OPSA: Efficient and Verifiable One-Pass Secure Aggregation with TEE for Federated Learning

Zhangshuang Guan, Yulin Zhao, Zhiguo Wan, and Jinsong Han

***Abstract*—In federated learning, secure aggregation (SA) protocols like Flamingo (S&P'23) and LERNA (ASIACRYPT'23) have achieved efficient multi-round SA in the malicious model. However, each round of their aggregation requires at least three client-server round-trip communications and lacks support for aggregation result verification. Verifiable SA schemes, such as VerSA (TDSC'21) and Eltaras et al.(TIFS'23), provide verifiable aggregation results under the security assumption that the server does not collude with any user. Nonetheless, these schemes incur high communication costs and lack support for efficient multi-round aggregation. Executing SA entirely within Trusted Execution Environment (TEE), as desined in SEAR (TDSC'22), guarantees both privacy and verifiable aggregation. However, the limited physical memory within TEE poses a significant computational bottleneck, particularly when aggregating large models or handling numerous clients.**

In this work, we introduce OPSA, a multi-round one-pass secure aggregation framework based on TEE to achieve efficient communication, streamlined computation and verifiable aggregation all at once. OPSA employs a new strategy of revealing shared keys in TEE and instantiates two types of masking schemes. Furthermore, a result verification module is designed to be compatible with any type of SA protocol instantiated under the OPSA framework with weaker security assumptions. Compared with the state-of-the-art schemes, OPSA achieves a 2$\sim$10$\times$ speedup in multi-round aggregation while also supporting result verification simultaneously. OPSA is more friendly to scenarios with high network latency and large-scale model aggregation.

***Index Terms*—Federated learning, secure aggregation, verifiable aggregation, trusted execution environment.**

I. Introduction

FEDERATED learning (FL) represents a paradigm shift in machine learning, replacing traditional centralized model training methods with decentralized collaborative frameworks [1]. In this approach, a global machine learning model is trained on multiple decentralized devices with the assistance of a server, each possessing its own local dataset. The distinguishing feature of FL is that model updates are computed locally on these devices and uploaded to the server, eliminating the necessity to transfer raw data to a central server. These devices (clients) and the server engage in interactions through the above operations for multiple rounds, ultimately achieving a convergent model. However, the original model update may also lead to the leakage of original private data [2], [3].

To protect the privacy of model updates, *secure aggregation* (SA) has been designed for model aggregation in FL. Its core idea is that each client protects its local model in a certain manner, the server then aggregates all hidden models to recover a plaintext aggregated model. Furthermore, the secret sharing scheme is used to ensure that the aggregated model can still be recovered after some clients drop out, but this results in each round of SA under the malicious model requiring four client-server round-trip communications: (1) secret sharing; (2) model transmission; (3) dropout list confirmation; (4) secret reconstruction. The above idea is first proposed by Bonawitz et al. [4][1], upgraded by Bell et al. [5], and subsequently adapted into various variants [6], [7]. However, these schemes are suitable for a single FL round, as each aggregation requires each client to regenerate its key and share it with others, which greatly increases the communication burden.

Fortunately, MicroFedML [8] addresses this issue by introducing a one-time setup phase to reuse secrets, Flamingo [9] designs a multi-round SA protocol based on a double masking scheme while LERNA [10] achieves the same goal based on a single masking mechanism. While these schemes eliminate one client-server round-trip communication through the reusable setup phase, they still require three client-server round-trip communications for each round of SA (as shown in Fig. 1), which poses a challenge for scenarios with high network latency or limited bandwidth. In fact, these multi-round SA protocols improve performance by introducing an additional group, such as decryptors in Flamingo and a committee in LERNA, which can be treated as a singular entity – essentially acting as a trusted party. Given this observation, could we potentially leverage hardware-based trusted execution environment (TEE) instead of the special group to optimize three client-server round-trip communications of SA into one-pass aggregation? Moreover, all the single-round and multi-round SA protocols mentioned above lack support for the verifiability of aggregation results, which can be forged by malicious servers (e.g., false aggregation) to launch privacy attacks [11]–[13]. While many verifiable SA schemes [14]–[18] have been proposed under different security assumptions, they all incur high communication costs and lack support for efficient multi-round aggregation.

While the trivial approach of executing SA entirely within TEE ensures both privacy and verifiable aggregation, the limited physical memory within TEE poses a significant

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[1]We write the SecAgg and SecAgg+ term as [4] and [5], respectively.

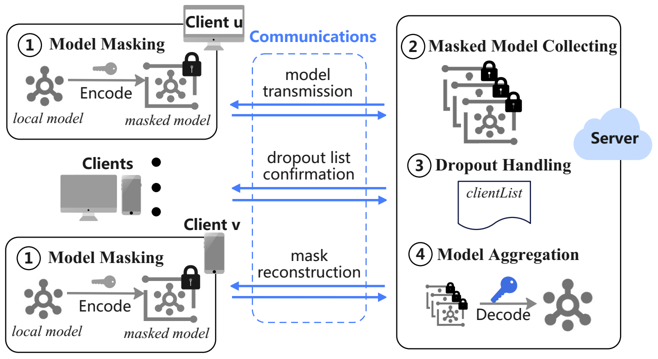

Fig. 1: Workflow of the state-of-the-art SA schemes

computational bottleneck, especially when aggregating large models or handling numerous clients. For example, a global model containing a million parameters takes about 3.8MB of memory, with each parameter represented in 4 bytes. However, in scenarios involving hundreds of clients, the memory requirements can easily exceed the 128MB physical memory capacity of TEE. To address this issue, SEAR [19] adopts a strategy of aggregating one layer of the models at a time. However, this approach does not alleviate the overall computation burden on TEE, and similar challenges may arise when processing layers with a large number of parameters. Of course, sparse gradient aggregation can reduce TEE memory usage, but Kato et al. [20] have introduced an attack targeting the gradient index within TEE.

In this work, we employ modularity to design a multi-round one-pass aggregation framework based on hardware-based TEE. Our key idea is for each client to share a secret seed with the server-side TEE and then utilize it to generate a mask for its local model. The server knows only the sum of the secret seeds but not any individual secret seed, so it cannot recover the mask of any client. Note that the secret seeds are never disclosed to the server, even in case of client dropout. As such, we propose OPSA, a highly efficient secure aggregation framework for FL. Our contributions can be summarized as follows:

- We propose OPSA, a multi-round one-pass secure aggregation framework based on hardware-based TEE to achieve efficient communication, streamlined computation and verifiable aggregation all at once. It addresses the performance bottleneck of TEE capacity for high-dimensional models and allows secret seeds to be shared only once and used forever. Based on this framework, we instantiate two types of SA protocols: a single masking scheme KhPRF-OPSA and a double masking scheme POT-OPSA, both of which only require one client-server round-trip communication during aggregation.
- We design a result verification module OPSA-RV to protect against forged aggregation results using commitments and proofs. Compared with state-of-the-art schemes, this module is compatible with any type of SA protocol instantiated under the OPSA framework and can be easily utilized to construct a communication-efficient multi-round verifiable SA protocol under the weaker security assumption that a malicious server can collude with any semi-honest client.
- We provide a rigorous security analysis to establish the theoretical safety guarantees of the OPSA framework. Furthermore, we implement two types of SA protocols instantiated under the OPSA framework and conduct extensive experiments to evaluate them alongside the state-of-the-art schemes for a comprehensive cost comparison. The results demonstrate that our framework performs well in terms of dropout resilience and efficiency.

II. Preliminaries

Before introducing the preliminaries, we list the notations used in this work.

Notations. Unless specified otherwise, we use λ to denote the security parameter, lowercase letters (e.g., n, k, r) to denote scalars, and bold lowercase letters (e.g., $\mathbf{x}, \mathbf{y}, \mathbf{k}$) to denote vectors. The format $\{s_u\}_u$ denotes a set of values indexed by u. The variable $\mathbf{x}_u^{(r)}$ denotes the input vector $\mathbf{x}$ held by client u in round r. The sets $\mathcal{U}, \mathcal{D}, \mathcal{V}$, where $\mathcal{U} = \mathcal{D} \cup \mathcal{V}$, contain all clients, dropped clients, and surviving clients, respectively. Note that we use the terms “user” and “client” interchangeably.

A. *Federated Learning*

A general federated learning (FL) scenario involves n clients and a server, all participants repeat the following processes for each round r until the current global model $\boldsymbol{\theta}^{(r)}$ converges:

- Local training: each client $u \in \mathcal{U}$ receives the global model $\boldsymbol{\theta}^{(r-1)}$, which is trained and aggregated in the previous round, and combines it with its private dataset to train a local model $\mathbf{x}_u^{(r)}$ to be sent to the server.
- Model aggregation: the server collects the individual model $\mathbf{x}_u^{(r)}$ from distinct clients and computes an aggregated model $\mathbf{z}^{(r)} = \sum_{u \in \mathcal{V}} \mathbf{x}_u^{(r)}$ to update the global model $\boldsymbol{\theta}^{(r)}$ to be delivered to clients for next round.

Note that these clients can drop out at any steps in each FL training round.

B. *Trusted Execution Environment*

Trusted Execution Environment (TEE), whose notable implementations include Intel Software Guard Extensions (SGX) and ARM TrustZone, is a hardware solution designed to ensure computational integrity and confidentiality by creating a secure and isolated space, often referred to as an enclave, where the data and its sensitive computations can be performed without the risk of interference or compromise. In particular, TEE allows remote users to verify the application and the hardware it is running via remote attestation.

Given the widespread use of Intel SGX in personal computers and cloud computing servers, we leverage it for secure aggregation in FL. However, Intel SGX presents the following challenges in achieving efficient SA protocols: (1) limited physical memory, Intel SGX v1 only has 128MB physical memory, exceeding its limit results in high overhead; (2) data transmission overhead, the SGX application is divided into trusted and untrusted parts, transmitting data between the two parts will incur significant overhead due to additional encryption/decryption operations; (3) side-channel attacks, which are an important factor to be considered, although they are not part of the Intel SGX threat model [21].

In this work, we assume that Intel SGX is trusted but with fewer cryptographic primitives and less data to be loaded into its enclave. The enclave stores a different shared key $k_{e,u}$ for each client $u \in \mathcal{U}$. Moreover, side-channel attacks are excluded from the scope of this work, as we can integrate some countermeasures [22], [23] into our framework to protect against them, and we also consider the prevention of side-channel information leakage as a responsibility falling more on enclave developers.

C. Cryptographic Primitives

In our protocols, we will employ the following cryptographic primitives for randomness generation and secure communication. A cryptographically secure pseudo-random generator (PRG) takes a uniformly random seed of some fixed length and outputs a string that is computationally indistinguishable from a random string; for example, it can be instantiated with AES-CTR in practice [4]. A cryptographically secure pseudo-random function (PRF) indexed by a key can also be regard as the PRG. A secure key-agreement (KA) protocol enables any user to input their private key and the public key of the other party, producing a shared secret key as output; for example, it can be instantiated with a Diffie–Hellman key agreement protocol followed by a key derivation function in practice [4], [5]. A standard secure signature scheme $\Pi_\sigma = (\mathsf{Sign}, \mathsf{VerSig})$ that is existentially unforgeable under chosen message attacks (EUF-CMA); for example, it can be instantiated with ECDSA followed by a key derivation function in practice. A commitment scheme that is perfectly hiding and computationally binding under the discrete logarithm assumption; for example, it can be instantiated with vector Pedersen commitment in practice [7].

III. OPSA Framework

In this section, we first give a threat model, and then present our OPSA framework after describing its high-level ideas.

A. Threat Model

Let $N = |\mathcal{U}|$, there are N clients and a single untrusted server equipped with TEE, each client u holds a local model $\mathbf{x}_u$, and all clients want to obtain the summation $\sum \mathbf{x}_u$ with the help of the server S revealing nothing about $\mathbf{x}_u$. Note that in FL, clients and the server need multiple rounds of aggregation to obtain the final converged model. Like previous works MicroFedML [8] and Flamingo [9], we target the following failures and attacks: (1) honest clients that may dynamically drop out or respond too slowly due to factors such as unstable network conditions, power loss, etc.; and (2) arbitrary actions by an adversary who has control over the server and a bounded fraction of the clients.

Overall, in any given aggregation round, we assume that at most $\delta \in [0,1]$ fraction of N clients drop out during any step,

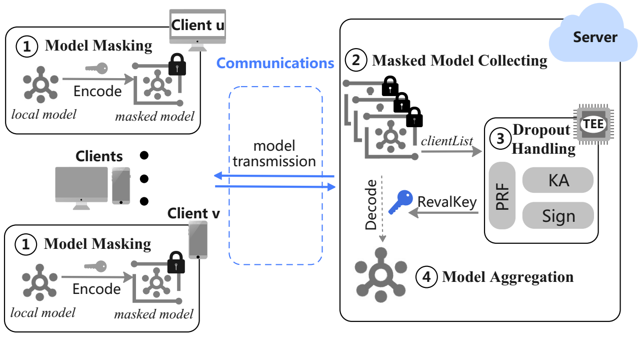

Fig. 2: Workflow of OPSA

and that the adversary compromises γN clients before each aggregation round begins, where $\gamma \in [0,1]$ is a maximum fraction of corrupt clients, possibly also colluding with the server. For KhPRF-OPSA and POT-OPSA, we also assume the server is fully malicious, but for OPSA-RV we prove security only in the case of semi-honest clients.

B. Intuition of the idea

Applying masks to local models has become an effective way to protect privacy in FL: each client masks its local model using a shared key, and then the server utilizes revealed keys to remove these masks during model aggregation. However, this method mandates each client to regenerate and share a new key per round, along with requiring at least three client-server round-trip communications to achieve dropout resilience. Moreover, message authentication codes (MACs) are commonly employed to verify the aggregation results, but it incurs a doubling of the communication cost.

We can utilize TEE for secure aggregation to address the aforementioned issues. However, the memory limit of TEE becomes a severe computational bottleneck, particularly when aggregating high-dimensional models or handling a large number of clients. To address such dilemma, we adopt a distinct strategy leveraging TEE for managing shared keys, with model aggregation and mask elimination performed outside TEE. Importantly, our mask computation requires a shared key, which is established between each client and TEE, ensuring that TEE can handle dropout to help server remove masks. We require that the inputs and cryptographic primitives run within TEE are as minimal as possible.

We give a brief workflow of OPSA in Fig. 2. At first, a shared key $k_{u,e}$ is generated between client u and the server's TEE through a key agreement protocol. For each round r, each client u utilizes $k_{u,e}$ to mask it local model $\mathbf{x}_u$ as follows:

$$\mathbf{y}_u = \mathbf{x}_u + \mathsf{Encode}(k_{u,e}, r)$$

Subsequently, the server collects masked models $\mathbf{y}_u$ from distinct clients to obtain an aggregated model as follows:

$$\mathbf{y} = \sum \mathbf{x}_u + \sum \mathsf{Encode}(k_{u,e}, r)$$

Given a list of surviving clients $\mathcal{V}$, the TEE can reveal some variants of shared keys $\{k'_{u,e}\}_{u \in V}$ to help the server unmask the aggregated model as follows:

$$\sum \mathbf{x}_u = \mathbf{y} - \mathsf{Decode}(\{k'_{u,e}\}_{u \in V}, r)$$

Finally, the server forms a proof proving that $\sum \mathbf{x}_u$ is correctly aggregated according to masked models received from distinct clients in the surviving list.

C. OPSA framework

Before introducing our OPSA framework, we formally define a multi-round SA protocol as follows:

Definition 1 (Multi-round SA protocol)**.** *A multi-round SA protocol involving a client set $\mathcal{U}$, a server S, and an integer R, consists of two phases:*

- **Setup phase***: it is executed only once at the initiation of the protocol.*
- **Training phase***: for round $r \in [1, R]$, the SA protocol is executed once, beginning with a client generating its local model $\mathbf{x}_u^{(r)}$ and ending with the server computing an aggregated model $\sum \mathbf{x}_u^{(r)}$.*

Based on the provided definition, our OPSA framework consists of three functional parts: one-time setup in the Setup phase, one-pass aggregation in the Training phase, and result verification in the Training phase. The red parts are required to provide verifiable aggregation results and are not required for the malicious setting.

One-Time Setup. During setup phase, all clients and the server execute the following Setup algorithm respectively to correctly generate public parameters.

- $\mathsf{pp} \leftarrow \mathsf{Setup}(1^\lambda, m)$: takes as inputs a security parameter λ, and a model dimension m. It outputs public parameters pp, which defines a key space $\mathcal{K}$, a model space $\mathcal{M}$, a mask space $\mathcal{Y}$, and commitment parameters $\mathsf{pp}_{\mathsf{com}}$.

Then, the server loads a program code into its TEE to create an instance, and distributes an initial global model to all clients. After verifying the correctness of the server's TEE instance through remote attestation, each client accepts the initial global model and proceeds to a FL training round.

We assume that all parties (client u, server S, and TEE instance M_e) have its own authenticated key pair (pk_*, sk_*) based on Public Key Infrastructure (PKI). Each client u can establish a key agreement with TEE instance M_e as a root seed to reuse its secret key as follows:

$$k_{u,e} = \mathsf{KA}(sk_u, pk_e) = \mathsf{KA}(sk_e, pk_u) = k_{e,u}. \qquad (1)$$

Note that all parties initialize a round as $r = 1$, and the TEE instance sets an extra round as $r_e = 0$. The constraint $r > r_e$ means that the server can only invoke the TEE instance only once in round r.

One-Pass Aggregation. Based on reusable shared keys and TEE, a SA protocol can be optimized to a version with one client-server round-trip communication, as long as the SA protocol can implement the following algorithms:

- $\mathbf{mask}_u \leftarrow \mathsf{Encode}(\mathsf{pp}, \mathsf{shKey}, r)$: takes as inputs public parameters pp, a set of shared keys shKey, and round r. It outputs a one-time mask $\mathbf{mask}_u$.
- $(\mathsf{reKey}, \mathsf{rand}) \leftarrow \mathsf{RevealKey}(\mathsf{pp}, \mathcal{V}, \mathcal{D}, r)$: takes as inputs public parameters pp, a list of surviving clients $\mathcal{V}$, a dropout list $\mathcal{D}$, and round r. It outputs a set of revealed keys reKey and a revealed random number rand.
- $\sum \mathbf{mask}_u \leftarrow \mathsf{Decode}(\mathsf{pp}, \mathsf{reKey}, r)$: takes as inputs public parameters pp, a set of revealed keys reKey, and round r. It outputs an aggregated mask $\sum \mathbf{mask}_u$.

More specifically, for each FL training round r, client $u \in \mathcal{U}$ runs the Encode algorithm to mask its local model $\mathbf{y}_u^{(r)} = \mathbf{x}_u^{(r)} + \mathsf{Encode}(\mathsf{pp}, \mathsf{shKey}, r)$. After obtaining the revealed keys $\mathsf{reKey} = \mathsf{RevealKey}(\mathsf{pp}, \mathcal{V}, \mathcal{D}, r)$ from the TEE instance, the server computes the plaintext aggregation model $\sum \mathbf{x}_u^{(r)} = \sum \mathbf{y}_u^{(r)} - \mathsf{Decode}(\mathsf{pp}, \mathsf{reKey}, r)$.

Result Verification (RV). To provide verifiable aggregation results, we divide the aggregation verification into two parts: a valid aggregation range, secured through the combination of a commitment scheme and TEE integrity, and an accurate aggregation result, guaranteed by a proof. Overall, the output of TEE, protected by its integrity, binds a valid aggregation range and proves the accuracy of an aggregation result within that range.

We require that a vector commitment scheme consists of the following sets of algorithms:

- $\mathsf{com}_{\mathbf{v}_i} \leftarrow \mathsf{Commit}(\mathbf{v}_i, \mathsf{rand}_i)$: takes as inputs a vector $\mathbf{v}_i$ and a random number rand_i. It outputs a vector commitment $\mathsf{com}_{\mathbf{v}_i}$.
- $b \leftarrow \mathsf{Open}(\mathsf{com}_{\mathbf{v}'_i}, \mathbf{v}_i, \mathsf{rand}_i)$: this algorithm takes as inputs a commitment $\mathsf{com}_{\mathbf{v}'_i}$, a vector $\mathbf{v}_i$, and a random number rand_i. It outputs a bit b, which equals 1 iff the equation $\mathsf{com}_{\mathbf{v}'_i} = \mathsf{Commit}(\mathbf{v}_i, \mathsf{rand}_i)$ holds.
- $\mathsf{com} \leftarrow \mathsf{Eval}(\{\mathsf{com}_u\}_u)$: takes as input a set of commitments $\{\mathsf{com}_u\}_u$. It outputs a final commitment com.

Each semi-honest client can run the Commit algorithm to commit to its local model $\mathsf{com}_u = \mathsf{Commit}(\mathbf{x}_u, \mathsf{rand}_u)$ where rand_u can be instantiated randomly via its shared key, and sign its commitment to mitigate the risk of a malicious server. Moreover, homomorphic commitments of any vector can be aggregated in the Eval algorithm.

Building upon the commitment scheme described above, a valid aggregation range $\mathcal{V}$ can be processed in TEE, as follows:

- assert: $\forall u \in \mathcal{V}, \mathsf{VerSig}(pk_u, \sigma_u, \mathsf{com}_u) = 1$.
- compute: $(\_, \mathsf{rand}) := \mathsf{RevealKey}(\mathsf{pp}, \mathcal{V}, \mathcal{D}, r)$.
- compute: $\mathsf{com} := \mathsf{Eval}(\{\mathsf{com}_u\}_{u \in \mathcal{V}})$.
- sign: $\sigma_e := \mathsf{Sign}(sk_e, \mathsf{com}||\mathsf{rand}||r)$.
- output: $(\sigma_e, \mathsf{com}, \mathsf{rand})$.

Subsequently, an accurate aggregation result $\sum \mathbf{x}_{u \in \mathcal{V}}$ can be guaranteed by the server, which takes the output of TEE as a proof satisfying the following relation:

$$\begin{cases} \mathsf{VerSig}(pk_e, \sigma_e, \mathsf{com}||\mathsf{rand}||r) = 1 \\ \mathsf{Open}(\mathsf{com}, \sum \mathbf{x}_u, \mathsf{rand}) = 1 \end{cases} \qquad (2)$$

Finally, the server sends the plaintext aggregated model along with its proof to all clients, and each client verifies this global model before initiating a new FL training round.

Putting it all Together. A complete description is provided in Fig. 3, OPSA first performs the Setup algorithm to generate public parameters, the server loads the TEE instance and delivers an initial model, and each client checks the TEE instance through remote attestation and negotiates a shared key with it (**Setup phase**).

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Parties: $N$ clients and a TEE-equipped server.
Let $r := 1$ be the round shared by all parties.
Let $r_e := 0$ be the round maintained by TEE.

Setup phase
  All parties compute $\mathsf{pp} := \mathsf{Setup}(1^\lambda, m)$.
  Server $S$:
  - load TEE instance $M_e$.
  - send the initial global model $\boldsymbol{\theta}^{(1)}$ to clients.
  Client $u \in \mathcal{U}$:
  - verify the validity of the server-side TEE $M_e$.
  - generate a shared key $k_{u,e} := \mathsf{KA}(sk_u, pk_e)$.
Training phase // repeat steps for all $r \in [1, R]$
 1. Mask step.
    Client $u \in \mathcal{U}$:                      // ① model masking
      • receive from the server $\boldsymbol{\theta}^{(r)}$ and a proof, and
        check the proof $\boldsymbol{\pi}^{\mathsf{valid}(\sum \mathbf{x}_u^{(r-1)})}$ if $r > 1$.
      • train a local model $\mathbf{x}_u^{(r)}$ based on $\boldsymbol{\theta}^{(r)}$.
      • send to the server a message $msg_u^{(r)}$ consisting of
        - $\mathbf{y}_u^{(r)} := \mathbf{x}_u^{(r)} + \mathsf{Encode}(\mathsf{pp}, \mathsf{shKey}, r)$,
        - $\mathsf{com}_u^{(r)} := \mathsf{Commit}(\mathbf{x}_u, \mathsf{rand}_u)$,
        - $\sigma_u^{(r)} := \mathsf{Sign}(sk_u, \mathsf{com}_u^{(r)})$.
    Server $S$:                                 // ② masked model collecting
      • collect $msg_u^{(r)}$ from users (denote with $\mathcal{V}^{(r)} \subseteq \mathcal{U}$).
      • $\mathsf{VerSig}(pk_u, \sigma_u^{(r)}, \mathsf{com}_u^{(r)}) = 1$ (otherwise abort).
      • load ($\mathcal{V}^{(r)}$, $\mathcal{D}^{(r)}$, $\{\mathsf{com}_u^{(r)}, \sigma_u^{(r)}\}_u$, $r$) into $M_e$.
 2. Unmask step.
    TEE instance $M_e$:                          // ③ dropout handling
      • if $r_e \geq r$, abort; otherwise, $r_e := r$.
      • assert $|\mathcal{V}^{(r)}| \geq \lceil (1-\delta)N \rceil$.
      • $\mathsf{VerSig}(pk_u, \sigma_u^{(r)}, \mathsf{com}_u^{(r)}) = 1$ for all $u \in \mathcal{V}^{(r)}$.
      • return to the server an output consisting of
        - $(\mathsf{reKey}, \mathsf{rand}) := \mathsf{RevealKey}(\mathsf{pp}, \mathcal{V}^{(r)}, \mathcal{D}^{(r)}, r)$,
        - $\mathsf{com} := \mathsf{Eval}(\{\mathsf{com}_u\}_{u \in \mathcal{V}^{(r)}})$,
        - $\sigma_e := \mathsf{Sign}(sk_e, \mathsf{com}||\mathsf{rand}||r)$.
    Server $S$:                                  // ④ model aggregation
      • $\sum \mathbf{x}_u^{(r)} := \sum \mathbf{y}_u^{(r)} - \mathsf{Decode}(\mathsf{pp}, \mathsf{reKey}, r)$.
      • update $\boldsymbol{\theta}^{(r)}$ to $\boldsymbol{\theta}^{(r+1)}$ using $\sum \mathbf{x}_u^{(r)}$.
      • form $\boldsymbol{\pi}^{\mathsf{valid}(\sum \mathbf{x}_u^{(r)})}$ according to Equation 2.
      • send $\boldsymbol{\theta}^{(r+1)}$ and $\boldsymbol{\pi}^{\mathsf{valid}(\sum \mathbf{x}_u^{(r)})}$ to clients.
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Fig. 3: Detailed description of the OPSA framework. Red parts are required to guarantee result verification (and not necessary in the malicious setting).

Upon receiving the global model, during the **Training phase**, all clients utilize a proof to validate the global model to start a new FL training round. Each client combines the approved global model with its private data to train a local model, which is then encoded as a masked model. To achieve aggregation verification, each client commits to its local model and signs the corresponding commitment. A message, including the masked model, commitment, and signature, is uploaded to the server (① *Model Masking*). Subsequently, the server collects masked models from distinct clients, which are appended into a list of surviving clients. Obtaining a dropout list becomes straightforward once the server has the surviving list, and both lists are then loaded into the TEE instance (② *Masked Model Collecting*). Following that, the TEE instance checks whether it has been invoked in the current round, ensuring it executes only once per round. Utilizing the loaded lists, the TEE instance publishes relevant keys, an aggregated commitment, and its signature to the server (③ *Dropout Handling*). Upon obtaining the output from the TEE instance, the server utilizes the relevant keys to unmask the aggregated model and takes the commitment and the signature as a proof, proving the model's accuracy (④ *Model Aggregation*). Finally, a new global model is updated and sent to all clients for the next round.

IV. Construction

Based on the OPSA framework, we instantiate two types of SA protocols: one is a single masking scheme based on the key-homomorphic pseudo-random function (KhPRF), and the other is a double masking scheme based on proxy oblivious transfer (POT) techniques. Moreover, the one-time setup and the result verification (RV) module are independent of SA protocols, allowing us to share these general modules for both constructions mentioned above.

A. Construction Based on KhPRF

We construct a single masking scheme with KhPRF [24] based on the learning with rounding (LWR) assumption [25].

Definition 2 (LWR [25]). *Given a security parameter λ, let $\ell = \ell(\lambda)$, $q = q(\lambda)$, $p = p(\lambda)$, and moduli $q \geq p \geq 2$ be integers, for a vector $\mathbf{s} \in \mathbb{Z}_q^\ell$, the LWR$_{\ell,q,p}$ assumption states that for any $\mathbf{a} \xleftarrow{\$} \mathbb{Z}_q^\ell$, $b \xleftarrow{\$} \mathbb{Z}_q$, the following indistinguishability holds: $(\mathbf{a}, \lfloor \langle \mathbf{a}, \mathbf{s} \rangle \rceil_p) \approx_c (\mathbf{a}, \lfloor b \rceil_p)$, where $\lfloor \cdot \rceil_p : \mathbb{Z}_q \to \mathbb{Z}_p$ is the rounding function defined as $\lfloor x \rceil_p = \lfloor x \cdot (p/q) \rceil \mod p$.*

Definition 3 (KhPRF by LWR [24]). *Let $H_1 : \mathcal{X} \to \mathbb{Z}_q^\ell$ be a hash function modeled as a random oracle, define the function $F_{\text{LWR}} : \mathbb{Z}_q^\ell \times \mathcal{X} \to \mathbb{Z}_p$ as $F_{\text{LWR}}(\mathbf{k}, x) \leftarrow \lfloor \langle \mathbf{k}, H_1(x) \rangle \rceil_p$ under the LWR$_{\ell,q,p}$ assumption. For every $\mathbf{k}_1, \mathbf{k}_2 \in \mathbb{Z}_q^\ell$, F_{LWR} is 1-almost key homomorphic in the sense that $F_{\text{LWR}}(\mathbf{k_1}, x) + F_{\text{LWR}}(\mathbf{k_2}, x) = \mathrm{F}(\mathbf{k_1} + \mathbf{k_2}, x) + e$ where $e \in \{0, 1\}$.*

Note that KhPRF can also be instantiated based on the Ring-LWR assumption [25]. In this work, we instantiate it as $\mathrm{KF}(\mathbf{k}, \mathbf{x}) = (\lfloor \langle \mathbf{k}, H_1(x_1) \rangle \rceil_p, \cdots, \lfloor \langle \mathbf{k}, H_1(x_m) \rangle \rceil_p)$.

Construction 1 (KhPRF-OPSA). *Let $F_1 : \mathbb{Z}_q \times \mathbb{Z}_q^* \to \mathbb{Z}_q^\ell$ be a secure PRF, and $F_0 : \mathbb{Z}_q \times \mathbb{Z}_q^* \to \mathbb{Z}_q$ be a secure PRF. Based on the* LWR$_{\ell,q,p}$ *assumption, let* $\mathrm{KF}(\cdot, \cdot)$ *be 1-almost KhPRF, the key space be $\mathcal{K} = \mathbb{Z}_q^\ell$, the model space be $\mathcal{M} = \mathbb{Z}_p^m$, and the mask space be $\mathcal{Y} = \mathbb{Z}_p^m$.*

- $\mathbf{mask}_u \leftarrow \mathsf{Encode}(\mathsf{pp}, \mathsf{shKey}, r)$*: each client u parses the shared key $k_{u,e}$ from* shKey*, computes a temporary key $\mathbf{k}_u = F_1(k_{u,e}, r)$, and outputs $\mathbf{mask}_u = \mathrm{KF}(\mathbf{k}_u, \mathbf{b})$ where $\mathbf{b} \in \mathbb{Z}_q^m$ is parsed from public parameters* pp.

- $(\mathsf{reKey}, \mathsf{rand}) \leftarrow \mathsf{RevealKey}(\mathsf{pp}, \mathcal{V}, \mathcal{D}, r)$: *TEE instance M_e loads the surviving list $\mathcal{V}$, computes the temporary key $\mathbf{k}_u = F_1(k_{e,u}, r)$ and $\mathsf{rand}_u = F_0(k_{e,u}, 0||r)$ for all $u \in \mathcal{V}$, and sums up temporary keys $\mathbf{k}_\mathcal{V} = \sum_{u\in\mathcal{V}} \mathbf{k}_u$ and random numbers $\mathsf{rand} = \sum_{u\in\mathcal{V}} \mathsf{rand}_u$. It outputs* $\mathsf{reKey} = \{\mathbf{k}_\mathcal{V}\}$ *and* rand.
- $\mathbf{mask}_\mathcal{V} \leftarrow \mathsf{Decode}(\mathsf{pp}, \mathsf{reKey}, r)$: *the server parses the revealed key $\mathbf{k}_\mathcal{V}$ from* reKey, *and outputs a mask $\mathbf{mask}_\mathcal{V} = \mathsf{KF}(\mathbf{k}_\mathcal{V}, \mathbf{b})$ where $\mathbf{b} \in \mathbb{Z}_q^m$ is parsed from public parameters* pp.

Since 1-almost KhPRF causes an error $\mathbf{e} \in \{0,1\}^m$, the summation of masks is given by $\sum_{u\in\mathcal{V}} \mathbf{mask}_u = \mathbf{mask}_\mathcal{V} + \mathbf{e}_\mathcal{V}$ where $|\mathbf{e}_{\mathcal{V},i}|_{i\in[m]} < |\mathcal{V}|$. To remove the mask correctly, we can set a model scaling factor Δ sufficiently large to ensure that errors are removed by the rounding operation. The process of the above construction is the same as shown in Fig. 3, except for the following modifications:

- In the mask step, each client u masks its local model
$$\mathbf{y}_u = \Delta \cdot \mathbf{x}_u + \mathsf{Encode}(\mathsf{pp}, \mathsf{shKey}, r).$$
- In the unmask step, the server obtains the model
$$\sum_{u\in\mathcal{V}} \mathbf{x}_u = \frac{1}{\Delta}\left(\sum_{u\in\mathcal{V}} \mathbf{y}_u - \mathsf{Decode}(\mathsf{pp}, \mathsf{reKey}, r)\right).$$

B. Construction Based on Proxy-OT

Here, we extend the notion of non-interactive proxy oblivious transfer (POT_2^1) defined by Choi et al. [26] to *k-out-of-n proxy oblivious transfer* (POT_n^k), and then utilize it to construct a double masking scheme.

We introduce the syntax of our POT_n^k protocol in Appendix A. The POT_n^k protocol involves three parties: a sender, a chooser, and a proxy. Let $F_2 : \mathbb{Z}_q \times \mathbb{Z}_q^* \to \mathbb{Z}_q^n$ be a secure PRF, and $k_{s,c} = \mathsf{KA}(pk_C, sk_S)$ be the shared key between the sender and the chooser, we can instantiate POT_n^k from the key agreement protocol as follows:

- $A \leftarrow \mathsf{Send}(r, sk_S, pk_C, \{m_i\}_{i\in[n]})$: the sender computes $(z_1, z_2, \cdots, z_n) = F_2(k_{s,c}, r)$ where $|z_i| = \lambda$, generates a permuted order $\pi := \mathsf{Perm}[n]$, and sets $A = \{ct_i\}_{i\in[n]}$ where $ct_{\pi(i)} = z_i \oplus m_i$.
- $B \leftarrow \mathsf{Choose}(r, sk_C, pk_S, \{b_j\}_{j\in[k]})$: the chooser computes $(z_1, z_2, \cdots, z_n) = F_2(k_{c,s}, r)$ where $|z_i| = \lambda$, generates a permuted order $\pi = \mathsf{Perm}[n]$, and reveals only the part associated with the choice $B = \{aux_j\}_{j\in[k]}$ where $aux_j = (\pi(b_j), z_{b_j})$.
- $M \leftarrow \mathsf{Proxy}(r, pk_S, pk_C, A, B)$: the proxy parses $A = (ct_1, ct_2, \cdots, ct_n)$ and $B = \{(b'_j, z_{b_j})\}_{j\in[k]}$, and computes $M = \{m_{b'_j}\}_{j\in[k]}$ where $m_{b'_j} = ct_{b'_j} \oplus z_{b_j}$.

In our POT_n^k protocol designed for one-pass aggregation, we designate the TEE as the chooser (rather than the proxy) to alleviate its processing burden, with the clients as the senders and the server as the proxy. Given that OPSA only requires safeguarding the privacy of clients, our focus is solely on ensuring *sender privacy* in POT. This implies that the proxy can know choice of the chooser, thereby enabling the TEE to make choices based on the client list provided by the server. Moreover, the permuted operation in the above instantiation can also be removed. Note that the chooser (i.e., TEE) is required to choose only once per round.

Construction 2 (POT-OPSA)**.** *Let $F_0 : \mathbb{Z}_q \times \mathbb{Z}_q^* \to \mathbb{Z}_q$ be a secure PRF, $G : \mathbb{Z}_q \to \mathbb{Z}_q^m$ be a secure PRG. Based on the instantiation POT_n^k, let the key space be $\mathcal{K} = \mathbb{Z}_q$, the model space be $\mathcal{M} = \mathbb{Z}_q^m$, and the mask space be $\mathcal{Y} = \mathbb{Z}_q^m$.*

- $\mathbf{mask}_u \leftarrow \mathsf{Encode}(\mathsf{pp}, \mathsf{shKey}, r)$: *each client u parses its shared keys $\{k_{u,v}\}_{v\in\mathcal{U}}$ from* shKey, *samples a temporary individual key $\widetilde{k}_u \xleftarrow{\$} \{0,1\}^\lambda$, and computes a temporary pairwise key $\widetilde{k}_{u,v} = F_0(k_{u,v}, r)$ for $v \in \mathcal{U}$. It outputs a one-time mask summation $\mathbf{mask}_u = G(\widetilde{k}_u) + \sum_{v\in\mathcal{U}, u<v} G(\widetilde{k}_{u,v}) - \sum_{v\in\mathcal{U}, u>v} G(\widetilde{k}_{u,v})$.*
- $(\mathsf{reKey}, \mathsf{rand}) \leftarrow \mathsf{RevealKey}(\mathsf{pp}, \mathcal{V}, \mathcal{D}, r)$: *TEE instance M_e loads the surviving list $\mathcal{V}$ and the dropout list $\mathcal{D}$, constructs a choice set $\{b_v\}_{v\in\mathcal{D}}$, and computes an auxiliary set $B_u = POT_n^k.\mathsf{Choose}(r, sk_e, pk_u, \{0\} \cup \{b_v\}_{v\in\mathcal{D}})$ and a random number $\mathsf{rand}_u = F_0(k_{e,u}, 0||r)$ for $u \in \mathcal{V}$. It outputs* $\mathsf{reKey} = \bigcup_{u\in\mathcal{V}} B_u$ *and* $\mathsf{rand} = \sum_{u\in\mathcal{V}} \mathsf{rand}_u$.
- $\mathbf{mask}_\mathcal{U} \leftarrow \mathsf{Decode}(\mathsf{pp}, \widetilde{\mathsf{reKey}}, r)$: *the server parses the revealed keys $\{\widetilde{k}_u, \widetilde{k}_{u,v}\}_{u\in\mathcal{V}, v\in\mathcal{D}}$ from* $\widetilde{\mathsf{reKey}}$, *and outputs the summation of all masks $\mathbf{mask}_\mathcal{U} = \sum_{u\in\mathcal{V}, v\in\mathcal{D}} \left(G(\widetilde{k}_u) + \sum_{u<v} G(\widetilde{k}_{u,v}) - \sum_{u>v} G(\widetilde{k}_{u,v})\right)$.*

In fact, POT_n^k is instantiated as $\mathrm{POT}_{|\mathcal{U}|}^{|\mathcal{D}|+1}$. For all $u \in \mathcal{V}$, the TEE instance chooses $\{0\}$ and $\{b_v\}_{v\in\mathcal{D}}$ to obtain the auxiliary messages corresponding to $\widetilde{k}_u$ and $\{\widetilde{k}_{u,v}\}_{v\in\mathcal{D}}$, respectively. The process of this construction is the same as shown in Fig. 3, except for the following new additions and modifications:

- In the mask step, each client u sends to the server
$$A_u = \mathrm{POT}_n^k.\mathsf{Send}(r, sk_u, pk_e, \{\widetilde{k}_u\} \cup \{\widetilde{k}_{u,v}\}_{v\in\mathcal{U}}),$$
and the server stores A_u received from distinct clients.
- In the unmask step, the server parses $\bigcup_{u\in\mathcal{V}} B_u$ from reKey, runs $\mathrm{POT}_n^k.\mathsf{Proxy}(r, pk_u, pk_e, A_u, B_u)$ to recover $\widetilde{\mathsf{reKey}}_u = \{\widetilde{k}_u\} \cup \{\widetilde{k}_{u,v}\}_{v\in\mathcal{D}}$, and obtains the model $\sum_{u\in\mathcal{V}} \mathbf{x}_u = \sum_{u\in\mathcal{V}} \mathbf{y}_u - \mathsf{Decode}(\mathsf{pp}, \widetilde{\mathsf{reKey}}, r)$ where $\widetilde{\mathsf{reKey}} = \bigcup_{u\in\mathcal{V}} \widetilde{\mathsf{reKey}}_u$.

To reduce the number of pairwise masks, we can employ the sub-graph technique [5], [9] to generate fewer pairwise masks, directly reducing the values of n and k to improve the performance of our POT_n^k for one-pass aggregation.

C. Construction of Result Verification

Let $\mathsf{pp}_{\mathsf{com}} = (\mathbf{g}, h)$ be commitment public parameters where $\mathbf{g} = (g_1, \cdots, g_m) \xleftarrow{\$} \mathbb{G}^m$ and $h \xleftarrow{\$} \mathbb{G}$, and $F_0 : \mathbb{Z}_q \times \mathbb{Z}_q^* \to \mathbb{Z}_q$ be a secure PRF. Each client u can generate a random number $\mathsf{rand}_u = F_0(k_{u,e}, 0||r)$ where r is the round and $k_{u,e}$ is the shared key between client u and TEE instance M_e.

Commitments. We first extend the Pedersen commitment scheme [27] on vectors as follows:

- $\mathsf{com}_u \leftarrow \mathsf{Commit}(\mathbf{x}_u, \mathsf{rand}_u)$: outputs a model commitment $\mathsf{com}_u = \mathbf{g}^{\mathbf{x}_u} h^{\mathsf{rand}_u}$.
- $b \leftarrow \mathsf{Open}(\mathsf{com}_{u'}, \mathbf{x}_u, \mathsf{rand}_u)$: outputs $b = 1$ iff the equation $\mathsf{com}_{u'} = \mathsf{Commit}(\mathbf{x}_u, \mathsf{rand}_u)$ holds.
- $\mathsf{com} \leftarrow \mathsf{Eval}(\{\mathsf{com}_u\}_u)$: outputs an aggregated commitment $\mathsf{com} = \prod_u \mathsf{com}_u$.

TEE Verification. Upon loading $(\mathcal{V}, \mathcal{D}, \{\mathsf{com}_u, \sigma_u\}_u, r)$, TEE instance M_e performs the following checks to make sure such the aggregation range $\mathcal{V}$ is valid:

- assert $\mathsf{VerSig}(pk_u, \sigma_u, \mathsf{com}_u) = 1$ for all $u \in \mathcal{V}$.
- run RevealKey to obtain $\mathsf{rand} := \sum_{u\in\mathcal{V}} \mathsf{rand}_u$.
- run Eval to obtain $\mathsf{com} := \prod_{u\in\mathcal{V}} \mathsf{com}_u$.
- generate $\sigma_e := \mathsf{Sign}(sk_e, \mathsf{com}||\mathsf{rand}||r)$.
- output $(\sigma_e, \mathsf{com}, \mathsf{rand})$.

In practice, these TEE operations can be encapsulated within another TEE instance, which only requires data and code integrity to be protected (transparent enclave model [28]) and can be deployed on any other party equipped with TEE.

Proofs. Based on the above instantiations, the server can form a proof $\boldsymbol{\pi}^{\mathsf{valid}(\sum \mathbf{x}_u)} = (\mathsf{rand}, \sigma_e)$ and send it along with an aggregated model $\sum_{u\in\mathcal{V}} \mathbf{x}_u^{(r)}$ to all clients. Each client first computes a commitment $\mathsf{com}' = \mathbf{g}^{\sum_{u\in\mathcal{V}} \mathbf{x}_u^{(r)}} h^{\mathsf{rand}}$ and then verifies the signature $\mathsf{VerSig}(pk_e, \sigma_e, \mathsf{com}'||\mathsf{rand}||r) = 1$ to ensure that $\sum_{u\in\mathcal{V}} \mathbf{x}_u^{(r)}$ is accurate.

V. Security Analysis and Discussion

Here, we first analyze the security of our framework given in Fig. 3, and then discuss its privacy attacks and robustness.

A. Security of OPSA

Following Definition 4.1 and Theorem 4.9 in SecAgg+ [5], we define a SA protocol as being α-secure if honest clients can be guaranteed that their private inputs are aggregated at most once with at least αN other inputs from honest clients. Note that the following ideal functionality can be queried once for round $r \in [1, R]$.

Definition 4 (α-Summation Ideal Functionality). *Let q, m, k be integers, and $\alpha \in [0, 1]$. Let $\mathcal{L} \subseteq \mathcal{U}$ and $\mathcal{X}_\mathcal{L} = \{\mathbf{x}_u\}_{u\in\mathcal{L}}$ where $\mathbf{x}_u \in \mathbb{Z}_q^m$. Let $\mathcal{V}_\mathcal{L}$ be the set of partitions of $\mathcal{L}$, i.e., all partitions $\{\mathcal{L}_1, \cdots, \mathcal{L}_k\} \in \mathcal{V}_\mathcal{L}$, the α-summation ideal functionality over $\mathcal{X}_\mathcal{L}$ for all subsets in $\mathcal{V}_\mathcal{L}$ is defined as $F_{\alpha,\mathcal{X}_\mathcal{L}}(\{\mathcal{L}_i\}_{i\in[1,k]}) = \{\mathbf{z}_i\}_{i\in[1,k]}$ where*

$$\forall i \in [1, k], \quad \mathbf{z}_i = \begin{cases} \sum_{u\in\mathcal{L}_i} \mathbf{x}_u & \text{if } |\mathcal{L}_i| \geq \alpha \cdot |\mathcal{L}|, \\ \perp & \text{otherwise.} \end{cases}$$

Then, the security of our protocol is given by the following theorems, and their full proofs, based on a standard hybrid argument, are presented in Appendix B.

Theorem 1 (Dropout resilience). *Given secure cryptographic primitives and TEE, as described in Section II, a dropout rate δ, and a fraction α defined in Definition 4, the OPSA framework (Fig. 3), instantiated with Construction 1 or 2 with parameter $(1 - \delta) \geq \alpha$, satisfies dropout resilience: when all parities follow the protocol, for round $r \in [1, R]$, all input vectors $\mathcal{X}^{(r)}$, and all sets of dropout clients $\mathcal{D} \subseteq \mathcal{U}$ with $|\mathcal{D}| \leq \lfloor \delta N \rfloor$, the server S outputs $\sum_{u\in\mathcal{U}\setminus\mathcal{D}} \mathbf{x}_u^{(r)}$ at the end of round r, except with negligible probability.*

Theorem 2 (Security). *Given secure cryptographic primitives and TEE, as described in Section II, a corruption rate γ, and a fraction α defined in Definition 4, the OPSA framework (Fig. 3), instantiated with Construction 1 or 2 with parameter $(1 - \gamma) \geq \alpha$, guarantees security: when there exists a PPT simulator* SIM *such that for any round $r \in [1, R]$, all input vectors $\mathcal{X}^{(r)}$, and all sets of corrupted parities $\mathcal{C} \subseteq \mathcal{U} \cup \{S\}$ of size $|\mathcal{C}\setminus\{S\}| \leq \lfloor \gamma N \rfloor$, the output of* SIM *is computationally indistinguishable from the view of a malicious adversary $\mathcal{A}$, i.e.,*

$$\mathsf{REAL}_{\mathcal{C},r}^{\mathcal{U},S,R}(\mathcal{A}, \{\mathbf{x}_u\}_{u\in\mathcal{U}\setminus\mathcal{C}}) \approx_c \mathsf{SIM}_{\mathcal{C},r}^{\mathcal{U},S,R,F_{\alpha,\{\mathbf{x}_u^{(r)}\}_{u\in\mathcal{U}\setminus\mathcal{C}}}}(\mathcal{A}).$$

Theorem 3 (Correctness against a malicious server). *Given secure cryptographic primitives and TEE, as described in Section II, a dropout rate δ, and a fraction α defined in Definition 4, the OPSA framework (Fig. 3), instantiated with Construction 1 or 2 providing result verification (subsection IV-C) with parameter $(1 - \delta) \geq \alpha$, ensures security (Theorem 2) and correctness against a malicious adversary $\mathcal{A}$ that only controls S: when all clients follow the protocol, for round $r \in [1, R]$, all input vectors $\mathcal{X}^{(r)}$, and all sets of dropout clients $\mathcal{D} \subseteq \mathcal{U}$ of size $|\mathcal{D}| \leq \lfloor \delta N \rfloor$, each client $u \in \mathcal{U}$ obtains $\sum_{u\in\mathcal{U}\setminus\mathcal{D}} \mathbf{x}_u^{(r)}$ at the end of round r, except with negligible probability.*

B. Privacy Attacks

Here, we discuss privacy attacks on SA protocols and analyze how to resist them within the OPSA framework. Fowl et al. [11] make changes to the shared model architecture on a malicious server, enabling it to directly access precise copies of user data from gradient updates. Pasquini et al. [12] manipulate model parameters on a malicious server to execute two privacy attacks targeting SA protocols. Zhao et al. [13] demonstrate how the privacy of SA protocols in FL can be compromised by a malicious server sending customized models to clients. It is evident that such attacks are initiated by a malicious server modifying the model, and result verification of the OPSA framework can prevent these attacks.

Furthermore, the work [29] proposes a privacy attack that leverages the aggregated models and participation information across multiple training rounds to reconstruct individual models, leading to privacy leakage. To counteract this attack, the OPSA framework requires hiding client participation information, either by enhancing the structured strategy for client selection [29] or mandating clients to form minimum batches [30] for uploading models. Another study [31] introduces $t-1$ sybil devices to assist a malicious server in reconstructing individual models, and the OPSA framework can prevent it by setting a low dropout rate, especially when there is a considerable number of training participants in FL. Overall, while the OPSA framework cannot protect against all privacy attacks, it can mitigate them with additional strategies.

C. Extension with Robustness

While the OPSA framework can prevent the server from tampering with the aggregation results when all clients are semi-honest, challenges arise when clients exhibit malicious behavior. In cases like model poisoning attacks, which involve intentional submission of errors or malicious models, the OPSA framework cannot guarantee the validity of the final aggregated model. To enhance client robustness, the OPSA framework can further integrate existing strategies to counteract these attacks. One strategy is to permit the server to aggregate models on a small scale, followed by scoring

TABLE I: Comparison of communication (Comm.) and computation (Comp.) overhead in a secure aggregation round.

Setting	**Flamingo**	**POT-OPSA**	**LERNA**	**khPRF-OPSA**
Client Comm.	Regular client: $O(m+L+A)$ Decryptor: $O(L+\delta AN+(1-\delta)N)$	$O(m+A)$	Regular client: $O(m)$ Committee: $O(m+M)$	$O(m)$
Client Comp.	Regular client: $O(mA+L)$ Decryptor: $O(\delta AN+(1-\delta)N+\epsilon N^2)$	$O(mA)$	Regular client: $O(m\log\ell)$ Committee: $O(m\log\ell+\delta N\ell)$	$O(m\log\ell)$
Server Comm.	$O((m+L+A)N)$	$O((m+A)N)$	$O(m(N+M))$	$O(mN)$
Server Comp.	$O(t^2+\delta mAN+(1-\delta)mN)$	$O(\delta mAN+(1-\delta)mN+\epsilon N^2)$ TEE: $O((1-\delta)AN)$	$O((1-\delta)mN+t^*m)$	$O((1-\delta)mN+m\log\ell)$ TEE: $(1-\delta)N\ell$
C/S Comm.	3	1	3	1

Remark N: the number of clients, m: the model vector size, δ: the dropout rate. C/S Comm. denotes the number of client-server round-trip communications.
Flamingo A: the number of neighbors of a client, L: the number of decryptors, ϵ: graph generation parameter, t: threshold of Shamir secret sharing.
LERNA M: the number of commitee members, ℓ: the key size of KhPRF, t^*: threshold of flat secret sharing.

the aggregation results using cosine similarity [32] to identify malicious clients. Another approach is to prove that the model input satisfies the L_∞ specification through zero-knowledge proofs [7]. However, when both the server and client may act maliciously simultaneously, it is essential to combine result verification with a robust defense strategy to ensure the correctness and validity of the final aggregation result.

VI. Evaluation

In this section, we compare two constructions under the OPSA framework with state-of-the-art schemes, conducting theoretical analysis and performance analysis, respectively.

A. Theoretical Analysis

The number of client-server communications has a critical impact on the overall execution time of SA protocols. In real-world FL training scenarios across wide area networks, the round-trip time (RTT) delay can reach tens of milliseconds, resulting in notable differences in the arrival time of messages from different clients. Consequently, the server spends considerable waiting time in each communication round.

Table I provides a comprehensive comparison of OPSA's communication and computation costs with those of Flamingo and LERNA. Compared with double masking schemes, the computation cost of single masking schemes increases more obviously with the model dimension. This is because single mask computations involve the multiplication of polynomials of the model dimensions by the Ring-LWR key polynomials, requiring a computational complexity of $O(m\log\ell)$ with NTT acceleration. In contrast, double mask calculations can be regarded as a PRG instantiated by AES encryption, involving an $O(m)$ computational complexity. When considering server computation cost, double masking schemes are more expensive than single masking schemes, especially in scenarios with a large number of dropped clients, which require recovering their pairwise masks. Moreover, single masking schemes support dynamic client access. Overall, among the two proposed constructions, KhPRF-OPSA is more suitable for scenarios with low-dimensional models and more dropped clients, while POT-OPSA is better suited for situations with high-dimensional models and fewer dropped clients.

B. Experimental Setup

Implementation. The OPSA framework is implemented in Python, and the TEE code is developed in C++. In our implementation, we leverage the Intel SGX SDK to construct trusted applications inside the enclave, instantiate cryptographic primitives as detailed in subsection II-C, and employ the NIST P-256 curve. For the input vector, each element is set to 64 bits, requiring the encoding of floating-point model weights into 64 bits. To achieve a 128-bit security level, we set the key size to 128 bits for AES-CTR, configure the RLWR dimension as 2^{11}, and set the modulus q to $n\Delta\cdot 2^{286}$, consistent with the LERNA setting. The hardness of this configuration can be validated by the evaluator [33].

Experimental environment. We integrate all of our code into the ABIDES simulation framework [34] and run simulation on a machine equipped with a 2.90GHz Intel Core i7-10700 CPU and 32GB memory, supporting Intel SGX and running 64-bit Ubuntu 20.04.2 LTS. Our baseline is set as the current state-of-the-art solutions, Flamingo and LERNA. Since the committee members or decryptors are selected from the clients, we set them to the same dropout rate. To ensure an equivalent level of security, Flamingo is set with 60 decryptors for a 1% dropout rate and 170 decryptors for a 5% dropout rate, while LERNA's committee size is consistently set to 2^{14}. Unless otherwise specified, the default dropout rate of clients in our experiments is set as $\delta = 5\%$.

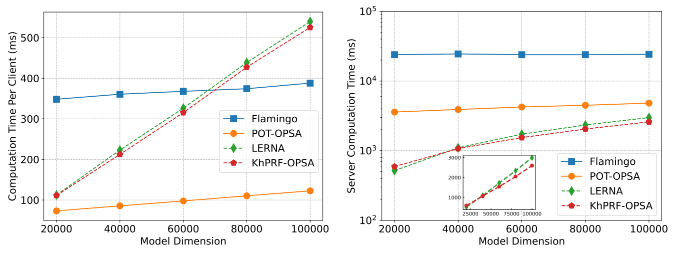
Training setting. We conduct extensive experiments using common datasets, MNIST and CIFAR-10. MNIST comprises 60K training images and 10K testing images of handwritten digits across 10 classes. CIFAR-10 consists of 60K total samples, each being a 32×32 pixel RGB image, divided into 50K training samples and 10K testing samples. The number of SA rounds for the global model is set to 50 for MNIST and 200 for CIFAR-10. In every SA round, each client undergoes 5 iterations of local mini-batch training, with batch size 32 and learning rate 0.01. To simulate realistic FL training, we distribute the training data among clients in a non-IID setting, using a Dirichlet distribution with hyperparameter 0.9 as described in [35].

To facilitate training on the above datasets, we employ two models based on the classic CNN structure. For MNIST, the model dimension is $21,840$. However, for CIFAR-10, we opt for a more intricate model network with larger convolutional and fully connected layers, along with batch normalization and dropout layers. Consequently, the model dimensions for CIFAR-10 is significantly higher, totaling $551,722$.

C. Experimental Performance

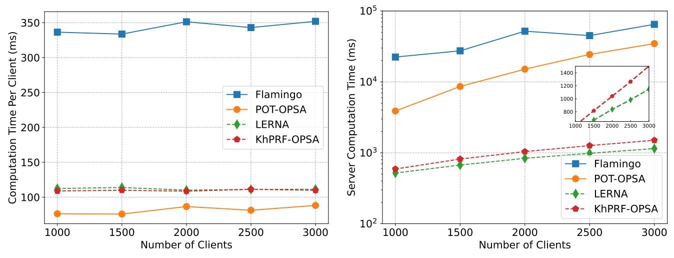
Here, we provide a benchmark to compare our two types of SA protocols with Flamingo and LERNA. For detailed comparison, we divide the entire protocol into five stages: "setup" (one-time setup phase), "mask" (masked model generation and upload), "check" (consistency check), "unmask" (aggregated model recovery), and "verify" (result verification).

Computation costs. To fairly evaluate the computation time of clients and server, we only choose the regular clients of Flamingo and LERNA for comparison with our scheme. Note that the server computation time of our scheme includes the execution time within TEE. For computation time measurements, we report an average over 10 experiment runs.



(a) Client computation time. (b) Server computation time.

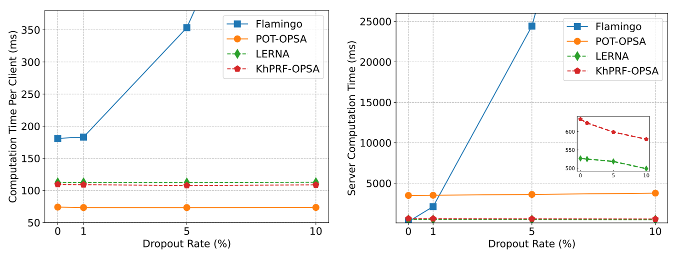
Fig. 4: Computation time vs. model dimension, with fixed number of clients $N = 1$K and dropout rate $\delta = 5\%$.



(a) Client computation time. (b) Server computation time.

Fig. 5: Computation time vs. number of clients, with fixed model dimension $m = 20$K and dropout rate $\delta = 5\%$.

Fig. 4 and Fig. 5 show the computation time for different model dimensions and different number of clients respectively. For double masking schemes, the client computation time of POT-OPSA is notably shorter than that of Flamingo. This advantage arises from the fact that Proxy-OT in our scheme utilizes simple XOR calculations instead of complex encryption operations. Moreover, at the server side, the process of mask recovery in POT-OPSA is significantly lighter compared to Flamingo, highlighting the efficiency of our approach. For single masking schemes, the server computation time of KhPRF-OPSA is slightly higher than that of LERNA due to the additional execution time required by the RevealKey operation within TEE, which is calculated by the committee in LERNA. However, when the model dimension is larger, our server computation time will be more advantageous, because TEE aggregates all low-dimensional secret keys, while LERNA aggregates all high-dimensional masks received from the committee. Overall, the computation time of KhPRF-OPSA is comparable to that of LERNA.



(a) Client computation time. (b) Server computation time.

Fig. 6: Computation time vs. dropout rate, with fixed number of clients $N = 1$K and model dimension $m = 20$K.

As shown in Fig. 6, Flamingo's computation time increases significantly as the dropout rate rises. This can be attributed to the varying number of decryptors required by Flamingo to maintain a same level of security across different dropout rates. In contrast, the client-side computation time for other schemes remains relatively stable, since the number of LERNA's committee is fixed, and our scheme only requires to interact with TEE. At the server side, double masking schemes experience a slight increase in computation time with the dropout rate due to their involvement in recovering pairwise masks of dropped clients. In contrast, the computation time of single masking schemes decreases as the dropout rate increases, as the server doesn't need to recover masks for dropped clients. Note that our scheme can resist larger dropout rates, whereas Flamingo and LERNA are limited to smaller dropout rates to maintain the same level of security.

TABLE II: Computation time for different stages per round of secure aggregation with $N = 1$K, $m = 20$K, and $\delta = 5\%$.

Scheme	Type	Stages for secure aggregation (ms)				
		setup	mask	check	unmask	verify
Flamingo	Server	40.37	335.75	7.94	24397.08	–
	Client	–	355.34	–	–	–
	Decryptor	7143.84	–	4.44	833.11	–
POT-OPSA	Server	1192.60	–	–	3914.28	–
	TEE	178.64	–	–	13.28	122.60
	Client	0.89	79.23	–	–	64.89
LERNA	Server	208.96	–	–	518.39	–
	Client	4245.30	107.33	–	–	–
	Committee	392.69	–	3.98	107.11	–
KhPRF-OPSA	Server	–	–	–	573.02	–
	TEE	178.73	–	–	104.16	123.94
	Client	0.37	111.97	–	–	65.44

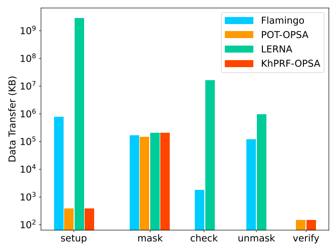
We compare our scheme with Flamingo and LERNA across various stages of a SA round, and their computation times are presented in Table II. The key advantage of our scheme lies in its significant reduction of the overall computation time. This efficiency is achieved by transforming the complex recovery operation carried out by Flamingo's decryptors and

LERNA's committee members into a concise and lightweight TEE responsible for performing the recovery of secret seeds. Moreover, our scheme provides verifiable aggregation results, and the detailed computation times are provided in Table III. Compared with VerSA [16] and the work proposed by Eltaras et al. [18] (which we call ESLAM), our OPSA-RV has fixed TEE computation time and communication cost.

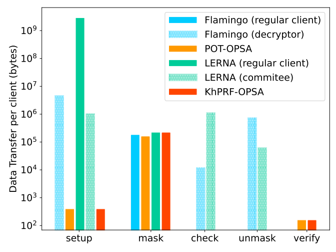
TABLE III: Computation time and communication (comm.) cost of result verification with $N = 1\text{K}$ and $\delta = 5\%$.

Model dimension	Scheme	Client (ms)		Server/TEE (ms)	Comm. cost per client (B)
		commit	verify		
20K	VerSA	768.07	6.22	23879.57	160000
	ESLAM	214.49	4.60	21.19	191506
	OPSA-RV	32.91	32.26	125.35	152
40K	VerSA	1526.02	10.18	43921.27	320000
	ESLAM	222.43	10.41	45.71	351506
	OPSA-RV	65.25	64.33	124.89	152
60K	VerSA	2223.32	14.14	64412.10	480000
	ESLAM	224.26	14.18	65.39	511506
	OPSA-RV	98.21	97.18	123.81	152
80K	VerSA	2998.85	18.49	86986.30	640000
	ESLAM	229.63	17.92	86.03	671506
	OPSA-RV	130.02	129.32	121.79	152
100K	VerSA	3769.42	22.45	108853.58	800000
	ESLAM	238.34	23.59	103.32	831506
	OPSA-RV	163.53	163.11	121.52	152

Communication cost. As shown in Fig. 7, we evaluate the communication cost across different stages of a single SA round. During the "setup" phase, our scheme requires only TEE and clients to execute the key agreement protocol and remote attestation, eliminating the need for secret sharing among clients. In the "mask" stage, all schemes must upload masked models, with the communication cost of single masking schemes slightly higher than that of double masking schemes due to the larger value of key-homomorphic PRF. Compared with Flamingo and LERNA, our scheme saves communication costs in the "check" and "unmask" stages with the help of TEE. Furthermore, during the "verify" stage, our communication cost is fixed for the size of a commitment and a signature, significantly lower than that of a global model, which is also provided in Table III.



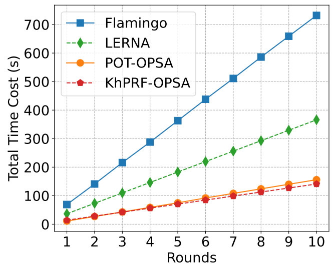
(a) Server communication cost.



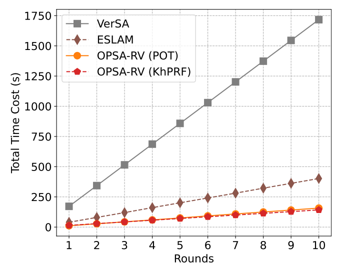
(b) Client communication cost.

Fig. 7: Communication cost for different stages in a single round over 1K clients, with $m = 20\text{K}$ and $\delta = 5\%$.

Total time cost. To demonstrate the practicality of our scheme, we evaluate the overall execution time required for the client and server to complete a 10-round SA across all schemes, including the server's wait time, the time for all messages to be delivered and received, and various computation times, but excluding the one-time setup time. As shown in Fig. 8, our scheme has significant advantages in both verifiable and non-verifiable SA. For SA without verification, our scheme is nearly 5× faster than Flamingo and almost 2× faster than LERNA. When verification is involved, our scheme is nearly 10× faster than VerSA [16] and almost 3× faster than ESLAM [18]. This improvement is expected to be even more significant in scenarios with high network latency, thanks to the one client-server round-trip communication provided by the OPSA framework.



(a) SA without verification.



(b) SA with verification.

Fig. 8: End-to-end completion time of 10 rounds of secure aggregation over 1K clients with $m = 20\text{K}$ and $\delta = 5\%$.

As shown in Table IV, our scheme demonstrates advantages in server-side runtime compared with SEAR [19]. Obviously, the runtime per client is independent of the number of clients, and the OPSA's server-side time cost is 4∼8 times lower than that of SEAR. Furthermore, it also shows that POT-OPSA is better suited for situations with high-dimensional models and fewer dropped clients. Additionally, our scheme enables clients to verify the codes of SA and the server's hardware it is running through remote attestation. Table V presents the total time required for remote attestation between TEE and the clients, considering different numbers of open threads. This process is generally carried out during the setup phase to ensure the integrity of the code executed by Intel SGX.

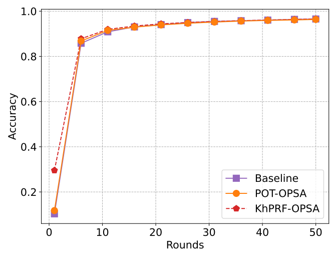
TABLE IV: Time cost comparison with the TEE-based SA scheme with $m = 500\text{K}$ and $\delta = 0$.

Scheme	Per client runtime (ms)		Server runtime (ms)	
	$N = 500$	$N = 1000$	$N = 500$	$N = 1000$
SEAR	82.79	82.99	33516.24	105756.45
POT-OPSA	438.65	463.08	5245.55	12163.33
KhPRF-OPSA	2578.46	2580.20	8542.36	13647.76

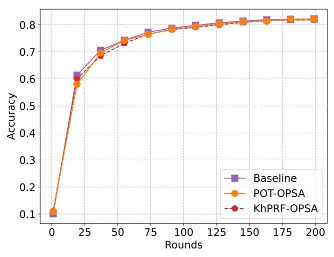
TABLE V: Execution time of remote attestation on the server with multiple threads for different numbers of clients.

Number of threads	Remote attestation (s)		
	$N = 1\text{K}$	$N = 2\text{K}$	$N = 3\text{K}$
20	367.97	737.72	1109.38
30	318.04	634.15	947.06
50	270.78	539.11	809.48

Training accuracy. To evaluate the feasibility of the OPSA framework, we deploy two types of SA protocols in the real model training process. We compare their performance with FedAvg, which serves as the baseline and does not employ any SA scheme. The evaluation is conducted on common datasets MNIST and CIFAR-10, with 100 clients participating in each training session, and its accuracy score is determined by the proportion of correctly predicted samples in the validation set relative to the total number of samples. Similar to Flamingo and LERNA, the primary deviation in our model training process from the baseline lies in the encoding of model floating-point parameters. As shown in Fig. 9, our SA scheme does not impact model performance and accuracy.



(a) MNIST.



(b) CIFAR-10.

Fig. 9: Accuracy comparison under different datasets.

VII. Related work

In this section, we mainly discuss three types of secure aggregation (SA): SA based on Differential Privacy (DP), SA based on Trusted Execution Environment (TEE), and SA based on One-Time Pad (OTP). Moreover, we also discuss some verifiable SA schemes.

DP-based SA. Differential Privacy (DP) is a concept in data privacy that aims to protect the sensitive information of individuals when analyzing or mining data. The fundamental idea behind DP is to add a controlled amount of noise to the data or query results to prevent the disclosure of specific details about any individual's contribution to the data set.

In DP-based SA schemes [36]–[38], each client adds statistical noise (e.g., Gaussian noise) to hide their local models, but this method introduces significant noise during model aggregation, affecting the accuracy of the results. Moreover, the work [31] has proposed an attack against FL protected with distributed differential privacy and secure aggregation.

TEE-based SA. TEE is a secure and isolated environment within a computer system or a microprocessor, providing a protected execution space for sensitive and critical operations. TEE is designed to prevent data and code from unauthorized access, tampering, and other security threats.

Secure aggregation can also be designed based on TEE [19], [39], [40], i.e., the TEE-equipped server decrypts models received from clients and aggregates them within TEE. However, this method may lead to a notable performance degradation when handling high-dimensional models or a large number of clients, due to the TEE's limited memory. Moreover, TEE still has the risk of being attacked, such as side-channel attacks [41].

OTP-based SA. One-time pad (OTP) is a cryptographic technique that employs a randomly generated secret key of the same length as the message to encrypt and decrypt information. It is a type of symmetric encryption algorithm where the key is used only once for a single message.

In OTP-based SA schemes, each client generates one-time pads as single or double masks to protect its local models, and the server then can eliminate the sum of masks to recover a original aggregated model. This approach is introduced by SecAgg [4] and the subsequent work, SecAgg+ [5], applies sub-grouping technique to create random connected graphs to reduce the cost of pairwise masks. FLDP [37] and ACORN [7] optimize one-time masks using the additive homomorphism of (Ring) LWE. As the secret keys are one-time in these schemes, each client is required to regenerate and share a new key with others per FL round, leading to a substantial increase in the communication burden.

To achieve a multi-round setting, MicroFedML [8] introduces a one-time setup phase to reuse secrets. Flamingo [9] designs a multi-round SA protocol integrating threshold decryption with a double masking scheme, while LERNA [10] achieves the same goal integrating flat secret sharing with a key-homomorphic pseudo-random function. These multi-round SA protocols introduce an additional group, such as decryptors in Flamingo and a committee in LERNA, to improve performance in handling dropout. Even then, it requires three client-server round-trip communications for every aggregation.

Verifiable SA. In SA protocols, a server provides a list of surviving clients who have successfully uploaded their masked models. The verifiability of the aggregation result, indicating that the result is indeed aggregated according to this list, is achieved by the verifiable SA, which ensures that a malicious server can perform aggregation honestly.

VerifyNet [14], based on a double masking scheme, introduces a homomorphic hash function and non-interactive zero-knowledge proofs (NIZK) to verify the aggregation result. VeriFL [15] builds upon this by replacing NIZK with a commitment mechanism. VerSA [16], derived from a double masking scheme, generates two sets of model masks and employs the message authentication code (MAC) concept for result verification. VOSA [17] designs a single mask scheme under the Decisional Composite Residuosity (DCR) assumption and utilizes NIZK to achieve result verification. Eltaras et al. [18] construct a single mask scheme based on key agreement protocols and also utilize the MAC concept for result verification.

In these verifiable SA schemes, all clients are considered to be semi-honest. VerifyNet [14] and VeriFL [15] further assume that the server is semi-honest but capable of forging the aggregation result. VerSA [16] and ESLAM [18], on the other hand, assume that the server is malicious but does not collude with any client at any stage. This assumption is primarily due to the MAC being computed by the same common factor among all clients, which is unknown to the server. Moreover, the client communication overhead in these schemes [16]–[18] is twice that of the original SA schemes, which put huge transmission pressure on clients, especially for high-dimensional models.

VIII. Conclusion

In this paper, we analyzed the limitations of existing SA protocols, focusing on computational efficiency, communication rounds, and result verifiability. To address these concerns, we introduced OPSA, a multi-round SA framework designed to achieve one client-server round-trip communication per aggregation for FL via hardware-assisted TEE. Moreover, we designed a result verification module compatible with any type of SA protocol instantiated under the OPSA framework to detect the forged aggregation results. Building upon the OPSA framework, we implemented a single masking scheme based on key-homomorphic PRF and a double masking scheme based on proxy-OT. Our extensive experiments showcase the remarkable improvements in effectiveness and dropout resilience brought by our OPSA framework.

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Appendix A
Proxy Oblivious Transfer

Here, we review the notion of non-interactive proxy oblivious transfer (POT_2^1) defined by Choi et al. [26]. A POT_2^1 protocol involves three parties: a sender, a chooser, and a proxy. The sender knows two inputs m_0 and m_1, and the chooser holds a choice $b \in \{0,1\}$. At the end of the protocol, the proxy learns m_b, while the two other parties learn nothing. Based on [26], a proxy OT protocol requires both *sender privacy* and *chooser privacy*. *Sender privacy* denotes that the proxy learns only the value of the sender input that corresponds to the chooser's input sequence. *Chooser privacy*, on the other hand, means that the proxy learns no information about the chooser's input sequence.

Now, we extend POT_2^1 to *k-out-of-n proxy oblivious transfer* (POT_n^k). First, we introduce the syntax of our POT_n^k protocol, which consists of the following algorithms:

- $A \leftarrow \mathsf{Send}(r, sk_S, pk_C, \{m_i\}_{i\in[n]})$: in the r-th POT_n^k execution, the sender takes as inputs its private key sk_S, the chooser's public key pk_C, and a plaintext set $\{m_i\}_{i\in[n]}$. It outputs an encoded message set $A = \{ct_i\}_{i\in[n]}$ to be sent to the proxy.
- $B \leftarrow \mathsf{Choose}(r, sk_C, pk_S, \{b_j\}_{j\in[k]})$: in the r-th POT_n^k protocol, the chooser takes as inputs its private key sk_C, the sender's public key pk_S, and a choice set $\{b_j\}_{j\in[k]}$. It outputs an auxiliary set $B = \{aux_j\}_{j\in[k]}$ to be sent to the proxy.
- $M \leftarrow \mathsf{Proxy}(r, pk_S, pk_C, A, B)$: in the r-th POT_n^k protocol, the proxy takes as inputs the sender's public key pk_S, the chooser's public key pk_C, the sender message A, and the chooser message B. It outputs a selected plaintext set $M = \{m_{b_j}\}_{j\in[k]}$.

Appendix B
Security Proofs

B.1 Proof of Theorem 1

Proof. The proof of dropout resilience is rather simple: in each round of the training phase, δ fraction of clients can drop out, i.e., $|\mathcal{D}| \le \lfloor \delta N \rfloor$. Since $|\mathcal{V}| \ge \lceil (1-\delta)N \rceil$ (Fig. 3), the TEE instance can always help the server to reveal the secret keys. Therefore, the dropout resilience property directly follows that of the underlying key agreement protocol instantiated with Equation 1. For each client $u \in \mathcal{U}$, there are two primary approaches to mask individual models.

For KhPRF-OPSA, client u masks its individual model as $\mathbf{y}_u^{(r)} = \Delta\cdot\mathbf{x}_u^{(r)} + \mathbf{mask}_u$ where $\mathbf{mask}_u = \mathrm{KF}(F_1(k_{u,e}, r), \mathbf{b})$. Here, F_1 is a secure pseudo-random function invoked on a round $r \in [1,R]$ and a shared key $k_{u,e}$ between client u and TEE instance M_e, and KF is a 1-almost key-homomorphic PRF invoked on a temporary key $\mathbf{k}_u = F_1(k_{u,e}, r)$ and a public parameter $\mathbf{b}$. For the surviving list $\mathcal{V}^{(r)}$, TEE computes $\mathbf{k}_{\mathcal{V}^{(r)}} = \sum_{u\in\mathcal{V}^{(r)}} F_1(k_{e,u}, r)$. Now, given $k_{u,e} = k_{e,u}$, we can observe that $\sum_{u\in\mathcal{V}^{(r)}} \mathrm{KF}(F_1(k_{u,e}, r), \mathbf{b}) = \mathrm{KF}(\mathbf{k}_{\mathcal{V}^{(r)}}, \mathbf{b}) + \mathbf{e}$ where $|\mathbf{e}_i| < \Delta$ for all $i \in [1,m]$, and obtain an aggregated model as follows:

$$\begin{aligned}
\sum_{u\in\mathcal{V}^{(r)}} \mathbf{x}_u^{(r)} &= \frac{1}{\Delta}\left(\sum_{u\in\mathcal{V}^{(r)}} \mathbf{y}_u^{(r)} - \mathrm{KF}(\mathbf{k}_{\mathcal{V}^{(r)}}, \mathbf{b})\right)\\
&= \frac{1}{\Delta}\left(\sum_{u\in\mathcal{V}^{(r)}} \Delta\cdot\mathbf{x}_u^{(r)} + \sum_{u\in\mathcal{V}^{(r)}} \mathbf{mask}_u - \mathrm{KF}(\mathbf{k}_{\mathcal{V}^{(r)}}, \mathbf{b})\right)\\
&= \frac{1}{\Delta}\left(\Delta \sum_{u\in\mathcal{V}^{(r)}} \mathbf{x}_u^{(r)} + \mathbf{e}\right)\\
&= \sum_{u\in\mathcal{V}^{(r)}} \mathbf{x}_u^{(r)} + \mathbf{0}
\end{aligned}$$

For POT-OPSA, each client $u \in \mathcal{U}$ masks its individual model as $\mathbf{y}_u^{(r)} = \mathbf{x}_u^{(r)} + \mathbf{mask}_u$ where $\mathbf{mask}_u = G(\widetilde{k}_u) + \sum_{v\in\mathcal{U}, u<v} G(F_0(k_{u,v}, r)) - \sum_{v\in\mathcal{U}, u>v} G(F_0(k_{u,v}, r))$. Here, F_0 is a secure pseudo-random function invoked on a round $r \in [1,R]$ and a shared key $k_{u,v}$ between client u and its neighbor v, and G is a secure pseudo-random generator invoked on a temporary individual key $\widetilde{k}_u \xleftarrow{\$} \{0,1\}^\lambda$ or a temporary pairwise key $\widetilde{k}_{u,v} = F_0(k_{u,v}, r)$. For the client list $\mathcal{U} = \mathcal{V}^{(r)} \cup \mathcal{D}^{(r)}$, the TEE instance helps the server to recover $\{\widetilde{k}_{v,u}\}_{v\in\mathcal{D}^{(r)}, u\in\mathcal{V}^{(r)}}$ for dropped clients and $\{\widetilde{k}_u\}_{u\in\mathcal{V}^{(r)}}$ for surviving clients. Then, the server computes $\mathbf{mask}_{\mathcal{U}}^{(r)} = \sum_{u\in\mathcal{V}^{(r)}, v\in\mathcal{D}^{(r)}} \left(G(\widetilde{k}_u) + \sum_{u<v} G(\widetilde{k}_{u,v}) - \sum_{u>v} G(\widetilde{k}_{u,v})\right)$. Now, given $k_{u,v} = k_{v,u}$ for all client u and v, we can observe that $\sum_{u,v\in\mathcal{L}, u<v} G(\widetilde{k}_{u,v}) = \sum_{u,v\in\mathcal{L}, u>v} G(\widetilde{k}_{u,v})$ for all $u, v \in \mathcal{L}$ and $\mathcal{L} \subseteq \mathcal{U}$, and obtain an aggregated model as follows:

$$\begin{aligned}
\sum_{u\in\mathcal{V}^{(r)}} \mathbf{x}_u^{(r)} &= \sum_{u\in\mathcal{V}^{(r)}} \mathbf{y}_u - \mathbf{mask}_{\mathcal{U}}^{(r)}\\
&= \sum_{u\in\mathcal{V}^{(r)}} \mathbf{x}_u^{(r)} + \sum_{u\in\mathcal{V}^{(r)}, v\in\mathcal{U}} \mathbf{mask}_u - \mathbf{mask}_{\mathcal{U}}^{(r)}\\
&= \sum_{u\in\mathcal{V}^{(r)}} \mathbf{x}_u^{(r)} + \sum_{u,v\in\mathcal{V}^{(r)}} \left(\sum_{u<v} G(\widetilde{k}_{u,v}) - \sum_{u>v} G(\widetilde{k}_{u,v})\right)\\
&= \sum_{u\in\mathcal{V}^{(r)}} \mathbf{x}_u^{(r)} + 0
\end{aligned}$$

This is satisfied when the number of surviving clients with $|\mathcal{V}| \ge \lceil (1-\delta)N \rceil$ and $(1-\delta) \ge \alpha$, where α is defined in Definition 4. □

B.2 Proof of Theorem 2

Proof. The proof is based on a standard hybrid argument using the simulator SIM. For any round $r \in [1,R]$, all input vectors $\mathcal{X}^{(r)}$, and all sets of corrupted clients $\mathcal{C} \subseteq \mathcal{U}$ of size $|\mathcal{C}| \le \lfloor \gamma N \rfloor$, we prove the output of SIM is computationally indistinguishable from the view of a malicious adversary $\mathcal{A}$, i.e., $\mathsf{REAL}_{\mathcal{C},r}^{\mathcal{U},S,R}(\mathcal{A}, \{\mathbf{x}_u\}_{u\in\mathcal{U}\setminus\mathcal{C}}) \approx_c \mathsf{SIM}_{\mathcal{C},r}^{\mathcal{U},S,R,F_{\alpha,\{\mathbf{x}_u^{(r)}\}_{u\in\mathcal{U}\setminus\mathcal{C}}}}(\mathcal{A})$ where $F_{\alpha,\mathcal{X}^{(r)}}$ is α-summation ideal functionality defined in Definition 4.

Following the MicroFedML [8] and Flamingo [9], we first define the behavior of our simulator SIM for KhPRF-OPSA:

- Setup phase:

(1) Each honest client u and TEE instance M_e follow the protocol description in one-time setup.
(2) For each corrupt client v, TEE instance M_e computes and stores $k_{e,v} = \mathsf{KA}(sk_e, pk_v)$.
(3) For each honest clients u, the simulator chooses $k_a \xleftarrow{\$} \{0,1\}^\lambda$ and sets $k^*_{u,e} = k^*_{e,u} = k_a$.

- The r-th round of the Training phase:
  (1) Each honest client u randomly chooses a random vector $\mathbf{y}^*_u$ and sends it the server.
  (2) The server S first adds the client u to the surviving list $\mathcal{V}^{(r)}$, and then the simulator makes a query to $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ to get $\mathbf{x}^{(r)}$.
  (3) For all honest clients $u \in \mathcal{V}^{(r)} \setminus \mathcal{C}$, the simulator randomly samples $\mathbf{x}^*_u \xleftarrow{\$} \mathcal{M}$ under the restriction $\sum_{u\in\mathcal{V}^{(r)}\setminus\mathcal{C}} \mathbf{x}^*_u = \mathbf{x}^{(r)}$, and then computes $\mathbf{mask}^*_u = \mathbf{y}^*_u - \mathbf{x}^*_u$ by programming the random oracle to set the output of KhPRF. The simulator sets $\mathbf{k}^*_u = \mathrm{PRF}(k^*_{u,e}, r)$ and samples a random vector $\mathbf{b}$ such that $\mathbf{mask}^*_u = \mathcal{R}_{\mathsf{KhPRF}}(\mathbf{k}^*_u, \mathbf{b})$ for each $u \in \mathcal{V}^{(r)} \setminus \mathcal{C}$, reveals masked keys $\mathbf{k}^*_{\mathcal{V}^{(r)}} = \sum_{u\in\mathcal{V}^{(r)}} \mathbf{k}^*_u$ for TEE instance M_e, and computes $\mathbf{mask}^*_{\mathcal{V}^{(r)}} = \mathcal{R}_{\mathsf{KhPRF}}(\mathbf{k}^*_{\mathcal{V}}, \mathbf{b})$ for the server.

Below, we present a series of subsequent hybrids to the real execution REAL of our KhPRF-OPSA protocol.

Hyb_0: This random variable is the joint views of all parties in $\mathcal{C}$ in the real execution.

Hyb_1: In this hybrid, the simulator, which knows all secrets of honest parties in every round, runs the execution of the KhPRF-OPSA protocol with $\mathcal{A}$. Therefore, the view of the adversary is the same as the previous hybrid.

Hyb_2: This hybrid is identical to Hyb_1 except that the simulator substitutes the shared key $k_{u,e} = \mathsf{KA}(sk_u, pk_e)$ between honest client u and TEE M_e with a random key $k_a \xleftarrow{\$} \{0,1\}^\lambda$. The 2ODH assumption [4] guarantees this hybrid is indistinguishable from the previous one.

Hyb_3: This hybrid is same as Hyb_2 except that the values of $\mathbf{y}_u$ computed by SIM on behalf of the honest client u and sent to the server, are substituted with uniformly sampled values $\mathbf{y}^*_u$. Since $\mathcal{A}$ does not know the secrets of honest parities and $\mathbf{y}_u$ has the same distribution as $\mathbf{y}^*_u$, the view of the adversary in this hybrid is statistically indistinguishable from the previous one.

Hyb_4: This hybrid is same as Hyb_3 except that the simulator replaces the revealed keys outputted by TEE instance M_e with $\mathbf{k}^*_{\mathcal{V}}$ and computes the aggregated mask $\mathbf{mask}^*_{\mathcal{V}}$ (as in Behavior 3 of Training phase of SIM) by querying the $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ and utilizing a random oracle $\mathcal{R}_{\mathsf{KhPRF}}$. Since $\mathcal{A}$ does not know the secrets of honest parities and the aggregated mask in SIM have the same distribution as the one in REAL, this hybrid is indistinguishable from the previous one.

Hyb_5: This hybrid is same as Hyb_4 except one modification: SIM sets the output of the ideal functionality $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ (as in Behavior 2 of Training phase of SIM) as the aggregated model $\mathbf{x}^{(r)}$. Note that the ideal functionality will not return $\perp$ in this case. This modification does not change the view seen by the adversary, and hence this hybrid is indistinguishable from the previous one.

After completing these hybrids, SIM simulates REAL without relying on inputs from the honest parties, indicating that the joint view of $\mathcal{A}$ in the real execution (Hyb_0) is computationally indistinguishable from the output of SIM (Hyb_5).

Here, we redefine the behavior of our simulator SIM for POT-OPSA:

- Setup phase:
  (1) Each honest client u and TEE instance M_e follow the protocol description in one-time setup.
  (2) For each corrupt client v, an honest client u computes and stores $k_{u,v} = \mathsf{KA}(sk_u, pk_v)$, and TEE instance M_e computes and stores $k_{e,v} = \mathsf{KA}(sk_e, pk_v)$.
  (3) For each honest clients u, the simulator chooses $k_a \xleftarrow{\$} \{0,1\}^\lambda$ and sets $k^*_{u,e} = k^*_{e,u} = k_a$. For each pair of honest clients u, v, the simulator chooses $k_b \xleftarrow{\$} \{0,1\}^\lambda$ and sets $k^*_{u,v} = k^*_{v,u} = k_b$.
- The r-th round of the Training phase:
  (1) Each honest client u randomly chooses a random vector $\mathbf{y}^*_u$ and sends it the server. For each corrupt client v, Each honest client u randomly chooses $ct^*_{u,v}$ as a ciphertext and sends it to the server.
  (2) The server S first adds the client u to the surviving list $\mathcal{V}^{(r)}$, and then the simulator makes a query to $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ to get $\mathbf{x}^{(r)}$.
  (3) For all honest clients $u \in \mathcal{V}^{(r)} \setminus \mathcal{C}$, the simulator randomly samples $\mathbf{x}^*_u \xleftarrow{\$} \mathcal{M}$ under the restriction $\sum_{u\in\mathcal{V}^{(r)}\setminus\mathcal{C}} \mathbf{x}^*_u = \mathbf{x}^{(r)}$, and then computes $\mathbf{mask}^*_u = \mathbf{y}^*_u - \mathbf{x}^*_u$ by programming the random oracle to set the output of PRG. The simulator sets $\{\widetilde{\mathbf{k}}^*_{u,v}\}_{v\in\mathcal{U}} = \{\mathcal{R}_{\mathsf{PRG}}(\widetilde{k}^*_{u,v})\}_{v\in\mathcal{U}}$ where $\{\widetilde{k}^*_{u,v}\}_{v\in\mathcal{U}} = \{\mathrm{PRF}(k^*_{u,v}, r)\}_{v\in\mathcal{U}}$, and samples a random $\widetilde{k}^*_u$ to set $\widetilde{\mathbf{k}}^*_u = \mathcal{R}_{\mathsf{PRG}}(\widetilde{k}^*_u)$ such that $\mathbf{mask}^*_u = \widetilde{\mathbf{k}}^*_u + \sum_{u<v} \widetilde{\mathbf{k}}^*_{u,v} - \sum_{u>v} \widetilde{\mathbf{k}}^*_{u,v}$ for each $u \in \mathcal{V}^{(r)} \setminus \mathcal{C}$ and $v \in \mathcal{U}$. The simulator computes $\{\widetilde{\mathbf{k}}^*_u, \widetilde{\mathbf{k}}^*_{u,v}\}_{u\in\mathcal{V}^{(r)}\setminus\mathcal{C}, v\in\mathcal{D}^{(r)}}$ for M_e, and computes $\mathbf{mask}^*_{\mathcal{U}} = \sum \widetilde{\mathbf{k}}^*_u + \sum\sum_{u<v} \widetilde{\mathbf{k}}^*_{u,v} - \sum\sum_{u>v} \widetilde{\mathbf{k}}^*_{u,v}$ where $u \in \mathcal{V}^{(r)} \setminus \mathcal{C}$ and $v \in \mathcal{D}^{(r)}$ for the server.

Below, we present a series of subsequent hybrids to the real execution REAL of our POT-OPSA protocol.

Hyb_0: This random variable is the joint views of all parties in $\mathcal{C}$ in the real execution.

Hyb_1: In this hybrid, the simulator, which knows all secrets of honest parties in every round, runs the execution of the POT-OPSA protocol with $\mathcal{A}$. Therefore, the view of the adversary is the same as the previous hybrid.

Hyb_2: This hybrid is identical to Hyb_1 except that the simulator substitutes the shared key $k_{u,e} = \mathsf{KA}(sk_u, pk_e)$ between honest client u and TEE M_e with a random key $k_a \xleftarrow{\$} \{0,1\}^\lambda$, and replaces the shared key $k_{u,v} = \mathsf{KA}(sk_u, pk_v)$ between honest client u and v with a random key $k_b \xleftarrow{\$} \{0,1\}^\lambda$. The 2ODH assumption [4] guarantees this hybrid is indistinguishable from the previous one.

Hyb_3: This hybrid is same as Hyb_2 except that the values of $(\mathbf{y}_u, \{ct_{u,v}\}_{v \in \mathcal{U}})$ computed by SIM on behalf of the honest client u and sent to the server, are substituted with uniformly sampled values $(\mathbf{y}^*_u, \{ct^*_{u,v}\}_{v \in \mathcal{U}})$ at random. Since $\mathcal{A}$ does not know the secrets of honest parities and $(\mathbf{y}_u, \{ct_{u,v}\}_v)$ has the same distribution as $(\mathbf{y}^*_u, \{ct^*_{u,v}\}_v)$, the view of the adversary in this hybrid is statistically indistinguishable from the previous one.

Hyb_4: This hybrid is same as Hyb_3 except that the simulator replaces the revealed keys outputted by TEE instance M_e with $\{\widetilde{\mathbf{k}}^*_u, \widetilde{\mathbf{k}}^*_{u,v}\}_{u,v}$ and computes the aggregated mask $\mathbf{mask}^*_{\mathcal{U}}$ (as in Step 3 of Training phase behavior of SIM) by querying the $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ and utilizing a random oracle $\mathcal{R}_{\mathsf{PRG}}$. Since $\mathcal{A}$ does not know the secrets of honest parities and the aggregated mask in SIM have the same distribution as the one in REAL, this hybrid is indistinguishable from the previous one.

Hyb_5: This hybrid is same as Hyb_4 except one modification: SIM sets the output of the ideal functionality $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ (as in Step 2 of Training phase behavior of SIM) as the aggregated model $\mathbf{x}^{(r)}$. Note that the ideal functionality will not return $\perp$ in this case. This modification does not change the view seen by the adversary, and hence this hybrid is indistinguishable from the previous one.

After completing these hybrids, SIM simulates REAL without relying on inputs from the honest parties, indicating that the joint view of $\mathcal{A}$ in the real execution (Hyb_0) is computationally indistinguishable from the output of SIM (Hyb_5).

For KhPRF-OPSA and POT-OPSA, SIM can simulate REAL without knowledge of the inputs from the honest parties, indicating the security of our OPSA framework in the malicious setting. Note that our malicious setting includes the semi-honest setting, thereby extending the scope of our security proof to encompass the latter.

□

B.3 Proof of Theorem 3

Proof. We first prove the security of individual models in the construction instantiated with Construction 1 or 2 providing result verification (subsection IV-C), following the proof of Theorem 2. As aforementioned, we assume that all clients are semi-honest and .

Now, we define how our simulator SIM behaves during result verification of KhPRF-OPSA or POT-OPSA. In fact, SIM behaves similarly to that in in the proof of Theorem 2, with the following new additions and modifications:

- The r-th round of the Training phase:
  (1) Each honest client u samples com^*_u at random. It then computes a signature $\sigma^*_u = \mathsf{Sign}(sk_u, \mathsf{com}^*_u)$ and sends $(\mathsf{com}^*_u, \sigma^*_u)$ to the server.
  (3) For all honest clients $u \in \mathcal{V}^{(r)} \setminus \mathcal{C}$, the simulator samples $\mathsf{rand}^*_u = \mathsf{PRF}(k^*_{u,e}, 0||r)$ such that $\mathsf{com}^*_u = \mathsf{Commit}(\mathbf{x}^*_u, \mathsf{rand}^*_u)$. For TEE instance M_e, the simulator computes $\mathsf{rand}^* = \sum_u \mathsf{rand}^*_u$ and $\mathsf{com}^* = \prod_u \mathsf{com}^*_u$ for all $u \in \mathcal{V}^{(r)} \setminus \mathcal{C}$ and generates a signature $\sigma^*_e := \mathsf{Sign}(sk_e, \mathsf{com}^*||\mathsf{rand}^*||r)$. The server sends $(\mathbf{x}^r, \mathsf{rand}^*, \sigma^*_e)$ to all clients.

Below, we present a series of subsequent hybrids to the real execution REAL of our KhPRF-OPSA protocol with result verification.

Hyb_0: This random variable is the joint views of all parties in $\mathcal{C}$ in the real execution.

Hyb_1: In this hybrid, the simulator, which knows all secrets of honest parties in every round, runs the execution of the KhPRF-OPSA protocol with result verification with $\mathcal{A}$. Therefore, the view of the adversary is the same as the previous hybrid.

Hyb_2: This hybrid is identical to Hyb_1 except that the simulator substitutes the shared key $k_{u,e} = \mathsf{KA}(sk_u, pk_e)$ between honest client u and TEE M_e with a random key $k_a \xleftarrow{\$} \{0,1\}^\lambda$. The 2ODH assumption [4] guarantees this hybrid is indistinguishable from the previous one.

Hyb_3: This hybrid is same as Hyb_2 except that the values of $(\mathbf{y}_u, \mathsf{com}_u, \sigma_u)$ computed by SIM on behalf of the honest client u and sent to the server, are substituted with uniformly sampled values $(\mathbf{y}^*_u, \mathsf{com}^*_u, \sigma^*_u)$. Since $\mathcal{A}$ does not know the secrets of honest parities and $(\mathbf{y}_u, \mathsf{com}_u, \sigma_u)$ has the same distribution as $(\mathbf{y}^*_u, \mathsf{com}^*_u, \sigma^*_u)$, the view of the adversary in this hybrid is statistically indistinguishable from the previous one.

Hyb_4: This hybrid is same as Hyb_3 except that the simulator replaces the output of TEE instance M_e with $(\mathbf{k}^*_{\mathcal{V}}, \mathsf{com}^*, \mathsf{rand}^*, \sigma^*_e)$ and computes the aggregated mask $\mathbf{mask}^*_{\mathcal{V}}$ (as in Behavior 3 of Training phase of SIM) by querying the $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ and utilizing a random oracle $\mathcal{R}_{\mathsf{KhPRF}}$. Since $\mathcal{A}$ does not know the secrets of honest parities and the aggregated mask in SIM have the same distribution as the one in REAL, this hybrid is indistinguishable from the previous one. Note that the indistinguishability of this hybrid relies on the hiding property of the underlying vector Pedersen commitment scheme and the security property of the signature schemes.

Hyb_5: This hybrid is same as Hyb_4 except one modification: SIM sets the output of the ideal functionality $F_{\alpha,\mathcal{X}^{(r)}}(\mathcal{V}^{(r)} \setminus \mathcal{C})$ (as in Behavior 2 of Training phase of SIM) as the aggregated model $\mathbf{x}^{(r)}$. The server sends $(\mathbf{x}^r, \mathsf{rand}^*, \sigma^*_e)$ to all clients. Note that the ideal functionality will not return $\perp$ in this case. This modification does not change the view seen by the adversary, and hence this hybrid is indistinguishable from the previous one.

After completing these hybrids, SIM simulates REAL without relying on inputs from the honest parties, and we can see that the joint view of $\mathcal{A}$ in the real execution (Hyb_0) is computationally indistinguishable from the output of SIM (Hyb_5).

Here, we omit the hybrids to the real execution REAL of our POT-OPSA protocol with result verification, as they undergo the same modifications as described above.

Next, we give the proof for correctness against a malicious server. At the end of round r, the server sends $(\mathbf{x}^{(r)}, \mathsf{com}^{(r)}, \mathsf{rand}^{(r)}, \sigma_e^{(r)})$ to all clients. Here, $\mathbf{x}^{(r)} = \sum_{u \in \mathcal{V}^{(r)}} \mathbf{x}_u^{(r)}$ represents an aggregated model computed honestly, $\mathsf{com}^{(r)} = \mathsf{Commit}(\mathbf{x}^{(r)}, \mathsf{rand}^{(r)})$ denotes a valid commitment with a random number $\mathsf{rand}^{(r)}$, and $\sigma_e^{(r)} := \mathsf{Sign}(sk_e, \mathsf{com}^{(r)} || \mathsf{rand}^{(r)} || r)$ is a signature generated by TEE instance M_e. Let $\widetilde{\mathbf{x}}^{(r)} = \mathbf{x}^{(r)} + \widetilde{\mathbf{e}}$ be a tampered global model, where $\widetilde{\mathbf{e}}$ is an error vector introduced by the malicious server. There are two situations where the client can accept $\widetilde{\mathbf{x}}^{(r)}$: one happens if the server generates $\widetilde{\mathbf{x}}^{(r)}$ based on $\mathsf{com}^{(r)}$ and $\mathsf{rand}^{(r)}$, and the other happens if the server utilizes $\widetilde{\mathbf{x}}^{(r)}$ to generate $\widetilde{\mathsf{com}}^{(r)}$ and $\widetilde{\mathsf{rand}}^{(r)}$ while forging the signature of TEE instance M_e. The former contradicts the binding property of vector Pedersen commitment scheme, and the latter violates the EUF-CMA secure signature scheme.

Therefore, for KhPRF-OPSA and POT-OPSA, we prove the security and correctness of our OPSA framework against the malicious server. $\square$