Communication Efficient Client Selection in Federated Learning

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ABSTRACT

Federated Learning (FL), an emerging distributed learning paradigm which trains machine learning (ML) models in a decentrelized manner, has tremendously attracted the attention of academia as well as industry. One of the key challenges of FL is related to the participant clients, which usually have different communication and computational capabilities, and their local data used for training are not distributed identically and independently (non-IID). Considering the limited communication bandwidth in FL and the unavailability of some clients from time to time in the network, a subset of clients can be chosen in each iteration of the FL process for sharing their updates for aggregation and forming the global model. Thus, selecting appropriate clients is so crucial in maximizing the overall FL performance, including training time and accuracy. This research reviews the state-of-the-art client selection techniques for FL that specifically focus on enhancing the FL process's communication efficiency. The existing works are categorized based on how they enhance communication efficiency. The current research works are investigated considering various factors. Then, future research roadmaps are designated. The connecting nature of our work is that this study connects the scientific disciplines of machine learning, distributed systems, and computer networks.

KEYWORDS

Communication efficiency, Federated learning, Machine learning, Client selection.

1 INTRODUCTION

Machine learning models are implemented by adopting a remarkable amount of data collected from various end devices and sensors. The collected data can be utilized for obtaining process optimization, helping with decision-making, and gaining insight discovery. Examples of sources that produce data can be various sensors, wearable devices, smart homes, and smartphones. Conventionally, for implementing predictive ML models, the data should be transmitted to a central server where the data can be stored and utilized for designing ML models for specific tasks. However, nowadays, since data privacy has become a challenging issue, the conventional centralized method would not be useful. Moreover, traditional methods have limitations in other computational challenges, such as energy consumption, bandwidth usage, and network communication. Thus, there should be an alternative solution for designing reliable ML algorithms. To this end, Federated Learning (FL) is an innovative method for implementing ML models and methods over decentralized data [8].

As an emerging distributed learning paradigm, FL has recently attracted attention because of the offered communication efficiency and data privacy. Pushing the computations and storage close to the end devices where data are generated makes FL a powerful learning method that reduces latency, energy consumption, and bandwidth usage. FL deals with scenarios where training data is distributed across a number of clients [9].

With regard to the limited communication bandwidth and the privacy requirement, FL usually selects only a fraction of clients in each communication round [1]. The chosen clients will conduct several rounds of local updating without disclosing their local datasets [9]. The clients and the server need to communicate the model updates during model training intensively. To this end, the system tries to select a proper subset of clients to participate in the aggregation process by sharing the local model updates with the aggregator service.

Selecting an appropriate subset of clients for participating in the communication rounds is one of the essential challenges [4]. Generally, the aim of the client selection process is to choose the possible maximum number of participants that are able to train their local model and transmit their local model updates to the aggregator before the predefined deadline during each global aggregation round. This is because selecting more participants contributes to accelerating the FL process convergence [10]. However, maximizing the number of participants may not lead to an efficient client selection method since having more participants can increase the overall energy usage in clients and bandwidth usage during the training and transmitting time. On the other hand, selecting less number of clients can decrease the model's accuracy. Thus, choosing an appropriate number of clients is significant.

Several client selection strategies in the literature have various purposes for improving the FL method in different aspects. This research focuses on communication-efficient client selection strategies for FL methods. In this regard, the existing works are investigated and classified into four groups, namely loss value-based, reputation-based, threshold-based, and multi-criteria-based client selection strategies as shown in Fig. 1. The poster version of our work will visually describe the importance of appropriate client selection for FL, and the state-of-the-art works classification. Moreover, FL architecture and open issues for the topic will be depicted graphically.

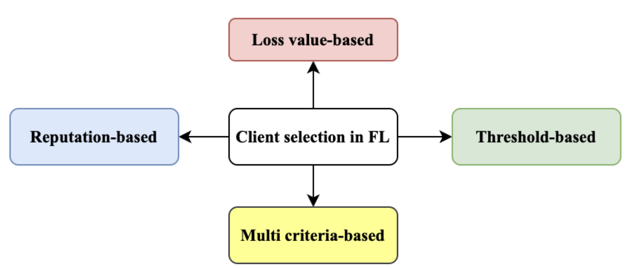

Figure 1: The categorization of client selection in FL

2 COMMUNICATION EFFICIENCY

Through each iteration of FL, a bunch of interactions between clients and server occurs, which include the broadcasting of the global model by the server to the clients and transmitting the local updates from clients to the aggregator server. These interactions can contribute to network traffic, congestion, and high communication cost. The communication between clients and the aggregator in FL is one of the most important and challenging parts of the FL process that needs to be optimized. Thus, an appropriate allocation of communication resources can remarkably enhance the performance of learning. This process enriches when the FL environment includes a large number of clients who need to communicate with the aggregator through a downlink (for local model update transmitting) and an uplink (for global model downloading). Thus, continual uplink and downlink transmission communication occur during the FL rounds. Considering the constraint bandwidth, power, and energy on clients, these communication rounds might be slow [6].

3 LOSS VALUE-BASED SELECTION

In the training procedure, the loss function values can be considered as the indicator to spot the local datasets' distributions. The changes in local loss of two adjacent iterations are determined as the utility for the fast convergence. The convergence analysis is presented in [3] aiming to optimize the FL with a biased client selection method and assess the impact of selection bias on the convergence speed. A correlation-based client selection technique is designed in [9] for FL, named FedCor, aiming at enhancing the FL convergence considering the heterogeneous settings.

4 THRESHOLD-BASED SELECTION

In the threshold-based client selection strategies, clients are allowed to accomplish their local training procedure before a pre-defined deadline. Generally, these strategies aim at selecting the maximum possible number of clients who can accomplish their local training before the determined deadline to obtain the proper performance. The authors in [5] have developed a deadline-based aggregation strategy to tackle the client selection issue in an environment with a volatile context, where the local training models conducted in heterogeneous clients are likely to get fail because of different reasons.

5 REPUTATION-BASED SELECTION

Unreliable and faulty clients may lead to undesired behaviors such as model poisoning, Sybil attacks, and data poisoning. Thus, it is important to develop an efficient and effective client selection model that preserves reliable model training. One of the ways to ensure reliability is the reputation metric to assess the trustworthiness of clients, considering their past interactions. Several state-of-the-art studies utilized reputation for selecting reliable clients to participate in the FL aggregation process. A context-aware online client selection method is developed in [7] for the network operator to help with selecting appropriate clients for FL aggregation.

6 MULTI-CRITERIA-BASED SELECTION

Taking several criteria into account for selecting clients for FL can lead to a more efficient and effective FL model since the model tries to enhance several aspects of the system. These aspects can be specific to the applied field or can be related to the structure of FL itself. A bi-level optimization strategy is designed in [2] that can effectively select the maximum number of clients for participation in the FL aggregation phase by taking the heterogeneity and constraint computation and communication resources of the clients into account.

7 FUTURE TRENDS

Existing works adopts various metrics to evaluate the performance where the final model accuracy, loss, and process time are the most used metrics. Since the focus is communication efficiency, it would be valuable to apply the proposed method in a network setup and evaluate the performance of the network in terms of communication efficiency, which is neglected by most of the investigated studies. Furthermore, FL, owing to its local training possibility paves the way for handling many different challenges such as data privacy, reducing latency, energy consumption, and network bandwidth in the machine learning and data management fields. However, most of the current studies have ignored highlighting these metrics. Furthermore, there are still many other unaddressed challenging problems in the field of communication efficient client selection in FL solutions. The most vital open challenges are selecting the optimal number of clients, large-scale scenarios, decentralized aggregation, determining an optimal and adaptive threshold, and considering highly dynamic environments.

ACKNOWLEDGMENT

This work is supported in part by TUBITAK (The Scientific and Technical Research Council of Türkiye) 2247-A National Leader Researchers Award 121C338.

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