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Fair Federated Learning in Wireless Communications

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Abstract : Federated Learning (FL) has emerged as a promising paradigm for training machine learning models on distributed data without the need for centralized data aggregation. In the realm of wireless communications, FL has the potential to leverage the vast amounts of data generated by wireless devices to improve model performance and enable intelligent applications. However, the fairness aspect of FL in wireless communications remains largely unexplored. This abstract presents an idea for fair federated learning in wireless communications, addressing the challenges of imbalanced data distribution, privacy preservation, and resource allocation. Firstly, the proposed approach aims to tackle the issue of imbalanced data distribution in wireless networks. In typical FL scenarios, the distribution of data across wireless devices can be highly skewed, resulting in unfair model updates. To address this, we propose a weighted aggregation strategy that assigns higher importance to devices with fewer samples during the aggregation process. By incorporating fairness-aware weighting mechanisms, the proposed approach ensures that each participating device's contribution is proportional to its data distribution, thereby mitigating the impact of data imbalance on model performance. Secondly, privacy preservation is a critical concern in federated learning, especially in wireless communications where sensitive user data is involved. The proposed approach incorporates privacy-enhancing techniques, such as differential privacy, to protect user privacy during the model training process. By adding carefully calibrated noise to the gradient updates, the proposed approach ensures that the privacy of individual devices is preserved without compromising the overall model accuracy. Moreover, the approach considers the heterogeneity of devices in terms of computational capabilities and energy constraints, allowing devices to adaptively adjust the level of privacy preservation to strike a balance between privacy and utility. Thirdly, efficient resource allocation is crucial for federated learning in wireless communications, as devices operate under limited bandwidth, energy, and computational resources. The proposed approach leverages optimization techniques to allocate resources effectively among the participating devices, considering factors such as data quality, network conditions, and device capabilities. By intelligently distributing the computational load, communication bandwidth, and energy consumption, the proposed approach minimizes resource wastage and ensures a fair and efficient FL process in wireless networks. To evaluate the performance of the proposed fair federated learning approach, extensive simulations and experiments will be conducted. The experiments will involve a diverse set of wireless devices, ranging from smartphones to Internet of Things (IoT) devices, operating in various scenarios with different data distributions and network conditions. The evaluation metrics will include model accuracy, fairness measures, privacy preservation, and resource utilization. The expected outcomes of this research include improved model performance, fair allocation of resources, enhanced privacy preservation, and a better understanding of the challenges and solutions for fair federated learning in wireless communications. The proposed approach has the potential to revolutionize wireless communication systems by enabling intelligent applications while addressing fairness concerns and preserving user privacy.

Keywords : federated learning, wireless communications, fairness, imbalanced data, privacy preservation, resource allocation, differential privacy, optimization

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