Towards Multimodal Federated Learning (Abstract)

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Context and Motivation. Federated Learning (FL) is a promising alternative to traditional machine learning, enabling multiple entities to collaboratively learn a model without sharing sensitive data with a central server. Most current FL methods are limited to datasets from a single modality, such as images or text [5] [2]. However, given the proliferation of sensor types and collection methods, there is a pressing demand to integrate information from different data modalities to improve model performance and provide more comprehensive insights while maintaining the advantages of FL.

Related Work. Multimodal machine learning preprocesses data from different modalities using fusion techniques like early, late, or feature fusion, depending on the task and data. Finally, the algorithm learns from all modalities together [4]. In the FL context, we can no longer access the raw data for privacy concerns, and we train a global model from shared local updates. The simplest criterion for tackling multimodal FL is considering the same access to all data modalities across clients [6] [3]. In practice, clients may have different computational capabilities and data resources. FedIoT [8] and FedMSplit [1] are capable of handling multimodal heterogeneity. However, FedIoT is limited by the need for manual tuning. Furthermore, both methods assume that all clients are using the same model architecture to represent the same data modality. CreamFL [7] overcomes constraints of the same architectures and data modalities between clients' models by sharing knowledge on a public dataset.

Open Scientific Issues and Research Directions. The challenge of non-IID data in FL is widely recognized, and heterogeneous modalities and architectures in multimodal models exacerbate the problem, leading to side effects known as bias and unfairness. Our project aims to enhance the recent work aforementioned. We want to investigate an innovative architecture to handle heterogeneity in data modalities and model architectures, analyzing the trade-off between communication costs and global performance. A further challenge, particularly relevant in the cross-device FL scale, is tackling different computation capabilities to ensure fairness across different local resources when simultaneously dealing with uni- and multimodal clients.

Keywords : Federated Learning, Multimodal Learning, Data Heterogeneity, Fairness

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