A Study on Enabling Compute-Aware Federated Learning over Opportunistic Edge Networks

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Abstract (should be within 1st page)

Conventional federated learning relies on assumptions of persistent connectivity, centralized coordination, and uniform computational resources. However, these conditions frequently fail in resource-constrained edge environments. In intermittent edge networks, communication is sparse, topologies are unpredictable, and devices exhibit extreme resource heterogeneity. To bridge this gap, this dissertation introduces compute-aware opportunistic machine learning to sustain decentralized intelligence under these volatile conditions. First, to mitigate parameter drift from asynchronous, encounter-driven training, we propose sequential independent subnetwork training. By circulating disjoint subnetworks, this approach enables conflict-free parallel learning, increasing accuracy on CIFAR-10 (89.38% vs. 87.99%) and MEDIC (68.86% vs. 63.56%) against model-homogeneous opportunistic averaging while exchanging and training only 1% of the total parameters per time step. Second, to bypass the structural rigidity of fixed subnetwork partitioning, we introduce opportunistic model ensembling. This method allows models to train completely independently without a shared architectural decomposition, combining their unique learning trajectories at prediction time. On the PlantVillage dataset with non-IID data, this formulation achieves 92.76–94.28% accuracy, outperforming the model-homogeneous baseline by up to 9.31 percentage points. Finally, to handle computational heterogeneity, we develop a training formulation using singular value decomposition (SVD) and low-rank approximation. This allows resource-constrained nodes to adapt their optimization rank while returning dense updates, limiting global accuracy drops to less than 0.5% even when 80% of participants are restricted. Together, these strategies relax the rigid assumptions of conventional federated learning, realizing an inclusive, robust paradigm for decentralized intelligence in opportunistic networks.