Decentralized Federated Learning for Meta Computing

Decentralized federated learning (DFL) is an ideal candidate for meta computing because of its ability to aggregate learning models from distributed clients without centralized server coordination, offering enhanced resilience to client failures and potential attacks compared to its centralized counterpart. Nonetheless, adoption of DFL in practical applications faces several major challenges, including communication bottleneck, privacy concern, Byzantine attacks, etc. Recent advances in DFL have begun to address individual challenges, but the lack of a comprehensive treatment still undermines the practical use of DFL. Realizing this gap, this paper develops a novel Communication-efficient Privacy-preserving, and Byzantine-robust (CPB-DFL) framework. The proposed framework is equipped with three simple yet powerful techniques to achieve communication efficiency, privacy preservation, and Byzantine robustness, i.e., multiple-local-updates, differential-private message exchange, and robust model aggregation. Weconduct extensive experiments to validate the joint impact of these three strategies to validate the potential of CPB-DFL for scalable meta computing.