

AEFGL: Reverse Auction and Value Evaluation-Based Federated Graph Learning Incentive Mechanism (Student Abstract)

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Abstract

Federated Graph Learning enables multiple clients to collaboratively train graph models while protecting local private data. However, most studies have assumed that all clients contribute data voluntarily and actively. Without reasonable incentives, clients are often reluctant to contribute personal data for model training. Furthermore, the budget for incentives is limited, and if clients with low-quality graph data are incentivized to participate in training, it will negatively impact the training performance of all parties in the system. To address this, we propose AEFGL, a Reverse Auction and Value Evaluation-Based Incentive Mechanism for Federated Graph Learning. First, we design a reverse auction mechanism combining graph structural attribute motifs with client production value. Then, we propose a method for evaluating client production value based on the comparison of the client's expected reward and actual value. This mechanism can incentivize clients with high-quality graph data to participate in training within budget constraints, thereby improving the model quality. Experimental results validate the superiority of the AEFGL mechanism and the economic properties it satisfies.

Introduction

Graph data, with unique and diverse connectivity, is often distributed across parties in real-world applications. Federated learning enables their collaborative training without raw data exposure, gaining widespread attention. In federated graph learning (FGL), clients train locally with private graph data, share gradients for global model training, to maximize accuracy.

However, prior FGL research (Xie et al. 2021) (Tan et al. 2023) mainly focused on improving model performance, neglecting clients' selfish behavior. Clients are reluctant to contribute data without compensation; only (Pan et al. 2024) has introduced an incentive mechanism in FGL to encourage client participation. However, this mechanism has certain economic limitations in real-world scenarios: clients may receive rewards lower than their costs, failing to motivate participation. Additionally, it overlooks the server's budget constraints, where recruiting all clients is unrealistic, and re-

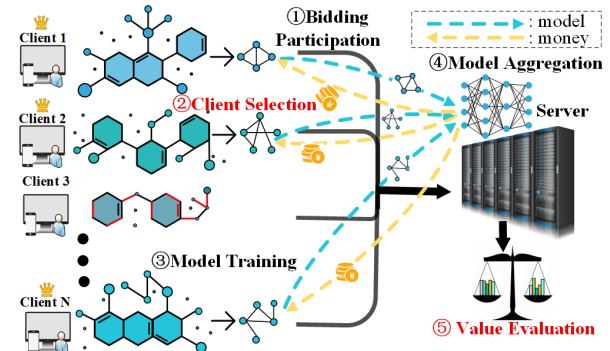


Figure 1: System Model

cruiting those with low-quality data (due to network, environment, etc.) also harms model quality.”

Based on the above discussion, we propose a reverse auction and value evaluation-based FGL incentive mechanism. To incentivize client participation and meet real-world economic needs, we design a motif-based reverse auction algorithm. It enables the selection of high-quality clients to enhance training quality. We also develop a production value evaluation method that compares expected rewards with actual client values. The evaluation results can be combined with the reverse auction to more effectively select high-quality clients. **As far as we know, we are the first to combine incentive-based game auction theory with FGL.**

Methodology

Our framework (Figure 1) consists of N clients with private data $D_i (i \in N)$ and a server with limited budgets. The system flow is as follows: **(1) Client Bidding:** in each round $t = 1, 2, 3, \dots, T$, client i submits a bid b_i^t to the server. **(2) Client selection:** the server uses reverse auction theory to select clients for training and calculates their expected reward. **(3) Model training:** the winning clients M train on local datasets and submit model parameters w_i^t . **(4) Model Aggregation:** the server aggregates models $w^t = \sum_{i=1}^M w_i^t$. **(5) Value Evaluation:** the server calculates the actual value and evaluates the production value R_i^t of each client. Finally, the updated global model w^t is distributed. This process repeats until convergence. **The key components are client se-**

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lection (2) and value evaluation (5).

Client Selection: The server selects clients based on the “total budget B^t ”, the graph’s unique structural attribute “motif V_1^i ”, the “bidding price b_i^t ”, and the “historical value evaluation records R_i^{t-1} ”. Motifs V_1^i are frequently occurring small subgraph structures in the graph, representing the graph’s patterns and complexity. The mechanism’s truthfulness ensures that the client’s bidding price b_i^t equals their true training cost c_i^t . The evaluation record R_i^{t-1} reflects the client’s performance in previous rounds.

After clients submit their bids b_i^t , the server calculates the unit motif price for each bidding client $q_i^t = b_i^t / V_i R_i^t$; The unit motif prices are then arranged in ascending order $q_1^t \leq q_2^t \dots \leq q_N^t$; The server sequentially selects m clients from the sorted list to form the training set M^t , ensuring that the total rewards for the selected clients do not exceed the total budget $m = \arg \max_m (\sum_{i=1}^M p_i^t \leq B^t)$; The expected reward for the winning clients is set as: $p_i^t = V_i R_i^t q_{m+1}^t$. The total reward for round t is defined as $P^t = \sum_{i=1}^M p_i^t$.

Our AEFGL satisfies these economic properties in game theory, including incentive compatibility (truthfulness), budget feasibility, and individual rationality.

Value Evaluation: The server assesses the production value of clients through a comparison of their expected rewards, cost prices, and actual values. After the t -th round of training is completed, the server tests the model of each participating client on its validation set and performs normalization ($\sum_{i=1}^M r_i^t = 1$). Based on the normalized values, the actual value is calculated as: $p_i^{t*} = r_i^t / \sum_{i=1}^M r_i^t P^t$, where p_i^{t*} is the actual value generated by client i in the t -th round.

When a client generates a positive return, it indicates that the client has passed the value evaluation. The different scenarios of clients regarding their expected rewards p_i^t , actual values p_i^{t*} , bids b_i^t , and failure to win the auction are as follows: **(a)** When $p_i^{t*} > p_i^t, n_i^{pass} \pm 1$. **(b)** When $p_i^t > p_i^{t*} > b_i^t, n_i^{pass} + 1$. **(c)** When $p_i^{t*} < b_i^t, n_i^{fail} + 1$, and the reward is reset to $p_i^t = b_i^t$. **(d)** If client i fails to win the auction, the value evaluation is still considered passed if $i \notin M, n_i^{pass} + 1$. We provide these clients with opportunities because their quality may change in subsequent rounds. We use the sigmoid function to quantify the recorded value assessment into production value, because it can smoothly map inputs into the interval (0,1): $R_i^t = 1/1 + e^{-kx}$, $x_i^t = \beta n_i^{pass} - 1 - \beta n_i^{fail} / \beta n_i^{pass} + 1 - \beta n_i^{fail}$. R_i^t will be used for client selection in the next round.

Experiments

We evaluate the proposed system on two molecular datasets, PROTEINS and DD, where the nodes and edges in the graphs represent atoms and chemical bonds. To simulate clients with different data quality levels, the clients are classified based on the settings from (Pan et al. 2024), with 6 clients classified as high-quality, 2 as medium-quality, and 2 as low-quality, based on the random removal of edges in the graph with proportions of [0, 0.1), [0.1, 0.3), and [0.3, 0.7), respectively. The remaining parameters are: $\beta = 0.3$, $k = 0.3, T = 500, B^t = 30, b_i^t \in [3, 4]$.

Dataset	FedAvg	GCFL	Fedstar	AEFGL	QAFL	RRAFL	AEFGL
PROTEINS	0.7048	0.7356	0.7498	0.7438	0.7122	0.7257	0.7554
DD	0.6392	0.6549	0.6705	0.6784	0.6402	0.6459	0.6834

Table 1: Accuracy Evaluation Experiment.

Cient	Round	Avg b_i^t	Avg p_i^t	Avg R_i^t	Avg P^t	Avg $select^t$
0-5	479.83	3.484	4.551	0.968		
6-7	44.00	3.126	3.455	0.665	27.82	6.06
8-9	22.50	3.053	3.346	0.645		

Table 2: Incentive Performance Across Different Clients.

AEFGL Improves Performance: As shown in Table 1, we conducted accuracy experiments with the FGL methods FedAvg, GCFL(Xie et al. 2021), and Fedstar(Tan et al. 2023), as well as the federated learning incentive methods QAFL(Zhang et al. 2024), RRAFL(Zhang, Wu, and Pan 2021), and the FGL incentive method TFGFL(Pan et al. 2024). On the PROTEINS and DD datasets, AEFGL outperforms all other models in accuracy.

AEFGL Incentive Performance: As shown in Table 2, high-quality clients exhibit significantly higher average participation rounds, rewards p_i^t , and evaluation values R_i^t than other clients. Even for low-quality clients, the rewards p_i^t obtained when winning the auction are higher than their costs b_i^t . It can also be observed that low-quality clients can only win when their bids are low, resulting in a lower average bid. Additionally, the average total reward P^t remains below the total budget B^t .

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