Client Selection Methods for Federated Learning with Deep Reinforcement Learning

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***Abstract*—Federated learning (FL) is a machine learning technique that allows clients to jointly learn a global deep neural network (DNN) model by aggregating locally trained DNN models without sharing their own data. Local data collected by each client is non-independent identically distribution (non-IID), which can degrade the performance of FL. And then simultaneously sending the training results from local clients increases the burden on the network and results in significant communication overhead. Therefore, client selection in FL is critical to improve performance for non-IID data and reduce communication overhead for clients. In this paper, we present a study of client selection methods in FL using deep reinforcement learning (DRL). After that, we discuss future research directions.**

Keywords—Client selection, federated learning, deep reinforcement learning

I. Introduction

Federated learning (FL) proposed by Google has emerged as a machine learning technique that leverages centralized and distributed methods [1]. FL allows clients to jointly learn a global deep neural network (DNN) model by aggregating locally trained DNN models without sharing their own data. Therefore, FL has the advantages of both centralized and distributed methods such as protecting data privacy.

However, FL still faces several challenges. First, data is generally not distributed evenly across clients. Local data collected by clients is non-independent identically distribution (non-IID). Due to non-IID data, the distribution of unbalanced data can lead to bias in model training and reduce the convergence of FL, which can degrade the performance of FL. Second, sending training results from local clients simultaneously increases the burden on the network and results in significant communication overhead.

Therefore, it is important to select optimal clients in FL to improve training performance on non-IID data and reduce communication overhead for clients. Several studies have been conducted to propose a client selection method to participate in FL and generate global and local DNN model updates. In this paper, we present research on client selection methods to improve the performance of FL by selecting the optimal clients, and then discuss future research.

II. Reseach on Client Selection Methods

Although there are studies on client selection for FL to optimize heterogeneous network [2-3] and energy resources [4], heuristic methods can only provide sub-optimal performance because they often rely on qualitative analysis without exploring optimal performance [5].

Therefore, deep reinforcement learning (DRL) is a widely applied framework for solving complex optimization problems related to sequential decision-making. There are many studies that use DRL to optimize FL [6]. Because the DRL agent observed a connection between the local dataset distribution of client and participating clients, it is possible to train how to select the appropriate client for the next training.

[7] proposed a DRL-based adaptive client selection method to minimize energy consumption and processing latency in model updating. However, it did not consider the convergence problem of FL.

Therefore, [5], [8] and [9] proposed a DRL-based client selection and early client termination methods by optimizing the trade-off between resource allocation and the accuracy of global model. That is, they jointly optimize computing and communication resources in the FL systems while considering the accuracy of the global model. These methods are responsible for selecting the optimal clients for each training round. In addition, [9] also propose DRL-based local epoch adjustment method to optimize the trade-off.

III. Future Research directions and Discussion

This paper presents a study of client selection methods in FL using DRL. However, research on client selection in FL still has many challenges to address. For example, most studies rarely take into account clients' mobility and/or clients' non-IID data. Therefore, the client selection in FL should be considered in a more dynamic environment, such as clients' mobility, the diversity of client distribution, and the diversity of data distribution. It is expected that we will be able to put a lot of effort into making better results in client selection study in this dynamic environment.

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