# Stakeholder-oriented Decision Support for Auction-based Federated Learning

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## Abstract

Auction-based federated learning (AFL) is an important area of FL incentive mechanism design. It effectively incentivizes high-quality data owners (DOs) to participate in data consumers' (DCs, i.e., servers') FL training tasks. However, AFL is still evolving, with existing methods primarily addressing optimal DC-DO matching or DC selection problems in monopoly markets. To enhance the practicality of AFL, we introduce stakeholder-oriented decision support in AFL. This facilitates optimal and strategic decision-making for all stakeholders, improving the efficiency and sustainability of the AFL ecosystem.

## 1 Introduction

Federated Learning (FL) [Yang *et al.*, 2019] has emerged as a useful collaborative machine learning (ML) paradigm by enabling collaborative model training without the need to expose local data, thereby enhancing data privacy and user confidentiality. Prevailing FL methods often assume that data owners (DOs, a.k.a, FL clients) are ready to join FL tasks by helping data consumers (DCs, a.k.a, FL servers) train models. In practice, this assumption might not always hold due to DOs' self-interest and trade-off considerations. To deal with this issue, the domain of auction-based federated learning (AFL) has emerged [Tang *et al.*, 2024b].

As shown in Fig. 1, the main actors in AFL include the auctioneer, DOs and DCs. The auctioneer functions as an intermediary, facilitating the flow of bid requests (i.e., asking prices and available data resources) from DOs to DCs. DCs then determine their bid prices to be submitted to the auctioneer. The auctioneer then consolidates the auction outcomes and informs the winners about the match-making results. The auctioneer undertakes a pivotal role in orchestrating the entire auction process, managing information dissemination, and ultimately determining the auction winners. Once FL teams have been established through auctions, they can carry out collaborative model training following standard FL protocols.

However, this field is still in its early stages, with most existing works focusing on one aspect of the auctioneer's decisions, such as optimal DC-DO matching and pricing to maximize social welfare or minimize social cost for the FL ecosystem [Xu *et al.*, 2023], or one aspect of the DCs decision on selecting DOs [Jiao *et al.*, 2020]. This leaves various issues unresolved, including how to enhance the competitiveness of the auctioneer, how DCs should bid for DOs and how DOs allocate their resources.

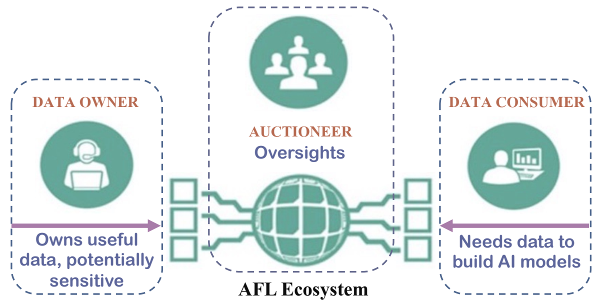


Figure 1: An overview of the AFL ecosystem.

## 2 Research Directions and Contributions

To deal with these issues, our research aims to provide intelligent stakeholder-oriented decision support to all three types of stakeholders: DCs, the auctioneer, and DOs. Our goal is to help them make optimal and strategic decisions to maximize their own objectives. Specifically, we plan to achieve the following breakthroughs in stakeholder-oriented decision support in AFL:

1) **DC-oriented decision support**: Existing approaches [Jiao *et al.*, 2020; Le *et al.*, 2020; Zhou *et al.*, 2021; Yuan *et al.*, 2021; Zhang *et al.*, 2021] for DCs often assume a monopoly AFL marketplace with only one DC. However, this assumption may not hold in open collaborative AFL marketplaces where multiple DCs simultaneously compete to attract DOs. To address this, we aim to provide DC-oriented decision support from the perspective of helping them bid optimally for DOs in a cost-effective manner, while maximizing their key performance indicators (e.g., accumulated expected utility) within or without the budget limit, while also considering the health of the whole ecosystem.

2) **DO-oriented decision support**: DOs need to determine the amount of resources to commit and the reserve price in order to maximize their profit in the auction process. However, few existing works have studied this problem, resulting

in potential loss for DOs due to low bids from DCs or over-high resource consumption. To bridge this gap, we aim to develop dynamic pricing strategies for DOs to support them in optimally determining the number of committed resources and the corresponding floor price to maximize their benefits, especially for those with high-quality data resources.

3) **Auctioneer-oriented decision support**: Existing methods [Xu *et al.*, 2023; Roy *et al.*, 2021; Mai *et al.*, 2022; Wang *et al.*, 2023] for the auctioneer mainly focus on optimal DC-DO matching and pricing for social welfare maximization and social cost minimization, assuming a monopoly data trading platform. However, in reality, there may be multiple trading platforms with different auction mechanisms coordinated by different auctioneers. Therefore, the auctioneer needs to improve its competitiveness by developing attractive auction mechanisms to attract new participants and enhance the stickiness of existing participants. To address this, we aim to frame the attractiveness of the auction platform from the perspective of fairness to both DOs and DCs, and develop selection time-aware and contribution-aware auction mechanisms to achieve selection fairness for DCs and contribution fairness for DOs, respectively.

Overall, our research aims to provide intelligent stakeholder-oriented decision support in AFL to help all three types of stakeholders, i.e., DCs, DOs, and auctioneers, make optimal and strategic decisions to achieve their desired objectives and enhance the overall efficiency and effectiveness of the AFL ecosystem.

Our current research focuses on DC- and DO-oriented decision support. Specifically, for the DCs, we have proposed FedBidder [Tang and Yu, 2023b], the first-of-its-kind bidding strategies, to help them bid for DOs in the competitive AFL marketplace with the aim of maximizing their utilities under the budget constraint. In addition, taking into consideration the intricate relationships among DCs, which can be simultaneously competitive and cooperative, we also propose to model the AFL ecosystem as a multi-agent system and propose MARL-AFL [Tang and Yu, 2023a] to guide DCs in strategically bidding towards an equilibrium with desirable overall system characteristics. In addition, we have introduced the first decision support method for DOs, called PAS-AFL [Tang *et al.*, 2024a]. It offers a systematic approach for joint decision-making on AFL bid acceptance, task sub-delegation, and pricing. This is based on Lyapunov optimization to maximize utility.

## 3 Future Works

In our future research, we plan to continue our focus on DC-oriented decision support, refining our bidding strategies to be more cost-effective and bias-free, thereby enhancing DCs' stickiness and reliance on the market, and attracting more DOs to join. We will then extend our research to provide support to DOs by developing dynamic pricing strategies to maximize their profit in the auction process. Finally, we will address the needs of auctioneers by designing fairness-aware auction mechanisms that promote fairness and competitiveness among DCs and DOs. Overall, our research aims to contribute to the improvement of the overall performance and health of the AFL ecosystem by providing decision support to all stakeholders.

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## References

[Jiao *et al.*, 2020] Yutao Jiao, Ping Wang, Dusit Niyato, Bin Lin, and Dong In Kim. Toward an automated auction framework for wireless federated learning services market. *TMC*, 20(10):3034–3048, 2020.

[Le *et al.*, 2020] Tra Huong Thi Le, Nguyen H Tran, Yan Kyaw Tun, Zhu Han, and Choong Seon Hong. Auction based incentive design for efficient federated learning in cellular wireless networks. In *WCNC*, pages 1–6, 2020.

[Mai *et al.*, 2022] Tianle Mai, Haipeng Yao, Jiaqi Xu, Ni Zhang, Qifeng Liu, and Song Guo. Automatic double-auction mechanism for federated learning service market in internet of things. *TNSE*, 9(5):3123–3135, 2022.

[Roy *et al.*, 2021] Palash Roy, Sujan Sarker, Md Abdur Razzaque, Md Mamun-or Rashid, Mohmmad Mehedi Hassan, and Giancarlo Fortino. Distributed task allocation in mobile device cloud exploiting federated learning and subjective logic. *JSA*, 113(2):doi:10.1016/j.sysarc.2020.101972, 2021.

[Tang and Yu, 2023a] Xiaoli Tang and Han Yu. Competitive-cooperative multi-agent reinforcement learning for auction-based federated learning. In *IJCAI*, pages 4262–4270, 2023.

[Tang and Yu, 2023b] Xiaoli Tang and Han Yu. Utility-maximizing bidding strategy for data consumers in auction-based federated learning. In *ICME*, 2023.

[Tang *et al.*, 2024a] Xiaoli Tang, Han Yu, and Xiaoxiao Li. Agent-oriented joint decision support for data owners in auction-based federated learning. *arXiv preprint arXiv:2405.05991*, 2024.

[Tang *et al.*, 2024b] Xiaoli Tang, Han Yu, Xiaoxiao Li, and Sarit Kraus. Intelligent agents for auction-based federated learning: A survey. *arXiv preprint arXiv:2404.13244*, 2024.

[Wang *et al.*, 2023] Fei Wang, Lei Jiao, Konglin Zhu, Xiaojun Lin, and Lei Li. Toward sustainable ai: Federated learning demand response in cloud-edge systems via auctions. In *INFOCOM*, pages 1–10, 2023.

[Xu *et al.*, 2023] Bo Xu, Lilin Zuo, Jiayi Jin, Liang Han, and Kun Hu. Cab: a combinatorial-auction-and-bargaining-based federated learning incentive mechanism. *WWW*, pages 1–22, 2023.

[Yang *et al.*, 2019] Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong. Federated machine learning: Concept and applications. *TIST*, 10(2):1–19, 2019.

[Yuan *et al.*, 2021] Yulan Yuan, Lei Jiao, Konglin Zhu, and Lin Zhang. Incentivizing federated learning under long-term energy constraint via online randomized auctions. *TWC*, 21(7):5129–5144, 2021.

[Zhang *et al.*, 2021] Jingwen Zhang, Yuezhou Wu, and Rong Pan. Incentive mechanism for horizontal federated learning based on reputation and reverse auction. In *WWW*, pages 947–956, 2021.

[Zhou *et al.*, 2021] Ruiting Zhou, Jinlong Pang, Zhibo Wang, John CS Lui, and Zongpeng Li. A truthful procurement auction for incentivizing heterogeneous clients in federated learning. In *ICDCS*, pages 183–193, 2021.