

Exploring the Privacy-Energy Consumption Tradeoff for Split Federated Learning

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Abstract—Split Federated Learning (SFL) has recently emerged as a promising distributed learning technology, leveraging the strengths of both federated learning and split learning. It emphasizes the advantages of rapid convergence while addressing privacy concerns. As a result, this innovation has received significant attention from both industry and academia. However, since the model is split at a specific layer, known as a cut layer, into both client-side and server-side models for the SFL, the choice of the cut layer in SFL can have a substantial impact on the energy consumption of clients and their privacy, as it influences the training burden and the output of the client-side models. Moreover, the design challenge of determining the cut layer is highly intricate, primarily due to the inherent heterogeneity in the computing and networking capabilities of clients. In this article, we provide a comprehensive overview of the SFL process and conduct a thorough analysis of energy consumption and privacy. This analysis takes into account the influence of various system parameters on the cut layer selection strategy. Additionally, we provide an illustrative example of the cut layer selection, aiming to minimize the risk of clients from reconstructing the raw data at the server while sustaining energy consumption within the required energy budget, which involve trade-offs. Finally, we address open challenges in this field. These directions represent promising avenues for future research and development.

1 INTRODUCTION

FEDERATED Learning (FL) fundamentally addresses the challenges associated with centralized learning by distributing the training process across multiple clients, enabling parallel processing. This approach also helps safeguard the privacy of raw data stored on clients by exchanging only model parameters. However, FL necessitates local training on each client, which can be a significant burden on clients with limited battery power and computational resources when dealing with large models like Deep Learning (DL). To mitigate this problem, Split Learning (SL) has emerged as a solution. SL involves breaking down a full DL model into two sub-models, which can be trained both at a main server and across distributed clients. This approach alleviates the local training burden associated with FL while preserving data privacy. Nevertheless, SL introduces its own set of challenges, primarily related to training time overhead, owing to its relay-based training method. In this relay-based approach, only one client engages in the training process with the main server at any given time, while other clients remain in an idle state. This sequential training method leads to inefficient distributed processing,

resulting in long training latency. To address this challenge, various strategies for parallelizing the training process of SL have been introduced [1]. Inspired by these efforts, Split Federated Learning, simply called SplitFed Learning, (SFL) has been recently proposed as a novel approach that leverages the strengths of both FL and SL. Unlike SL, in SFL, all clients perform their local training in parallel while actively engaging with the main server and the federated server (fed server). In SFL, the fed server plays a pivotal role in aggregating the local model updates from clients using pre-defined aggregation techniques, such as FedAvg¹. This aggregation process occurs synchronously in each round of training. By introducing this additional aggregation server, SFL combines the advantages of both FL and SL seamlessly [2].

Despite the advantageous integration of SL and FL in SFL, the current SFL still presents several privacy concerns. Notably, the exchanged output of the client-side models, known as smashed data, and model updates between clients and servers have correlations with the raw data, leaving them susceptible to potential reconstruction attacks, where adversaries attempt to reconstruct the raw data from the correlated information. In this regard, differential privacy (DP) is currently the gold standard for privacy, known for its effectiveness against reconstruction and membership inference attacks by adding noise to the data or query responses that are released to untrusted parties, thereby obfuscating the outputs related to the sensitive data [3], [4]. Nevertheless, the adoption of DP mechanisms presents an added computational load for clients. Furthermore, since SFL still imposes notable latency due to computation and communication overhead until the model converges, implementing sophisticated DP can also pose practical deployment challenges.

To tackle this growing concern, this article advocates for determining an appropriate split point between client-side and server-side models, specifically known as cut layer selection in the SFL, with the goal of mitigating the risk of reconstruction attacks while sustaining energy consumption within the required energy budget. This is particularly im-

1. FedAvg is the most popularly used weighted aggregation in FL, assigning varying weights to clients during aggregation based on the size of their datasets.

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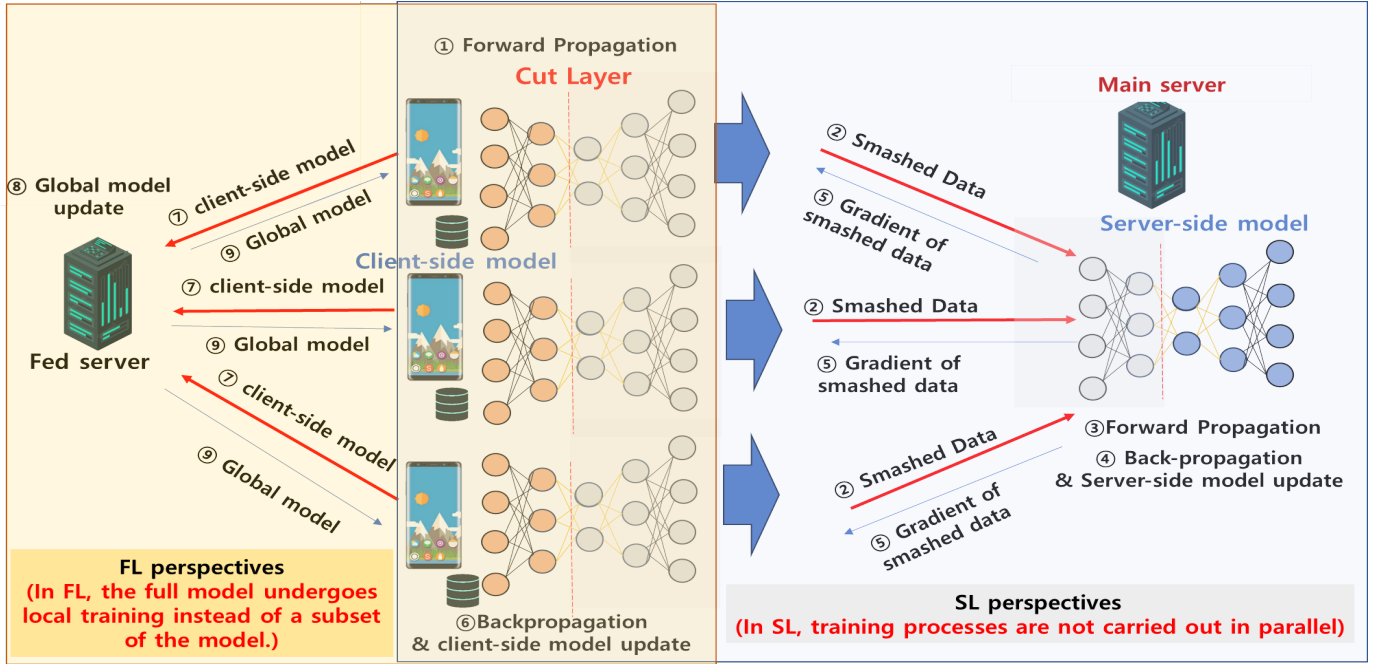


Fig. 1: Workflow of SFL: Combining both FL and SL perspectives.

portant for clients operating on limited battery power. It is worth noting that the selection of the cut layer significantly influences the outcome of the smashed data, impacting computational and communication overhead, as well as the level of privacy. For example, as discussed in [5], there is an ongoing study focused on the adaptive selection of cut layer, taking into account the varying computing and networking capabilities of clients. Nevertheless, prior research has not thoroughly analyzed both energy consumption and privacy in the context of cut layer selection, despite some studies focusing on empirical and analytical studies of reducing overall latency in SFL. This motivates us to provide an analysis of both energy consumption and privacy levels related to cut layer selection and a potential solution for developing novel cut layer selection techniques.

The contributions of this article can be summarized as follows:

- We provide a comprehensive overview of the overall process of SFL along with an in-depth examination of how the choice of the cut layer impacts SFL in terms of both privacy and energy consumption.
- Building upon this analysis, we propose a potential solution for optimizing cut layer selection, seeking to minimize the risk of reconstruction attacks while ensuring that energy consumption remains within the specified energy budget.
- Finally, we shed light on several prospective avenues for future research and conclude the paper.

2 WHY IS CUT LAYER SELECTION IMPORTANT?

2.1 Background about SFL

The SFL framework consists of two servers such as i) a fed server and ii) main server, and multiple clients. The entire model is divided into two distinct sub-models: i) the client-side model and ii) the server-side model. As a practical

concern, to reduce communication latency, the main server and fed server are set up using either of containers (such as Kubernetes) or virtual machines on the same or different physical multi-access computing (MEC) servers. The workflow of SFL is depicted in Fig. 1. Each client performs forward propagation on the client-side model using its dataset and passes the smashed data and corresponding label to the centralized main server (Step 1-2). The main server performs forward propagation from the smashed data on the server-side model and back-propagation by calculating the loss between the true label and predicted label, which can be done in parallel. Afterward, the server-side model is obtained by using FedAvg (Step 3-4) and the main server passes the gradient of the smashed data to each client for the client-side local model update (Step 5-6). Then, the fed server receives updated client-side local models from all clients and aggregates them by using FedAvg (Step 7-8). Finally, the fed server sends the updated client-side global model to all clients, enabling synchronization of client-side models (Step 9).

2.2 A Brief Survey of SFL

2.2.1 Communication efficiency Issues

Despite the advantageous integration of SL and FL in the SFL to alleviate the computational burden on clients and address privacy concerns, it still imposes significant communication overhead. This is primarily due to the transmission of smashed data and gradients between clients, the main server, and the fed server, indicating the need for improvements [6]. Nevertheless, there remains a scarcity of research focusing on the analytical modeling of SFL, in contrast to the abundance of empirical studies [7]. Notably, [2], [8] have contributed analytical models that investigate the impact of total model training time (i.e., latency) concerning the cut layer point. Correspondingly, based on such

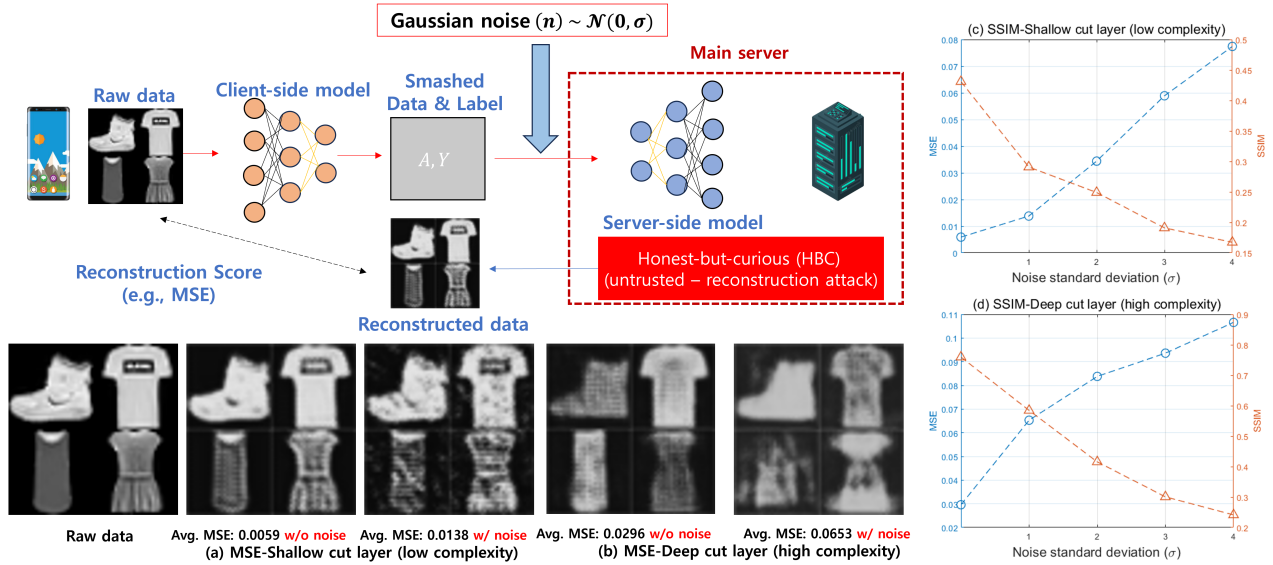


Fig. 2: Example of reconstruction attacks in SFL as a privacy concern: This highlights the tradeoff between the client model complexity and privacy. Additionally, it explores the effects of Gaussian noise addition on privacy issues.

analysis, there have been various approaches to improve the communication efficiency in SFL [1], [6], [8]. Specifically, [8] introduced an optimal cut layer selection based on latency analysis. Remarkably, most prior research has concentrated on analyzing and optimizing latency in SFL, yet there is a notable absence of studies addressing the impact of energy consumption concerning the cut layer selection in SFL. This aspect is crucial for estimating the associated costs for clients with limited battery power.

2.2.2 Privacy Issues

In SFL, privacy concerns arise from the interactions between clients and servers, including both the main server and the fed server. During the forward phase, when clients transmit smashed data to the main server, this data becomes susceptible to reconstruction attacks [4], jeopardizing the privacy of the original information. Furthermore, the exchange of model updates with the fed server introduces another potential vulnerability to the raw data. To mitigate these risks, several privacy-preserving mechanisms can be employed. One effective strategy is the implementation of *noise addition*, where random noise is added to the data or model updates, thereby disrupting any attempts to reconstruct the original data. This method, often used in conjunction with *subsampling* techniques, ensures that each update's information is based on a random subset of the data, further complicating potential attacks. Another approach is *homomorphic encryption*, which allows computations to be performed on encrypted data, enabling the server to process data updates without actually viewing the original data. These mechanisms, rooted in the principles of DP, work synergistically to protect client data during both the forward and backward phases of interaction, thereby reinforcing the confidentiality of sensitive information amidst the continual exchanges in federated environments. However, it is worth noting that this approach does introduce added complexity on the client side. In a recent study [9] on SL, researchers conducted an empirical investigation into the impact of selecting the cut

layer on reconstruction attacks during the forward phase. Their findings indicate that a greater depth of layers on the client side implies more non-linear functions, which compress the raw data by eliminating less informative features, thereby enhancing its resistance to reconstruction attacks. Similarly, the work of [10] also presented empirical studies on how the distance correlation between raw data and smashed data influences privacy leakage in SL in relation to the selection of cut layer. Building on this insight, we will conduct empirical studies of SFL in a similar fashion, which can be extended to explore cut layer selection strategies that strike a balance between energy consumption and privacy level.

2.3 Cut Layer Selection Impact

2.3.1 Energy Efficiency Perspective

In the context of SFL, energy consumption of clients occurs from both networking and computing perspectives. Specifically, from a computing perspective, clients engage in local training on their datasets using client-side models. From a networking perspective, there is energy expenditure associated with uplink transmission and downlink receiving between clients and the federated server as well as main server. Regarding downlink receiving energy consumption, it tends to be negligible due to the relatively small amount of energy required compared to uplink transmission power. In the case of uplink transmission energy consumption, energy is needed for transmitting smashed data to the main server. Additionally, each client must transmit its client side local model to the fed server for aggregation. It is worth noting that the cut layer selection strategy can have an impact on the size of the client-side model (i.e., model complexity). Consequently, as the size of the client-side model increases, energy consumption for both computation and model transmission to the fed server also increases. Therefore, to reduce energy consumption, a sophisticated management strategy for cut layer selection should be considered.

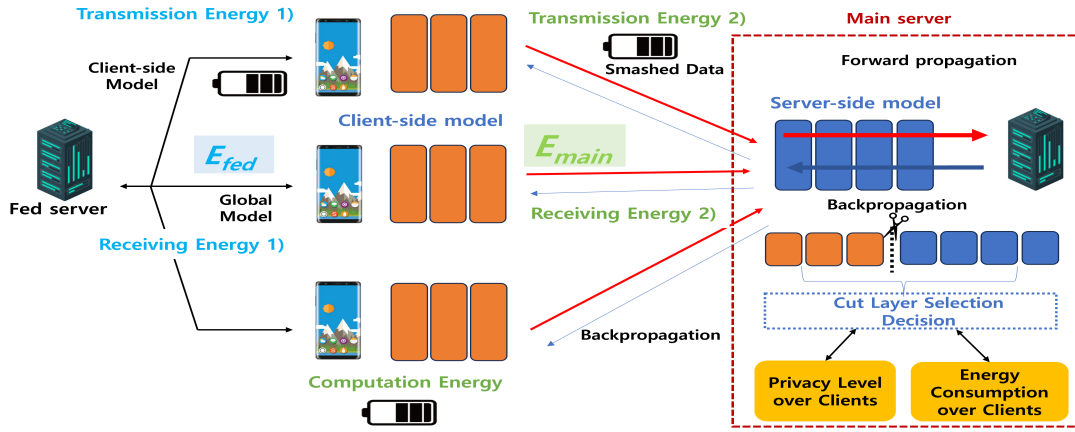


Fig. 3: Proposed cut layer selection considering both energy consumption and privacy level.

2.3.2 Privacy Level Perspective

As shown in Fig. 2, when we assume that the main server is honest but curious (HBC), it is still possible for the main server to reconstruct the original input data from the smashed data (specifically, the embedded features) received from clients. This process is referred to as a reconstruction attack. In this context, we can assess the privacy risks associated with this reconstruction attack by measuring the human perceptual similarity between the original and the reconstructed images, known as the structural similarity index (SSIM). This SSIM, which ranges from [0, 1], is widely used as a metric to measure the attack and defense performance, where 1 denotes the most similar. Fig. 2 illustrates the relationship between client model complexity and privacy leakage. It highlights the effects of altering the cut layer on the quality of images reconstructed at the main server. Notably, as the cut layer index increases, indicating a rise in model complexity, the quality of the reconstructed image degrades. This degradation is interchangeable with enhanced privacy. The reason is that the complexity of the model deployed at the client’s end introduces advanced non-linearities in its output. This added intricacy can make it more challenging for adversaries to reverse-engineer and retrieve private input data. Moreover, Fig. 2 also presents an illustrative example to practically demonstrate the application of noise addition, a fundamental strategy in achieving differential privacy. Here, our focus will center on one widely adopted noise addition mechanism: the *Gaussian* mechanism where it is instrumental in introducing carefully calibrated noise to sensitive data, effectively masking individual information while preserving the utility of the overall dataset. The Gaussian mechanism employs a Gaussian distribution for this purpose, providing distinct privacy-accuracy trade-offs. In this context, it is evident that introducing Gaussian noise to smashed data further degrades the quality of the reconstructed image, as indicated by the mean square error (MSE) representing the differences in pixels between the original and the reconstructed images. As the level of Gaussian noise rises, the MSE also increases, leading to a decrease in the SSIM in both shallow and deep cut layer scenarios. We also confirmed that the classification accuracy remains within an acceptable range (i.e., 92.6-94.4%) regardless of the level of

Gaussian noise, which means that Gaussian mechanism has less sacrifice of accuracy while having larger privacy gains. This simple example will serve to illuminate the intricacies and operational dynamics of this noise addition technique, offering insights into their strategic implementation in contexts demanding stringent data privacy measures².

3 CASE STUDY: CUT LAYER SELECTION

3.1 An Illustrative Example

Based on the latency analysis of SFL in [2] and [8], and leveraging the energy consumption insights gained from FL studies [11], this section examines the overall energy consumption associated with SFL. Note that the analysis is based on the vanilla version of SFL rather than SFLv2/v3. However, the core concepts and intuitions are easily applicable to the higher versions. Similar to FL, as shown in Fig. 3, the total energy consumption E of each client during SFL encompasses both i) computing and ii) networking energy. However, it requires customization to account for model splitting and interactions with both the fed server and the main server, distinctive features introduced in the SFL. Taking these considerations into account, to formulate the energy consumption model, consider a scenario with K clients. Then, K clients engage in the SFL framework for g_e global epochs, representing the overall number of rounds necessary to achieve a specific training loss [12]. The client-side models synchronize at each global epoch, enabled by the fed server. In each global epoch, leveraging this synchronized client-side model, both clients and the main server conduct training for l_e local epochs. Specifically, for simplicity, as in [2] and [8], considering homogeneous clients in a single local epoch, each client trains D_b randomly sampled data items, commonly referred to as a mini-batch, from its dataset. By using transmission power P_t , they can communicate with the fed server and main server with total uplink (downlink) transmission rates R_1^U and R_2^U (R_1^D and R_2^D), respectively. Consequently, the uplink (downlink)

2. Various noise addition mechanisms exist, including the *Laplacian* mechanism, which introduces noise following a Laplace distribution. However, since the selection of noise addition mechanisms is beyond the scope of this paper, we focus on exploring the impact of Gaussian noise to provide straightforward insight.

transmission rates for each client reduce to $\frac{R_1^U}{K}$ and $\frac{R_2^U}{K}$ ($\frac{R_1^D}{K}$ and $\frac{R_2^D}{K}$), respectively. Note that the entire model $W = [W_C; W_S]$, where W_C , and W_S are the client-side model, and the server-side model, respectively. As in [2] and [8], we also assume the same size of smashed data denoted as q sent from clients to the main server. Let $|W|$ be the number of model parameters in the entire model W where all model parameters have the same size b , and let α be the fraction of model parameters, which serves as the model cut layer point for SFL in W_C , where $|W_C| = \alpha|W|$ and $|W_S| = (1 - \alpha)|W|$. And, T represents the time taken for one forward and backward propagation on the full model. In backward propagation, gradients of a constant size, denoted as q' , are transmitted. Therefore, in SFL, energy consumption during interaction with the main server, denoted as E_{main} , requires each client i) to proceed forward and backward propagation using W_C , incurring energy consumption αTP_C and ii) to transmit the smashed data (or receive the gradients) to (from) the main server per each sampled data item, incurring energy consumption $\frac{qK}{R_2^U} P_t$ (or $\frac{q'K}{R_2^D} P_r$). Here, P_r is the receiving power consumption at each client. In parallel, energy consumption for interaction with the fed server, denoted as E_{fed} , requires each client i) to send its local model to the fed server aggregation, incurring energy consumption $\frac{\alpha b|W|K}{R_1^U} P_t$, and ii) to receive the updated global model from the fed server, incurring energy consumption $\frac{\alpha b|W|K}{R_1^D} P_r$ during one global epoch. Finally, total energy consumption $E(\alpha)$ of each client for the SFL is given by

$$E(\alpha) = g_e(l_e D_b E_{main} + E_{fed}). \quad (1)$$

As previously discussed, under the assumption of an HBC main server, the privacy risks associated with the reconstruction attack can be evaluated by measuring the SSIM between the original input and the reconstructed images with respect to α , denoted as $RS(\alpha)$. To evaluate the impact of cut layer selection in terms of $RS(\alpha)$ and $E(\alpha)$, we utilize a training-based adversarial inversion approach [13]. Note that the reconstruction model is implemented to reflect the inverted structure of classifier W with transposed convolutional and Tanh activation layers. In our experiment, the overall classifier model W for SFL is designed with four convolution blocks (Conv-BN-ReLU-Conv-BN-ReLU-Conv-BN-Max-ReLU) and one linear block. Linear block consists of two fully-connected layers and a Softmax function. The cut layer is selected between blocks to divide client and server-side models. For performance evaluation, the Fashion-MNIST dataset was employed³. The input image was resized to 32×32 and the D_b was 128. We used an Adam optimizer and the learning rate was set to 0.0002. The betas for Adam were set to (0.5, 0.999). We trained the classifier model for SFL up to 50 global training epochs and 75 local training epochs. The reconstruction model was trained up to 50 epochs under the same optimizer and settings as the classifier model. More detailed parameters are summarized at Table 1.

As depicted in Fig. 4, the RS exhibits a consistent decrease as the depth of the cut layer increases. This phe-

TABLE 1: Parameter Settings.

Parameters	Values
K	5
W	31,484,464
D_b	128
q, q'	491,520 bits, 491,520 bits
b	32 bits
T	0.00055 seconds
$(R_1^U, R_2^U), (R_1^D, R_2^D)$	200 Mbit/s, 100 Mbit/s
P_c, P_t, P_r	4W, 0.2W, 0.2W

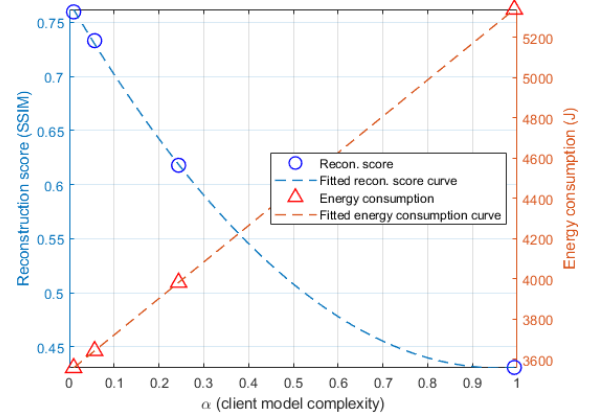


Fig. 4: Reconstruction score and energy consumption with respect to the depth of cut layer: This represents the tradeoff between energy consumption and privacy.

nomenon implies that the depth of the cut layer can be directly correlated with the complexity of the client-side model, potentially make attackers to reconstruct the image from the smashed data more difficult. Consequently, in this empirical study, we demonstrated that a convex model can effectively approximate the behavior of RS, yielding a Root Mean Square Error (RMSE) of only 0.0019. As a result, RS can be estimated as $RS(\alpha) = 0.367\alpha^2 - 0.7045\alpha + 0.7686$. Consequently, we can optimize the selection of the cut layer, denoted by α , to minimize privacy leakage from reconstruction attacks, as measured by $RS(\alpha)$, while ensuring that energy consumption (E) remains within an acceptable energy budget (E_{req}). Thus, the problem can be formulated as follows:

$$\begin{aligned} & \underset{\alpha}{\text{minimize}} && RS(\alpha) \\ & \text{subject to} && E(\alpha) \leq E_{req}, \quad 0 \leq \alpha \leq 1. \end{aligned} \quad (2)$$

Note that $E(\alpha)$ within the constraint should be calculated as an average across clients when dealing with heterogeneous client scenarios. The problem of (2) is a convex optimization problem since it features a convex objective function and affine constraints, which guarantees global optimal solution and can be simply solved using a CVX solver. Based on our empirical findings, the objective function $RS(\alpha)$ is strictly decreasing. Therefore, the optimal cut layer selection is expected to be located at the constraint boundary. In practice, a continuous value for α should be translated into an integer-valued cut layer index. If the depth of the entire network is not excessively large and the estimated $RS(\alpha)$ and $E(\alpha)$ function are not provided, exhaustive search remains a viable option. Based on the intuition from analytical study,

3. <https://github.com/zalandoresearch/fashion-mnist>

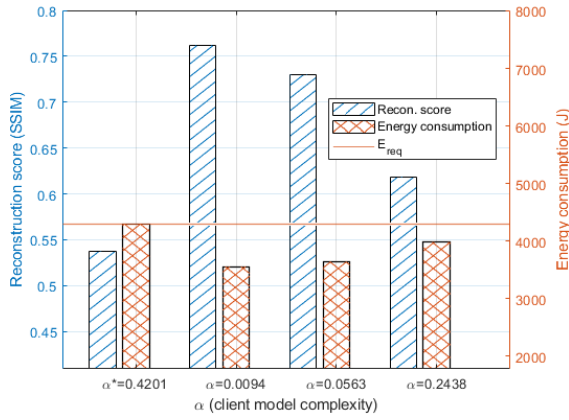


Fig. 5: Privacy gain of proposed scheme: It represents that optimal cut layer selection achieves minimum privacy leakage while satisfying the required energy budget.

this exhaustive search involves verifying the energy budget constraint as the depth of the cut layer increases. Thus, as depicted in Fig. 5, by optimizing the cut layer selection while ensuring the energy consumption budget, $R(\alpha)$ can be minimized in comparison to other cut layer selections within the feasible range of α . This indicates that a thoughtful cut layer selection can strike a balance between privacy levels and energy consumption. In practical scenarios, such cut layer selection can be jointly optimized with other system parameters, all working towards similar objectives as well as multi-objectives (i.e., including latency). This may result in a more intricate problem, which we will delve into in the following subsection.

3.2 Other Types of Control Variables

- Computation resource control: The computation resource (denoted as f_i) of each client participating in SFL plays a pivotal role in optimizing performance. However, due to the early stage of this field, there has been a lack of rigorous analysis for SFL. Fundamentally, f_i is known to affect computation latency, denoted as T_i in our analysis, which in turn impacts energy consumption within the field of FL [11].
- Power control: As studied in other studies of FL [11], the clients participating in the SFL can also improve their performance by optimizing their transmission power P_t . This optimization has a significant impact on both uplink transmission rates, which were assumed to be constant in our initial analysis for simplicity, and energy consumption during the transmission period. Consequently, we can further enhance energy efficiency and convergence speeds by adjusting transmission power.
- Radio resource management: Similar to power control, the allocation of radio resources (i.e., bandwidth allocation over clients) has been regarded as a crucial control parameter managed by base stations. This is because efficient bandwidth allocation can significantly impact both the uplink and downlink transmission rates of clients participating in FL. In the case of SFL, where more data transmission is

required than FL process, such as client models and smashed data exchanges between clients and the main server or fed server, radio resource allocation can be designed with a more elaborate approach.

- Client selection: The high mobility of clients can affect the wireless network conditions between clients and the main server as well as the fed server, respectively. Furthermore, the clients often have unbalanced and non-independent and identically distributed (non-IID) datasets, which can result in slower convergence speeds. Therefore, taking these issues into account, it can be beneficial to explore dynamic client selection management within SFL to enhance both accuracy and convergence speed.

As we reviewed, the performance of SFL, concerning both energy efficiency and convergence speed, etc., is noteworthy. However, achieving an optimal balance with respect to these multiple variables often requires substantial complexity in the pursuit of a global optimum. In some instances, adopting a modular design approach can be advantageous, transforming the overall problem into several sub problems such as a convex optimization one. Even when dealing with non-convex scenarios, a range of heuristic techniques can be devised to efficiently attain sub-optimal solution.

4 OPEN CHALLENGES

4.1 Deep Reinforcement Learning

Given the dynamic nature of networking and the computing capabilities of clients, the deep reinforcement learning (DRL) holds the potential to strike a balance between privacy and energy consumption in the SFL by intelligently selecting the appropriate cut layer, in conjunction with other essential control parameters, as we have discussed. In this context, the key challenges in applying DRL to address various SFL issues revolve around precisely defining the agent, environment, state, action, and reward. Additionally, the selection of an appropriate DRL model and the fine-tuning of hyperparameters become pivotal for improving convergence speed, especially when dealing with complex and dynamic environments.

4.2 Privacy and Security Protection

As in [14], when clients and the main server hold their data and labels, respectively, it is important to protect these from exposure due to privacy concerns (e.g., vehicles communicating with roadside infrastructure, or smart remote sensing where network owners collaborate in training). In such situations, attackers could be malicious data owners or eavesdroppers trying to intercept gradients shared from the main server to clients. The similarity in cut layer gradients among data samples can disclose their connection to labels, which is known as a label inference attack. A common technique for this attack involves using clustering mechanisms, assuming the attacker is aware of the number of classes and has auxiliary data to initiate the clustering algorithm. Therefore, to mitigate risks, both reconstruction and label inference attacks must be addressed by carefully choosing the cut layer and implementing DP. Moreover, security attacks to SFL can significantly degrade model training,

bringing it down to unacceptable performance levels due to actions by malicious clients. Given that SFL involves communication with both the fed server and the main server, it is more vulnerable to attacks. These attacks could involve directly poisoning the client-side local model or the smashed data. Therefore, it is crucial to explore advanced methods for detecting malicious clients as a defense mechanism to enhance the security of SFL.

4.3 Quantization Optimization

To enhance the efficiency of SFL, it is beneficial to consider the quantization approach. This technique has gained extensive attention in the fields of FL [15] and holds promise for addressing the significant communication overhead observed between clients and servers. In the context of SFL, adopting a quantization approach can substantially reduce the size of both local model updates and intermediate data. This reduction leads to several advantages, including reduced bandwidth usage, lower transmission energy, and reduced storage needs. Furthermore, quantization introduces inherent privacy guarantees. This is because by reducing the precision of transmitted data, it inherently obfuscates the exact values, thereby adding an extra layer of protection for sensitive information, which is crucial in maintaining data privacy. Consequently, it is advisable to further research and develop an appropriate quantization approach tailored to SFL. This research direction aims to achieve the above benefits while maintaining an acceptable level of accuracy.

5 CONCLUSIONS

This article has provided an overview of the SFL, mainly focusing on its communication efficiency and privacy issues. By studying the impact of the cut layer selection on both energy consumption and privacy, we have provided a concrete example of an efficient cut layer selection to minimize the risk of reconstruction attacks within the required energy budget. Finally, we have suggested various other adjustable factors and highlighted some promising research directions within this field.

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