Edge-assisted Opportunistic Federated Learning for Distributed IoT systems

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***Abstract*—The paper introduces Opportunistic Federated Learning (OFL) as an approach to enhance the efficiency of distributed learning in intelligent IoT systems. OFL allows any node in the network to initiate a learning task and collaboratively use local resources. The framework enables nodes to adapt configurations based on circumstances, optimizing resource utilization. Hence, this paper proposes a reliable node selection mechanism that accommodates the dynamic nature of local data and computing resources. Incentives for participating nodes are explored through a peer-to-peer communication using the Bertrand game to determine optimal pricing strategies. Results demonstrate the Nash equilibrium of the game-based incentive mechanism in a realistic FL setup.**

***Index Terms*—Distributed learning, reputation analysis, game theory, Nash equilibrium, edge computing.**

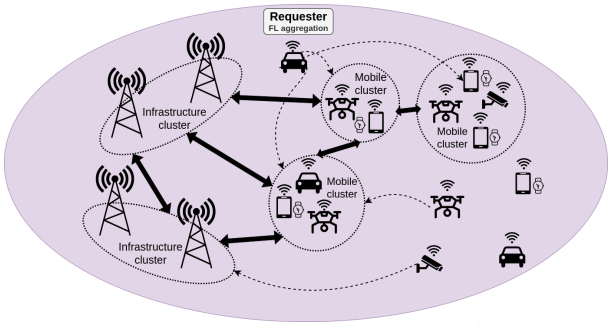

Fig. 1: The proposed OFL system architecture.

I. Introduction

The increasing interest in enhancing people's lives through intelligent, efficient, and secure IoT systems is hindered by challenges in implementing centralized Machine Learning (ML) techniques in distributed systems [1]. Centralized learning, while useful for applications like image recognition, faces privacy concerns and high communication bandwidth requirements. Decentralized learning, exemplified by federated learning (FL), is explored to address these challenges. This approach enables distributed training without sharing raw data, preserving privacy and utilizing local resources efficiently. However, challenges arise from limited computing nodes and their effectiveness in dynamic environments [2], [3].

To address these challenges, this paper proposes Decentralized Opportunistic Federated Learning (OFL) as a framework. OFL leverages opportunistic learning, allowing edge nodes to adapt based on conditions and benefits. The framework enables any node to initiate a learning task, engaging a subset of available nodes by exchanging weights based on local data. The proposal enhances task performance by considering the reliability of participating nodes, incorporating various reliability metrics. OFL is particularly valuable for ML-based intelligent IoT systems, enabling flexible distributed learning with collective responsibility [4].

Furthermore, to effectively utilize FL at the network edge, attention is needed on obstacles such as resource management and incentive mechanisms. Incentive mechanisms encourage user engagement in developing a global FL model, incorporating user-defined utility and monetary rewards. Various frameworks, including auction theory and game theory, can be employed for designing these rewards, factoring in communication and computation costs [5].

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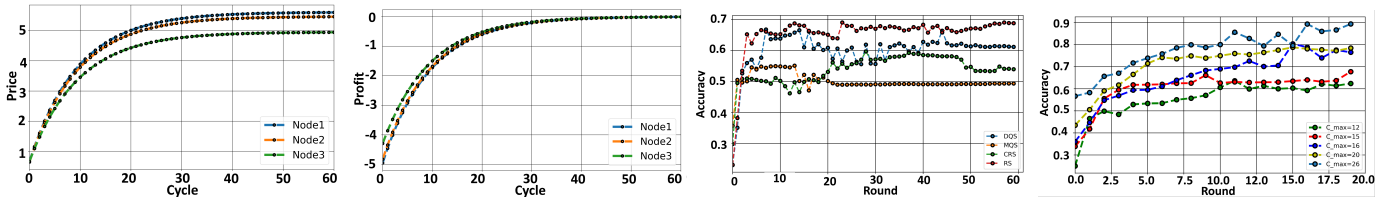
II. System Model

In the OFL architecture, a critical aspect is the selection of computing nodes for learning tasks. To enhance this process, a reliable node selection scheme has been developed, aiming to identify the optimal subset of computing nodes proficient in executing a specific learning task effectively. The approach considers the reliability of available computing nodes and the associated learning cost, to facilitate optimal selection. The scheme operates by selecting the optimal subset of Machine Learners (MLs) for each learning iteration of the requester, accounting for constraints such as node availability, minimum reliability, and maximum cost. The overarching goal is to maximize the total reliability at the requester R_t, which incorporates the reliability R_i of each selected computing node i and the total number of selected nodes M. The computation of R_i involves three quality metrics: model reliability r_i^m, data quality D_i^q, and computational reliability r_i^c. The model reliability metric evaluates the quality of the local model generated by node i based on the number of epochs k, following a logarithmic relationship established through empirical predictability. Additionally, in our framework, the learning cost refers to the monetary cost paid by the requester to the selected computing nodes at each Federated Learning iteration, represented as $C_r = \sum_{i=1}^{N} C_i \cdot R_i$, where C_i is the computational and communication cost of node i to train and upload its local model (for more details, refer to [6], [7]).

$$R_t = 1 - \prod_{i=1}^{M} (1 - R_i) = 1 - \prod_{i=1}^{M} (1 - r_i^m \cdot D_i^q \cdot r_i^c) \ . \quad (1)$$



(a) (b) . (c) (d)

Fig. 2: Performance of the reliability-based selection. 2a shows price convergence for i-th node while 2b profit convergence for i-th node. In 2c and 2d, we show the performance of the FL model with the proposed solution. Fig. 2d shows the influence of selecting more nodes (increasing $C_{\max}$) over the perfromance of the FL model.

III. The Construction of Bertrand Game

This section introduces an incentives allocation algorithm reliant on the reputation of available nodes within the OFL architecture. The framework assumes a Bertrand game between the requester and participating nodes, wherein nodes seek to maximize profit while ensuring the requester's total reliability. Participants offer differentiated goods (ML models) at discrete-time periods upon the requester's request. The requester estimates the initial price of each ML model based on reliability, and a utility function $U(q_n)$ represents the requester's preferences. The utility function considers price p_i, selection indicator q_i, and total reliability for the i-th node. The ω parameter denotes the degree of differentiation between products, influencing diversification. The initial price for each model is calculated by maximizing the utility function at each node. The participants' profit incorporates price p_i, selection indicator q_i, and a strategic parameter θ_i. The discrete dynamical system governs participants' price decisions, reaching equilibrium when marginal profit is non-negative. The requester, following Nash equilibrium, selects nodes optimizing reliability and cost. The presented lemma establishes that participants are chosen based on their ability to achieve maximum reliability and minimal cost while ensuring maximum payoff. The equilibrium position is achieved when participants maximize their payoff through the non-negative solution of the algebraic system. The paper analyzes a static Bertrand duopoly game in the FL setting, considering fixed initial conditions and potential for a dynamic Bertrand game with changing conditions . We consider q_i to be the selection parameter of each participant and that the requester's preferences are represented by the following demand function:

$$U(q_n) = \sum_{i=1}^{N} (p_i q_i) - \omega C \sum_{i=1}^{N} (R_i q_i) \tag{2}$$

IV. Performance Evaluation

We consider a Convolutional Neural Network (CNN) model at each node with 10 layers and 0.001 learning rate. The model is trained using the healthcare dataset in [8], with $60,000$ samples and 13 classes, i.e., representing the physical activity of a person such as setting, walking, and running. This split across 10 CNs, with a non-IID data distribution. The requester receives the weights from each participant, then use the FL model for aggregation.

In Fig. 2c, we compare our reliability-based selection scheme (RS) with three baseline schemes: Model Quality-based selection (MQS), Data Quality-based selection (DQS), and Computational reliability-based selection (CRS). The results show that the RS algorithm outperforms baseline algorithms in terms of accuracy.

The OFL framework offers flexibility in network customization to meet the diverse Quality of Service (QoS) requirements of various ML models. This flexibility allows for the selection of different numbers of collaborators with varying capabilities based on the specific needs of the ML model. Fig. (2d) shows that accuracy improves as more users participate in the learning process, although at a higher cost.

V. Conclusion

The paper presents a novel framework, called Opportunistic Federated Learning (OFL), which enables effective and large-scale collaborative learning for any ML task. Furthermore, the paper proposes a reliability-dependent node selection method that enhances the OFL system's performance while satisfying various the requirements of learning Models. To incentivize opportunistic collaboration among available nodes in the system and a node requesting help for ML model training, we leverage the heterogeneous case of the Bertrand game. We demonstrate the Nash equilibrium of the game-based incentive mechanism, as well as the FL performance with our proposed node selection algorithm.

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