verify the effectiveness of our algorithm and the utility of privacy-preserving methods, we designed comparative experiments of the following four algorithms:

- **Extra-Trees (ET):** The non-federated implementation of the extremely randomized trees.
4.2 Overall Performance
The overall performance is shown in Table 2. Each experiment was repeated for 30 times, and the mean and variance of the accuracy and F1 score are given. We can see these points from the Table 2.

- **Accuracy**: On different scales of datasets, our algorithms have achieved comparable results to the non-federated Extra-Trees. For both binary and multiclass classification tasks, our FET method performs even better than the basic ET model on some datasets.

- **Utility of privacy-preserving methods**: As observed in most tests, DP-based methods have brought a loss to the accuracy, but overall this loss is acceptable. The performances of both FET-LDP and FET-GDP are close to that of FET. This is because the framework of Extra-Trees is inclusive and can accommodate the fluctuations caused by the perturbations. The other reason is that the perturbed data is used to select features, not directly involved in numerical modeling.

- **Stability**: The variance values show the stability of FET-series algorithms compared with ET. Our LDP-based approach presented relatively smaller variances than the GDP method and maintained almost the same stability as the privacy-free FET. The datasets we used have covered a wide range of data volume and feature types, which besides shows the adaptability of our algorithm.

To analyze the impacts of the number of clients and tree parameters on the models, we experimented with the algorithmic efficiency of the three federated algorithms with different parameters on two datasets: the binary-class Credit-card dataset and the multi-class Letter-recognition dataset.

4.3 Effect of Client Numbers
In this set of experiments, the number of trees and the maximum tree depth were fixed to 20. We have randomly divided both datasets into 9 folds, and each was placed on one client. As is shown in Figure 3 (a,d), when we have more clients modeling together, there is a constant increase in the accuracy. This has supported our vision that by uniting more institutions a better modeling performance could be achieved.
| Metric       | Dataset  | ET       | FET     | FET-LDP | FET-GDP |
|--------------|----------|----------|---------|---------|---------|
| **Accuracy** |          |          |         |         |         |
| Spambase     | 0.934±0.005 | 0.932±0.009 | 0.920±0.009 | 0.919±0.013 |
| Credit-Card  | 0.805±0.002 | 0.814±0.004 | 0.815±0.003 | 0.811±0.012 |
| MIMIC        | 0.639±0.003 | 0.641±0.011 | 0.645±0.008 | 0.638±0.010 |
| **F1 Score** |          |          |         |         |         |
| Spambase     | 0.943±0.004 | 0.934±0.021 | 0.920±0.009 | 0.915±0.018 |
| Credit-Card  | 0.885±0.001 | 0.890±0.002 | 0.852±0.040 | 0.889±0.005 |
| MIMIC        | 0.776±0.001 | 0.781±0.006 | 0.645±0.008 | 0.776±0.005 |

Table 2: Experimental Results

| Metric       | Dataset  | ET       | FET     | FET-LDP | FET-GDP |
|--------------|----------|----------|---------|---------|---------|
| **Accuracy** |          |          |         |         |         |
| Waveform     | 0.842±0.005 | 0.886±0.010 | 0.882±0.011 | 0.876±0.012 |
| Letter       | 0.953±0.002 | 0.971±0.004 | 0.940±0.007 | 0.972±0.003 |
| KDD CUP 99   | 0.994±0.001 | 0.994±0.002 | 0.993±0.002 | 0.993±0.002 |
| **F1 Score** |          |          |         |         |         |
| Waveform     | 0.842±0.005 | 0.886±0.010 | 0.882±0.011 | 0.876±0.012 |
| Letter       | 0.953±0.002 | 0.971±0.004 | 0.940±0.007 | 0.972±0.003 |
| KDD CUP 99   | 0.994±0.001 | 0.994±0.002 | 0.993±0.002 | 0.993±0.002 |

LDP method was also applied to protect the data privacy of each client.

4.4 Effect of Tree Settings
We tested the effects of the number of trees and the maximum tree depth respectively. When experimenting with the effect on the number of trees, the maximum tree depth is set to 20, and vice versa. By observing the change of the fold lines in Figure 3, we could find:

- **The number of trees:** The accuracy rate has been greatly improved from a single tree to multiple trees, which demonstrates the advantages of forest structure. However, in the comparison of multiple trees, the increase in the tree numbers has minimal impact on the results.

- **The maximum tree depth:** The maximum tree depth has a greater influence on the results. The accuracy of Federated Extra-Trees models is rising continuously as the tree depth threshold grows. When the maximum depth reaches 20 or so, the model converges.

5 Conclusions
In this paper, we proposed a novel privacy-preserving federated machine learning method, called Federated Extra-Trees, which achieves competitive performance on the modeling accuracy and protects the data privacy. We also developed a secure multi-institutional federated learning system that allows the modeling task can be jointly processed across different clients with the same attribute sets but different user samples. The raw data on each client will never be exposed, and only a limited amount of intermediate modeling values were exchanged to reduce the communication and secure data privacy. The introduction of local differential privacy and a third-party trusted server strengthens privacy protection and makes it impossible to backdoor the actual statistical information from the clients. We set up multiple clients to simulate real-world situations and performed experiments on public datasets. The experimental results presented a superior performance for the classification tasks, and there was no loss on the modeling accuracy by comparing to the non-federated approach that requires data gathered in one place. We also proved that the introduction of local differential privacy does not affect the overall performance. The efficiency and robustness of our proposed system were also verified. To summarize, the Federated Extra-Trees successfully solved the data island problem and provided a brand new approach to protect the data privacy while realizing the cross-institutional collaborative machine learning, and it is strong practical for real-world applications.
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