

A Framework for Double-Blind Federated Adaptation of Foundation Models

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Abstract

Foundation models (FMs) excel in zero-shot tasks but benefit from task-specific adaptation. However, privacy concerns prevent data sharing among multiple data owners, and proprietary restrictions prevent the learning service provider (LSP) from sharing the FM. In this work, we propose **BlindFed**, a framework enabling collaborative FM adaptation while protecting both parties: data owners do not access the FM or each other's data, and the LSP does not see sensitive task data. **BlindFed** relies on fully homomorphic encryption (FHE) and consists of three key innovations: (i) **FHE-friendly architectural modifications** via polynomial approximations and low-rank adapters, (ii) a **two-stage split learning** approach combining offline knowledge distillation and online encrypted inference for adapter training without backpropagation through the FM, and (iii) a **privacy-boosting scheme** using sample permutations and stochastic block sampling to mitigate model extraction attacks. Empirical results on four image classification datasets demonstrate the practical feasibility of the **BlindFed** framework, albeit at a high communication cost and large computational complexity for the LSP. The code can be found at <https://github.com/nurbek/blindfed>.

1. Introduction

Foundation models (FMs) have transformed artificial intelligence, achieving state-of-the-art results across machine learning, computer vision, and natural language processing. Prominent examples include GPT [7, 46], CLIP [47], BERT [12, 18, 37], Stable Diffusion [49], Segment Anything [28], and Vision Transformers [13, 38]. Though vision and multimodal FMs have demonstrated good zero-shot performance, there is often scope for performance improvement when faced with challenging out-of-domain tasks (e.g., medical images or satellite imagery). Hence, it becomes essential to adapt the FM for the downstream task.

Adaptation of FMs for downstream tasks involves two main challenges: *computational complexity* and *data avail-*

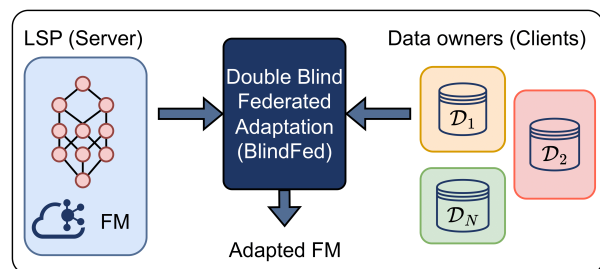


Figure 1. Conceptual illustration of **BlindFed** framework for double-blind federated adaptation of a foundation model.

ability. The simplest approach is transfer learning, where the FM serves as a frozen feature extractor, and only a classification head is trained – linear probing is this head is a single linear layer. It is also possible to perform *partial* (only a selected subset of parameters are adapted) or *full finetuning* of the parameters of the FM based on the downstream data. Recent parameter-efficient fine-tuning (PEFT) methods fall into two categories: (i) *prompt learning* [23], which learns input or intermediate prompts without modifying FM parameters, and (ii) *adapters* [11, 21, 41], which add trainable components to the FM. Adapters include sequential (e.g., low-rank adaptation a.k.a. LoRA [21]) and parallel (e.g., low-rank side adaptation a.k.a. LoSA [41]) variants. Except for transfer learning and parallel adapters, all the other adaptation techniques require partial or complete backpropagation through the FM, which is computationally expensive. *Zeroth-order optimization* (ZOO) offers a backpropagation-free alternative for black-box FMs but incurs high cost due to numerous forward passes.

The other major challenge in FM adaptation is the unavailability of downstream training data to the learning service provider (LSP) who owns the FM. Moreover, this data may be distributed across multiple data owners (e.g., multiple hospitals or banks) and cannot be collated due to privacy concerns and regulations. Thus, FM adaptation requires collaboration between the LSP and data owners. Federated learning (FL) [40] addresses this challenge by en-

abling collaborative training across entities while preserving data confidentiality. FL has been applied in many applications [3, 5, 15, 36, 39, 54, 59] and operates mainly in two settings: cross-silo (few data owners) and cross-device FL (large number of data owners) [26].

In this work, we focus on cross-silo federated adaptation of an FM (for an out-of-domain downstream image classification task) by an LSP (server) through collaboration with multiple data owners (clients) under two core constraints: (i) *Model privacy* - the LSP wants to retain full ownership of the FM and does not want to share the FM with the data owners; and (ii) *Data privacy* - clients do not want to reveal their data to the LSP or to each other. We jointly refer to these constraints as *double-blind privacy* (see Figure 1). We make the following four contributions:

- We propose the BlindFed framework for double-blind federated adaptation of FMs based on well-known cryptographic tools such as fully homomorphic encryption (FHE) and secure multiparty computation (MPC).
- We modify the given FM into an FHE-friendly architecture, leveraging existing ideas such as polynomial approximations and low-rank parallel adapters.
- We propose a two-stage split learning approach, where the FHE-friendly FM blocks are first pre-trained via offline knowledge distillation, followed by online encrypted inference to train local parallel adapters, with MPC-based secure aggregation for the global adapter.
- For stronger model privacy, we introduce a privacy boosting scheme based on sample-level permutation and stochastic block sampling.

2. Related Work

Foundation models: FMs have been highly successful in computer vision [13, 38, 47], natural language processing [10, 18, 37, 46, 61], and beyond [48, 51]. In particular, the two-stage training strategy has shown to be effective, where FMs are first pre-trained on a large dataset for general understanding and then fine-tuned on a small downstream dataset to learn task-specific features. However, their vast scale introduces significant challenges, particularly in fine-tuning, that hinder their practical applicability.

Private inference: The advent of machine learning as a service (MLaaS) has underscored the need for privacy-preserving techniques in ML, particularly in inference tasks. The concept of private inference (PI) has emerged as a pivotal solution to safeguard data and model privacy [22, 32, 42, 52, 53, 55, 67]. While vision transformers (ViTs) achieve strong performance, their high computational cost makes PI challenging, especially under cryptographic techniques such as FHE [1, 8, 14] and MPC [16, 29]. Most PI literature focuses on reducing computational and communication overheads while preserving accuracy. SAL-ViT [67] improves ViT efficiency in

PI, whereas Iron [17] optimizes matrix multiplication and key non-linear transformer operations (Softmax, GELU, LayerNorm). Another direction involves PI-friendly transformer designs, such as MPC-ViT [62], which adapts ViTs for MPC with an accuracy-efficiency trade-off, and MPCFormer [32], which combines MPC and knowledge distillation to reduce latency and maintain inference quality.

Adaptation of foundation models: The primary issue in adapting FMs is their massive size, making it impractical for individual users or clients with limited computational resources to fine-tune or even store them. Various PEFT techniques such as adapters [20, 35], prompt learning [33], low-rank adaptation (LoRA) [21], and low-rank side adaptation (LoSA) [41] have been proposed. Numerous variants of LoRA, such as AdaLoRA [66], Delta-LoRA [70], IncreLoRA [63], QLoRA [11], LoRA-GA [58], and LoFT [56] further optimize adaptation efficiency. These methods specifically target the transformer attention blocks, with LoRA modifying weight matrices to enable efficient fine-tuning with lower computational load. However, LoRA still requires backpropagation through the backbone, increasing the total time taken to update the model. PEFT in federated settings has also been explored for LLMs [64, 68].

3. Problem Formulation

Suppose that a foundation model (FM) $\mathcal{M}_\psi$ that is already pre-trained on a large-scale dataset is available with the learning service provider (LSP). The LSP aims to collaborate with the K data owners to adapt the FM for a downstream image classification task. Each data owner $\mathcal{P}_k$ has access to a local training dataset $\mathcal{D}_k = \{\mathbf{x}_i^k, y_i^k\}_{i=1}^{N_k}$ corresponding to the downstream task. Here, $\mathbf{x}_i^k$ denotes the i^{th} input image of $\mathcal{P}_k$, y_i^k is the corresponding class label, N_k is the number of training samples with $\mathcal{P}_k$, and $k \in [1, K]$.

Problem Statement: Let $\widetilde{\mathcal{M}}_{\widetilde{\psi}}$ denote the FM adapted for the downstream task. The goal of the BlindFed framework is to collaboratively learn the parameters $\widetilde{\psi}$ under the following constraints: (i) *Data Privacy*: the LSP does not learn anything about the local datasets $\{\mathcal{D}_k\}_{k=1}^K$ and the data owner $\mathcal{P}_k$ does not learn anything about other local datasets $\mathcal{D}_j$, where $j \neq k$; (ii) *Model Privacy*: the data owners do not learn anything about the original FM $\mathcal{M}_\psi$.

Assumptions: To simplify the double-blind federated adaptation problem and make it practically feasible, we make the following assumptions: (i) *Auxiliary dataset for preliminary adaptation*: We assume that the LSP has access to an independent auxiliary dataset $\mathcal{D}_{\text{aux}}$, which allows it to perform preliminary adaptation of the given FM into an image classifier. Note that this public dataset may not even correspond to the target image classification task. (ii) *Modularity of FM*: We further assume that the FM has a modular architecture, which can be represented as a sequence of L blocks,

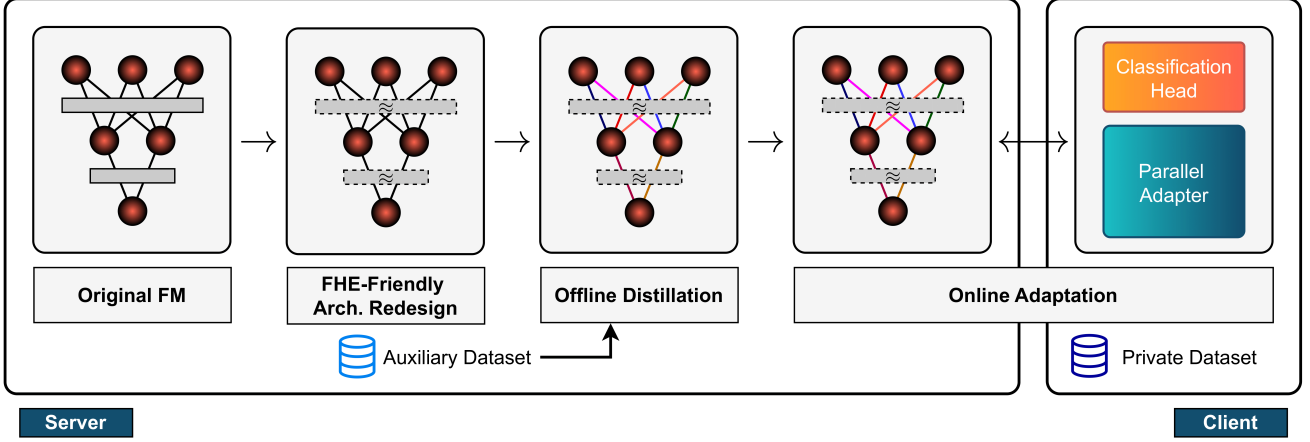


Figure 2. **Overview of the proposed BlindFed framework for double-blind federated adaptation.** The framework consists of three main components: (1) FHE-friendly architecture redesign, where the original foundation model (FM) is modified by approximating non-linear operations; (2) offline distillation, where the approximated blocks are fine-tuned via knowledge distillation using an auxiliary dataset; and (3) online adaptation, where clients interact the FHE-enabled FM under homomorphic encryption, performing local updates on the parallel adapter and classification head.

i.e., $\mathcal{M}_\psi = \mathcal{B}_{\psi_1} \circ \mathcal{B}_{\psi_2} \cdots \circ \mathcal{B}_{\psi_L}$. Specifically, a transformer architecture is considered in this work. (iii) *Thin client*: The data owners do not have the resources to store the FM (or an encrypted version of it) and perform inference (or encrypted inference) using the FM. However, we assume that the data owners have sufficient computational resources to perform fully homomorphic encryption and decryption operations. (iv) *Powerful server*: The LSP has enough computational resources to perform private inference on encrypted data transmitted by the data owners. Henceforth, we refer to the LSP and data owners as server and clients, respectively. (v) *Semi-honest threat model*: Both the server and the clients are assumed to be semi-honest, i.e., they follow the adaptation protocol honestly, but may attempt to violate the privacy constraints.

Vanilla Federated Adaptation: Let $\mathcal{L}_k(\tilde{\psi}) = \frac{1}{N_k} \sum_{i=1}^{N_k} \mathbb{L}(\hat{y}_i^k, y_i^k)$ be the average loss at client k , where $\mathbb{L}$ denotes the per-sample loss and $\hat{y}_i^k = \mathcal{M}_{\tilde{\psi}}(\mathbf{x}_i^k)$ is the prediction output by the adapted model. Federated adaptation can be posed as a distributed optimization problem [40], where the goal is to learn the global model parameters $\tilde{\psi}$ such that:

$$\min_{\tilde{\psi}} \sum_{k=1}^K \alpha_k \mathcal{L}_k(\tilde{\psi}), \quad (1)$$

where $\alpha_k = \frac{N_k}{\sum_{j=1}^K N_j}$. In each round t of FL adaptation, the server broadcasts the previous model parameters $\tilde{\psi}^{(t-1)}$. Each client computes the local model parameters $\tilde{\psi}_k^{(t)}$, and these local updates are aggregated by the server to obtain the current global model parameters $\tilde{\psi}^{(t)}$. For example, simple

FedAvg aggregation function can be represented as follows:

$$\tilde{\psi}^{(t)} = \sum_{k=1}^K \alpha_k \tilde{\psi}_k^{(t)}. \quad (2)$$

Note that $t \in [1, T]$, where T is the number of communication rounds and the model parameters $\tilde{\psi}_k^{(0)}$ for the first round are typically initialized randomly by the server.

Challenges: The above vanilla federated adaptation is not privacy-preserving because it requires computation of $\hat{y}_i^k = \mathcal{M}_{\tilde{\psi}}(\mathbf{x}_i^k)$, where the core FM $\mathcal{M}_\psi$ is available only at the server and the local training datasets are available only with the respective clients. Hence, it is essential to design a mechanism for computing $\mathcal{M}_{\tilde{\psi}}(\mathbf{x}_i^k)$ without violating the data and model privacy constraints. Moreover, the sharing of local updates $\tilde{\psi}_k^{(t)}$ with the server could also potentially leak information about the local datasets [69]. Hence, the aggregation step in Eq. 2 must be performed securely without revealing the local updates to the server.

4. Proposed BlindFed Framework

The BlindFed framework for double-blind federated adaptation (Figure 2) comprises two components: (1) **FHE-friendly Architecture Redesign** – The FM is first modified into an FHE-friendly model by approximating non-linear operations and adding a classification head as well as a parallel adapter; (2) **Two-stage Split Learning** – In the first *offline* stage, the approximated individual blocks are fine-tuned through knowledge distillation from the original FM using an auxiliary dataset. In the second *online* stage, clients encrypt their local data using FHE and interact with the server to perform encrypted inference. Based on inter-

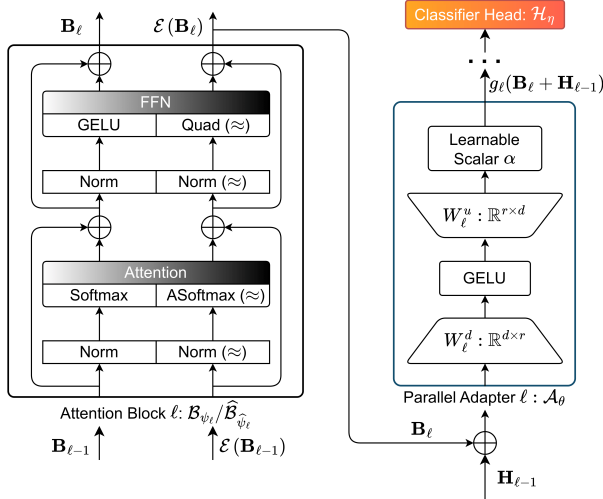


Figure 3. **FHE-friendly architecture redesign.** Each transformer block’s non-linear operations – GELU activations, Softmax attention, and the division step in LayerNorm – are replaced with low-degree polynomial approximations (denoted “Quad” for GELU and “ASoftmax” for Softmax). A lightweight parallel adapter and classification head are then trained on the client side.

mediate outputs from the server, clients locally update the parallel adapter and classification head. The server then uses an MPC-based secure aggregation to combine these updates into global parameters, which are shared back with all clients. The overall training workflow of the proposed framework is summarized in Figure 3. During inference, the encrypted inference step is repeated. Based on the intermediate outputs received from the server, the client utilizes the global parallel adapter and classifier to obtain the final class prediction. To enhance model privacy, the server can further incorporate sample-level permutations and stochastic block sampling.

4.1. FHE-friendly Architecture Redesign

The first step in the proposed framework is to redesign the given FM into an FHE-friendly model by leveraging existing techniques. Assuming that the given FM follows a modular transformer encoder architecture with L attention blocks (Figure 4), let $\mathbf{b}_{\ell-1}$ be the input to the ℓ^{th} attention block $\mathcal{B}_{\psi_\ell}$ and $\mathbf{b}_\ell$ be the corresponding output. We want to learn an FHE-friendly approximation of the block $\mathcal{B}_{\psi_\ell}$, denoted as $\widehat{\mathcal{B}}_{\widehat{\psi}_\ell}$, such that, for encrypted input $\mathcal{E}(\mathbf{b}_{\ell-1})$, the server computes encrypted output as $\mathcal{E}(\mathbf{b}_\ell) = \widehat{\mathcal{B}}_{\widehat{\psi}_\ell}(\mathcal{E}(\mathbf{b}_{\ell-1}))$, with the redesigned FM denoted as $\widehat{\mathcal{M}}_{\widehat{\psi}}$ consisting of a sequence of FHE-friendly blocks $\widehat{\mathcal{B}}_{\widehat{\psi}_\ell}$.

Approximating Non-linear Functions: Encrypted inference is limited to polynomial operations in most FHE schemes (e.g., CKKS [8]), requiring polynomial approximations for non-linear functions in transformer blocks:

Softmax, GELU, and LayerNorm. In this work, Softmax is approximated using a Taylor series approximation of the exponential function (e^x):

$$e^x = \sum_{i=0}^{\infty} \frac{x^i}{i!} \approx \sum_{i=0}^d \frac{x^i}{i!}, \quad (3)$$

followed by normalization through division by the sum of the calculated exponential values. The error bound of this approximation is the remainder term, e.g. $\frac{e^\xi}{(d+1)!}x^{d+1}$, for some ξ between 0 and x . Furthermore, GELU activation is approximated via a simple quadratic function:

$$\text{GELU}(x) \approx \text{Quad}(x) = 0.125x^2 + 0.25x + 0.5. \quad (4)$$

The LayerNorm function and Softmax require a division, which is implemented via Goldschmidt’s algorithm [9]:

$$\begin{aligned} \frac{1}{x} &= \frac{1}{1 - (1 - x)} = \prod_{i=0}^{\infty} (1 + (1 - x)^{2^i}) \\ &\approx \prod_{i=0}^d (1 + (1 - x)^{2^i}), \end{aligned} \quad (5)$$

where $x \in (0, 2)$.

A task-specific classification head $\mathcal{H}_\eta$ and a parallel adapter $\mathcal{A}_\theta$ are appended to the approximated FM to enable adaptation. The choice of a parallel adapter is critical in the FHE-friendly redesign because sequential adapters like LoRA require backpropagation through the FM during adaptation, which is practically infeasible when the data remains encrypted. Thus, the redesigned FHE-friendly model can be considered a combination of the approximated FM, the parallel adapter, and the classifier, i.e., $\widehat{\mathcal{M}}_{\widehat{\psi}} = (\widehat{\mathcal{M}}_{\widehat{\psi}} || \mathcal{A}_\theta) \circ \mathcal{H}_\eta$, where $||$ indicates that these functions operate in parallel and $\circ$ is the composition operator. Though ideas such as the approximation of non-linear operations and a parallel adapter exist in the literature, we have carefully assembled these pieces to redesign the FM into an FHE-friendly model.

4.2. Two-stage Split Learning

In the re-designed FHE-friendly FM, only the server stores the approximated FM; each client keeps a local parallel adapter and classifier. Training proceeds in two stages.

Stage 1: Offline Distillation. Before any collaboration, the server trains the approximated FM (student) from the original FM (teacher) on the auxiliary dataset $\mathcal{D}_{aux}$. After replacing all non-linearities (Softmax, GELU, and Inverse) with their approximations, we distill four types of representations: (i) embeddings, (ii) attention matrices (pre-normalization), (iii) hidden states after each block, and (iv) final prediction layer [19, 24, 32]. Following [24], the first

half of epochs distills (i)-(iii); the second half distills (iv). Details of the distillation process appear in Appendix C.

Stage 2: Online Adaptation. This step is performed via an interactive protocol between the clients and the server, which can be further divided into three phases: (i) encrypted inference, (ii) local learning, and (iii) secure aggregation.

4.2.1. Encrypted Inference

FMs exceed the multiplicative depth supported by current FHE schemes; evaluating the whole network homomorphically would incur large approximation errors or require frequent (and impractical) bootstrapping, especially under the thin client assumption. Hence, we propose performing encrypted inference only over a single transformer block at a time. After each block, the client decrypts and re-encrypts the intermediate representation $\mathcal{E}(\mathcal{F}(\mathcal{E}(\mathbf{b}_\ell)))$, and returns it back to the server. Here, $\mathcal{F}$ is the decryption operation.

The overall encrypted inference protocol can be summarized as follows. At the beginning of the collaboration, each client $\mathcal{P}_k$ encrypts (using its public key) its local inputs and labels $\{\mathcal{E}(\mathbf{x}_i), \mathcal{E}(y_i)\}_{i=1}^{N_k}$ and sends them to the server. The server applies the embedding function on the encrypted data to obtain the input to the first attention layer $\{\mathcal{E}(\mathbf{b}_0^i)\}_{i=1}^{N_k}$. Subsequently, for each FL round, the server randomly selects a batch of n samples from this set, say $\mathcal{E}(\mathbf{B}_0) = [\mathcal{E}(\mathbf{b}_0^1), \mathcal{E}(\mathbf{b}_0^2), \dots, \mathcal{E}(\mathbf{b}_0^n)]$, and sequentially performs encrypted inference on each FHE-friendly block $\hat{\mathcal{B}}_{\psi_\ell}$. After block ℓ , the client decrypts these representations (using its private key), re-encrypts them again (using its public key), and returns them to the next block.

When the client receives the output of the final transformer attention block $\mathcal{E}(\mathbf{b}_L)$, the decrypted representations are passed through the classification head and the final predictions are again encrypted to get $\mathcal{E}(\hat{\mathbf{Y}}) = [\mathcal{E}(\hat{y}^1), \mathcal{E}(\hat{y}^2), \dots, \mathcal{E}(\hat{y}^n)]$. These encrypted predictions are sent back to the server for per-sample loss computation in the encrypted domain. The server computes the batch loss and sends this encrypted average loss to the client. The client decrypts this loss and uses it for local learning. Throughout, all the operations on the server are carried out in the encrypted domain. Since the server does not have access to the client's private key, the server learns no information about the client's local data. On the other hand, the client receives a batch of intermediate representations (in plaintext) after each attention block.

4.2.2. Local Learning

Though various model adaptation strategies are available, the proposed framework requires an adaptation method that does not require backpropagation of gradients through the FM. This leaves us with only two possible choices: *transfer learning* (where only the classification head is learned) and *parallel adapter* (where both the classification head and a side adapter are learned). In this work, we adopt the low-

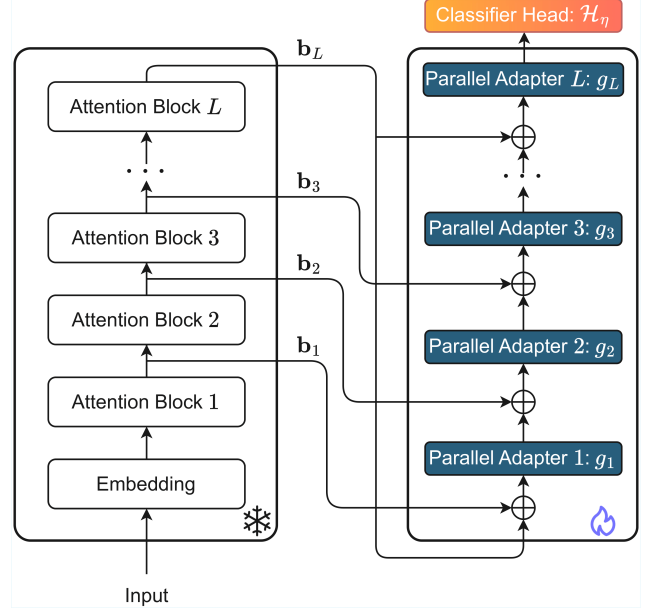


Figure 4. Illustration of the parallel adapter design.

rank parallel adapter method proposed in [41] (see Figure 4). This method requires access to intermediate representations after every transformer attention block, which is readily available (in plaintext) through the encrypted inference protocol described in Section 4.2.1.

The output of the low-rank parallel adapter corresponding to the attention block ℓ can be expressed as:

$$\mathbf{h}_\ell = g_\ell(\mathbf{b}_\ell + \mathbf{h}_{\ell-1}) + \mathbf{h}_{\ell-1}, \quad (6)$$

where $\mathbf{h}_0 = \mathbf{b}_L$. The adapter function g_ℓ is given by:

$$g_\ell(\mathbf{z}) = \alpha \mathbf{W}_\ell^u \text{GELU}(\mathbf{W}_\ell^d \mathbf{z}), \quad (7)$$

where $\mathbf{W}_\ell^d$ and $\mathbf{W}_\ell^u$ are the down- and up-projection matrices and α_ℓ is the scaling factor at block ℓ . Finally, the client locally updates the parallel adapter and classification head in the plaintext domain based on the average loss received from the server, employing the same procedure as in [45].

4.2.3. Secure Aggregation

To ensure the secure aggregation of parameter updates from clients, we leverage secure multi-party computation (MPC) [6]. This approach enables the aggregation server to compute the average of client updates without gaining access to the individual updates themselves. In BlindFed, the local adapters and classifiers are securely aggregated via FedAvg to obtain the global adapter and classification head.

4.3. Model Privacy Boosting

The downsides of performing encrypted inference over one attention block at a time are two-fold. Firstly, it increases the communication cost because encrypted intermediate

outputs are exchanged between the client and the server after every block in every FL round. Since communication efficiency is not one of our core constraints, we consider the increased communication cost as a limitation, not a red flag. However, since the intermediate representations $\mathbf{b}_\ell$ after every attention block are accessible to the client in plaintext form, a malicious client could use $(\mathbf{b}_{\ell-1}, \mathbf{b}_\ell)$ pairs for multiple training samples to mount a model extraction attack [34] and learn the parameters of each transformer block. This clearly violates the model privacy constraint. To circumvent this problem and preserve model privacy, we introduce two changes to the online adaptation stage, namely, *sample-level permutation* and *stochastic block sampling*.

4.3.1. Sample-level Permutation

Each communication round processes a batch of samples. Let $\mathcal{E}(\mathbf{B}_\ell) = [\mathcal{E}(\mathbf{b}_\ell^1), \mathcal{E}(\mathbf{b}_\ell^2), \dots, \mathcal{E}(\mathbf{b}_\ell^n)]$ be a batch of encrypted intermediate representations corresponding to a client, where n is the batch size. Before sending these representations to the client, the server applies a $n \times n$ permutation matrix Π_ℓ and sends only the permuted batch $\mathcal{E}(\mathbf{B}_\ell) \cdot \Pi_\ell = [\mathcal{E}(\mathbf{b}_\ell^{\pi(1)}), \mathcal{E}(\mathbf{b}_\ell^{\pi(2)}), \dots, \mathcal{E}(\mathbf{b}_\ell^{\pi(n)})]$ to the client. Here, $[\pi(1), \pi(2), \dots, \pi(n)]$ represents a random permutation of $[1, 2, \dots, n]$. This permutation matrix Π_ℓ can be randomly selected for each block ℓ in each communication round. Thus, the client never sees corresponding pairs $(\mathbf{b}_{\ell-1}^i, \mathbf{b}_\ell^i)$ for any training sample i in the batch, ensuring some protection against model extraction attacks.

Because the adapter in Eq. 7 is applied per sample, the permutation of samples within a batch does not affect this computation. However, the adapter output in Eq. 6 depends on values from two consecutive blocks, which have undergone different permutations. Hence, it is necessary to ensure consistent permutation of the inputs. When operating on a batch of samples, Eq. 6 can be reformulated as:

$$\mathbf{H}_\ell = g_\ell(\mathbf{B}_\ell + \mathbf{H}_{\ell-1}) + \mathbf{H}_{\ell-1}, \quad (8)$$

where $\mathbf{H}_0 = \mathbf{B}_L$. Note that the client receives only a permutation of intermediate representations, i.e., $(\mathbf{B}_\ell \cdot \Pi_\ell)$ and not the original $\mathbf{B}_\ell$, $\forall \ell \in [1, L]$. Hence, to facilitate the computations associated with the parallel adapter, the server also sends $(\Pi_{\ell-1}^{-1} \cdot \Pi_\ell)$ for all $\ell \in [2, L]$ as well as $(\Pi_L^{-1} \cdot \Pi_1)$ to the client. When the client receives $(\mathbf{B}_L \cdot \Pi_L)$, it can compute $\mathbf{H}'_0 = (\mathbf{B}_L \cdot \Pi_L) \cdot (\Pi_L^{-1} \cdot \Pi_1) = (\mathbf{B}_L \cdot \Pi_1) = (\mathbf{H}_0 \cdot \Pi_1)$. This can be directly used in Eq. 8 along with $(\mathbf{B}_1 \cdot \Pi_1)$ to compute $\mathbf{H}'_1 = (\mathbf{H}_1 \cdot \Pi_2)$. Following the same logic, it is possible to compute $\mathbf{H}'_\ell = (\mathbf{H}_\ell \cdot \Pi_{\ell+1})$, $\forall \ell \in [1, L]$. When the server receives the final encrypted predictions from the client, it can permute the encrypted labels of the batch using Π_{L+1} before computing the per-sample losses and aggregating them. It must be emphasized that revealing $(\Pi_{\ell-1}^{-1} \cdot \Pi_\ell)$ for all $\ell \in [2, L]$ as well as $(\Pi_L^{-1} \cdot \Pi_1)$ to the client does not leak any information about Π_ℓ as shown in Proposition 1.

Proposition 1. Let $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ be $n \times n$ permutation matrices. Given only $\mathbf{A}^{-1}\mathbf{B}$, $\mathbf{B}^{-1}\mathbf{C}$, and $\mathbf{C}^{-1}\mathbf{A}$, it is computationally infeasible to uniquely recover the individual matrices $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ without additional information.

Proof of Proposition 1. See Appendix A. □

4.3.2. Stochastic Block Sampling (SBS)

Sample-level permutation ensures that samples in each batch are randomly permuted based on Π_ℓ . Because the client never sees Π_ℓ , it is not straightforward to mount a model extraction attack when the batch size n is sufficiently large. However, intermediate representations of the same sample by two successive transformer blocks are likely to have higher similarity than representations from different samples (Appendix B). This similarity can be exploited to recover individual permutation matrices or, at the very least, reduce the brute-force search space. To mitigate this risk, we introduce stochastic block sampling (SBS): at each server-side forward pass, we return only a subset of block outputs and set the rest to zero, so the full sequence of representations is never revealed.

A key consideration in this strategy is avoiding the sampling of consecutive (neighboring) blocks, as this could still enable similarity-based attacks. As shown in Figure

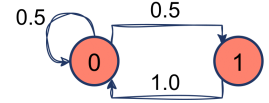


Figure 5. Stochastic block sampling strategy.

5 (and Appendix B), feature similarity is negligible when blocks are separated by at least one layer. We therefore use a structured sampling process: (i) if block ℓ is sampled (state 1), the next block $\ell + 1$ is not sampled (probability 1); (ii) if block ℓ is not sampled (state 0), the next block $\ell + 1$ is sampled with a probability of 0.5. Thus, the proposed model privacy boosting techniques ensure that the encrypted inference protocol is double-blind, even though the intermediate representations are exposed in plaintext form.

5. Experiments and Results

5.1. Datasets

To validate and implement our approach, we utilize a well-known vision transformer (ViT) pretrained on ImageNet-1K (ViT-Base) as the FM. The public auxiliary datasets for distilling the FHE-friendly FM are: **Tiny-Imagenet** [31] is a subset of the larger ImageNet dataset, containing 200 different classes, each with 500 images, 100 validation/test images, totaling 120K images. **Fed-ISIC2019** [57] is a multi-class dataset of dermoscopy images containing 23247 images across 8 melanoma classes, with high label imbalance. This dataset provides an opportunity to test our framework

Datasets	Methods	Is double-blind?	Centralized	Federated ($K = 5$)		
			Pooled	Dirichlet ($\alpha = 100$)	Dirichlet ($\alpha = 1$)	Dirichlet ($\alpha = 0.01$)
CIFAR-10	Full fine-tuning	✗	0.9635	0.9759	0.9725	0.8857
	LoRA	✗	0.9592	0.9736	0.9718	0.8979
	Adapter tuning	✗	0.8992	0.8681	0.8539	0.6754
	Linear probing	✓	0.9226	0.9203	0.9191	0.7447
	BlindFed	✓	0.9428	0.9471	0.9413	0.8540
	BlindFed + SBS	✓	0.9443	0.9486	0.9427	0.8489
CIFAR-100	Full fine-tuning	✗	0.8361	0.8684	0.8611	0.7882
	LoRA	✗	0.8349	0.8593	0.8568	0.7647
	Adapter tuning	✗	0.6594	0.6495	0.6396	0.4489
	Linear probing	✓	0.7476	0.7486	0.7414	0.5317
	BlindFed	✓	0.7930	0.7929	0.7808	0.6620
	BlindFed + SBS	✓	0.7869	0.7861	0.7789	0.6584
SVHN	Full fine-tuning	✗	0.9680	0.9763	0.9692	0.7601
	LoRA	✗	0.9659	0.9656	0.9709	0.7545
	Adapter tuning	✗	0.5201	0.5251	0.4785	0.3325
	Linear probing	✓	0.5938	0.5879	0.5732	0.3385
	BlindFed	✓	0.9232	0.9329	0.9249	0.7431
	BlindFed + SBS	✓	0.9257	0.9298	0.9256	0.7434

Table 1. Comparison of accuracy achieved by our proposed method against baseline approaches on three datasets (CIFAR-10, CIFAR-100, and SVHN) in both centralized and federated learning scenarios. Federated experiments involve five clients ($K = 5$) with data partitioned using a Dirichlet distribution at varying levels of heterogeneity ($\alpha = 100, 1, 0.01$). The best-performing results among double-blind algorithms are highlighted in bold.

within the healthcare domain. For the distillation phase of our experiments, we exclusively use data from client 1.

The private downstream datasets are: **CIFAR-10** and **CIFAR-100** [30] datasets are standard benchmarks for image classification, containing 60000 color images across 10 and 100 classes, respectively. **SVHN** [43] dataset is a benchmark for digit recognition, consisting of over 73257 images of house numbers for training and 26032 for testing. **Fed-ISIC2019**. The remaining data points for centers 2-6 are used in the fine-tuning experiments, aligning well with the federated setup, as the dataset is tailored for federated learning. For the centralized setup, all data points are pooled into a single client.

5.2. Experimental Setup

We employ the Vision Transformer (ViT) [13], pre-trained on the ImageNet-1k dataset [50] (ViT-Base), with a backbone dimension of 384×384 . For the first phase of our framework, obtaining the FHE-friendly FM, we use Adam optimizer with a learning rate of 10^{-4} for distilling the transformer blocks for 15 epochs and 10^{-5} for distilling the prediction layer for the remaining 15 epochs, totaling 30 epochs. We set the batch size to 16 due to the substantial memory demands. We use MSE loss for the first phase of the distillation and the combination of cross-entropy loss and Kullback-Leibler (KL) divergence losses for the second phase. We set the polynomial order of exponential approxi-

mation to 6 and the order of the inverse to 7. For the second phase of our framework, federated adaptation, we use SGD optimizer with a learning rate of 0.001 for linear probing and our proposed method and $5 \cdot 10^{-5}$ for full fine-tuning experiments. We set the total number of communication rounds to $T = 50$, and we use a learning rate scheduler with a decay factor of 0.1 at rounds [25, 40]. We set the batch size to 16 unless otherwise specified. We use cross-entropy loss to evaluate the effectiveness of the global model and report balanced accuracy. We use Dirichlet distribution-based splitting for all our experiments except the Fed-ISIC2019 dataset, which is naturally partitioned. All our experiments are conducted on NVIDIA A100-SXM4-40GB GPUs on an internal cluster server, with each run utilizing a single GPU.

5.3. Results

Main results: In Table 1, the performance of our proposed method and baseline methods across three datasets (CIFAR-10, CIFAR-100, and SVHN) is evaluated under both centralized and federated learning settings. The federated learning experiment uses a Dirichlet partitioning strategy with varying levels of data heterogeneity, controlled by the Dirichlet concentration parameter α (ranging from 100 to 0.01). The results demonstrate that full fine-tuning achieves the highest accuracy across all datasets and settings, particularly excelling in more homogeneous federated scenarios, but it is computationally expensive and not double-blind.

Public dataset	Methods	Is DB?	Centralized	Federated
Fed-ISIC2019 (center=0) (InD)	Full fine-tuning	✗	0.7811	0.6752
	LoRA	✗	0.7347	0.6844
	Adapter tuning	✗	0.6601	0.5762
	Linear probing	✓	0.6599	0.5856
	BlindFed	✓	0.7090	0.6679
	BlindFed + SBS	✓	0.7169	0.6831
Tiny-Imagenet (OOD)	Full fine-tuning	✗	0.7817	0.6985
	LoRA	✗	0.7330	0.6880
	Adapter tuning	✗	0.6702	0.6074
	Linear probing	✓	0.6372	0.5789
	BlindFed	✓	0.7051	0.6481
	BlindFed + SBS	✓	0.7127	0.6581

Table 2. Performance comparison of our method with baseline approaches on the Fed-ISIC2019 dataset with five clients ($K = 5$), using two auxiliary datasets: Fed-ISIC2019 (center=0) as an in-distribution (InD) dataset and Tiny-ImageNet as an out-of-distribution (OOD) dataset. DB refers to Double-Blind.

Linear probing maintains reasonable performance in homogeneous settings but fails drastically on SVHN and under extreme heterogeneity, confirming its limitations in adaptation. Our approach delivers robust and competitive performance, closely aligning with LoRA in accuracy while maintaining significantly lower computational demands (see Appendix D.2). Among the model privacy boosting techniques, sample-level permutation does not have any impact on the accuracy of the adapted model, but SBS may affect local learning because of missing intermediate representations. However, in practice, BlindFed+SBS demonstrates comparable performance to BlindFed without SBS, suggesting that SBS has minimal impact on adapted model performance while boosting model privacy. In some cases, these missing values add robustness to the learning process, leading to marginally better generalization performance.

Fed-ISIC2019 results: Table 2 compares the performance of our method and baselines on the Fed-ISIC2019 dataset with five centers. The auxiliary datasets used at the LSP include (1) Fed-ISIC2019 with only the first center (treated as an in-distribution dataset) and (2) Tiny-ImageNet (treated as an out-of-distribution dataset). The results demonstrate that knowledge transfer from the OOD dataset is effective for all the methods, highlighting that the auxiliary dataset used for offline distillation can be any available dataset.

Scalability Results: Table 3 illustrates the scalability of our method and the baseline approaches on the CIFAR-10 dataset with an increasing number of clients ($K = \{10, 20, 50\}$) using Dirichlet partitioning ($\alpha = 1.0$) and a fixed batch size of 8. Full fine-tuning achieves the highest accuracy for $K = 10$ and $K = 20$ but becomes infeasible for $K = 50$ due to GPU limitations (we use only one GPU for each of our experiments). Linear probing demonstrates stable performance, but our method outperforms linear probing in all the settings, balancing compute efficiency,

Methods	Is DB?	$K = 10$	$K = 20$	$K = 50$
Full fine-tuning	✗	0.9739	0.9513	N/A
LoRA	✗	0.9661	0.9584	0.9482
Adapter tuning	✗	0.8696	0.8494	0.8165
Linear probing	✓	0.9167	0.9142	0.9007
BlindFed	✓	0.9446	0.9422	0.9287
BlindFed + SBS	✓	0.9425	0.9411	0.9388

Table 3. Scalability analysis of the proposed method to baseline approaches on the CIFAR-10 dataset, with varying number of clients $K \in \{10, 20, 50\}$ under a Dirichlet concentration parameter of 1.0 for data partitioning. N/A - one GPU is insufficient to run the experiment. DB refers to Double-Blind.

scalability, and accuracy, and demonstrating its suitability for federated setups with a large number of clients.

Communication Overhead: In standard FL (FedAvg [40]), the communication cost depends on the foundation model (FM) size. In our work, ViT-Base is used as a FM consisting of $\approx 86M$ parameters requiring $\approx 344MB$ of bandwidth. In practice, LSPs often deploy larger FMs, e.g., ViT-Huge or even bigger models ($\approx 22B$ parameters), which require $\approx 88GB$ of bandwidth. In contrast, BlindFed requires the transmission of an encrypted intermediate representation (IR) for each transformer block. In our work, an IR is a 577×768 tensor, which requires **6.21MB** in plaintext and $C=17.33MB$ after encryption ($\approx 2.8\times$ expansion) (see Appendix D.5). Ignoring the tiny adapter update (0.25M params. $\approx 1MB$), the total communication cost of BlindFed is $(N_k * L * C)$, transmitted in batches, where N_k is the local training dataset size and L is the no. of transformer blocks. For federated adaptation tasks, N_k is expected to be small, and not all IRs need to be transmitted for SBS. Hence, the communication overhead of BlindFed will be significantly higher compared to FedAvg for smaller FMs, but becomes comparable when adapting large FMs with limited local data (which is often the case in practice). Other ablation studies and computational complexity analysis are reported in Appendix D.

6. Conclusions

This paper offers a promising framework for adapting foundation models for critical downstream applications without compromising on the data confidentiality and model privacy. However, the BlindFed framework is just a first step and needs to be improved in many dimensions before it is ready for practical adoption. Firstly, the high communication cost of BlindFed and high computational complexity at the server need to be mitigated. Secondly, more rigorous model privacy guarantees would be required before LSPs can expose valuable proprietary models to collaborators. Finally, the robustness of the framework in the presence of malicious collaborators should be carefully analyzed.

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