Incentive Mechanism in Multi-modal Federated Learning

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1 Project Overview

1.1 Motivation and Background

Federated Learning (FL) has emerged as a privacy-preserving distributed machine learning paradigm, which enables model training across multiple devices or servers while keeping the data localized. Instead of sending raw data to a central server, FL involves training models locally on each device and then aggregating the model updates (e.g., weights, gradients) on a central server.

Multi-modal Federated Learning (MMFL) is an extension of FL that involves training on data from multiple modalities (e.g., text, images, audio) in a decentralized manner. The idea is that combining information from different sources can result in more robust and accurate models. For example, in medical imaging, combining visual data (MRI scans) with structured data (patient records) can lead to better predictions.

Existing research on MMFL generally assumes that data owners are innately willing to participate in FL process and contribute their data honestly. In practice, without properly designed incentives, data owners may be reluctant to participate, as participating in FL incurs both high computation/communication costs and potential privacy risks. Moreover, data owners are autonomous agents, who can determine when, where and how to participate in FL. Faced with different compensation schemes from different federations, participants may adopt disparate training strtegies, affecting the performance of FL models.

Thus, it is important to design an effiective incentive mechanism to engourage data owners to actively participante in MMFL.

1.2 Goal

In this project, we hope to design a transparent and efficient incentive mechanism for Multi-modal federated learning, which consists of two parts:

1. **Contribution Assessment**: In order to allocate proper incentives to participants, contribution of each modality needs to be evaluated first. Although the amount of data for some modalities is small, it has a greater impact on the performance of the final model.

2. **Reward Allocation**: Once contributions of modalities have been measured, a reward allocation scheme is adopted to distribute the incentive budget among the participants. We may leverage game theory, auction theory and contract theory to design the reward.

2 Prerequisites

- Get acquainted with the related work[1, 2, 3, 4].
- Strong programming skills (proficient with Pytorch or Tensorflow).
- Good knowledge of federated learning. It would be better to be familiar with game theory, auction theory and contract theory.
- Good English especially in writing and communicating.
- Being motivated and ready to produce publishable work.

3 Postscript

- This project is for a master thesis or a semester project.
- Publications are highly encouraged. Besides, we support the computation resource (GPUs) and the cost for benchmark construction if needed.

References

[1] X. Tu, K. Zhu, N. C. Luong, D. Niyato, Y. Zhang, and J. Li, "Incentive mechanisms for federated learning: From economic and game theoretic perspective," *IEEE transactions on cognitive communications and networking*, vol. 8, no. 3, pp. 1566–1593, 2022.

[2] L. Che, J. Wang, Y. Zhou, and F. Ma, "Multimodal federated learning: A survey," *Sensors*, vol. 23, no. 15, p. 6986, 2023.

[3] Z. Liu, Y. Chen, H. Yu, Y. Liu, and L. Cui, "Gtg-shapley: Efficient and accurate participant contribution evaluation in federated learning," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 13, no. 4, pp. 1–21, 2022.

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