Boosting Privately: Privacy-Preserving Federated Extreme Boosting for Mobile Crowdsensing

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Abstract—The state-of-the-art federated learning brings a new direction for the data privacy protection of mobile crowdsensing machine learning applications. However, besides being vulnerable to GAN based user data construction attack, the existing gradient descent based federate learning schemes are lack of consideration for how to preserve the model privacy. In this paper, we propose a secret sharing based federated extreme boosting learning framework (FedXGB) to achieve privacy-preserving model training for mobile crowdsensing. First, a series of protocols are designed to implement privacy-preserving extreme gradient boosting of classification and regression tree. The protocols preserve the user data privacy protection feature of federated learning that XGBoost is trained without revealing plaintext user data. Then, in consideration of the high commercial value of a well-trained model, a secure prediction protocol is developed to protect the model privacy for the crowdsensing sponsor. Additionally, we operate comprehensive theoretical analysis and extensive experiments to evaluate the security, effectiveness and efficiency of FedXGB. The results show that FedXGB is secure in the honest-but-curious model, and attains approximate accuracy and convergence rate with the original model in low runtime.

Index Terms—Privacy-Preserving, Crowdsensing Applications, Federated Learning, Extreme Boosting Learning, Secret Sharing

I. INTRODUCTION

Extreme gradient boosting learning (XGBoost) is one of the most state-of-the-art machine learning model that performs noticeably well on processing both classification and regression tasks in applications, like malware detection \cite{1} and consumption behaviour prediction \cite{2}. Its success is mainly due to its excellent predictive performance, highly optimized multicore, mature distributed implementation and the ability to handle sparse data \cite{3}. However, just like the other machine learning models, its high performance is still based on the support of large-scale database. Building a reliable big database usually requires the professional data analyst to collect and analyze tens of years statistic data, whose cost is unaffordable for most companies \cite{4}. Thus, mobile crowdsensing which implements data collection tasks through volunteers becomes popular in real-world applications. One of the most representative examples is the crowdsensing based smart recommendation service for news app \cite{5}.

For the existing mobile crowdsensing architecture, two drawbacks are hindering its further development. One is the limited computation power and storage space of the central cloud server \cite{6}. To resolve it, an ideal countermeasure is distributed learning, yet in the framework, data are usually owned by different parties. The high-level parties (e.g. service provider) always collect user private data (e.g. age, income or address) under the pretext of training machine learning model and improving user experience. From the data security incidents of recent years, the damages caused by this type of privacy leakage have not been only towards individual security or company finance, but also expanded to the national future. For example, in 2018, the Facebook-Cambridge Analytica data incident reveals the big IT company’s secret harvest of millions of people’s personal data to sway the country’s leadership election \cite{7}. Consequently, how to preserve data privacy for the distributed learning of mobile crowdsensing becomes the other obstacle required to overcome. Towards the above challenges, federated learning, which groups the distributed devices and remote cloud servers into a loose federation and allows model training with no original user data uploaded, is proposed \cite{8}.

Nevertheless, for current federated learning architectures, there are three serious but unattended problems.

Model Privacy. A well-trained model is the product of massive investment. An example is that, to develop high-performance machine learning and deep learning models, Google pays $162 millions for “DeepMind” in 2016 \cite{9}. Existing federated learning schemes usually choose to publish newly obtained model to users or third-party cloud platforms to continue the next round of training \cite{10}. This means the trained model can be stolen by users with very little expense, like only some computation power and registration cost. And the victim companies may lose the investment in model training because of model privacy leakage.

User Dropout. As the mobile crowdsensing based online learning framework, one of the most prominent features is the instability of users. During any stage of each learning round, there is a great chance that user dropout occurs. For the original federated learning framework \cite{8} and other follow-up researches \cite{10}, the condition is not taken into full consideration. Their default assumption that all users can maintain...
completely steady connections may make them unpractical in applications.

**Data Reconstruction Attack.** Recent researches point out that the federated learning schemes are vulnerable to GAN based user data reconstruction attack \([11]\). The attack allows the malicious server to exploit the gradient aggregation results uploaded by users, which are originally used for model updating, to derive user data with GAN.

To address the mentioned challenges, in this paper, we propose a secret sharing based federated extreme boosting learning framework (FedXGB) to achieve privacy-preserving model training for crowdsensing applications. The main contributions of FedXGB are listed as follows.

- **Extreme Boosting Privately.** The privacy-preserving federated extreme gradient boosting learning architecture, FedXGB, achieves efficiently training of XGBoost model for mobile crowdsensing without revealing user private data to servers.

- **Model privacy preservation.** Considering the high commercial value of the well-trained model in applications, FedXGB develops a privacy-preserving prediction protocol that allows the model inference operated with key parameters in the encrypted format.

- **Robustness against dynamic user change.** In FedXGB, a full countermeasure against user dropout is proposed, which minimizes the cost lost and reserve as much efficiency as possible.

- **Provable security and low performance loss.** Comprehensive security analysis is operated to prove the secure of FedXGB in the honest-but-curious model. And extensive experiments are operated to confirm that FedXGB has negligible accuracy loss and high efficiency.

## II. PRELIMINARY

### A. Notations

Some frequently-used notations of the paper are summarized in Table I.

| Notation | Description |
|----------|-------------|
| \(l(\cdot)\) | an arbitrary loss function with second-order derivative |
| \(\theta_i\) | the first-order derivative of \(l(\cdot)\) |
| \(h_i\) | the second-order derivative of \(l(\cdot)\) |
| \(\zeta_u\) | the secret share distributed to the user \(u\) |
| \(\kappa_u\) | the secret mask set owned by the user \(u\) |
| \(\mathcal{F}\) | a finite field \(\mathbb{F}_p\), e.g. \(\mathbb{F}_p = \mathbb{Z}_p\) for some large prime \(p\) |
| \(f_k\) | the CART obtained from the \(k\)-th iteration of XGBoost |
| \(\langle \cdot \rangle_u\) | keys of \(u\) for signature, encryption or secret mask generation |

### B. Extreme Boosting Learning

Extreme boosting learning (XGBoost) is one of the most outstanding ensemble learning methods because of its excellent performance in processing regression, classification, and Kaggle tasks \([12]\). An XGBoost model is composed of multiple classification and regression trees (CARTs), which are trained by the gradient boosting method. For the \(k\)-th iteration, the objective of the XGBoost is to minimize,

\[
\mathcal{L}^k = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{k-1} + f_k(x_i)) + \Omega(f_k),
\]

where \(n\) is the total number of training samples, \(i\) is the index of each sample, and \(y_i\) is the label of the \(i\)-th sample. \(\hat{y}_i^{k-1}\) represents the predicted label of the \(i\)-th sample at the \((k-1)\)-th iteration. \(\Omega\) is a regularization item to avoid the over-fitting issue, which can be expanded as:

\[
\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{T} \omega_j^2
\]

where \(\gamma\) and \(\lambda\) are two constant values. \(T\) is the number of tree leaves and \(\omega_j\) represents the weight of leaf \(j\). After the expansion of \(\Omega\) and the use of second-order Taylor approximation, the scoring function \(\hat{L}^k(f_k)\) to measure the quality of \(f_k\) is displayed as:

\[
\hat{L}^k(f_k) = -\frac{1}{2} \sum_{j=1}^{T} \frac{(\sum_{i \in I_j} y_i)^2}{\sum_{i \in I_j} h_i} + \gamma T,
\]

where \(I_j\) represents the set of training samples. According to the score function \(\hat{L}^k\), we can retrieve an optimal tree for the \(k\)-th iteration.

### C. Secret Sharing

Since attackers can easily derive users’ private data by exploiting the uploaded gradients \([11]\), the \((t,n)\) Secret Sharing (SS) scheme \([13]\) is adopted in our scheme. For the \((t,n)\) SS scheme, a secret \(s\) is allowed to be split into \(n\) shares, \(s\) can be recovered only if at least \(t\) random shares are provided; otherwise, it cannot be obtained. The share generation algorithm is illustrated as SS.share\((s,t,n) = \{(u,\zeta_u)|u \in \mathcal{U}\}\), in which \(n\) represents the number of participants involved in SS and \(\mathcal{U} = \{1,2,...,n\}\) is the set of participants. \(\zeta_u\) describes the share for each user \(u\). To recover each secret, the Lagrange polynomials based SS.recon\((\{(u,\zeta_u)|u \in \mathcal{U}'\},t)\) is used. It is required that \(\mathcal{U}' \subseteq \mathcal{U}\) has to contain at least \(t\) participants. The following is a previously proposed secret sharing protocol \([14]\) to fulfill secure comparison in FedXGB.

- **Secure Comparison Protocol (SecCmp) \([14]\):** Given two sets of secret shares, \(SS . Share(s_1,t,n) = \{(u,\zeta_u)|u \in \mathcal{U}\}\) and \(SS . Share(s_2,t,n) = \{(u,\zeta_u)|u \in \mathcal{U}\}\), random shares of the comparison result \(SS . Share(s,t,n) = \{(u,\zeta_u)|u \in \mathcal{U}\}\) is generated. Having at least \(t\) shares, i.e., \(|\mathcal{U}'| > t\), the secret can be recovered. If \(s_1 > s_2\), \(SS . Recon((\{(u,\zeta_u)|u \in \mathcal{U}'\},t) = 0\); otherwise, \(SS . Recon((\{(u,\zeta_u)|u \in \mathcal{U}'\},t) = 1\).

## III. SYSTEM ARCHITECTURE

In this section, we introduce the learning framework of secret sharing based federated extreme boosting FedXGB, illustrated in Fig. 1.
A. System Model

FEDXGB consists of three types of entities: users $U$, edge servers $E$, and a remote central cloud server $S$. Details are presented as follows:

**Users.** $U = \{U_1, U_2, ..., U_6\}$. $U_i = \{u_{i1}, u_{i2}, ..., u_{in}\}$ is a set of users belonging to the same domain. Users are data generators and volunteer to participate in the crowdsensing model training for FEDXGB.

**Edge Servers.** $E = \{e_1, e_2, ..., e_6\}$, where $e_i \in E$ is an edge server. Edge servers are provided by various operators. Each edge server provides the communication service for the users that belong to the domain it controls. In FEDXGB, $E$ aggregates gradients and uploads results to $S$.

**Central Cloud Server.** According to the aggregation results uploaded by $E$, $S$ trains the model without knowing users’ private data. The trained model only belongs to $S$, not publicly accessible.

B. Security Model

In FEDXGB, we use the curious-but-honest model as our standard security model. The definition of the adversary $A$ in the security model is formalized as follows:

**Definition 1** [15]. In a communication protocol, a legitimate participant, $A$, does not deviate from the defined protocol, but attempts to learn all possible information from the legitimately received messages.

Any $u \in U$, $e \in E$ and $S$ can be an $A$ with the following abilities: 1) corrupt or collude with at most $t$ legitimate participants and get their inputs; 2) cannot extract the information from the other good parties (e.g., legitimate inputs, random seeds); 3) have limit computing power to launch attacks. FEDXGB is required to achieve the two requirements.

- **Data Privacy.** $e \in E$ and $S$ are unable to learn the private data of any $u \in U$, especially by the data reconstruction.
- **Model Privacy.** $u \in U$ and $e \in E$ are unable to learn the key model parameters owned by $S$.

IV. FEDERATED EXTREME BOOSTING LEARNING

In the section, we discuss implementation details of FEDXGB. The basic idea of FEDXGB to preserve privacy is to implement the extreme CART boosting of XGBoost without requiring any users’ private data. And the building of CART is implemented by invoking the federated extreme gradient boosting protocol (SecBoost). During the CART building process, an essential operation is finding the optimal split. To achieve privacy-preserving split finding, we propose the secure split finding protocol (SecFind). Additionally, the secure prediction protocol (SecPred) is designed to obtain prediction results of the newly obtained CART without model privacy disclosure. Finally, we discuss the robustness of FEDXGB against user dropout in real-world applications.

A. Cryptographic Definition

Prior to introducing the details of FEDXGB, two essential cryptographic functions are defined firstly.

1) **Key Agreement.** We apply three algorithms for key agreement in FEDXGB: key setup $\text{KEY.Set}$, key generation $\text{KEY.Gen}$, and key agreement $\text{KEY.Agr}$. Specifically, the key setup algorithm, $\text{KEY.Set}(\ell)$, is for setting up a public parameter $p_{pub}$. $\ell$ is a security parameter that defines the field size of a secret sharing scheme $F_p$. $\text{KEY.Set}(\ell)$ outputs a quaternion $p_{pub} \leftarrow (G, p, g, H)$. $G$ is an additive cyclic group with a large prime order $p$ and a generator $g$. Consider two arbitrary users, $u$ and $v$, $u$ first applies the key generation algorithm $\text{KEY.Gen}(p_{pub})$ to generate outputs $\langle k^u_{pri}, x^u \rangle \leftarrow x_u$ and $\langle k^v_{pub}, g_x \rangle$. Then, $u$ uses the key agreement algorithm $\text{KEY.Agr}(\langle k^u_{pri}, k^v_{pub} \rangle)$ to create a shared key $\langle sk^u, g^v \rangle$, which is shared with $v$.

2) **Identity Based Encryption and Signature.** To ensure secure data transmission in FEDXGB, we applied an identity-based encryption algorithm and a signature algorithm for message encryption and identity verification, respectively. Given a key pair $\langle (ek)^{enc}, (ek)^{dec} \rangle \leftarrow \text{KEY.Gen}$ or a share key $\langle (ek)^{enc} \rangle \leftarrow \text{KEY.Agr}$, the encryption function $\text{IDE.Edc}$ outputs $c = \text{IDE.Enc}(ek^{enc}, t)$. And the decryption function $\text{IDE.Dec}$ recover the plaintext $t$ by computing $t = \text{IDE.Dec}(ek^{dec}, c)$. Similarly, the signature algorithms, $\text{SIG.Sign}$ and $\text{SIG.Verf}$, are defined. Given the key pair for signature $\langle (k)^{sig}, (k)^{ver} \rangle \leftarrow \text{KEY.Gen}$, $\text{SIG.Sign}$ outputs the signature $\sigma = \text{SIG.Sign}(k^{sig}, t)$. If $\text{SIG.Verf}(k^{ver}, t, \sigma) = 1$, $\sigma$ is proved to be valid; otherwise, $\sigma$ is invalid.

B. Secure Boosting

SecBoost completes the privacy-preserving extreme gradient boosting process as shown in Protocol[1]. In the protocol, all users are orderly labeled with unique indexes 1, 2, ..., $n$ to identify their identities. Each of users deploys a small local dataset $\mathcal{D}_u = \{(x_{u1}, y_{u1}), (x_{u2}, y_{u2}), \ldots\}$. Note that we briefly describe the situation of sending a message $M$ from $A$ to $B$ as $A \Rightarrow B : M$. And the data exchange between users from different domains needs edge servers to serve as communication bridge. The overview of SecBoost is illustrated in Fig.2. Steps are proceeded in detail as below.

**Step 1. System Setup:** $U$, $E$, and $S$ setup public parameters for key generation and model training. Firstly, apply...
KEY.Set(ℓ) to setup cryptographic parameters ppub. Then, FEDXGB is given the input space field F_q, the secret sharing field F_p, and the publicly known XGBoost parameters including λ, γ, loss function l(.), maximum tree depth d_max. The trusted third party T generates a signature key (k)_u^{sig} and a corresponding verification key (k)_u^{ver}.

Step 2. User Selection: To minimize the cost of recovering lost data for dropout users, SecBoost selects the more active users to participate in the subsequent model training process. The selection is based on some manually defined standards such as the keeping active time, the connection stability, and the maximum number of users. The set of selected users are expressed as U' ⊆ U. Based on U', the number of total users |U'| = n_j and the secret sharing threshold t_j are determined. The legitimacy of selected users is verified by confirming whether their signature for key distribution is valid.

Step 3. Secret Mask Collection: In the step, the secret masks for masking the sub-aggregation of the first-order and second-order gradients are generated. The masks are random shares of the mask key from different users. Each user generates random shares of its own mask key by computing \{ (u, ζ^k_{u,v}) | v ∈ U' \} ← SS.share((sk)_u^{pri}, t, n) and sends them to the corresponding user v in the encrypted format. The random masks share between two users u and v are encrypted by c_{u,v} ← IDE.Enc(KEY.Agr((ek)_u^{pri}, (ek)_v^{pri}), u||v||ζ^k_{u,v}). Each user computes IDE.Dec(KEY.Agr((ek)_u^{pri}, (ek)_v^{pri}), c_{u,v}) to extract ζ^k_{u,v} and build the mask value set \mathcal{R}_u = \{(v, ζ^k_{u,v}) | v ∈ U'\}.

Step 4. Boosting: Assume that the feature set of the training samples is \mathcal{Q} = \{α_1, α_2, ..., α_q\}. For boosting, S randomly selects a sub-sample \mathcal{Q}' ⊆ \mathcal{Q}, and invokes SecFind(\mathcal{Q}', U', \mathcal{E}((u, \mathcal{R}_u))_{u ∈ \mathcal{E}_k}) to find the optimal split. The implementation detail of SecFind is given in Section IV-C. To build a new boosting tree with an optimal structure, S has to successfully operate the boosting process until the current tree depth reaches d_max or other termination conditions [16] are met. Finally, SecBoost the newly fulfilled tree as f_k. Moreover, each user updates the value of ŷ for the new round of training after receiving the newly constructed CART. For the privacy of both user data and training model, the prediction is completed by invoking SecPred whose details are given in Section IV-D. By repeatedly invoking SecBoost, we can get a trained XGBoost model f(x) = \sum_{k=1}^{K_{max}} f_k(x), where K is the maximum training round, and \mathcal{K} is a functional space corresponding to all possible CART.

**Protocol 1 Federated Extreme Gradient Boosting Tree Building (SecBoost)**

**Input:** A central server S, a set of users U = \{u_1, ..., u_0\} and a trusted third party T.

**Output:** A well-trained CART.

1. **Step 1:** S selects security parameter ppub ← KEY.Set(ℓ) and publishes the parameters for model training ppub, λ, γ, l(·), d_max.
2. **Step 2:** T generates signature key pair ((k)_u^{sig}, (k)_u^{ver}) for u ∈ U, and operates T ⇒ U : ((k)_u^{sig}, (k)_u^{ver}).
3. **Step 3:** \exists j ∈ \mathcal{E} selects proper active user set U'_j, secret sharing threshold t_j and operates \exists j ⇒ U'_j : (U'_j, t_j).
4. **Step 4:** \exists u ∈ U'_j invokes \{(sk)_u^{pri}, (sk)_u^{pub}\} ← KEY.gen(ppub), \{(ek)_u^{pri}, (ek)_u^{pub}\} ← KEY.gen(ppub).
5. **Step 5:** u ⇒ \exists j ⇒ S : (u, (sk)_u^{pub}, (ek)_u^{pub}, \sigma_u) ← SIG.Sign((k)_u^{sig}, (sk)_u^{pub} || (ek)_u^{pub}).
6. **Step 6:** E and S verify SIG.Verif((k)_u^{ver}, (sk)_u^{pub} || (ek)_u^{pub}, \sigma_u) = 1 and forward e_j ⇒ U'_j : (u, (sk)_u^{pub}, (ek)_u^{pub}, \sigma_u).
7. **Step 7:** Other users in U'_j verify whether SIG.Verif((k)_u^{ver}, (sk)_u^{pub} || (ek)_u^{pub}, \sigma_u) = 1.
8. **Step 8:** u ∈ U'_j computes the shares of shared key \{(sk)_u^{pri} \} by invoking \{(u, c_{u,v})\} \forall v ∈ U'_j \leftarrow SS.share((sk)_u^{pri}, t, n).
9. **Step 9:** u ⇒ e_j ⇒ v : c_{u,v} ← IDE.Enc(KEY.Agr((ek)_u^{pri}, (ek)_v^{pri}), u||v||ζ^k_{u,v}).
10. **Step 10:** u ∈ U'_j decrypts ζ^k_{u,v} ← IDE.Dec(KEY.Agr((ek)_u^{pri}, (ek)_v^{pri}), c_{u,v}), and collects \mathcal{R}_u = \{(v, c_{u,v}) \} v ∈ U'_j.
11. **Step 11:** S randomly selects a feature sub-sample \mathcal{Q}' from full feature set \mathcal{Q}.
12. **Step 12:** S invokes SecFind(\mathcal{Q}', U', \mathcal{E}, ((u, \mathcal{R}_u))_{u ∈ \mathcal{U}' }) to determine the current optimal split.
13. **Step 13:** Repeat **Step 3** until reaching the termination condition.
Protocol 2 Secure Split Finding (SecFind)

**Input:** All candidate features \( A = \{\alpha_1, \alpha_2, ..., \alpha_m\} \), the user set \( U = \{U_1, U_2, ..., U_0\} \), the edge server set \( E \), the secret mask \( \{(u, R_u)\}_{u \in U_1}, \{(u, R_u)\}_{u \in U_2}, ..., \{(u, R_u)\}_{u \in U_0}\). 

**Output:** The optimal split for feature \( \alpha \) and its score.

1. for \( 1 \leq j \leq \theta \) do
   2. Each \( u \in U_j \) generates a random value \( r_u \) and its random shares \( \{(u, c^r_u)\}_{v \in U_j} \leftarrow SS.share(r_u, t, n) \).
   3. \( u \Rightarrow e_j \Rightarrow v : c_{u,v} \leftarrow IDE.Enc((ek)^{share}_{u,v}, u||c^r_u) \).
   4. Each \( v \in U_j \) receives \( c_{u,v} \) and decrypts \( c^r_u \leftarrow IDE.Dec((ek)^{share}_{u,v}, u||c^r_u) \).
5. end for

6. for \( 1 \leq j \leq \delta \) do
   7. \( u \in U_j \) extracts \( c^s_{u,u} \) from \( R_u \) and computes \( c^H_u \leftarrow \sum_{1 \leq k \leq D_a^u} h_k + r_u + \sum_{v \in U_j, u<v} c^s_{u,v} - \sum_{v \in U_j, u>v} c^s_{v,u} \), \( c^G_u \leftarrow \sum_{1 \leq k \leq D_a^u} g_k + r_u + \sum_{v \in U_j, u<v} c^s_{u,v} - \sum_{v \in U_j, u>v} c^s_{v,u} \).
   8. \( u \Rightarrow e_j : c_{u,e_j} \leftarrow IDE.Enc((ek)^{share}_{u,e_j}, c^H_u || c^G_u || \{c^r_u\}_{v \in U_j}) \).
   9. \( e_j \) decrypts \( c_{u,e_j} \) and reconstructs \( r_u = SS.Recon(\{c^r_u\}_{v \in U_j}, t) \).
   10. \( e_j \Rightarrow S : H_j \leftarrow IDE.Enc((ek)^{share}_{e_j,S}, \sum_{u \in U_j} (c^H_u - r_u)), G_j \leftarrow IDE.Enc((ek)^{share}_{e_j,S}, \sum_{u \in U_j} (c^G_u - r_u)) \).
11. end for

12. \( S \) calculates \( H \leftarrow \sum_{j=1}^{\theta} IDE.Dec((ek)^{share}_{e_j,S}, H_j) \) and \( G \leftarrow \sum_{j=1}^{\theta} IDE.Dec((ek)^{share}_{e_j,S}, G_j) \).
13. for \( 1 \leq q \leq \delta \) do
14. \( S \) enumerates every possible candidate split \( A_{\alpha q} = \{a_1, a_2, ..., a_m\} \) for feature \( \alpha_q \) and publishes them to each user \( u \in U \) through \( E \).
   15. \( u \in U_j \) computes \( c^{H,L}_{u,u} \leftarrow \sum_{a_1 \leq a \in A_m} h_l + r_u + \sum_{v \in U_j, u<v} c^s_{u,v} - \sum_{v \in U_j, u>v} c^s_{v,u} \) and \( c^G_{u,u} \leftarrow \sum_{a_1 \leq a \in A_m} g_l + r_u + \sum_{v \in U_j, u<v} c^s_{u,v} - \sum_{v \in U_j, u>v} c^s_{v,u} \).
   16. \( u \Rightarrow e_j : c_{u,e_j} \leftarrow IDE.Enc((ek)^{share}_{u,e_j}, c^{H,L}_{u,u} || G_{l,u}) \).
   17. \( e_j \Rightarrow S : H^L_j \leftarrow IDE.Enc((ek)^{share}_{e_j,S}, \sum_{u \in U_j} c^{H,L}_{u,u} - r_u), G^L_j \leftarrow IDE.Enc((ek)^{share}_{e_j,S}, \sum_{u \in U_j} (c^G_{u,u} - r_u)) \).
18. \( S : H^L \leftarrow \sum_{j=1}^{\theta} IDE.Dec((ek)^{share}_{e_j,S}, H^L_j), H_R = H - H^L \) and \( G^L \leftarrow \sum_{j=1}^{\theta} IDE.Dec((ek)^{share}_{e_j,S}, G^L_j), G_R = G - G^L \).
19. \( S \) then obtains \( score \leftarrow \max(score, \frac{G_R^2}{H_R + \lambda} + \frac{G_L^2}{H_L + \lambda} - \frac{G^2}{H + \lambda}) \).
20. end for
21. return the split with maximum score.

D. Model Privacy Protection with Secure Prediction

For existing federated learning schemes, an indispensable operation is to refresh each user’s local model at the end of each round of training [8]. The refreshed model is used for obtaining prediction results to update the \( y_i^{k-1} \) in Eq. [1] that are essential to the next round of training. However, users are honest-but-curious entities. They potentially steal the model information to benefit themselves (e.g. sell the model to the competitors of \( S \)). To prevent the privacy leakage, we provide an optional security service in FEDXGB to protect the privacy of models. Instead of transmitting the newly generated CART model in plaintext, FEDXGB executes a lightweight secret sharing protocol SecFred, presented in Protocol [3] to proceed the prediction.

In SecFred, \( S \) takes a CART as input and \( U \) takes as input the weights of leaf nodes in the CART. \( S \) and \( U \) secretly and separately send the shared model parameters (optimal split for each node) and user data to edge servers. Then, \( E \) executes SecCmp and returns the comparison results to the corresponding user. Finally, \( U \) decides the leaf node for each sample based on the comparison results and collects prediction results. In this way, we guarantee nodes of the CART are unable to be accessed by \( U \) and \( E \).

E. Robustness Against User Dropping Out.

In FEDXGB, the problem of user dropping out (UDO) might happen during the model training process. It is categorized into the following three cases. The feasibility of the countermeasures to UDO is based on the incremental learning, an online learning method supported by XGBoost [16].

Case 1: A user \( u_0 \) drops out at the Step 1 or Step 2 of Protocol [1]. Thus, \( E \) cannot receive messages from \( u_0 \) anymore. In such case, \( E \) just refuses \( u_0 \) to be involved in
Denote the views of user and edge server as proof.

Theorem 2. The protocol \( \text{view} \) for the adversary \( \xi \) is a probabilistic polynomial-time simulator. We say that a protocol \( \pi \) recovers the secret mask of \( e_k \) in the real world and the view is computationally indistinguishable from its real view.

Theorem 1. The protocols \( \text{SecFind} \) is secure in the honest-but-curious security model. proof. Denote the views of user and edge server as \( \mathcal{V}_u = \{\text{view}_{u_1}, ..., \text{view}_{u_n}\} \) and \( \mathcal{V}_e = \{\text{view}_{e_1}, ..., \text{view}_{e_q}\} \). From the operation process of \( \text{SecFind} \), we can derive \( \text{view}_{u_0} = \{\text{view}_{u_1}, \text{view}_{u_2}, ..., \text{view}_{u_n}\} \) as mentioned in [17]. And for the edge server and the cloud server, their views \( \{\text{view}_{e_1}, ..., \text{view}_{e_q}\} \) and \( \{\text{view}_{e_1}, ..., \text{view}_{e_q}\} \) are simulatable for the simulator \( \xi \) and the simulated views cannot be distinguished in polynomial time by the adversary. Based on Definition 1, \( \text{SecBoost} \) is proved to be secure.

Lemma 1. A protocol is perfectly simulatable if all its sub-protocols are perfectly simulatable.

VI. PERFORMANCE EVALUATION

In this section, we conduct several extensive experiments to evaluate the effectiveness and efficiency of \( \text{FedXGB} \).

A. Experiment Configuration

Environment. We utilized an Ubuntu 16.04 desktop, with an Intel(R) Core(TM) i7-7920HQ CPU @3.10GHz and 64.00GB of RAM, to serve as our central server. Additionally, we set up ten desktops (Ubuntu 16.04) with an Intel(R) Core(TM) i5-7400 CPU @3.00GHz and 8.00GB of RAM. By launching multiple processes, each of them simulates at most two edge servers. We also deployed 50 standard BeagleBone Black development boards, that runs Ubuntu 14.04, AM335
Dataset. We collected two datasets commonly applied on mobile apps. ADULT\(^2\) and MNIST\(^3\) which contain 48k instances with 123 features and 70k instances with 784 features, respectively. The dataset of ADULT is for adult income prediction, i.e., binary classification, which provides 32k instances are training data and 16k instances are for testing. The dataset of MNIST is for handwriting digit classification, i.e., multiple classification, which divides the instances into 60k for training and 10k for testing.

Setup. We set up parameters in FedXGB as, step size \(\eta = 0.3\), minimum loss reduction \(\gamma = 0.1\), regulation rate \(\lambda = 1.0\), user number \(n = 300\), maximum tree depth \(d_{\text{max}} = 3\), and edge server number \(\theta = 10\). We used Elliptic-Curve Diffie-Hellman\(^{21}\) over the NIST P-256 curve, composed with a SHA-256 hash, to fulfill key agreement. Authenticated encryption is operated by 128-bit AES-GCM\(^{22}\). Given each dataset, we averagely assigned the instances to each user. User dropout is assumed to occur every 10 rounds of boosting in our experiment. that is, 0%, 10%, 20%, 30% of users are randomly selected to be disconnected at each 10\(^{th}\) round of training. Meanwhile, the same number of replacements are rearranged to substitute the lost users.

B. Effectiveness Analysis

To assess the effectiveness of FedXGB, we computed the classification accuracy and loss by comparing FedXGB and the non-federated XGBoost. The loss functions are the logistic regression for ADULT and the softmax for MNIST. Fig. 3 presents the accuracy and loss of each round of training in FedXGB. More specific, Fig. 3(a) and Fig. 3(b) describe the accuracy and loss of ADULT, and Fig. 3(c) and Fig. 3(d) show the result of MNIST. Compared with XGBoost, FedXGB only introduces the accuracy loss with less than 1%. Consider the user dropout rate increased from 0% to 30%, FedXGB is robust against the user changes during online training.

C. Efficiency Analysis

1) Theoretically Analysis: The theoretical analysis of computation cost for SecBoost, SecFind and SecPred in Table I Represent \(|D|\) as the number of training instances. The computation costs of each user, each edge server and the central server for SecBoost are \(O((n/\theta + (n/\theta) \cdot d_{\text{max}} \cdot |D|))\), \(O((n/\theta + (n/\theta)^2 \cdot d_{\text{max}} |D|))\) and \(O(n + \delta d_{\text{max}})\). As shown in Protocol I, SecBoost has four steps. Since the system setup stage can be operated offline, its computation and communications cost are ignored. The remaining three steps are divided into two parts. One part contains the second and third steps. In the part, each user executes \(2(n/\theta)\) key agreement, signature and encryption operations, which take \(O(n/\theta)\) time. Each edge server executes \(n/\theta\) signature operations, which also take \(O(n/\theta)\) time. The central server executes \(n\) signature operations, which take \(O(n)\) time. The other part is composed of \(d_{\text{max}}\) invocation of SecFind. And for SecFind, the derivate aggregation is operated for \(\delta\) times, which takes \(O((n/\theta) \cdot \delta |D|), O((n/\theta)^2 \cdot \delta |D|)\) and \(O(\delta \cdot |D|)\) for each user, each edge server and the central server. As for the SecPred, it invokes \(d_{\text{max}}\) SecCmp, which takes \(O(|D|)\), \(O(d_{\text{max}} |D|)\) and \(O(d_{\text{max}})\) time.

2) Experiment Results: In order to further evaluate the efficiency of FedXGB, we then experiment with the runtime and communication overhead under different user numbers and edge server numbers as shown in Fig. 4. In the experiments, we set \(|D| = 50K\) and \(\delta = 100\).

Number of Users. When the involved users increase, the runtime for each user grows linearly, and inversely, the communication overhead for each user decreases, shown in Fig. 4(a) and Fig. 4(b), respectively. The linear growth of the runtime is caused by the incremental cost of user selection and secret mask collection steps. And due to the less samples distributed to each user, the communication overhead for each user decreases. The user dropout rate barely influences the runtime because the correlated active user only need to transmit one secret sharing for secret mask reconstruction. Considering the impact of the incremental user number performed on each edge server, the runtime for each edge server follows the quadratic growth, described in Fig. 4(c). The data reconstruction for dropped users has the main effect on the increase of the runtime cost. Nonetheless, the communication overhead is barely influenced because only a little overhead increment is caused for the secret mask collection. The increase of client number can only bring a little more secret mask transmission overhead, yet the higher

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\(^{2}\)ADULT: https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/binary.html

\(^{3}\)MNIST: http://yann.lecun.com/exdb/mnist/
TABLE II

|                  | User                              | Edge Server                      | Central Server                  |
|------------------|-----------------------------------|-----------------------------------|---------------------------------|
| SecBoost         | \(O(n/\theta + (n/\theta) \cdot d_{max} | \(O(n/\theta + (n/\theta)^2 \cdot d_{max} | \(O(n + \theta d_{max})|
| SecFind          | \(O(n/\theta \cdot | \(O((n/\theta)^2 \cdot | \(O(\theta) |
| SecPred          | \(O(|D|)                      | \(O(d_{max}|D|)                 | \(O(d_{max})                  |

Fig. 4. Efficiency Analysis with different numbers of users and edge servers.

(a) Runtime per user with different number of users.
(b) Communication overhead per user with different number of users.
(c) Runtime per edge server with different number of users.
(d) Communication overhead per edge server with different number of users.
(e) Runtime for the central server with different number of users.
(f) Runtime per user with different number of edge servers.
(g) Runtime per edge server with different number of edge servers.
(h) Communication overhead per edge server with different number of edge servers.

TABLE III

| Stage               | RunTime (s)        |
|---------------------|--------------------|
|                     | User | Edge Server | Central Server |
| User Selection      | 0.285 | 1.112       | 3.288          |
| Mask Collection     | 1.333 | 1.458       | N.A.           |
| Boosting            | 18.802 | 23.308     | 26.863         |
| Secure Prediction   | 5.182 | 5.987       | 6.961          |
| Total               | 25.602 | 31.865     | 37.112         |

user dropout always causes more time to reconstruct lost data via the time-consuming Lagrange polynomials. Specially, the central server deploys less computation tasks than edge server, but has more runtime as illustrated in Fig. 4(e). The phenomenon is caused by the reason that the central server has to wait for collecting every edge server’s response to continue subsequent computation. The communication overhead plots about central server are omitted, because, for central server, its communication overhead is just the edge server number multiplied the difference between the edge server overhead and the user overhead.

**Number of Edge Servers.** When the involved edge servers increase, the runtime cost for each user decreases, illustrated in Fig. 4(f). Because the number of user in each domain managed by each edge server reduces, the computational cost of secret sharing also becomes less for each user. Similarly, the runtime cost of each edge server decreases, Fig. 4(g) while the computation of secret sharing assigned on each edge server reduces. As more edge servers are involved for computation, the communication overhead of each server decreases, shown in Fig. 4(h). For each user, the communication overhead does not have obvious change because the assigned instances are static. And the cost of central server performs similar to Fig. 4(e) with 300 users. Due to the space limitation, we omit these two plots in this paper.

In Table III we list the runtime cost of different stages in FedXGB. It indicates that the major overhead in FedXGB is caused by the boosting stage, namely, the optimal split finding algorithm, because numerous loop operations are proceeded.

D. Defense Against User Data Reconstruction Attack

Reconstruction attack [6, 11] is one of the most common and effective attacks against federated learning. Based on the generative adversarial networks (GAN), the attack reconstructs user data by solving an optimization problem. However, FedXGB is protected against such GAN-based
attack because the CART in FedXGB partitions the input space into discrete regions and the optimization problem is unable to be resolved. In order to validate how well FedXGB is protected, we conducted two experiments by launching the user data reconstruction (UDR) attack against the federated learning approach [8] and FedXGB. We use the dataset of MNIST and the results are shown in Fig. 5.

The left column of Fig. 5 illustrates that the federated learning approach is attacked successfully. The attacker (i.e., the central server), $S$, first collects the gradient aggregations uploaded by the specific victim $\nabla G_v$ and other users $\nabla G_i$, $1 \leq i \leq n - 1$. Based on $\nabla G_v$ and $\nabla G_i$, the attacker derives the representatives $X_i$ of the victim by solving the optimization problem $Op = \arg \min_{\hat{G}} ||\nabla G_v - \nabla G_{\hat{G}}||^2 + \Omega_{\hat{G}}$, where $\Omega_{\hat{G}}$ is a regularization item and $\nabla G_{\hat{G}}$ is the gradient of $X_i$. Given $X_i$, GAN outputs almost identical images.

The right column of Fig. 5 presents the UDR attack launched on FedXGB. Suppose that $\nabla G_i$ is the gradient aggregation obtained by an edge server $e_j$, the attacker, $e_j$, is unable to solve the optimization problem $Op$. Because of the discrete input, the optimizer can only advance towards random directions and outputs images that looks like random noises. And the gray-level frequency histograms in the last row of Fig. 5 further illustrate that, for FedXGB, UDR can hardly fit the features of original images.

### Conclusion

In this paper, we proposed a privacy-preserving federated extreme boosting learning framework for crowdsensing applications. For securely building classification and regression forest in the extreme boosting way, we designed a series of secret sharing based protocols. The protocols guaranteed that the privacy of user data, learning gradients and model parameters were simultaneously preserved during the model training process of XGBoost. Moreover, comprehensive experiments were operated to evaluate the performance of FedXGB. Experiment results showed that, with FedXBG, we could let massive crowdsensing users work together to efficiently train a high-performance extreme boosting model with no need to concern about data privacy leakage.

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