GuardHFL: Privacy Guardian for Heterogeneous Federated Learning

Hanxiao Chen [1 2] **Meng Hao** [1] **Hongwei Li** [1] **Kangjie Chen** [3] **Guowen Xu** [3] **Tianwei Zhang** [3] **Xilin Zhang** [1]

Abstract

Heterogeneous federated learning (HFL) enables clients with different computation and communication capabilities to collaboratively train *their own customized models* via a query-response paradigm on auxiliary datasets. However, such a paradigm raises serious privacy concerns due to the leakage of highly sensitive query samples and response predictions. We put forth GuardHFL, the *first-of-its-kind* efficient and privacy-preserving HFL framework. GuardHFL is equipped with a novel HFL-friendly secure querying scheme built on lightweight secret sharing and symmetric-key techniques. The core of GuardHFL is two customized multiplication and comparison protocols, which substantially boost the execution efficiency. Extensive evaluations demonstrate that GuardHFL significantly outperforms the alternative instantiations based on existing state-of-the-art techniques in both runtime and communication cost.

1. Introduction

As a promising variant of federated learning (FL), heterogeneous federated learning (HFL) (Li & Wang, 2019) enables clients equipped with different computation and communication capabilities to collaboratively train their own customized models that may *differ in size, numerical precision or structure* (Lin et al., 2020). In particular, the knowledge of models is shared via a query-response paradigm on auxiliary datasets, such as unlabeled datasets from the same task domain (Choquette-Choo et al., 2021) or related datasets from different task domains (Li & Wang, 2019; Lin et al., 2020). In such a paradigm, each client queries others with samples in the auxiliary querying dataset, and obtains aggregated response predictions via a centralized cloud server[1]. Then the client retrains his local model on the query data and corresponding predictions. This flexible approach facilitates customized FL-driven services in areas like healthcare and finance (Gao et al., 2022), while resolving the intellectual property concerns of FL models (Tekgul et al., 2021).

However, HFL suffers from several privacy issues. First, directly sharing query samples violates their privacy. For example, in healthcare applications, the auxiliary dataset may contain patients' medical conditions. Disclosure of such highly sensitive information is illegal under current regulations like General Data Protection Regulation. Second, disclosing response predictions may still compromise the privacy of local data (Papernot et al., 2016). Specifically, the predicted logits indicate how confident the model is in classifying the query samples, e.g., reflecting the capabilities of medical diagnostic systems. Even worse, they may imply the knowledge of model parameters and training samples.

Although in traditional FL systems, the privacy issue could be mitigated through well-studied secure gradient aggregation protocols (Bell et al., 2020), it becomes more challenging to realize this guarantee in HFL, due to the heterogeneity of the clients' models (refer to Appendix B.3). To bridge this gap, a possible solution is to structurally integrate into HFL existing secure querying (a.k.a. private inference) schemes (Rathee et al., 2020; Huang et al., 2022; Wagh et al., 2019; Tan et al., 2021). These schemes utilize various cryptographic primitives, including homomorphic encryption (HE) (Gentry, 2009), garbled circuit (GC) (Yao, 1986) or oblivious transfer (OT) (Ishai et al., 2003), to provide rigorous privacy guarantees for query data and response predictions. Although with non-trivial modifications, these secure querying schemes can be extended to HFL scenarios (refer to Section 2.3), they have two major limitations: (1) lacking customized protocol designs and (2) relying on heavy cryptographic primitives. These bottlenecks lead to poor performance and hinder the efficient instantiation of HFL. Therefore, it is necessary but challenging to design customized protocols and implement a privacy-preserving HFL with desirable performance.

[1]University of Electronic Science and Technology of China, China [2]This work was done at NTU as a visiting student. [3]Nanyang Technological University, Singapore. Correspondence to: Hongwei Li <hongweili@uestc.edu.cn>.

Proceedings of the 40^{th} International Conference on Machine Learning, Honolulu, Hawaii, USA. PMLR 202, 2023.

[1]As demonstrated in Bonawitz et al. (2017); Bell et al. (2020), the clients (e.g., mobile devices) in real-world applications are generally widely distributed and coordinated only by the server.

We introduce GuardHFL, the *first-of-its-kind* efficient and privacy-preserving HFL framework to address the above challenges[2]. GuardHFL is built upon the standard HFL training paradigm (Li & Wang, 2019), which contains three stages: local training, querying, and local re-training. To provide privacy guarantees for HFL, GuardHFL proposes an HFL-friendly secure querying scheme based on lightweight secret sharing and sysmmetric-key primitives. The core of this scheme is the customized multiplication and comparison protocol, which substantially boosts execution efficiency. More precisely, (1) we design a new multiplication protocol based on pseudo-random functions, which is not only suitable for practical HFL scenarios with cross-client communication constraints, but also is efficient, e.g., only communicating 3 elements in an ℓ-bit ring. (2) We provide a customized comparison protocol based on the advanced adder, such as parallel prefix adder (PPA) (Harris, 2003). We utilize an adder to evaluate comparison operations because the adder contains only AND and XOR gates, where AND can be efficiently computed based on our multiplication protocol and XOR is cost-free. Besides, we provide formal security analysis for the designed protocols, and evaluate GuardHFL on different datasets (SVHN, CIFAR10, Tiny ImageNet), system configurations (IID and Non-IID training sets) and heterogeneous models. Extensive experiments demonstrate that GuardHFL outperforms the alternative instantiations based on the state-of-the-art techniques by about $4.4 \sim 75.6\times$ while ensuring the model utility.

2. Background

2.1. Heterogeneous Federated Learning

We briefly review the workflow of the standard HFL training paradigm (Li & Wang, 2019), where clients independently design their own unique models. Due to such model heterogeneity, clients cannot directly share model parameters with each other as in the traditional FL. Instead, they learn the knowledge of other models via a query-response mechanism, which is similar to the knowledge distillation technique (Hinton et al., 2015). To be more precise, each client P_Q (called the querying party) performs three-phase operations collaboratively with a server. (1) *Local training*: P_Q first trains the local model on his private dataset. (2) *Querying*: The server selects C fraction of clients as the responding parties P_A who provide predictions given the auxiliary querying dataset. The server receives the prediction results from these P_A, computes the aggregated result and returns it back to P_Q. (3) *Local re-training*: P_Q then retrains the local model based on the private dataset, as well as the query samples and corresponding predictions. Each client in HFL can play the roles of the querying party and the responding party at the same time, and the above process is iterated until each local model meets the pre-defined accuracy requirement. Note that as illustrated in existing works (Bonawitz et al., 2017; Bell et al., 2020), the server is responsible for routing the messages between clients, since the clients (e.g., mobile devices) generally cannot establish direct communication channels with others.

GuardHFL is in line with the above paradigm with the additional benefit of privacy protection. The only difference lies in the acquisition of auxiliary query samples in the querying stage. In general HFL, there is a large public auxiliary dataset (used as query samples) that every party can access. However, considering the privacy limitation, such a dataset is hard to collect in real-world scenarios such as healthcare. To tackle this problem, in GuardHFL, each party can locally construct a synthesized querying set based on his private training samples, by utilizing existing data augmentation strategies (refer to Section 3.4).

2.2. Threat Model

As described in Section 1, in the querying phase of HFL, the query samples, response predictions and model parameters may contain sensitive information that is of interest to adversaries. In line with prior works (Phong et al., 2018; Sun & Lyu, 2021; Choquette-Choo et al., 2021), we consider an honest-but-curious adversary setting (Goldreich, 2009), where each entity (including the clients and the server) strictly follows the specification of the designed protocol but attempts to infer more knowledge about this private information of other clients. Moreover, to maintain its reputation and provide more services, the server does not collude with any clients, namely that an attacker either corrupts the server or a subset of clients but not both.

Security is modeled in the simulation paradigm (Canetti, 2001), which defines a *real* interaction and an *ideal* interaction. In the real interaction, the parties execute protocols according to the specification in the presence of an adversary $\mathcal{A}$ and the environment $\mathcal{Z}$. In the ideal interaction, the parties send their inputs to an ideal functionality that faithfully executes the operation. Secure inference requires that no environment can computationally distinguish between real and ideal interactions. The protocols in GuardHFL invoke multiple sub-protocols, and we use the *hybrid model* to describe them similar to prior works (Rathee et al., 2020; 2021). This is analogous to the real interaction, except that sub-protocols are replaced by the corresponding ideal functionalities. By convention, a protocol invoking a functionality $\mathcal{F}$ is referred

[2] Choquette-Choo et al. (2021) presented a general collaborative learning scheme, called CaPC, which enables each party to improve his local model from others' models directly using the existing secure querying scheme (Boemer et al., 2019b). However, it cannot be directly applied to the HFL scenario as it requires cross-client communication. Meanwhile, it causes high overhead (refer to Section 4.1).

to as the "$\mathcal{F}$-hybrid model".

2.3. Extend existing secure querying solutions to HFL

To provide privacy guarantees against honest-but-curious adversaries in Section 2.2, the clients and the server need to securely execute the querying process. Although this process consists of three entities (i.e., P_Q, the server and P_A), it is non-trivial to directly extend existing secure 3-party computation protocols (3PC) (Wagh et al., 2019; 2021; Knott et al., 2021; Tan et al., 2021) to instantiate this process. The main reason is the incapability of direct communication between P_Q and P_A in realistic HFL scenarios (Bonawitz et al., 2017; Bell et al., 2020), which hinders the usage of these 3PC solutions in HFL, unless we redesign the underlying protocols and make substantial modifications to their corresponding implementations. On the other hand, we can extend state-of-the-art 2PC solutions (Rathee et al., 2020; Huang et al., 2022) into this process via using the server as the communication medium with adaptive protocol modifications (refer to Appendix B.4). Unfortunately, as mentioned in Section 1, such extensions come at the cost of heavy computational and communication complexity. Motivated by these challenges, we design various lightweight and customized protocols to improve the efficiency of the secure querying phase, which show significant performance gains over extending the advanced 2PC schemes to HFL.

2.4. Cryptographic Primitives

Secret sharing. `GuardHFL` adopts the 2-out-of-2 arithmetic sharing scheme (Shamir, 1979; Demmler et al., 2015) over a ring $\mathbb{Z}_{2^\ell}$. Specifically, the sharing algorithm takes x as input and outputs random shares $[x]_0$ and $[x]_1$ such that $x = [x]_0 + [x]_1 \mod 2^\ell$. The reconstruction algorithm takes the two shares as input and outputs $x = [x]_0 + [x]_1 \mod 2^\ell$. Besides, the boolean sharing is also employed in `GuardHFL`, where $x \in \mathbb{Z}_2$ is shared as $[x]_0^B$ and $[x]_1^B$ satisfying $[x]_0^B \oplus [x]_1^B = x$. Arithmetic operations can be evaluated on secret-shared values. Given two secret-shared values $[x]$ and $[y]$ owned by two parties, addition and subtraction operations ($[z] = [x] \pm [y]$ in $\mathbb{Z}_{2^\ell}$) can be realized locally without any communication, i.e., each party P_i computes $[z]_i = [x]_i \pm [y]_i \mod 2^\ell$ for $i \in \{0, 1\}$. In Appendix B.2, we review existing protocols for multiplication operations.

Pseudo-random Function. A pseudo-random function $y \leftarrow \text{PRF}(Sk, x)$ is a deterministic function that takes a uniformly random seed Sk and a payload x as input and outputs a fixed-length pseudo-random string y. The security of PRFs ensures that the output is indistinguishable from the uniform distribution. In `GuardHFL`, PRFs enable two parties to generate the same pseudo-random values without communication.

Algorithm 1 The `GuardHFL` framework

Input: Each client P_j, $j \in [n]$, holds a private dataset $\mathcal{D}_j$ and a customized local model M_j. *iter* is the number of iterations. B is the number of query samples and $\mathcal{C}$ is the set of selected responding parties in the current query-response phase.
Output: Trained models M_j, $j \in [n]$.

for each $j \in [n]$ **do**
  P_j locally trains the local model M_j on $\mathcal{D}_j$ using the stochastic gradient descent optimization.
end for
for each *iter* **do**
  for each querying party P_Q^j, $j \in [n]$ **do**
    P_Q^j randomly samples query data $\{x_b\}_{b \in [B]}$ from the auxiliary querying dataset that is generated via the data argumentation strategies described in Section 3.4.
    for each responding party P_A^i, $i \in \mathcal{C}$ **do**
      P_Q^j secret-shares $\{[x_b]\}_{b \in [B]}$ with P_A^i and the server, based on the protocol Π_{Share} in Section 3.1.
      P_A^i, P_Q^j and the server jointly perform the secure model prediction protocol in Section 3.2.
      P_A^i secret-shares the predictions $\{[y_b^i]\}_{b \in [B]}$ to P_Q and the server.
    end for
    P_Q^j obtains $\{y_b\}_{b \in [B]}$, where $y_b = \sum_{i \in \mathcal{C}} y_b^i$, via the protocol Π_{Agg} in Section 3.3 with the server.
    P_Q^j retrains M_j based on the query dataset $\{x_b, y_b\}_{b \in [B]}$ and $\mathcal{D}_j$.
  end for
end for

3. GuardHFL

`GuardHFL` is built upon standard HFL systems as discribed in Section 2.1 and enhances their privacy protection with cryptographic techniques. Figure 1 shows the overview of `GuardHFL` and the detailed description is given in Algorithm 1. Similar to vanilla HFL, it includes three phases: *local training*, *secure querying* and *local re-training*. Since *local training* and *local re-training* are standard HFL training processes without privacy issues, below we focus on formalizing our core construction, i.e., *secure querying*. As detailed in Section 2.3, extending existing secure querying solutions to HFL introduces expensive overhead due to the usage of heavy cryptographic primitives and the lack of customized protocols. To tackle this challenge, we propose a tailored secure querying scheme utilizing lightweight secret sharing and PRF techniques, which is decomposed into three steps: *secure query-data sharing*, *secure model prediction* and *secure result aggregation*.

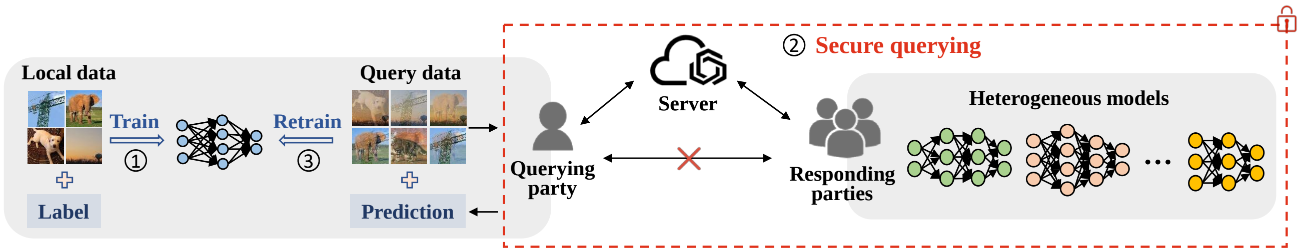


Figure 1. The high-level view of GuardHFL

In general, P_Q first constructs querying samples locally using data argumentation strategies (Section 3.4). Since querying samples imply the semantic information of private training data, they cannot be directly exposed to the server and P_A for prediction. Therefore, GuardHFL secret-shares query samples to the server and P_A using the designed secure query-data sharing protocol (Section 3.1). Then given the secret-shared samples, P_A, P_Q and the server jointly execute the proposed secure model prediction scheme (Section 3.2) to obtain the secret-shared inference logits. After that, the secure result aggregation protocol (Section 3.3) comes in handy, which takes as input the secret-shared logits and returns the aggregated results to P_Q.

3.1. Secure Query-data Sharing

To perform secure model prediction based on secret sharing techniques, P_Q first secret-shares the query data x with the server and P_A. Considering the communication constraint between P_Q and P_A, we utilize PRFs to share x. Specifically, we first construct PRF seeds in pairs for P_Q, P_A and the server, denoted as Sk_{QA}, Sk_{SA}, and Sk_{SQ}, which are used to generate the same random values between two parties without communication (refer to Figure 12 in Appendix B.2). After that, P_Q can share x using the protocol Π_{Share} as shown in Figure 2. In particular, P_Q non-interactively shares $[x]_0 = r$ with P_A using PRFs on the seed Sk_{QA}. Then P_Q computes $[x]_1 = x - r$ and sends it to the server.

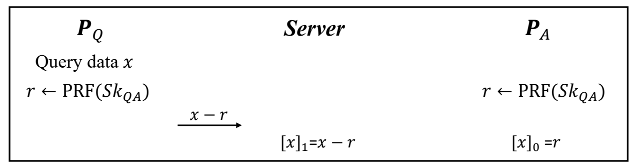


Figure 2. Secure query-data sharing protocol Π_{Share}

Theorem 3.1. *The protocol Π_{Share} in Figure 2 securely realizes the functionality $\mathcal{F}_{\text{Share}}$ in Table 5 in the $\mathcal{F}_{\text{PRF}}$-hybrid model.*

Proof. The formal proof is provided in Appendix C. □

3.2. Secure Model Prediction

In this step, the server and P_A execute secure model prediction on the secret-shared query data with the assistance of P_Q. Similar to prior secure prediction schemes (Rathee et al., 2020; Huang et al., 2022), neural networks include three types of layers: linear layers, ReLU and MaxPooling. When evaluating each layer of models, GuardHFL maintains the following *invariant*: the server and P_A begin with secret shares of inputs, and after each layer, end with secret shares of outputs over the same ring. This allows us to sequentially stitch the proposed protocols to obtain a fully secure prediction scheme. Figure 11 in Appendix B.1 gives an end-to-end graphic depiction. Below we elaborate the customized protocols for these three components.

Linear layers. Linear layers consist of fully-connection, convolution and batch normalization, and the main operation of these layers is matrix multiplication (Wagh et al., 2019; Huang et al., 2022). We design a customized matrix multiplication protocol Π_{Matmul}, which is not only compatible with the communication-limited HFL setting but also improves communication efficiency. Specifically, as shown in Figure 3, P_A and the server aim to compute ωx, where the model parameter ω is held by P_A and the shares $[x]_0$ and $[x]_1$ of x are held by P_A and the server, respectively. Given that $\omega x = \omega[x]_0 + \omega[x]_1$, P_A can compute $\omega[x]_0$ locally. To evaluate $\omega[x]_1$, P_Q first generates three random matrices as a, b and $[c]_0$ using PRFs, and then computes and sends $[c]_1$ that satisfies $[c]_1 + [c]_0 = ab$ in $\mathbb{Z}_{2^\ell}$ to the server[3]. At the same time, using PRFs, the server generates the same b and P_A generates the same a and $[c]_0$. Then P_A and the server can learn $[y]_0$ and $[y]_1$ (i.e., the secret shares of ωx), respectively, through one round of interaction. Overall, the communication cost is 3ℓ bits within 1 communication round.

[3] $(a, b, [c]_0, [c]_1)$ with the constrain $c = ab$ in $\mathbb{Z}_{2^\ell}$ can be seen as a variant of the Beaver's multiplication triple. Details refer to Appendix B.2.

Remark. Similar to Rathee et al. (2020); Huang et al. (2022), to be compatible with cryptographic protocols, we use the fixed-point representation, where the truncation technique is needed to prevent values from overflowing after each multiplication operation. Consistent with existing works (Mishra et al., 2020; Wagh et al., 2019), we use the truncation method from Mohassel & Zhang (2017). This method simply truncates the extra least significant bit (LSB) of a fixed-point value, albeit at the cost of a 1-bit error of the fractional part with the probability of $2^{\ell_x+1-\ell}$. Here, ℓ_x is the fractional prediction, and ℓ is the size of the secret-sharing ring. In GuardHFL, $\ell_x = 20$ and $\ell = 64$, thus an error of about 10^{-6} may occur with the probability of $\frac{1}{2^{43}}$, which is negiliable.

Theorem 3.2. *The protocol Π_{Matmul} in Figure 3 securely realizes the functionality $\mathcal{F}_{\mathsf{Matmul}}$ in Table 5 in the $\mathcal{F}_{\mathsf{PRF}}$-hybrid model.*

Proof. The formal proof is provided in Appendix C. □

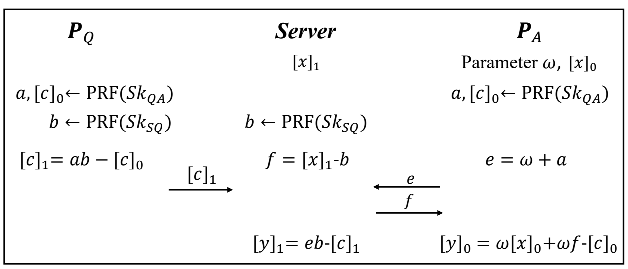


Figure 3. Secure matrix multiplication protocol Π_{Matmul}

ReLU. The ReLU activation can be redefined as $\mathsf{ReLU}(x) = x \cdot (1 \oplus \mathsf{MSB}(x))$, where $\mathsf{MSB}(x)$ equals 0 if $x \geq 0$ and 1 otherwise. Thus, the evaluation of ReLU consists of a MSB (i.e., comparison) operation, followed by a multiplication operation. Below, we first provide a customized MSB protocol built on the advanced adder such as parallel prefix adder (PPA)[4] (Harris, 2003), and then describe the subsequent multiplication implementation.

Customized MSB evaluation. Given that $[x]_0 = e_\ell || \ldots || e_1$ and $[x]_1 = f_\ell || \ldots || f_1$, an ℓ-bit adder is applied to perform the binary addition $e_i + f_i$ for each $i \in [\ell]$ to produce the carry bits $c_\ell, \ldots, c_1$. Thus, the MSB of x can be learned via $\mathsf{MSB}(x) = e_\ell \oplus f_\ell \oplus c_\ell$, and the key task is to compute c_ℓ. Obviously, we have $c_\ell = c_{\ell-1} \wedge (e_{\ell-1} \oplus f_{\ell-1}) \oplus (e_{\ell-1} \wedge f_{\ell-1})$. Further, PPA defines a set of *carry signal tuples* $\{(g_i^0, p_i^0)\}_{i\in[\ell]}$, and sets $g_i^0 = e_i \wedge f_i$, $p_i^0 = e_i \oplus f_i$ for each $i \in [\ell]$. Then, c_ℓ can be expressed as $c_\ell = g_{\ell-1}^0 \oplus (p_{\ell-1}^0 \wedge g_{\ell-2}^0) \oplus \cdots \oplus (p_{\ell-1}^0 \wedge \cdots \wedge p_2^0 \wedge g_1^0)$. PPA computes this equation by constructing a $\log \ell$-depth boolean circuit with inputs $\{(g_i^0, p_i^0)\}_{i\in[\ell]}$. And each node k of depth n in the circuit performs the following operations, where $n \in [\log \ell]$.

$$g_k^n = g_{j+1}^{n-1} \oplus (g_j^{n-1} \wedge p_{j+1}^{n-1})$$
$$p_k^n = p_{j+1}^{n-1} \wedge p_j^{n-1}. \tag{1}$$

Namely, it takes as input two adjacent signal tuples $(g_{j+1}^{n-1}, p_{j+1}^{n-1})$ and (g_j^{n-1}, p_j^{n-1}), and outputs a signal tuple (g_k^n, p_k^n). In the end, the circuit outputs $g_1^{\log \ell}$, which is exactly equal to c_ℓ. Thus, we have $\mathsf{MSB}(x) = e_\ell \oplus f_\ell \oplus g_1^{\log \ell}$.

We can carefully utilize our HFL-friendly multiplication protocol Π_{Matmul} in Figure 3 to evaluate AND gates in the above circuit. Specifically, the AND operation used to generate signal tuples (g_k^n, p_k^n) for $n > 0$ can be formalized as $([a]_0^B \oplus [a]_1^B) \wedge ([b]_0^B \oplus [b]_1^B) = ([a]_0^B \wedge [b]_0^B) \oplus ([a]_1^B \wedge [b]_1^B) \oplus ([a]_1^B \wedge [b]_0^B) \oplus ([a]_0^B \wedge [b]_1^B)$. The first two items

Algorithm 2 Secure MSB Protocol Π_{msb}

Input: The arithmetic shares $[x]$
Output: The boolean shares $[\mathsf{MSB}(x)]^B$

P_A and the server initiate vectors g^* and p^* with size ℓ, where g_i^* and p_i^* are the i-th positions of g^* and p^* respectively.
Let $e_\ell, \ldots, e_1$ and $f_\ell, \ldots, f_1$ denote the bit strings of $[x]_0$ and $[x]_1$ respectively.
For $i \in [\ell]$, P_A, P_Q and the server invoke an instance of Π_{Matmul} with inputs e_i and f_i to obtain $[g_i^*]^B$.
For $i \in [\ell]$, P_A sets $[p_i^*]_0^B = e_i$ and the server sets $[p_i^*]_1^B = f_i$.
for $r \in [2, \log \ell + 1]$ **do**
  if $r = 2$ **then**
    For $i \in [2, \frac{\ell}{2}]$, P_A, P_Q and the server invoke two instances of Π_{Matmul} with inputs $[g_{2i-2}^*]^B$ and $[p_{2i-1}^*]^B$ to obtain $[t_i]^B$. Then the server and P_A set $[g_i^*]_1 = [g_{2i-1}^*] \oplus [t_i]$.
    For $i \in [2, \frac{\ell}{2}]$, P_A, P_Q and the server invoke two instances of Π_{Matmul} with inputs $[p_{2i-1}^*]^B$ and $[p_{2i-2}^*]^B$ to obtain $[p_i^*]^B$.
  else
    For $i \in [1, \frac{\ell}{2^{r-1}}]$, P_A, P_Q and the server invoke two instances of Π_{Matmul} with inputs $[g_{2i-1}^*]^B$ and $[p_{2i}^*]^B$ to obtain $[t_i]^B$. Then the server and P_A set $[g_i^*]_1 = [g_{2i}^*] \oplus [t_i]$.
    For $i \in [1, \frac{\ell}{2^{r-1}}]$, P_A, P_Q and the server invoke two instances of Π_{Matmul} with inputs $[p_{2i}^*]^B$ and $[p_{2i-1}^*]^B$ to obtain $[p_i^*]^B$.
  end if
end for
P_A sets $[\mathsf{MSB}(x)]_0^B = e_\ell \oplus [g_1^*]_0^B$ and the server sets $[\mathsf{MSB}(x)]_1^B = f_\ell \oplus [g_1^*]_1^B$.

[4]The PPA-based solution was also used in existing works (Mohassel & Rindal, 2018; Patra et al., 2021), but in GuardHFL we give customized design for better efficiency.

are computed locally by P_A and the server, respectively, and the last two items will be obtained by invoking the protocol Π_{Matmul} twice. Moreover, for the evaluation of $g_i^0 = e_i \wedge f_i$ with $i \in [\ell]$, the parties only need to jointly invoke the protocol Π_{Matmul} once to obtain $[g_i^0]$ since the server and P_A own f_i and e_i, respectively. Overall, this method contains $3\ell - 4$ AND gates, which totally requires $15\ell - 24$ bits of communication within $\log \ell + 1$ communication rounds. Algorithm 2 gives the detailed construction of our MSB protocol Π_{msb}.

Theorem 3.3. *The protocol Π_{msb} in Algorithm 2 securely realizes the functionality $\mathcal{F}_{\mathsf{msb}}$ in Table 5 in the $\mathcal{F}_{\mathsf{Matmul}}$-hybrid model.*

Proof. The formal proof is provided in Appendix C. □

After obtaining $[\mathsf{MSB}(x)]^B$, we need to compute $[x] \cdot (1 \oplus [\mathsf{MSB}(x)]^B)$, i.e., the secret shares of $\mathsf{ReLU}(x)$. Given that $z_0 = [\mathsf{MSB}(x)]_0^B$ and $z_1 = 1 \oplus [\mathsf{MSB}(x)]_0^B$, we have $\mathsf{ReLU}(x) = ([x]_0 + [x]_1)(z_0 + z_1 - 2z_0z_1) = z_0[x]_0 + z_1[x]_1 + z_1(1-2z_0)[x]_0 + z_0(1-2z_1)[x]_1$. The first two terms can be computed locally by P_A and the server respectively, while the latter two terms are evaluated using our multiplication protocol Π_{Matmul}. Taking $z_1(1-2z_0)[x]_0$ as an example, the protocol Π_{Matmul} takes as input $t_0 = (1-2z_0)[x]_0$ from P_A and z_1 from the server, and outputs $[t_0z_1]_0$ to P_A and $[t_0z_1]_1$ to the server. Finally, P_A and the server learn $[y] = [\mathsf{ReLU}(x)]$. The detailed secure ReLU protocol Π_{ReLU} is shown in Figure 4.

Theorem 3.4. *The protocol Π_{ReLU} in Figure 4 securely realizes the functionality $\mathcal{F}_{\mathsf{ReLU}}$ in Table 5 in the ($\mathcal{F}_{\mathsf{msb}}$, $\mathcal{F}_{\mathsf{Matmul}}$)-hybrid model.*

Proof. The formal proof is provided in Appendix C. □

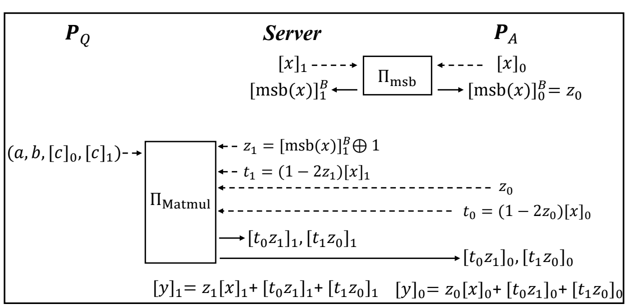


Figure 4. Secure ReLU protocol Π_{ReLU}

Maxpooling. Maxpooling can be evaluated using the protocol Π_{ReLU} as well as a tree-based round optimization that recursively partitions the values into two halves and then compares the elements of each half. Precisely, the parties arrange the input of m elements into a 2-ary tree with the depth of $\log m$, and evaluate the tree in a top-down fashion. In each comparison of two secret-shared elements $[x]$ and $[y]$, we observe that $\mathsf{max}([x], [y]) = \mathsf{ReLU}([x] - [y]) + [y]$. Hence the complexity of Maxpooling mainly comes from the evaluation of $m - 1$ ReLU. Besides, as illustrated in Wagh et al. (2019); Mishra et al. (2020), AvgPooling can be evaluated locally without communication.

3.3. Secure Result Aggregation

After the secure prediction on a sample, the predicted logit $[x_i]$ is secret-shared between the server and each responding party P_A^i, where $i \in [C]$ and C is the set of responding parties in the current query-response phase. To prevent privacy leakage from a single prediction (Salem et al., 2019; Ganju et al., 2018; Yang et al., 2019), we return the aggregated logit to P_Q via the secure aggregation protocol Π_{Agg} in Figure 5. Specifically, P_A^i and P_Q first generate a random value r_i based on PRFs. Then each P_A^i computes and sends $[x_i]_0 - r_i$ to the server. The server sums all received values and sends the masked aggregation to P_Q, which will reconstruct the aggregated logits of the query sample. Notice that our secure aggregation protocol can be extended to output the aggregated label rather than the logit, using the above Π_{ReLU} protocol.

Theorem 3.5. *The protocol Π_{Agg} in Figure 5 securely realizes the functionality $\mathcal{F}_{\mathsf{Agg}}$ in Table 5 in the $\mathcal{F}_{\mathsf{PRF}}$-hybrid model.*

Proof. The formal proof is provided in Appendix C. □

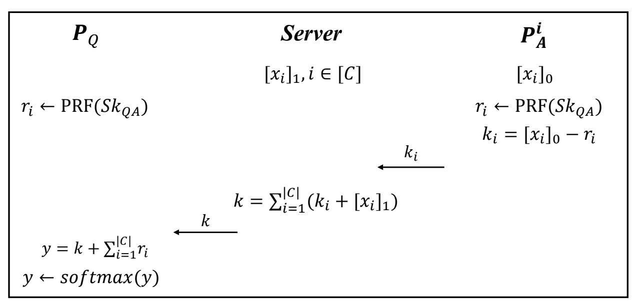


Figure 5. Secure result aggregation protocol Π_{Agg}

3.4. Discussion

Query data construction. Unlike existing HFL works relying on auxiliary datasets as the query data (Choquette-Choo et al., 2021; Lin et al., 2020), we demonstrate the feasibility of model knowledge transfer in GuardHFL by constructing a synthesized query set based on private training data, to alleviate potential limitations (e.g., privacy, acquisition and storage) of public auxiliary datasets. A simple solution is to directly use the private training data to query, like well-studied knowledge distillation (Hinton et al., 2015). Moreover, we also construct a synthesized dataset via the mixup method (Zhang et al., 2018) (refer to Appendix A.2). The synthesized dataset construction is a universal and modular method, and it can be readily extended with advanced data augmentation strategies, such as cutout (DeVries & Taylor, 2017) and cutmix (Yun et al., 2019). Note that this process does not reveal any private information, since the samples are constructed locally by the querying party based on the local training data, without involving any other parties and their private datasets. We present some exploration and experiments in Appendix A.2 and Figure 10(c).

GPU-friendly evaluation. Our scheme is friendly with GPUs and can be processed by highly-optimized CUDA kernels (Tan et al., 2021). As discussed above, the cryptographic protocols of GuardHFL only involve simple vectorized arithmetic operations, rather than homomorphic encryption and garbled circuits in prior works (Rathee et al., 2020; Huang et al., 2022; Choquette-Choo et al., 2021). As a result, GuardHFL is suitable for batch querying (i.e., executing multiple querying at the same time) with a lower amortized cost. We evaluate the designed protocols on GPUs in Section 4.1 and show the advantage of GPU acceleration over CPUs in Figure 6.

4. Evaluation

Datasets and models. We evaluate GuardHFL on three image datasets (SVHN, CIFAR10 and Tiny ImageNet). By default, we assume independent and identically distributed (IID) training data among clients. We also simulate disjoint Non-IID training data via the Dirichlet distribution $\mathsf{Dir}(\alpha)$ in Lin et al. (2020). The value of α controls the degree of Non-IID-ness, where a smaller α indicates a higher degree of Non-IID-ness. Moreover, we simulate the heterogeneity property in HFL. In particular, for SVHN and CIFAR10, we set the number of clients $n = 50$ and use VGG-7, ResNet-8 and ResNet-10 as the clients' local models. For Tiny ImageNet, we set $n = 10$ and use ResNet-14, ResNet-16, and ResNet-18 architectures. Each model architecture is used by $n/3$ clients. Besides, the query data are constructed via two methods as shown in Section 3.4: using the private training data (Q-priv) or synthesizing samples (Q-syn) via mixup (Zhang et al., 2018).

Experimental configuration. Each of the entities, i.e., P_Q, P_A, and the server, is run on the Ubuntu 18.4 system with Intel(R) 562 Xeon(R) CPU E5-2620 v4(2.10 GHz) and 16 GB of RAM and NVIDIA 1080Ti GPU. Following existing works (Rathee et al., 2020; Tan et al., 2021), we set the secret-sharing protocols over a 64-bit ring $\mathbb{Z}_{2^{64}}$, and encode inputs using a fixed-point representation with 20-bit precision. The security parameter κ is 128 in the instantiation of PRFs. Unless otherwise stated, we only report the performance on the GPU accelerator. More experimental setup is given in Appendix A.1.

Table 1. Extra runtime (sec) of GuardHFL over vanilla HFL systems in the plaintext environment. CIFAR10 and SVHN have the same runtime due to the same input size and model architecture.

Dataset	# of Queries	1. Query data sharing	2. Secure prediction			3. Result aggreg.
			VGG-7	ResNet-8	ResNet-10	
CIFAR10 (SVHN)	1000	5.08	205.46	270.78	305.46	0.09
	2500	7.16	511.63	657.83	758.16	0.12
	5000	11.32	1019.12	1346.79	1521.23	0.30
			ResNet-14	ResNet-16	ResNet-18	
Tiny ImageNet	1000	9.87	2700.96	2971.47	3084.81	0.18
	2500	18.78	6815.69	7217.28	7503.50	0.32

Table 2. Comparison with CaPC on runtime (sec) over MNIST and three heterogeneous models as the batch size (BS) of query data increases.

Model	CryptoNets		CryptoNets-ReLU		MLP	
	GuardHFL	CaPC	GuardHFL	CaPC	GuardHFL	CaPC
BS=128	**0.03**	17.75	**0.24**	48.83	**0.75**	65.01
BS=256	**0.05**	17.56	**0.31**	70.14	**0.83**	86.37
BS=512	**0.07**	17.62	**0.50**	112.42	**1.05**	129.81
BS=1024	**0.13**	17.77	**0.89**	201.42	**1.58**	216.61

4.1. Efficiency

We report the efficiency of GuardHFL, and compare it with CaPC (Choquette-Choo et al., 2021) and HFL instantiations based on state-of-the-art secure querying protocols (Rathee et al., 2020; Huang et al., 2022).

End-to-end performance. We show the extra overhead introduced by GuardHFL compared with the vanilla HFL system in the plaintext environment. This is caused by the secure querying phase, which consists of three steps described in Section 3. Table 1 reports the runtime of each step for different models and datasets[5]. We observe that the cost is dominated by the secure model prediction step. Specifically, it takes 16.9 minutes to evaluate 5000 query samples securely on VGG-7 and CIFAR10, and only 11.32 second and 0.3 second are spent on the secure query-data sharing and secure result aggregation steps. More time is required to evaluate Tiny ImageNet because of larger input sizes and model architectures.

Comparison with CaPC. As described in Section 1, similar to GuardHFL, CaPC (Choquette-Choo et al., 2021) was proposed to support private collaborative learning utilizing the secure querying scheme (Boemer et al., 2019b), but

[5]To clearly illustrate the efficiency of GuardHFL, unless otherwise specified, we only report the overhead of one pair of querying and responding parties, as well as the server, in each iteration as described in Section 3.

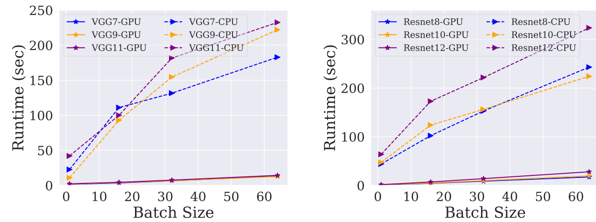
Table 3. Comparison with advanced secure prediction protocols on runtime (sec) and communication (MB) cost over three heterogeneous models.

Method	VGG-7		ResNet-8		ResNet-10	
	TIME	COMM.	TIME	COMM.	TIME	COMM.
CRYPTFLOW2	48.70	651.51	56.21	1110.39	97.46	1395.18
CHEETAH	3.95	116.14	4.29	94.51	6.79	169.35
CRYPTGPU	1.61	144.51	2.02	131.39	2.79	221.57
GUARDHFL	**0.73**	**75.52**	**0.98**	**87.60**	**1.29**	**120.26**

with the unrealistic cross-client communication. In Table 2, we compare the secure querying process of GuardHFL with CaPC. Following CaPC's setup, we evaluate three small-scale models (CryptoNets (Gilad-Bachrach et al., 2016), CryptoNets-ReLU (Gilad-Bachrach et al., 2016) and MLP (Boemer et al., 2019b)) on MNIST. We observe that GuardHFL is two orders of magnitude faster than CaPC on these three models. In terms of communication overhead, we provide a theoretical comparison. (1) For linear layers, CaPC requires to communicate 2 homomorphic ciphertexts within 2 rounds. GuardHFL needs communicating 3 ring elements (each with 64-bit). Note that the size of ciphertexts is much larger than the size of the ring elements. (2) For non-linear layers, e.g., ReLU, CaPC adopts the GC technique that requires 2 rounds with $8\ell\lambda - 4\lambda$ communication bits ($\lambda = 128$ and $\ell = 64$ in our setting) (Rathee et al., 2020). GuardHFL only requires communicating $15\ell - 3\log\ell - 12$ bits, a 70× improvement over CaPC.

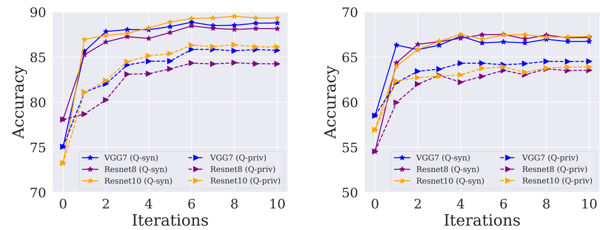
Comparison with alternative instantiations. To further demonstrate the efficiency of GuardHFL, we instantiate HFL based on advanced secure inference schemes, including Cheetah (Huang et al., 2022) and CrypTFlow2 (Rathee et al., 2020), using the methods described in Appendix B.4. Table 3 reports the comparison of the secure querying phase over CIFAR10. We observe that GuardHFL achieves a significant efficiency improvement on three heterogeneous models. For example, GuardHFL requires 57.4∼75.6× less runtime and 8.6∼12.7× less communication compared to CrypTFlow2. This is because the latter needs heavy HE-based multiplication and OT-based comparison operations within multi-communication rounds. Moreover, as shown in Section 2.3, extending 3PC protocols such as CryptGPU (Tan et al., 2021) to HFL is non-trivial. Nevertheless, since GryptGPU is one of the most advanced protocols under GPU analogs, we also compare with it assuming no communication limitation. We would like to mention that despite such an unfair comparison, GuardHFL still has performance advantages, i.e., roughly 2.1× and 2.0× in runtime and communication overhead, respectively.

Impact of GPU acceleration. To explore the impact of GPU acceleration, we evaluate GuardHFL on both CPU and GPU settings with different batch sizes of query data.



(a) VGG-style (b) ResNet-style

Figure 6. The runtime of GuardHFL on CIFAR10 under CPU/GPU with varied batch sizes of query data.



(a) SVHN (b) CIFAR10

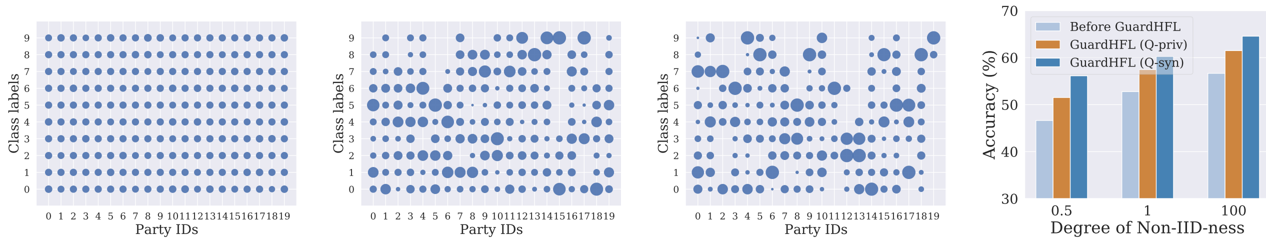
Figure 7. Accuracy curves of each heterogeneous model in GuardHFL as the number of iterations increases.

Figure 6 reports the results of VGG-style and ResNet-style networks on CIFAR10, where the GPU-based setting is always superior to the CPU analogs. As the batch size increases, the advantage of GPU-based protocols becomes more pronounced.

4.2. Accuracy

We report the accuracy of each heterogeneous model in GuardHFL, and explore the impact of various factors on the model accuracy such as the Non-IID setting, and the number of query data.

End-to-end model accuracy. Table 4 reports the model accuracy on three datasets in GuardHFL. We observe that for SVHN and CIFAR10, using Q-priv to query can increase the accuracy by about 4%, while the accuracy gain is about 10% when using 10K query samples with Q-syn. The main reason is that synthetic samples could provide a good coverage of the manifold of natural data. We also observe that more synthetic query data can achieve better performance from Table 4. Furthermore, with an increased number of participating clients, the accuracy improves slightly. Figure 7 shows the accuracy curves versus the number of iterations. We use SVHN and CIFAR10 as examples, as they converge much faster with better readable curves than Tiny ImageNet. We can observe that each heterogeneous model on both datasets can converge well based on two types of query data, and Q-syn shows better performance.



(a) $\alpha = 100$ (b) $\alpha = 1$ (c) $\alpha = 0.5$ (d) Accuracy

Figure 8. Visualization of Non-IID-ness among clients with different Dirichlet distribution α on CIFAR10. The size of scattered points indicates the number of training samples of that class.

Table 4. The model accuracy of three datasets in `GuardHFL` on different ratios of participating clients (0.6, 0.8 and 1), and querying strategies (Q-priv and Q-syn).

Dataset		SVHN			CIFAR10			Tiny ImageNet		
Ratio of clients		0.6	0.8	1	0.6	0.8	1	0.6	0.8	1
Before GuardHFL			75.46			56.66			22.26	
Q-priv		79.43	79.56	80.29	60.82	61.01	61.49	24.89	25.11	25.23
Q-syn	2.5K	80.09	80.32	81.69	62.87	63.05	63.23	25.82	26.03	26.23
	5.0K	83.32	83.52	83.82	63.04	63.44	63.69	26.22	26.46	26.75
	7.5K	84.54	84.78	85.12	62.97	63.64	63.88	27.14	27.54	27.75
	10K	84.58	84.97	85.62	63.79	63.82	64.56	27.67	28.19	28.46

Impact of Non-IID datasets. We illustrate the impact of Non-IID data on model accuracy in Figure 8, using CIFAR10 as an example. Figures 8(a), 8(b) and 8(c) visualize the distributions of Non-IID samples among clients with different Dir(α). When $\alpha = 100$, the distribution is close to uniform sampling. When $\alpha = 0.5$, the sample distribution of each class among clients is extremely uneven. From Figure 8(d) we observe that the higher the degree of Non-IID-ness, the lower the accuracy of models. Notably, `GuardHFL` can still significantly improve the performance of models under the Non-IID environment.

Impact of other factors. Due to space constraints, we report other experimental results in Appendix A.2. Briefly, Figure 9 shows the accuracy of each heterogeneous model with different numbers of query data. As the number of query data increases, accuracy increases by about 5%. Figures 10(a) and 10(b) illustrate the impact of different numbers of private training data on SVHN and CIFAR10. We observe that as the number of training data increases, the model performance is on the rise. Figure 10(c) details the impact of different query data construction methods. The results show that existing data augmentation strategies, such as Cutmix, Cutout, and Mixup, are effective for query data construction and improve the model accuracy.

5. Conclusion

We propose `GuardHFL`, an efficient and private HFL framework to formally provide the privacy guarantee of query samples, model parameters and response predictions. The core construction of `GuardHFL` is a customized secure querying scheme, in which two efficient multiplication and comparison protocols are designed based on lightweight secret sharing and PRF techniques. Extensive experiments demonstrate that `GuardHFL` outperforms prior art in both communication and runtime performance.

We consider the following future directions. (1) The communication cost of `GuardHFL`, which is also the limitation of the standard HFL paradigm, will be further improved. One possible mitigation is to extend the insight of the k-regular graph in FL (Bell et al., 2020) to HFL, and carefully design protocols from scratch. The main idea is that in FL it is enough for each party to speak to $k < n - 1$ other parties via the server, where n is the number of parties. (2) The security of `GuardHFL` will be improved to defeat more powerful malicious adversaries who may deviate from the protocol specifications. Unfortunately, even using the best-known techniques, the overhead will be increased by several orders of magnitude. We leave these improvements as future work.

Acknowledgements

The authors would like to thank the anonymous reviewers for their insightful comments. This work is supported by the National Key R&D Program of China under Grant 2022YFB3103500, the Key-Area Research and Development Program of Guangdong Province under Grant 2020B0101360001, the National Natural Science Foundation of China under Grants 62020106013 and 61972454, the Fundamental Research Funds for Chinese Central Universities under Grant ZYGX2020ZB027, the Natural Science Foundation of Chongqing, China under Grant cstc2019jcyjmsxmX0322, and Singapore Ministry of Education (MOE) AcRF Tier 2 MOE-T2EP20121- 0006.

References

Abdalla, M., Bellare, M., and Rogaway, P. The oracle diffie-hellman assumptions and an analysis of dhies. In *Proceedings of CT-RSA*, pp. 143–158. Springer, 2001.

Bell, J. H., Bonawitz, K. A., Gascón, A., Lepoint, T., and Raykova, M. Secure single-server aggregation with (poly) logarithmic overhead. In *Proceedings of ACM CCS*, 2020.

Boemer, F., Costache, A., Cammarota, R., and Wierzynski, C. ngraph-he2: A high-throughput framework for neural network inference on encrypted data. In *Proceedings of the ACM Workshop on Encrypted Computing & Applied Homomorphic Cryptography*, 2019a.

Boemer, F., Lao, Y., Cammarota, R., and Wierzynski, C. ngraph-he: a graph compiler for deep learning on homomorphically encrypted data. In *Proceedings of the ACM International Conference on Computing Frontiers*, 2019b.

Bonawitz, K., Ivanov, V., Kreuter, B., Marcedone, A., McMahan, H. B., Patel, S., Ramage, D., Segal, A., and Seth, K. Practical secure aggregation for privacy-preserving machine learning. In *proceedings of ACM CCS*, 2017.

Brutzkus, A., Gilad-Bachrach, R., and Elisha, O. Low latency privacy preserving inference. In *Proceedings of ICML*, 2019.

Canetti, R. Universally composable security: A new paradigm for cryptographic protocols. In *Proceedings of FOCS*, 2001.

Chen, H., Dai, W., Kim, M., and Song, Y. Efficient multi-key homomorphic encryption with packed ciphertexts with application to oblivious neural network inference. In *Proceedings of ACM CCS*, 2019.

Choquette-Choo, C. A., Dullerud, N., Dziedzic, A., Zhang, Y., Jha, S., Papernot, N., and Wang, X. Capc learning: Confidential and private collaborative learning. In *Proceedings of ICLR*, 2021.

Demmler, D., Schneider, T., and Zohner, M. Aby-a framework for efficient mixed-protocol secure two-party computation. In *Proceedings of NDSS*, 2015.

DeVries, T. and Taylor, G. W. Improved regularization of convolutional neural networks with cutout. *arXiv preprint arXiv:1708.04552*, 2017.

Diao, E., Ding, J., and Tarokh, V. Heterofl: Computation and communication efficient federated learning for heterogeneous clients. In *Proceedings of ICLR*, 2021.

Diffie, W. and Hellman, M. New directions in cryptography. *IEEE Transactions on Information Theory*, 22(6):644–654, 1976.

Dinh, C. T., Tran, N. H., and Nguyen, T. D. Personalized federated learning with moreau envelopes. In *Proceedings of NeurIPS*, 2020.

Fallah, A., Mokhtari, A., and Ozdaglar, A. Personalized federated learning with theoretical guarantees: A model-agnostic meta-learning approach. In *Proceedings of NeurIPS*, 2020.

Ganju, K., Wang, Q., Yang, W., Gunter, C. A., and Borisov, N. Property inference attacks on fully connected neural networks using permutation invariant representations. In *Proceedings of ACM CCS*, 2018.

Gao, D., Yao, X., and Yang, Q. A survey on heterogeneous federated learning. *arXiv preprint arXiv:2210.04505*, 2022.

Gentry, C. Fully homomorphic encryption using ideal lattices. In *Proceedings of ACM STOC*, 2009.

Gilad-Bachrach, R., Dowlin, N., Laine, K., Lauter, K., Naehrig, M., and Wernsing, J. Cryptonets: Applying neural networks to encrypted data with high throughput and accuracy. In *Proceedings of ICML*, 2016.

Goldreich, O. *Foundations of cryptography*. Cambridge university press, 2009.

Harris, D. A taxonomy of parallel prefix networks. In *Proceedings of Asilomar Conference on Signals, Systems & Computers*, pp. 2213–2217, 2003.

Hinton, G., Vinyals, O., and Dean, J. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.

Huang, Z., Lu, W.-j., Hong, C., and Ding, J. Cheetah: Lean and fast secure two-party deep neural network inference. In *Proceedings of USENIX Security*, 2022.

Ishai, Y., Kilian, J., Nissim, K., and Petrank, E. Extending oblivious transfers efficiently. In *Proceedings of Crypto*, volume 2729, pp. 145–161, 2003.

Jayaraman, B. and Evans, D. Evaluating differentially private machine learning in practice. In *Proceedings of USENIX Security*, 2019.

Jayaraman, B. and Wang, L. Distributed learning without distress: Privacy-preserving empirical risk minimization. In *Proceedings of NeurIPS*, 2018.

Juvekar, C., Vaikuntanathan, V., and Chandrakasan, A. Gazelle: A low latency framework for secure neural network inference. In *Proceedings of USENIX Security*, 2018.

Keller, M. and Sun, K. Secure quantized training for deep learning. In *Proceedings of ICML*, 2022.

Knott, B., Venkataraman, S., Hannun, A., Sengupta, S., Ibrahim, M., and van der Maaten, L. Crypten: Secure multi-party computation meets machine learning. In *Proceedings of NIPS*, 2021.

Langley, P. Crafting papers on machine learning. In *Proceedings of ICML*, pp. 1207–1216, 2000.

Lee, J., Lee, E., Lee, J.-W., Kim, Y., Kim, Y.-S., and No, J.-S. Precise approximation of convolutional neuralnetworks for homomorphically encrypted data. *arXiv:2105.10879*, 2021.

Li, D. and Wang, J. Fedmd: Heterogenous federated learning via model distillation. In *Proceedings of NeurIPS Workshop on Federated Learning for Data Privacy and Confidentiality*, 2019.

Lin, T., Kong, L., Stich, S. U., and Jaggi, M. Ensemble distillation for robust model fusion in federated learning. In *Proceedings of NeurIPS*, 2020.

Mishra, P., Lehmkuhl, R., Srinivasan, A., Zheng, W., and Popa, R. A. Delphi: A cryptographic inference service for neural networks. In *Proceedings of USENIX Security*, 2020.

Mohassel, P. and Rindal, P. Aby3: A mixed protocol framework for machine learning. In *Proceedings of ACM CCS*, 2018.

Mohassel, P. and Zhang, Y. Secureml: A system for scalable privacy-preserving machine learning. In *Proceedings of IEEE S&P*, 2017.

Papernot, N., Abadi, M., Erlingsson, U., Goodfellow, I., and Talwar, K. Semi-supervised knowledge transfer for deep learning from private training data. In *Proceedings of ICLR*, 2016.

Patra, A., Schneider, T., Suresh, A., and Yalame, H. Aby2.0: Improved mixed-protocol secure two-party computation. In *Proceedings of USENIX Security*, 2021.

Phong, L. T., Aono, Y., Hayashi, T., Wang, L., and Moriai, S. Privacy-preserving deep learning via additively homomorphic encryption. *IEEE TIFS*, 13(5):1333–1345, 2018.

Rathee, D., Rathee, M., Kumar, N., Chandran, N., Gupta, D., Rastogi, A., and Sharma, R. Cryptflow2: Practical 2-party secure inference. In *Proceedings of ACM CCS*, 2020.

Rathee, D., Rathee, M., Goli, R. K. K., Gupta, D., Sharma, R., Chandran, N., and Rastogi, A. Sirnn: A math library for secure rnn inference. In *Proceedings of IEEE S&P*, pp. 1003–1020, 2021.

Riazi, M. S., Weinert, C., Tkachenko, O., Songhori, E. M., Schneider, T., and Koushanfar, F. Chameleon: A hybrid secure computation framework for machine learning applications. In *Proceedings of AsiaCCS*, 2018.

Salem, A., Zhang, Y., Humbert, M., Berrang, P., Fritz, M., and Backes, M. Ml-leaks: Model and data independent membership inference attacks and defenses on machine learning models. In *Proceedings of NDSS*, 2019.

Sav, S., Pyrgelis, A., Troncoso-Pastoriza, J. R., Froelicher, D., Bossuat, J.-P., Sousa, J. S., and Hubaux, J.-P. Poseidon: Privacy-preserving federated neural network learning. In *Proceedings of NDSS*, 2021.

Shamir, A. How to share a secret. *Communications of the ACM*, 22(11):612–613, 1979.

Sun, L. and Lyu, L. Federated model distillation with noise-free differential privacy. In *Proceedings of IJCAI*, 2021.

Tan, S., Knott, B., Tian, Y., and Wu, D. J. Cryptgpu: Fast privacy-preserving machine learning on the gpu. In *Proceedings of IEEE S&P*, 2021.

Tekgul, B. G., Xia, Y., Marchal, S., and Asokan, N. Waffle: Watermarking in federated learning. In *Proceedings on IEEE SRDS*, 2021.

Wagh, S., Gupta, D., and Chandran, N. Securenn: 3-party secure computation for neural network training. *Proceedings on Privacy Enhancing Technologies*, 2019(3):26–49, 2019.

Wagh, S., Tople, S., Benhamouda, F., Kushilevitz, E., Mittal, P., and Rabin, T. Falcon: Honest-majority maliciously secure framework for private deep learning. *Proceedings on Privacy Enhancing Technologies*, 1:188–208, 2021.

Yang, Z., Zhang, J., Chang, E.-C., and Liang, Z. Neural network inversion in adversarial setting via background knowledge alignment. In *Proceedings of ACM CCS*, 2019.

Yao, A. C.-C. How to generate and exchange secrets. In *Proceedings of IEEE FOCS*, 1986.

Yoon, T., Shin, S., Hwang, S. J., and Yang, E. Fedmix: Approximation of mixup under mean augmented federated learning. In *Proceedings of ICLR*, 2021.

Yun, S., Han, D., Oh, S. J., Chun, S., Choe, J., and Yoo, Y. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of ICCV*, 2019.

Yurochkin, M., Agarwal, M., Ghosh, S., Greenewald, K., Hoang, N., and Khazaeni, Y. Bayesian nonparametric federated learning of neural networks. In *Proceedings of ICML*, 2019.

Zhang, H., Cisse, M., Dauphin, Y. N., and Lopez-Paz, D. mixup: Beyond empirical risk minimization. In *Proceedings of ICLR*, 2018.

Zhu, Z., Hong, J., and Zhou, J. Data-free knowledge distillation for heterogeneous federated learning. In *Proceedings of ICML*, 2021.

A. More Details on Experiment Evaluation

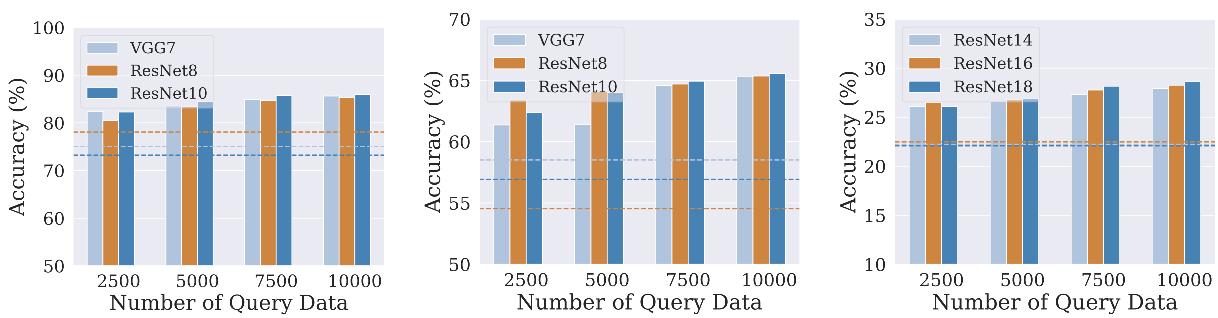
A.1. Experimental Setup

Datasets. We evaluate GuardHFL on the following standard datasets for image classification: (1) SVHN is a real-world image dataset obtained from house numbers in Google Street View images, which contains 600,000 32×32 RGB images of printed digits from 0 to 9. (2) CIFAR10 consists of 60,000 32×32 RGB images in 10 classes. There are 50,000 training images and 10,000 test images. (3) Tiny ImageNet contains 100,000 images of 200 classes downsized to 64×64 colored images. Each class has 500 training images, 50 validation images and 50 test images.

Training procedure. At the *local training* phase, each client trains the local model from scratch using stochastic gradient descent optimization. For SVHN, CIFAR10, and Tiny ImageNet, the loss function is cross-entropy with the learning rate of 0.5, 0.1, 0.01, respectively. Besides, the batch size is 256, 64 and 64, respectively. When the clients retrain the local model at the *local retraining* step, they use Adam optimizer for 50 epochs with learning rate of 2e-3 decayed by a factor of 0.1 on 25 epochs, where the batch size is 256 on SVHN, and 64 on both CIFAR10 and Tiny ImageNet.

A.2. Experimental Results

Impact of the number of query data. Figure 9 shows the accuracy of each heterogeneous model with different numbers of query data. We observe that GuardHFL consistently improves the model accuracy on the above datasets and heterogeneous models. Specifically, as the number of query data increases (from 2.5K to 10K), the accuracy of all three models increases by about 5%.



(a) SVHN (b) CIFAR10 (c) Tiny ImageNet

Figure 9. The accuracy of each heterogeneous model as the number of query data increases. Dashed lines represent the model accuracy before GuardHFL.

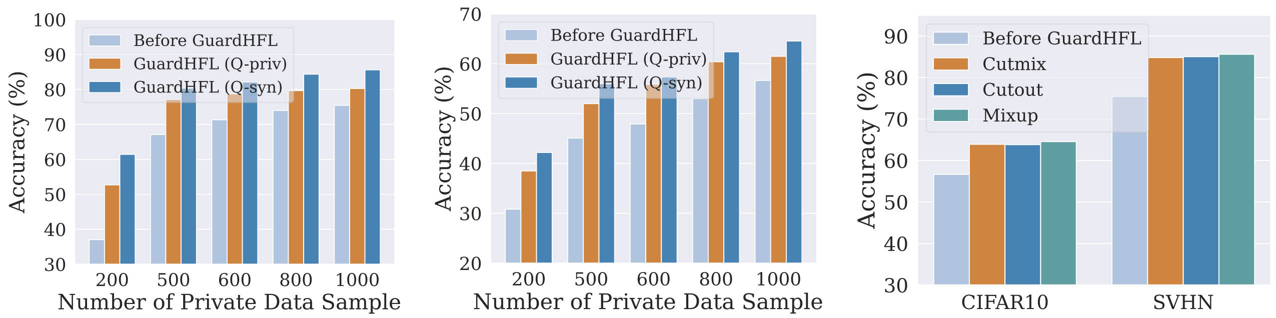
Impact of the number of private training data. Figures 10(a) and 10(b) illustrate the model accuracy of GuardHFL under different number of private training data on SVHN and CIFAR10. We can observe that as the number of training data increases, the model performance is on the rise. The main reason is that models can learn better on more training data and can construct more synthetic samples to query, so as to promote the transfer of model knowledge.

Impact of query data construction strategies. Figure 10(c) gives the model accuracy under three advanced data augmentation strategies, including cutmix (Yun et al., 2019), cutout (DeVries & Taylor, 2017), and mixup (Zhang et al., 2018). Cutmix (Yun et al., 2019) can be formulated as $\tilde{x}_{i,j} = M \cdot x_i + (1 - M) \cdot x_j$, where $M \in \{0, 1\}^{W \times H}$ is a binary mask matrix of size $W \times H$ to indicate the location of dropping out and filling from the two images x_i and x_j. Cutout (DeVries & Taylor, 2017) augments the dataset with partially occluded versions of original samples. Mixup (Zhang et al., 2018) constructs synthetic samples by a convex combination on two images x_i and x_j with different coefficients λ, in which $\tilde{x}_{i,j} = \lambda \cdot x_i + (1 - \lambda) \cdot x_j$. We observe that those strategies are good choices for the query data construction in GuardHFL.

B. More Details on the Designed Scheme

B.1. Graphic depiction of end-to-end secure prediction scheme

Figure 11 gives a graphic depiction to illustrate the end-to-end secure prediction scheme, where the input is a secret-shared sample $[x]$. The whole process maintains the following *invariant*: the server and P_A begin with secret shares of the



(a) SVHN (b) CIFAR10 (c) Various query data construction methods

Figure 10. The model accuracy under different number of training data and query data construction methods on SVHN and CIFAR10.

input and after each layer, end with secret shares (over the same ring) of the output. The honest-but-curious security of `GuardHFL` will follow trivially from sequential composibility of individual layers. To be specific, $[x]$ first passes through a convolutional layer that can be formalized as the secure matrix multiplication operation $\omega_1[x]$ (ω_1 is the parameter) using the protocol Π_{Matmul} in Figure 3. The secret-shared outputs of this layer, i.e., $[y_1]_0$ and $[y_1]_1$, are obtained by P_A and the server, respectively. For the subsequent ReLU layer, the protocol Π_{ReLU} in Figure 4 is executed to return $[y_2]_0$ and $[y_2]_1$ to P_A and the server respectively. Then Maxpooling on $[y_2]$ can be evaluated via the protocol Π_{ReLU} as described in Section 3.2, to output the secret-shared values $[y_3]_0$ and $[y_3]_1$. When the secure prediction reaches the final fully-connected layer with inputs $[y_{n-1}]_0$ and $[y_{n-1}]_1$, the protocol Π_{Matmul} is executed. In the end, P_A and the server obtain the secret-shared predicted logit, i.e., $[\text{logit}]_0$ and $[\text{logit}]_1$, respectively.

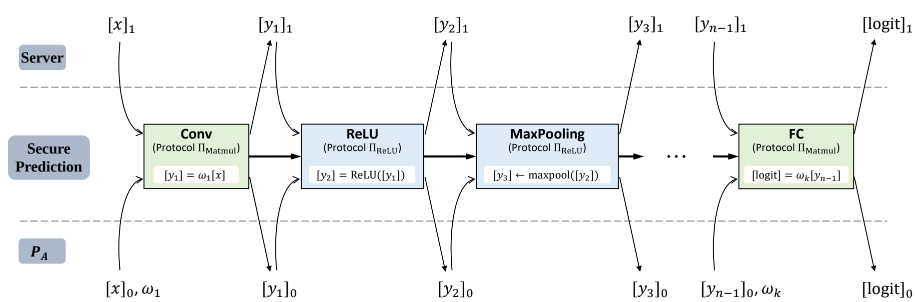


Figure 11. End-to-end secure model prediction protocol. Green boxes represent linear layers (including convolutional/fully connected layers), and blue boxes represent non-linear layers (including ReLU/Maxpooling layers).

B.2. More details on cryptographic protocols

Secret sharing and Beaver's multiplication protocol. As shown in Section 2.4, `GuardHFL` utilizes the arithmetic secret sharing primitive to protect the privacy of sensitive information. Given two secret-shared values $[x]$ and $[y]$ owned by two parties P_i, $i \in \{0, 1\}$, addition and subtraction operations ($[z] = [x] \pm [y]$ in $\mathbb{Z}_{2^\ell}$) can be realized locally without any communication, i.e., each P_i computes $[z]_i = [x]_i \pm [y]_i \mod 2^\ell$. Besides, multiplication operation, i.e., $[z] = [x][y]$, is evaluated using Beaver's multiplication triples (Demmler et al., 2015), where each triple refers to (a, b, c) with the constraint $c = ab$. The triples are generated by cryptographic techniques (Demmler et al., 2015) or a trusted dealer (Riazi et al., 2018). Specifically, the multiplication over secret-sharing values can be evaluated in the following:

$$z = xy = ([x]_0 + [x]_1)([y]_0 + [y]_1) = \overbrace{[x]_0[y]_0}^{P_0} + \overbrace{[x]_1[y]_1}^{P_1} + [x]_0[y]_1 + [x]_1[y]_0 \tag{2}$$

where for $i \in \{0, 1\}$, $[x]_i[y]_i$ can be computed locally, and $[x]_i[y]_{1-i}$ will be evaluated as follows. Taking $[x]_0[y]_1$ as an example, assuming P_0 and P_1 already hold $(a, [c]_0)$ and $(b, [c]_1)$, respectively, P_0 first sends $[x]_0 + a$ to P_1, while P_1 sends

$[y]_1 - b$ to P_0. Then P_0 computes one share as $[x]_0([y]_0 - b) - [c]_0$, and P_1 computes another as $([x]_1 + a)[y]_1 - [c]_1$, locally. In this way, the outputs are still in the form of secret sharing.

Diffie-Hellman key agreement protocol. In GuardHFL, we utilize PRFs to overcome the cross-client communication limitation, where the consistent PRF seed between clients are generated using the Diffie-Hellman (DH) key agreement protocol (Diffie & Hellman, 1976). Note that the consistent seed between the server and the client can be directly sampled by the server and then sent to the client without the DH protocol. Figure 12 gives the secure seed generation protocol Π_{seed}. Formally, the DH protocol consists of the following three steps:

- $\mathsf{DH.param}(k) \rightarrow (\mathbb{G}, g, q, H)$ generates a group $\mathbb{G}$ of prime order q, along with a generator g, and a hash function H.
- $\mathsf{DH.gen}(\mathbb{G}, g, q, H) \rightarrow (x_i, g^{x_i})$ randomly samples $x_i \in \mathbb{G}$ as the secret key and let g^{x_i} as the public key.
- $\mathsf{DH.agree}(x_i, g^{x_j}, H) \rightarrow s_{i,j}$ outputs the *seed* $s_{i,j} = H((g^{x_j})^{x_i})$.

Correctness requires that for any key pairs (x_i, g^{x_i}) and (x_j, g^{x_j}) generated by two paries P_i and P_j using $\mathsf{DH.gen}$ under the same parameters $(\mathbb{G}, g, q, H)$, $\mathsf{DH.agree}(x_i, g^{x_j}, H) = \mathsf{DH.agree}(x_j, g^{x_i}, H)$. Besides, in GuardHFL, security requires that for any adversary who steals g^{x_i} and g^{x_j} (but neither of the corresponding x_i and x_j), the agreed secret $s_{i,j}$ derived from those keys is indistinguishable from a uniformly random value (Abdalla et al., 2001).

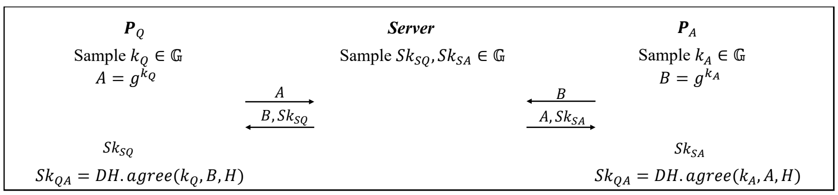


Figure 12. Secure PRF seed generation protocol Π_{Seed}

B.3. Distinguish GuardHFL from other private settings.

GuardHFL is in line with the standard HFL paradigm (Li & Wang, 2019) with the additional benefit of privacy protection. As declared in the Introduction, GuardHFL is the first-of-its-kind privacy-preserving HFL framework, which is different from existing privacy-preserving training efforts. The latter can be divided into two categories: (1) privacy-preserving federated learning (Bonawitz et al., 2017; Bell et al., 2020), and (2) secure multi-party training (Tan et al., 2021; Keller & Sun, 2022). In the following, we give a detailed analysis.

Comparison to privacy-preserving federated learning. In the privacy-preserving federated learning (FL), each clients locally computes the gradient with his private database, and then a secure aggregation protocol is executed at the server side for aggregating the local gradients and updating the global model. However, as described in the Introduction, secure gradient aggregation cannot be realized in HFL, due to the heterogeneity of the clients' models. Instead, GuardHFL follow a general HFL training paradigm (Li & Wang, 2019), which contains three steps: local training, querying, and local re-training. GuardHFL focuses on solving the privacy issue caused by the querying stage, and mainly proposes a query datasets generation (refer to Section 3.4) and a secure querying protocol (refer to Section 3.1 - Section 3.3).

Comparison to secure multi-party training. Secure multi-party training is typically an outsourced training setting, where resource-constrained clients outsource the entire training task to non-colluding multiple servers in a privacy-preserving manner. It requires a secure training protocol to finally yield a well-trained model. Different from secure multi-party training, GuardHFL enables clients to collaboratively and securely train their own customized models that may differ in size and structure. Moreover, as discussed above, the general HFL paradigm contains three steps: local training, querying and local re-training, where the local training and re-training stages are evaluated locally without revealing privacy. Therefore, the privacy-preserving HFL requires an HFL-friendly secure querying protocol (i.e., a customized inference protocol).

B.4. Extend existing 2PC protocols to HFL

With non-trivial adaptation, existing secure 2-party querying schemes (Mishra et al., 2020; Rathee et al., 2020; Huang et al., 2022) can be extended to the communication-limited HFL setting. However, as shown in Section 4.1, such extension introduces expensive communication and computation overheads compared with our GuardHFL. In the following we divide these schemes into three categories, i.e., pure OT-based protocols, pure HE-based protocols, and hybrid protocols, and give the corresponding extension designs.

To extend the pure OT-based secure querying protocols such as CrypTFlow2 (Rathee et al., 2020) into HFL, P_Q first secret-shares query samples to the server and P_A using our protocol Π_{Share} in Section 3.1. Then the server and P_A execute secure prediction based on the method proposed in Rathee et al. (2020). After that, adopting our secure aggregation protocol Π_{Agg} in Section 3.3, the aggregated predictions will be returned to P_Q. Although the OT-based schemes can be extended to HFL by combining the designed protocols in GuardHFL, it requires too many communication rounds due to the usage of OT primitives.

To extend the pure HE-based secure querying protocols (Gilad-Bachrach et al., 2016; Lee et al., 2021) to HFL, P_Q first encrypts the query samples and asks the server to pass them to P_A. After that, P_A evaluates secure prediction non-interactively in the ciphertext environment. Then P_A sends encrypted predictions to the server. The server aggregates these encrypted predictions utilizing the additive homomorphism of HE and sends the aggregated results to P_Q. Although it is trivial to extend the schemes equipped with the HE-based scheme to the communication-limited setting, they have two key problems: 1) activation functions need to be approximated as low-degree polynomials, which leads to serious accuracy loss; 2) the HE-based secure prediction protocol is difficult to extend to large-scale models due to the inherent high computation complexity.

For hybrid secure querying protocols that evaluates linear layers using HE and non-linear layers using OT or GC, such as Cheetah (Huang et al., 2022), we discuss the extension algorithm for each layer separately. *For the linear layer*, 1) P_Q encrypts query samples with HE and sends the ciphertext to P_A through the server[6]. 2) P_A evaluates linear layers locally, and returns the encrypted masked outputs to P_Q through the server. 3) P_Q decrypts it to obtain the masked outputs, which are then sent to the server. As a result, the masked outputs of linear layers are secret-shared between the server and P_A. *For the non-linear layer*, given that the server and P_A hold shares of the linear layer's outputs, the two parties invoke the OT-based protocols to evaluate non-linear functions. Therefore, such an extension comes at the cost of heavy computational and communication complexity.

In summary, although existing 2PC protocols can be extended to the HFL setting with the cross-communication restriction, they sacrifice efficiency due to the lack of customized protocols and the adoption of heavy cryptographic primitives. Therefore, it is necessary to design an efficient cryptographic framework for HFL. And GuardHFL shows better adaptability and efficiency in the natural HFL scenarios.

C. Security analysis

Intuitively, GuardHFL only reveals the aggregated prediction to P_Q without the responding parties' model parameters, and the server and P_A learn zero information about the querying parties' data. This is because all intermediate sensitive values are secret-shared. Next, we give a formal analysis.

Our security proof follows the standard ideal-world/real-world paradigm (Canetti, 2001): in the real world, three parties (i.e., the server, P_Q, and P_A) interact according to the protocol specification, and in the ideal world, they have access to an ideal functionality shown in Table 5. When a protocol invokes another sub-protocol, we use the $\mathcal{F}$-hybrid model for the security proof by replacing the sub-protocol with the corresponding functionality. Note that our proof works in the $\mathcal{F}_{\mathsf{PRF}}$-hybrid model where $\mathcal{F}_{\mathsf{PRF}}$ represents the ideal functionality corresponding to the PRF protocol. The executions in both worlds are coordinated by the environment Env, who chooses the inputs to parties and plays the role of a distinguisher between the real and ideal executions. We will show that the real-world distribution is computationally indistinguishable to the ideal-world distribution.

Theorem C.1. Π_{Share} *securely realizes the functionality* $\mathcal{F}_{\mathsf{Share}}$ *in the* $\mathcal{F}_{\mathsf{PRF}}$*-hybrid model.*

Proof. Note that P_Q and P_A receive no messages in Π_{Share}, and hence the protocol is trivially secure against the corruption of P_Q and P_A. Next, the only message that the server receives is the value $[x]_1$. However, $[x]_1 = x - r$, where given the security of PRF, r is a random value unknown to the server. Thus, the distribution of $[x]_1$ is uniformly random from the server's view and the information learned by the server can be simulated. □

[6] To be more precise, this step is for the input layer. In the hidden layer, one of the input shares of the linear layer should be encrypted by the server and sent to P_A.

Table 5. The ideal functionality

Input sharing functionality $\mathcal{F}_{\mathsf{Share}}$:

- **Input**: P_Q: query data x.
- **Output**: P_A: $[x]_0 \in \mathbb{Z}_{2^\ell}$. Server: $[x]_1 = x - [x]_0 \bmod 2^\ell$.

Matrix multiplication functionality $\mathcal{F}_{\mathsf{Matmul}}$:

- **Input**: Server: $[x]_1 \in \mathbb{Z}_{2^\ell}$. P_A: $[x]_0 \in \mathbb{Z}_{2^\ell}$, model parameter ω.
- **Output**: Server: $[y]_1 \in \mathbb{Z}_{2^\ell}$. P_A: $[y]_0 = \omega x - [y]_1 \bmod 2^\ell$.

MSB functionality $\mathcal{F}_{\mathsf{msb}}$:

- **Input**: Server: $[x]_1 \in \mathbb{Z}_{2^\ell}$. P_A: $[x]_0 \in \mathbb{Z}_{2^\ell}$.
- **Output**: Server: $[\mathsf{msb}(x)]_1^B \in \mathbb{Z}_2$. P_A: $[\mathsf{msb}(x)]_0^B = \mathsf{msb}(x) \oplus [\mathsf{msb}(x)]_1^B \bmod 2$.

ReLU functionality $\mathcal{F}_{\mathsf{ReLU}}$:

- **Input**: Server: $[x]_1 \in \mathbb{Z}_{2^\ell}$. P_A: $[x]_0 \in \mathbb{Z}_{2^\ell}$.
- **Output**: Server: $[y]_1 \in \mathbb{Z}_{2^\ell}$. P_A: $[y]_0 = \mathsf{ReLU}(x) - [y]_1 \bmod 2^\ell$.

Result aggregation functionality $\mathcal{F}_{\mathsf{Agg}}$:

- **Input**: Server: $[x_i]_1 \in \mathbb{Z}_{2^\ell}$, $i \in [C]$. P_A^i: $[x_i]_0 \in \mathbb{Z}_{2^\ell}$.
- **Output**: P_Q: $y = \mathsf{softmax}(\sum_{i=1}^{|C|} x_i)$.

Theorem C.2. Π_{Matmul} *securely realizes the functionality* $\mathcal{F}_{\mathsf{Matmul}}$ *in the* $\mathcal{F}_{\mathsf{PRF}}$*-hybrid model.*

Proof. Note that P_Q receives no messages in Π_{Matmul}, and hence the protocol is trivially secure against corruption of P_Q. The only message that P_A receives is the value $[x]_1 - b$. However, given the security of PRF, b is a random value unknown to P_A. Thus, the distribution of $[x]_1 - b$ is computationally indistinguishable from a uniformly random distribution in P_A's view, and the information learned by P_A can be simulated. Next, during the protocol, the server learns $[c]_1$ and $w + a$. However, the distribution of $[c]_1$ and $w + a$ is computationally indistinguishable from a uniformly random distribution in the server's view, since given the security of PRF, a and $[c]_1$ are random values unknown to the server. Thus, the information learned by the server can be simulated. □

Theorem C.3. Π_{msb} *securely realizes the functionality* $\mathcal{F}_{\mathsf{msb}}$ *in the* $\mathcal{F}_{\mathsf{Matmul}}$*-hybrid model.*

Proof. Note that as shown in Section 3.2, Π_{msb} just consists of AND gates, which is instantiated by the protocol Π_{Matmul}. Therefore, the msb protocol is trivially secure in the $\mathcal{F}_{\mathsf{Matmul}}$-hybrid model. □

Theorem C.4. Π_{ReLU} *securely realizes the functionality* $\mathcal{F}_{\mathsf{ReLU}}$ *in the (*$\mathcal{F}_{\mathsf{Matmul}}$, $\mathcal{F}_{\mathsf{msb}}$*)-hybrid model.*

Proof. Note that as shown in Section 3.2, Π_{ReLU} consists of Π_{msb} and Π_{Matmul}. Therefore, the ReLU protocol is trivially secure in the ($\mathcal{F}_{\mathsf{Matmul}}$, $\mathcal{F}_{\mathsf{msb}}$)-hybrid model. □

Theorem C.5. Π_{Agg} *securely realizes the functionality* $\mathcal{F}_{\mathsf{Agg}}$ *in the* $\mathcal{F}_{\mathsf{PRF}}$*-hybrid model.*

Proof. Note that P_A receives no messages in Π_{Agg}, and hence the aggregation protocol is trivially secure against the corruption of P_A. Next, the only message that the server receives is the value $[x_i]_0 - r_i$. However, given the security of

Table 6. Comparison with prior works on properties necessary for federated learning

Framework	Privacy		Usability		Efficiency	
	Data Privacy	Model Privacy	Model Heterogeneity	w/o Dataset Dependency	GPU Compatibility	Protocol Efficiency
Bonawitz et al. (2017)	✓	✗	✗	✓	✗	✓
Bell et al. (2020)	✓	✗	✗	✓	✗	✓
Sav et al. (2021)	✓	✓	✗	✓	✗	✗
Jayaraman & Wang (2018)	✓	✗	✗	✓	✗	✓
Li & Wang (2019)	✗	✓	✓	✗	✓	-
Choquette-Choo et al. (2021)	✓	✓	✓	✗	✗	✗
Lin et al. (2020)	✗	✗	✓	✗	✓	-
Sun & Lyu (2021)	✗	✓	✓	✗	✓	✓
Diao et al. (2021)	✗	✗	✓	✓	✓	-
GuardHFL	✓	✓	✓	✓	✓	✓

PRF, r_i is a random value unknown to the server. Thus, the distribution of $[x_i]_0 - r_i$ is computationally indistinguishable from a uniformly random distribution in the server's view and the information learned by the server can be simulated. After the aggregation, P_Q only learns the aggregated result $\sum_{i\in[C]} x_i$, but is unknown to each x_i. Therefore, the aggregation protocol is secure assuming the aggregation result will not reveal privacy. □

D. Related Work

D.1. Heterogeneous federated learning

Federated learning (FL) achieves collaboration among clients via sharing model gradients. While successful, it still faces many challenges, among which, of particular importance is the heterogeneity that appear in all aspects of the learning process. This consists of *model heterogeneity* (Li & Wang, 2019) and *statistical heterogeneity* (Zhu et al., 2021). Statistical heterogeneity means that parties' data comes from distinct distributions (i.e., Non-IID data), which may induce deflected local optimum. Solving the statistical heterogeneity has been extensively studied, such as Dinh et al. (2020); Zhu et al. (2021); Yurochkin et al. (2019); Fallah et al. (2020); Yoon et al. (2021), and is out of the scope of this work. Nevertheless, GuardHFL may help to alleviate the statistical heterogeneity due to the customized model design and the knowledge distillation-based aggregation rule.

Our work mainly focuses on the model heterogeneity that has been explored in recent works (Li & Wang, 2019; Lin et al., 2020; Choquette-Choo et al., 2021). In particular, Li & Wang (2019) proposed the first FL framework FedMD supporting heterogeneous models by combining transfer learning and knowledge distillation techniques. They first used a public dataset to pre-train the model and transferred to the task of private datasets. After that, to exchange the knowledge, each party used the public data and the aggregated predictions from others as carriers for knowledge distillation. To further improve model accuracy, Lin et al. (2020) proposed FedDF, similar to FedMD, which also used the model distillation technique for knowledge sharing. The difference is that they first performed FedAvg on parties' local models and integrated knowledge distillation on the aggregated model. The dependence on model averaging leads to limited model heterogeneity. Later, Diao et al. (2021) focused on heterogeneous parties equipped with different computation and communication capabilities. In their framework, each party only updated a subset of global model parameters through varying the width of hidden channels, which reduces the computation and communication complexity of local models. However, this approach only learns a single global model, rather than unique models designed by parties. Moreover, as described in the Introduction, HFL suffers from several privacy issues, which are not considered in the above works. To address the privacy concern, GuardHFL provides end-to-end privacy-preserving HFL services.

The privacy-preserving techniques (i.e., secure aggregation) have been studied in federated learning (Bonawitz et al., 2017; Bell et al., 2020; Sav et al., 2021; Jayaraman & Wang, 2018). However, these techniques can not be directly extended to privacy-preserving HFL. Recently, Sun & Lyu (2021) proposed a noise-free differential privacy solution for HFL to guarantee each party's privacy. However, as shown in Jayaraman & Evans (2019), there is a huge gap between the upper bounds on privacy loss analyzed by advanced mechanisms and the effective privacy loss. Thus, differentially private mechanisms offer undesirable utility-privacy trade-offs. To further formally guarantee the privacy, Choquette-Choo et al. (2021) proposed CaPC, leveraging hybrid cryptographic primitives to realize confidential and private collaborative learning. Specifically, parties learn from each other collaboratively utilizing a secure inference strategy based on 2PC and HE protocols and a private aggregation method. As noted in the Introduction, the usage of heavy cryptography in CaPC leads to huge efficiency and communication overheads.

In summary, we give a comparison between prior FL works and `GuardHFL` in Table 6.

D.2. Secure neural network prediction

Since secure prediction is a critical component of `GuardHFL`, we briefly introduce its recent progress. Neural networks present a challenge to cryptographic protocols due to their unique structure and exploitative combination of linear computations and non-linear activation functions. In real scenarios, model prediction can be viewed as a two-party computation case, where one party with private query data wants to obtain prediction results from the other party who owns the model. During the whole process, the cryptographic protocols, typically HE and secure multi-party computation (MPC), are applied to ensure the confidentiality of the private data and model parameters.

Many existing works (Boemer et al., 2019b; Gilad-Bachrach et al., 2016; Brutzkus et al., 2019) support pure HE protocols for secure predictions. Typically, nGraph-HE (Boemer et al., 2019b;a) allows linear computations using the CKKS HE scheme. However, since a solution that builds upon HE protocols should be restricted to compute low degree polynomials, the non-polynomial activation functions, such as Maxpooling and ReLU, are forced to be evaluated in the clear by the party who owns private query data. This leaks the feature maps, from which adversaries may deduce the model weights. To solve this problem, Gilad-Bachrach et al. (2016) and Chen et al. (2019) use low-degree polynomial approximation to estimate non-linear functions. Unfortunately, such approximations affect the inference accuracy, and lead to huge computation overhead.

On the other hand, several libraries (Mohassel & Zhang, 2017; Knott et al., 2021; Wagh et al., 2019) employ primarily MPC techniques in secure predictions, which provide linear and non-linear protocols through the usage of oblivious transfer (OT), garbled circuit (GC) and secret sharing. In particular, CryptTen (Knott et al., 2021) performs linear operations based on n-out-of-n arithmetic secret sharing over the ring $\mathbb{Z}_{2^l}$. However, it requires a trusted third party to assist the secure prediction process, which is unrealistic in the real-world setting. CrpytGPU (Tan et al., 2021) builds on CrypTen, working in the 3-party setting based on the *replicated secret sharing* primitive. Although the scalability is poor, it introduces an interface to losslessly embed cryptographic operations over secret-shared values in a discrete somain into floating-point operations, which can implement the whole inference process on the GPU. Recently, Keller & Sun (2022) proposed a secure quantized training protocol that outperforms CryptGPU in the cryptographic performance. Unfortunately, this work cannot be applied in HFL and is not comparable to `GuardHFL`. The main reasons are: (1) `GuardHFL` and Keller & Sun (2022) are concerned with completely different tasks. `GuardHFL` builds on the standard HFL setting, where multiple parties collaboratively train individual models with the assistance of a server. Keller & Sun (2022) focuses on the outsourced training scenario, i.e., multiple servers jointly execute standard model training algorithm to obtain a well-trained model. (2) Moreover, the protocols in Keller & Sun (2022) are designed for a specific network architecture, i.e., quantized neural networks, which cannot be applied to the general models in `GuardHFL`. Therefore, Keller & Sun (2022) and `GuardHFL` are two fully orthogonal works.

In addition, many works focus on hybrid protocols, in which they combine the advantages of HE and MPC to improve prediction efficiency (Juvekar et al., 2018; Mishra et al., 2020; Rathee et al., 2020; Huang et al., 2022). For example, HE-transformer (Boemer et al., 2019a) employs nGraph-HE (Boemer et al., 2019b) for the evaluation of linear operations, and utilizes GCs of the ABY framework (Demmler et al., 2015) for the evaluation non-linear functions. However, GC is inefficient especially for large networks with thousands of parameters, since non-linear operations cannot be parallelized between query samples. After that, CrypTFlow2 (Rathee et al., 2020) implements two types of protocols for linear operations, i.e., the HE-based method and OT-based method. For non-linear layers, they also design efficient protocols based on OTs. More recently, Cheetah (Huang et al., 2022) improves CrypTFlow2 with customized HE-based linear protocols and improved OT-based non-linear protocols, which achieves the state-of-the-art efficiency. Nevertheless, as shown in Section 4.1, directly extending the protocols in Cheetah into HFL cannot obtain satisfying performance. Therefore, we propose `GuardHFL`, which avoids the adoption of heavy cryptographic tools like HE and OT, and only employs secret sharing and PRFs to achieve high efficiency, confidentiality and practicability.