FedMLO: A Communication-Efficient Federated Learning with Multi-Link Operation

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Abstract

A federated learning that uses the entire data without sharing the data itself is attracting attention. However, the federated learning method can result in clients dropping out of the learning round due to network heterogeneity problems, causing significant latency to servers and other clients while waiting for slow clients and causing a waste of resources. Therefore, this study proposed FedMLO (Federated Learning Multi-Link Operation) to increase communication efficiency by utilizing Multi-Link Operation (MLO), one of the core functions of 802.11be, for federated learning.

keywords: federated learning; multi-link operation; communication-efficient

1 Introduction

With the rise of intelligent devices, including IoT (Internet of Things) devices, vast amounts of data are produced and collected. The federated learning is attracting attention to ensure privacy while processing vast amounts of data [1]. However, clients participating in federated learning have different network performance, and a straggler problem arises in which clients drop out of the learning round [2]. This causes significant latency for the server and other clients and wastes resources [2]. Therefore, this study proposed FedMLO (Federated Learning with Multi-Link Operation) to increase communication efficiency by utilizing Multi-Link Operation (MLO) for federated learning.

2 Proposed Method

FedMLO supports multi-link devices, and when receiving or transmitting information from clients, it can send data using multiple links simultaneously rather than using only one link. Accordingly, throughput may be improved in the transmission process between the server and the client. Figure 1 shows the FedMLO process, and the operation process is as follows:
The server randomly initializes the learning model and delivers the initialized model and configuration to clients participating in federated learning (steps 1 and 2). After that, the clients perform local learning, respectively, and transmit the local model to the server (steps 3 to 4). The server receives the local model through the multi-link, aggregates it, and generates a global model (step 5). The global model is delivered to the participating clients (step 6).

The 7th International Conference on Mobile Internet Security (MobiSec'23), Dec. 19-21, 2023, Okinawa, JAPAN, Article No.P-39

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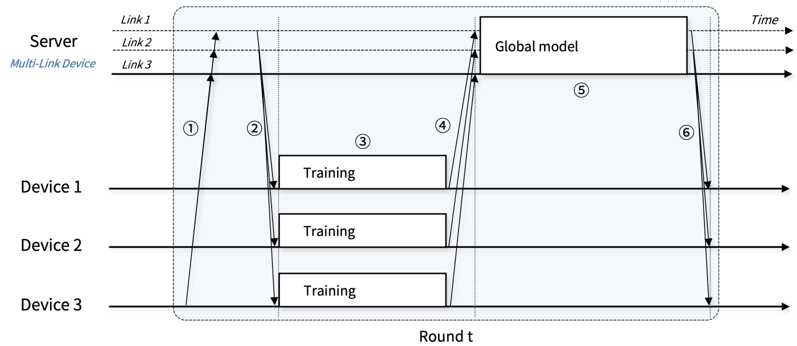

Figure 1: FedMLO Process

3 Conclusion

Federated learning draws attention as a way to process a large amount of data while ensuring privacy. In this paper, we tried to increase efficiency in communication oligopoly by using multi-link, one of the 802.11be functions, for federated learning. In future research, we intend to prove the conventional single-link-based and multi-link-based combined learning methods through experiments. In addition, by reflecting the individual characteristics of devices and applications, devices are grouped based on bias, data generation frequency, and latency and mapped to links to improve performance degradation caused by network data imbalance and sparse problems.

Acknowledgement: This work was partly supported by grants of the Korea Institute for Advancement of Technology (KIAT) funded by the Korean Government (MOTIE) (P0008703, The Competency Development Program for Industry Specialist) and the MSIT under the ICAN (ICT Challenge and Advanced Network of HRD) program (No. IITP-2022-RS-2022-00156310) supervised by the Institute of Information & Communication Technology Planning & Evaluation (IITP). This work was supported by Korea Foundation for Women In Science, Engineering and Technology (WISET) grant funded by the Ministry of Science ICT (MSIT) under the team research program for female engineering students (WISET-2023-136).

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