A Review on
TiFL: A Tier-based Federated Learning System

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Disclaimer: I am not the writer of the original paper. I only reviewed the paper as part of the demonstration of my research interest and capability. Also, I want to mention that I am not an expert; instead, I want to consider myself a novice researcher in this field. Therefore, I assume that this review or part of this review will not be cited as a reference in future studies. The original paper is cited in this review. Please check the reference section.

***Abstract*—While data privacy is a big concern in collecting data in centralized storage, Federated Learning (FL), also known as collaborative learning, is the concept to overcome the situation. FL is a decentralized form of Machine Learning technique where data is not necessary to send outside of the edge device. Instead, every edge device receives a model, and its device data will train that, and then the model will be shared and merged with the global model to improve accuracy. Although Fl has such benefits, Fl encounters model prediction and system efficiency issues due to resource heterogeneity. This paper prototype TiFL, a Tier-based Federated Learning System that can handle resource and data heterogeneity by grouping users with similar computation delays and selected for aggregation to mitigate the straggler problem. The paper claimed that TiFL outperformed traditional FL, where the training time is 3× faster and 6% more accurate.**

I. STRENGTHS

I enjoyed the idea of TiFL that is presented in this paper. I enjoyed the whole reading; of course, this paper enlightened me in this field. The paper addressed the facts, related works, challenges, and efforts. A few of the strong points I documented below:

A. Edge device grouping

Training efficiency and communication efficiency flaws are two common challenges in synchronous and asynchronous federated learning. TiFL, a hierarchical-based federated learning system, solved these limitations by dividing edge devices into small tiers according to the user's response delay.

B. Adaptive grouping in runtime

TiFL adaptively groups edge devices in runtime into tiers based on the continuously monitored training performance. In this way, TiFL mitigates heterogeneity impact and static selection method limitation.

C. Promising results

TiFL is evaluated with state-of-the-art- FL benchmark LEAF. It is shown that TiFL can improve 6X training time in resource heterogeneity cases without considering the accuracy and 3X faster in data quantity heterogeneity cases compared to traditional FL.

II. WEAKNESS (MINOR FACTS)

A. CPUs configuration

Section 3.3 [1] states that 4 CPUs, 2 CPUs, 1 CPU, 1/3 CPU, and 1/5 CPU are assigned for every client from groups 1 through 5, respectively, to emulate the resource heterogeneity. But what is the configuration of the allocated CPUs?

B. Optimizer in local training

Section 5.2 [1] mentions that RMSprop used local training as an optimizer. But it is not clearly stated why the RMSprop optimizer was chosen over other promising choices like adam optimizer.

REFERENCES

[1] Zheng Chai, Ahsan Ali, Syed Zawad, Stacey Truex, Ali Anwar, Nathalie Baracaldo, Yi Zhou, Heiko Ludwig, Feng Yan, and Yue Cheng. Tifl: A tier-based federated learning system, 2020. URL `https://arxiv.org/abs/2001.09249`.