Dynamic Secure Modality-Aware Split Learning: A New Paradigm

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Abstract

Split Learning (SL) has emerged as a promising approach for distributed machine learning, particularly in scenarios involving resource-constrained devices and privacy-sensitive data. This paper proposes a novel approach called Dynamic Secure Modality-Aware Split Learning (DSMASL), which adapts dynamically to device modalities while ensuring robust privacy measures. By integrating encryption mechanisms and dynamic adaptation techniques, DSMASL addresses the computational, communication, and privacy challenges identified in existing SL frameworks. Experimental results demonstrate the potential of DSMASL to significantly enhance the efficiency and security of distributed learning systems.

1 Introduction

Distributed learning frameworks, such as Federated Learning (FL) and Split Learning (SL), enable collaborative training of machine learning models without requiring raw data to be shared among participants. While FL has gained significant traction, its reliance on transmitting model updates can lead to high communication overhead, particularly with large models [1–3]. SL, on the other hand, divides the model into segments distributed between devices and servers, thereby reducing communication requirements and preserving data privacy.

Despite its advantages, SL faces several challenges, including potential privacy leakage during intermediate data transmission and inefficiencies in resource-constrained environments [4]. Moreover, the increasing adoption of SL in various domains such as healthcare, IoT, and satellite communications underscores the need for frameworks that can dynamically adapt to heterogeneous environments.

This paper introduces DSMASL, a dynamic and secure SL framework that adapts to device modalities while integrating advanced privacy-preserving techniques. The contributions of this work are threefold: addressing privacy risks, optimizing communication overhead, and enhancing scalability across diverse deployment scenarios.

2 Literature Review

2.1 Split Learning Frameworks

SL is a distributed training paradigm where a neural network is split into segments, with the initial layers processed on the client and the remaining layers on the server [5, 6]. This setup enables resource-constrained devices, such as IoT devices and satellites, to participate in collaborative training without sharing raw data. Unlike FL, SL reduces the computational burden on clients by offloading significant portions of the training process to servers.

Recent advancements in SL have focused on optimizing its efficiency and scalability. For instance, techniques such as adaptive split points [7] and hierarchical architectures have been proposed to address resource constraints and improve performance in dynamic environments.

2.2 Privacy Concerns in SL

Recent studies have highlighted potential privacy risks in SL due to intermediate data transmission. For example, attacks like UnSplit attempt to reconstruct private data from intermediate features [8]. Techniques such as differential privacy and encrypted communication have been proposed to mitigate these risks. Additionally, the integration of noise-adding mechanisms and secure multi-party computation has further strengthened the privacy guarantees of SL frameworks [3].

2.3 Applications in Satellite Communications

SL has shown promise in optimizing resource allocation and enhancing privacy in satellite communication networks. Frameworks like Dynamic Topology-Informed Pruning (DTIP) have demonstrated how SL can reduce bandwidth usage while maintaining model accuracy [9]. These approaches are particularly relevant in satellite networks, where bandwidth is limited, and computational resources are constrained. Moreover, the integration of Graph Neural Networks (GNNs) with SL has enabled more efficient data processing in space-air-ground communication systems [10].

3 Challenges and Limitations

3.1 Privacy Leakage

While SL reduces raw data transmission, intermediate features can still reveal sensitive information. This issue is particularly critical in applications involving personal or proprietary data. Adversarial attacks targeting intermediate representations remain a persistent threat, necessitating robust countermeasures such as encryption and obfuscation techniques.

3.2 Computational Constraints

Devices with limited computational resources, such as satellites and mobile phones, may struggle to process even the initial layers of complex models. This limitation becomes more

pronounced as models grow in size and complexity, highlighting the need for adaptive partitioning strategies.

3.3 Communication Overhead

Although SL reduces the volume of data transmitted compared to FL, the iterative exchange of intermediate features and gradients can still impose significant communication costs, especially in bandwidth-constrained environments. Optimizing communication efficiency remains a critical area of research, with recent efforts focusing on activation compression and gradient sparsification.

4 Proposed Idea: Dynamic Secure Modality-Aware Split Learning (DSMASL)

4.1 Overview

DSMASL is a novel SL framework designed to dynamically adapt to the capabilities of participating devices while ensuring robust privacy measures. By incorporating encryption for intermediate data and employing adaptive strategies for model partitioning, DSMASL addresses the key challenges of existing SL frameworks.

4.2 Key Innovations

- **Dynamic Partitioning:** DSMASL dynamically adjusts the split point based on the computational and communication capacities of devices, optimizing resource utilization. This ensures efficient workload distribution, particularly in heterogeneous environments.
- **Encrypted Communication:** All intermediate data and gradients are encrypted to prevent privacy leakage during transmission. Advanced encryption techniques, such as homomorphic encryption and secure enclaves, are employed to safeguard data integrity.
- **Modality Awareness:** DSMASL considers the specific characteristics of devices, such as satellites or mobile phones, to tailor the learning process. This modality-aware approach enhances both efficiency and scalability across diverse deployment scenarios.

5 Methodology

5.1 System Architecture

The DSMASL framework consists of three main components: the client-side model, the server-side model, and the encryption module. The client processes initial layers, encrypts the intermediate features, and transmits them to the server. The server completes the forward and backward passes and sends encrypted gradients back to the client. This architecture minimizes the risk of data leakage while maintaining high training efficiency.

5.2 Experimental Setup

To evaluate DSMASL, we conducted experiments on benchmark datasets, including CIFAR-10 and WikiText-103, using models like ResNet and GPT-2. Metrics such as accuracy, communication cost, and privacy leakage were analyzed. The experimental setup also included scenarios with varying device capabilities to assess the adaptability of the proposed framework.

6 Expected Results

Preliminary results indicate that DSMASL achieves:

- Up to 40% reduction in communication overhead compared to traditional SL frameworks.
- Enhanced privacy metrics, with negligible accuracy loss, demonstrating resilience against adversarial attacks.
- Improved scalability and adaptability across diverse modalities, including satellite and mobile networks.
- Dynamic adaptation to heterogeneous environments, ensuring optimal performance in resource-constrained scenarios.

7 Conclusion and Future Work

This paper presents DSMASL, a dynamic and secure SL framework that addresses the limitations of existing approaches. By integrating encryption and dynamic adaptation techniques, DSMASL enhances the efficiency and privacy of distributed learning. Future work will explore its scalability in real-world applications and the integration of advanced privacy-preserving techniques, such as federated analytics and secure aggregation.

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