Incentive Strategies of Clients in Decentralized Federated Learning Using Evolutionary Game

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Abstract. The decentralized federated learning framework combined with blockchain technology can significantly enhance the data credibility and security of traditional federated learning. To solve challenges like low data quality and "free riding", it is essential to introduce more effective incentive strategies that can be practically applied. In this paper, we propose a more general decentralized federated learning framework to establish an evolutionary game model with twelve variables that affect the incentive strategies of clients. By discussing the interaction mechanism among clients, we aim to determine effective incentive strategies. Additionally, we conduct numerical simulation to analyze the impact of these twelve variables on stable strategies in the evolutionary game. The results demonstrate the effectiveness of our proposed model and associated algorithms. The experiment results indicate that an increase in the willingness to cooperate of either party will increase the probability of the overall evolution towards the optimal outcome. Factors such as reducing training costs, adjusting incentive levels, minimizing additional losses, increasing the recognition probability, and offering additional benefits can expedite the implementation of the evolutionarily stable strategy (ESS) among clients.This study can provide valuable insights to improve the training quality of clients and boost overall model efficiency.

Keywords: Blockchain, decentralized federated learning, evolutionary game, evolutionarily stable strategy (ESS), incentive mechanism.

1 Introduction

Machine learning has emerged as a prominent approach for analyzing and sharing big data. However, acquiring and integrating widely available data presents significant challenges and comes with social concerns like privacy and competition for performance gains. As a result, a limited willingness among companies to share data, blocked sharing channels, and other phenomena have become commonplace. The rise of federated learning (FL) has provided an effective solution to these problems, readers can refer to some valuable references in published survey papers [1-3]. Decentralized federated facilitates efficient aggregation of reliable local models, ensuring public transparency and immutability of transaction information [4-6], specific incentives are necessary to motivate clients to engage in training. Previous studies have introduced diverse incentive mechanisms in FL [7-9], most studies still focus on traditional federated learning, centered around three driving factors: user contribution, reputation, and resource allocation. Therefore, the environment's ever-changing nature necessitates incentive mechanisms that can adapt more quickly.

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Traditional FL studies are predominantly tailored for traditional federated learning or a specific decentralized framework, limiting their applicability to a broader range of architectures. Moreover, there lacks a general decentralized framework for federated learning. Given that EGT aligns well with the dynamic, employing EGT to analyze client behavior strategies within a general FL framework is highly feasible and valuable. Based on this, the contribution of this paper is threefold: This paper sets up a general decentralized federated learning framework; This paper establishes an evolutionary game model for the clients of decentralized federated learning; This paper combines theoretical analysis with numerical simulation to qualitatively explore the impact of different variables.

2 A General Decentralized Federated Learning Framework

Witt et al. [10] conducted a systematic literature review (SLR) by examining 422 publications from 12 scientific databases in the field of computer science. Based on this, this paper summarizes decentralized federated learning as the blockchain layer and the client layer.

The steps can be described as follows: First, training clients download the initial global model from blockchain, obtain and upload local updates to the validation clients through the interface. Then, validation clients validate local updates using local data, aggregate and upload the local model updates and scores to the blockchain. Finally, the blockchain stores the aggregated global model on a reliable distributed ledger. The workflow of the interaction is shown in figure 1.

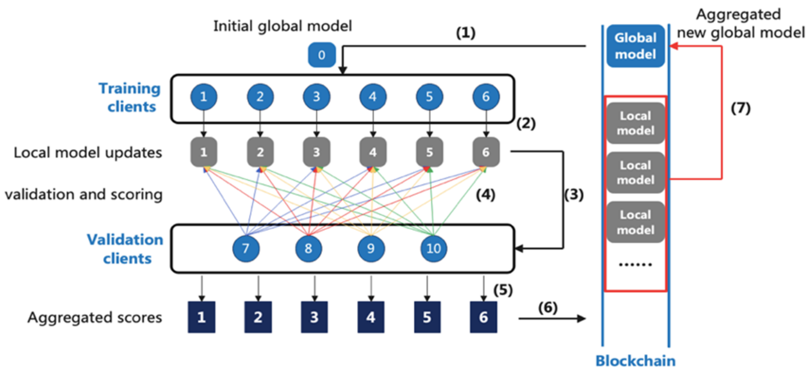

Figure 1. Workflow of a general decentralized federated learning framework.

3 Evolutionary Game Model

3.1 Model Descriptions

The incentive model for the two types of clients is based on the following assumptions:

1) Training clients (T) and validation clients (V) both exhibit bounded rationality and information asymmetry, and their choices dynamically change as the game progresses. The strategies for training clients are "High-Quality Training (HT)" or "Low-Quality Training

(LT)", and that for validation clients are "Strong Validation (SV)" or "Weak Supervision (WV)". The probability HT is x, and the probability of LT is $1-\mathrm{x}$.

2) If training clients choose HT, they need to pay an additional cost of C. If they choose LT, due to factors such as poor data quality, it will result in an overall loss in model payoff. The loss for validation clients is $\mathrm{R_l}$, and for training clients is $\mathrm{I_l}$. Additionally, the identification probability of LT is θ, $\mathrm{P}(1-\theta)$ is used as incentive for training clients identified as not choosing LT, where $0 \leq \theta \leq 1$. Considering the impact of identification probability and the payoff distribution mechanism, the validation clients will receive income $\mathrm{R_{S1}}$ under HT and $\mathrm{R_{S2}}$ under LT.

3.2 Parameter Settings

According to the basic assumptions, the model parameters are set as shown in Table 1.

Table 1. Model parameters settings.

Symbol	Description
R	Model revenue received by validation clients
I	Model revenue received by training clients
C	Additional cost of adopting HT for training clients
S	Additional cost of adopting SV for validation clients
P	Incentive for validation clients to adopt SV spending
R_S	Validation clients adopt SV, additional revenue of validation clients
I_S	Validation clients adopt SV, additional revenue of training clients
R_l	Training clients adopt LT, additional loss for validation clients
I_l	Training clients adopt LT, additional loss of training clients
θ	The recognition probability of the validation clients recognizing LT
x	Probability of adopting SV for validation clients
y	Probability of adopting HT for training clients

3.3 Evolutionary Game Model

The payoff matrix for each combination of strategies is shown in Table 2.

Table 2. Income matrix of EGT.

Validation Clients V	Training Clients T	
	High-quality training HT (y)	Low-quality training LT $(1-y)$
Strong validation SV (x)	$R-S-P+R_S$ $I+P-C+I_S$	$R-R_l-S-P(1-\theta)+R_S$ $I-I_l+P(1-\theta)+I_S$
Weak validation WV $(1-x)$	R $I-C$	$R-R_l$ $I-I_l$

From Table 2, the expected return function and average expected function for SV and WV are

$$U_{V1} = y(R-S-P+R_{S1}) + (1-y)[R-R_l-S-P(1-\theta)+R_{S2}] \quad (1)$$

$$U_{V2} = y(R) + (1-y)(R-R_l) \quad (2)$$

$$\bar{U}_V = xU_{V1} + (1-x)U_{V2}. \tag{3}$$

The expected return function and average expected function for HT and LT are

$$\mathrm{U_{TI}} = \mathrm{x(I + P - C) + (I - x)(I - C)} \tag{4}$$

$$U_{T2} = x[I - I_l + P(1-\theta)] + (1-x)(I - I_l) \tag{5}$$

$$\bar{U}_T = yU_{T1} + (1-x)U_{T2}. \tag{6}$$

The dynamic replicator equations for the training clients and the validation clients are as follows:

$$F_1(x) = \frac{dx}{dt}x(\bar{U}_{V1} - \bar{U}_{V2}) = x(1-x)(U_{V1} - U_{V2}) \tag{7}$$

$$F_2(y) = \frac{dy}{dt}y(\bar{U}_{T1} - \bar{U}_{T2}) = y(1-x)(U_{T1} - U_{T2}) \tag{8}$$

3.4 Evolutionary Stable Strategy Analysis

According to the dynamic replicator equations, let $\mathrm{F_1(x)} = 0$, $\mathrm{F_2(y)} = 0$, the system equilibrium points of the game are (0,0), (0,1), (1,0), (1,1) and $(\mathrm{x^*, y^*})$, where

$$0 < x^* = \frac{C - I_l}{P\theta} < 1 \tag{9}$$

$$0 < y^* = \frac{P(1-\theta) - I_S + S}{R_S - I_S - P\theta} < 1. \tag{10}$$

Using Friedman's method and Jacobian matrix, it is possible to determine whether each equilibrium point is an evolutionary stable strategy. The Jacobian matrix is as follows:

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} \end{bmatrix} = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix}. \tag{11}$$

Only when $\mathrm{Det}(J) = J_{11}J_{22} - J_{12}J_{21} > 0$ and $\mathrm{Tr}(J) = J_{11} + J_{22} < 0$, the equilibrium point will satisfy the optimal solution, which is an ESS. Let $\mathrm{R_S - I_S - P}\theta > 0$, $\mathrm{P}(1-\theta) - \mathrm{I_S} + \mathrm{S} > 0$ and $\mathrm{R_S - I_S - P}\theta > \mathrm{P}(1-\theta) - \mathrm{I_S} + \mathrm{S}$, the parameters situation are shown in Table 3.

Table 3. Equant stability analysis.

Equilibrium	$Det(J)$	$Tr(J)$	Local stability
O (0,0)	+	−	ESS
A (0,1)	+	+	Local Instability
B (1,1)	+	−	ESS
C (1,0)	+	+	Local Instability
D (x^*, y^*)	−	= 0	Saddle Point

In the table 3, O and B are ESS, A and C are local instability, and D is the saddle point, the game phase diagram of both participants can be drawn, as shown in figure 2.

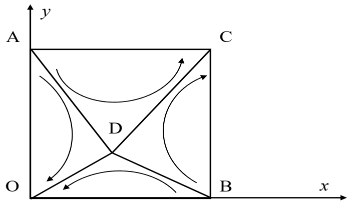

Figure 2. Evolutionary game phase diagram.

It is thus clear that when $S_{OADB} < S_{ACBD}$, D is closer to $(0,0)$. The area can be expressed as:

$$S_{ACBD} = 1 - \frac{1}{2}(x^* + y^*) = 1 - \frac{1}{2}\left(\frac{C - I_l}{P0} + \frac{P(1-\theta) - R_{S2} + S}{R_{S1} - R_{S2} - P0}\right) \tag{12}$$

The relative sizes of the two quadrilateral areas primarily depend on the position of the saddle point D, and it is determined by the parameter in the payoff matrix.

4 Numerical Simulation and Analysis

To increase the probability of both participants adopting (SV, HT), parameters are divided into the four groups for discussion: (1) Cost group: C, S; (2) Incentive group: P; (3) Identification probability group: θ; (4) Additional income group: R_s, I_s.

4.1 Cost Optimization

Under the initial conditions of $x, y = 0.8, 0.6$, take C to be 6, 8, and 10, take S to be 4.5, 5.5, and 6.5, the evolutionary paths are shown in figure 3.

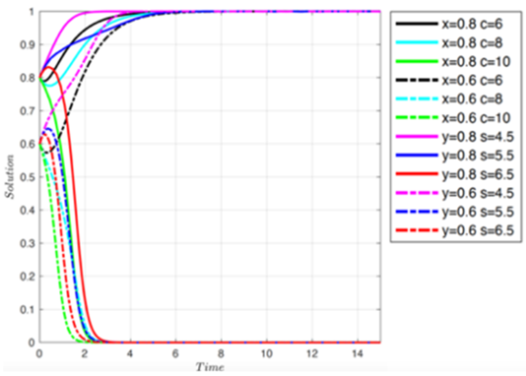

Figure 3. Evolutionary paths under cost optimization C and S.

Observing the results, when x is 0.6, the probability of SV tends to approach 1 only when C gradually decreases to 6. The smaller the value of C, the faster it reaches 1.

4.2 Incentive Optimization

In addition to incurring costs, clients also need to provide incentives, and the range is $0.225 < P < 10$. Specifically, when P is 9 to 0.5, the evolutionary paths are shown in figure 4.

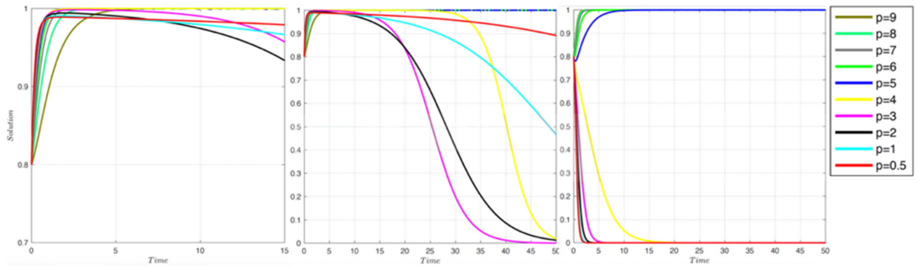

Figure 4. Evolutionary Paths under Incentive Optimization. (a) x=0.8. Time < 15. (b)x=0.8. (c)y=0.8.

For clarity, (a) represents *Time* ranging from 0 to 15 in (b). And (c) shows the evolutionary strategies of the training clients with the change of P when the initial y is 0.8. As P decreases, the upward trend becomes steeper. However, when $P < 5$, smaller incentives to (WV, LT).

4.3 Identification Probability Optimization

The identification probability θ satisfies the constraint of $0.5 < \theta < 1$, assigning 0.95, 0.8 and 0.65 to θ respectively, the evolutionary paths are shown in figure 5.

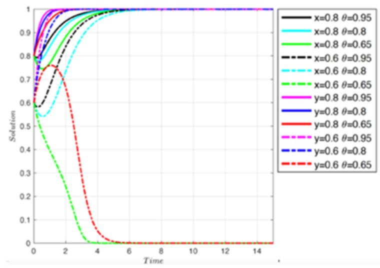

Figure 5. Evolutionary paths under identification probability optimization θ.

When $\theta = 0.95$, both the curves quickly approach 1 and remain stable, with y having a faster rate. As θ decreases to 0.65, the curve of x shows a firm tendency towards 0.

4.4 Additional Income Optimization

When verification clients choose SV, in addition to incurring costs and incentives, they will also receive income R_{S1} and R_{S2}. Under $y = 0.8, 0.6$, the evolutionary paths are shown in figure 6.

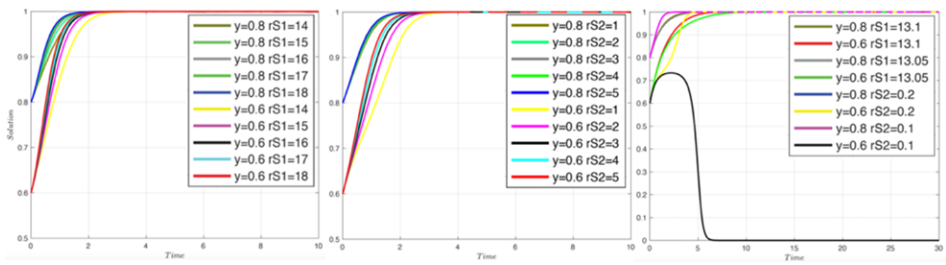

Figure 6. Evolutionary paths under additional income optimization. (a) R_{S1}. (b) R_{S2} .(c) Thresholds.

When setting R_{S1} and R_{S2} to explore the thresholds, only when R_{S2} takes a value of 0.1, the curve eventually converges to 0 under $y = 0.6$.

5 Conclusion

This paper adopts EGT to address the issues of lacking effective incentive mechanism in current decentralized federated learning. A general framework for decentralized federated learning is abstracted, and based on this, the strategy choices of validation clients and training clients under bounded rationality are analyzed. Based on the above analyses, this paper proposes three suggestions for the further development of decentralized federated learning:

1) Utilizing incentive compensation and pre-selection to mitigate cost expenditures, simplifying the flow of information for greater transparency. Secondly, considering factors such as data volume, past ratings, and reputation, pre-selection of clients can be implemented to minimize initial cost investment.
2) Update technologies and adjust weights to maintain high recognition probability. Try to continuously improve the identification for identifying LT clients and consider applying continuous penalties to clients who have previously participated in LT training.
3) Adjust the proportion of clients and distribution mechanism of rewards. Improve the overall system efficiency through optimizing model training accuracy, computing capabilities, and address disparities in basic resources, enhancing the overall performance of the model and income for clients.

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