A Novel Layered GSP Incentive Mechanism for Federated Learning Combined with Blockchain

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Abstract. Federated Learning (FL) has shown great potential as a solution to the problem of data islands. It enables collaborative modeling while adhering to data privacy and security. But how to ensure participants remain active in FL and make rewards reasonable are issues. Although various game theory models, such as Stackelberg, Cournot, and Leader price, give a pricing method for participants, these models don't consider the roles in FL and the security. We presented the FL incentive mechanism, B-LSP, based on the Generalized Second Price Auction (GSP). This mechanism can overcome the issue of unmanageable incentives while calculating the reward values. Furthermore, a magnitude stratification is introduced to ensure the participants remain active and the basic need for data volume in FL. The requester sets the basic volume requirement for participants, *Initial*, and volume comparison standard, *Interval*, to ensure the basic effectiveness of FL and categorize participants into different layers according to their data volume. In B-LSP, requester can control its costs and keep the federation's stability. And the blockchain is a crucial part to audit everyone's contribution and guarantee our mechanism safe. The analysis results show that the B-LSP is more reasonable and scientific, and it satisfies both security and traceability when compared to other game theory models.

Keywords: Federated Learning · Incentive mechanism · Smart Contract · B-LSP

1 Introduction

Enterprises' decisions are largely reliant on the power of data. However, their data often contain considerable amount of private information, and according to data privacy and protection laws, these data cannot be centralized or exchanged directly, posing challenges to mining data value. Federated Learning (FL), which has been proposed in recent years, may provide a solution of allowing users to collaborate without exchanging genuine facts [1]. Each member in FL retains its data locally to ensure that it does not breach existing laws and regulations. During the collaborative model training, members merely transmit the intermediate parameters, and subsequently utilize the aggregation algorithm to construct a complete model.

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Though FL is a viable answer, the key to applying FL is to persuade participants to share their data and keep the federation active. The primary issue is the incentive mechanism. Members will be unmotivated to join the federation if there are no fair incentives [2]. Most mechanisms concern about how to allocate the benefits provided by the final model, and many studies are based on the theory of Output Competition, Price Leader, and Analytic Hierarchy Procedure methods, such as Cournot and Stackelberg models [3]. These models show that price is negatively correlated with the output, which means that higher output causes lower price. However, this may not be consistent with the FL condition. Additionally, these methods ignore the cost generated by data and don't distinguish requester and participants.

1.1 Contribution

B-LSP considers the energy costs of various roles and is designed to cover the complete procedure of the FL task. The contributions of this article are as follows:

- Introduce GSP to encourage members to compete for bonus: we treat extra bonus as auction objects and the data volume provided by members as their quotations, so that members compete for bonus on the data volume they agreed to share [4]. Each participant will be ranked based on volume, and the first one will get the bonus.
- Introduce Magnitude Stratification Mechanism to regulate incentives: the requester determines the volume requirement and comparison standard for distinct layers, and the Incentive Control Line (ICL). Members are classified into layers based on the quotations. The ICL and member's location decide the auction winner's bonus.
- Introduce Smart Contracts to ensure open and effective rules: B-LSP uses blockchain to implement data auditing and automatic incentives. The data audit will run automatically before FL training to check member's data. The Shapley value is used to calculate member's contribution to the federation [5]. The data authentication, quotation, winner's information, bonus, and basic cost information are merged by a blockchain based smart contract [6] (Fig. 1).

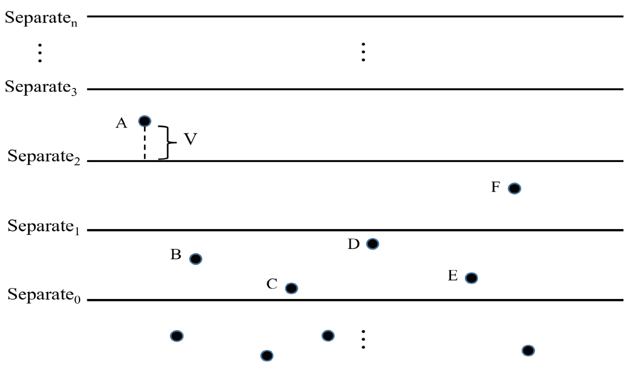

Fig. 1. A novel layered GSP incentive mechanism

The follow-up arrangements for this article are Part II, related work; Part III, B-LSP in FL; Part IV, Theoretical Analysis; Part V, Conclusion and Outlook.

2 Related Work

Yufeng Zhan, Peng Li, Zhihao Qu and others have proposed a deep reinforcement learning (DRL) based incentive mechanism combined with the Stackelberg model [2]; Latif U. Khan, Shashi Raj Pandey, Nguyen H. Tran and others designed an incentive mechanism based on the Stackelberg model for the application of FL in mobile scenarios [7]. The Stackelberg model is widely used in incentive mechanism design which can ensure profitability and steady decisions for advantageous enterprises. However, Stackelberg model is lack of concern for SMEs (Small and Medium Enterprises) which are the essential part of FL. Jiawen Kang, Zehui Xiong, Dusit Niyato and others think that it is necessary to consider the cost of the members, this paper uses the hardware parameters of each member to calculate the energy consumption [8]; Ismael Martinez, Sreya Francis, Abdel-hakim Senhaji Hafid and others combined blockchain with federated learning by using Enterprise Operation System (EOS) to record and reward members' contributions of FL, and proposed Class-Sampled Validation-Error Scheme (CSVES) to verify valuable participants and only reward these valuable members [9]; In addition, Yuan Liu, Zhengpeng Ai, Shuai sun and others proposed to build a FedCoin combined blockchain with FL which is a payment system for federated learning [10]. The combination of energy costs, blockchain, and member contributions makes incentive mechanism more reasonable and scientific, but we still lack a comprehensive solution to organically link these technologies. To meet all our objectives for fairness, security, and profit, we presented the B-LSP mechanism, which comprises of GSP, Magnitude Stratification, and Blockchain.

3 B-LSP in FL

To separate members into distinct layers in B-LSP, the requester will set *Initial* and *Interval*. The member layer and Incentive Control Line are determined by the *Initial* and *Interval*. B-LSP ensures data quantity for federated learning by *Initial* and controls the maximum amount of extra bonus via *Interval*. The ICL is denoted as:

$$Separate_k = Initial + k * Interval,\ k = 0, 1, 2, \ldots, N \tag{1}$$

In B-LSP, the requester can ensure its basic interests by *Initial* and *Interval*, while the requester will pay the basic cost of members during the FL and the benefits from collaborative model will be allocated based on the contributions of each participant. B-LSP consists of three essential technologies: 1. Layered GSP with blockchain; 2. Basic Cost Calculation Method; 3. Shapley Value Method and Smart contract.

3.1 B-LSP Process

This paper proposes a mechanism that combines GSP and Magnitude Stratification (B-LSP) to motivate members to provide as much data as possible while also rewarding members fairly for their contributions [11]. The procedure details of B-LSP are:

1. The requester establishes the fundamental requirement for data volume based on its revenue aim, and the payment for participants' base costs can be controlled by volume comparison standard. Additionally, B-LSP will calculate the bonus using the requester's hardware parameters.
2. Participants compete for the extra bonus by their quotation, and for each quotation, they must upload data authentication to the blockchain. If the first and second quotations are at the same layer, the extra bonus is calculated by the difference between them; If they are not at the same layer, the extra bonus is calculated by the difference between the first quotation and the nearest ICL.
3. The quotation, data authentication, data date, hardware parameters and winner are all uploaded to blockchain for subsequent verification and data auditing.
4. After passing the data audit, start federated training using the quotations (promised data from each member) and record the training iteration, training time and communicating times for next computation.
5. After completing the federated model training, compute each member's basic cost in the training procedure using the hardware parameters and allow the requester of this FL job pay the basic cost for each member. Furthermore, the extra bonus is calculated by requester and allocated to the winner based on the winner's identification information on the blockchain.
6. Shapley Value can be used to calculate member contributions and upload them to the blockchain. When the final model creates business profits, the income will be allocated to members in proportion to their contribution.

The above process is carried out automatically as a smart contract, and the requester will pay the costs of operation and maintenance in the FL job. The B-LSP process is shown in the Fig. 2 and the algorithm is Algorithm 1:

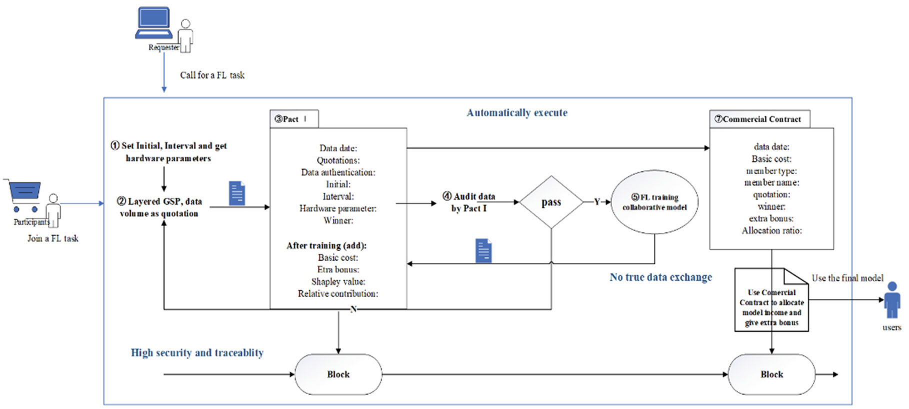

Fig. 2. B-LSP workflow with blockchain

Algorithm 1 B-LSP

Parameter: Users' information and quotations, <*user*, *quotation*>
Results: Contract, (*Cost, V, Allocation ratio*)
if *Every user agrees the contract* **then**
  Each member executes:
    Price for the bonus
  Requester executes:
    Set ***Initial*** and ***Interval***
    Ranking and select winner
    Get $H(r)$, winner's δ and $Separate_k$
  if $winner - Separate_k \leq winner - second$ **then**
    $Num = winner - Separate_k$
  else
    $Num = winner - second$
  end
  $V = f(Num) + g(\delta)$, Upload V and quotation to blockchain
  Starting Federated Learning
  Calculate allocation ratio and *Cost*
else
  Restart the auction
end

3.2 Basic Cost Calculation Method

The basic cost of FL can be estimated using hardware parameters [8]. The hardware detection can be expressed as $H(i)$, the cost of computing power of the participants is calculated via $f(Num)$, the calculation of the participants' communication costs is $g(\delta)$. Suppose the amount of data provided by member i is Num_i, its CPU cycle frequency is f_i and the number of CPU cycles required for training one single data is C_i; The effective chip capacitance is ξ.

Table 1. Basic cost parameters and functions

Parameters and functions	Denotation
Amount of data provided by member i	Num_i
CPU cycle frequency	f_i
Number of CPU cycles required for training one single data	C_i
Effective chip capacitance	ξ
Member i's intermediate parameter size	δ_i
Hardware detection function	$H(i)$
Computing power	$f(Num)$

(*continued*)

Table 1. (*continued*)

Parameters and functions	Denotation
Communication cost	$g(\delta)$
Transmission power	ρ_i
Transmission bandwidth	B
Channel gain	h_i
Background noise	N_0

Then, the local training time of member i is $\frac{c_i \cdot Num_i}{f_i}$, the energy consumption of computing in a local iteration is $f(Num_i) = \xi \cdot c_i \cdot Num_i \cdot f_i^2$. Suppose that local iterations before member i communicates with the coordinator is $iteration_i$, transmission bandwidth is B, transmission power is ρ_i, channel gain between i and coordinator is h_i, background noise is N_0, the size of intermediate parameter transmitted is δ_i. We calculate the time for one communication between i and coordinator is $\frac{\delta_i}{B\ln\left(1+\frac{\rho_i h_i}{N_0}\right)}$, the energy consumption of one communication between i and coordinator is $g(\delta_i) = \frac{\delta_i \rho_i}{B\ln\left(1+\frac{\rho_i h_i}{N_0}\right)}$. If i communicates with the coordinator t a second, the basic cost in federated learning is $Cost_i = t \cdot (iteration_i \cdot f(Num_i) + g(\delta_i))$. The hardware detection obtains the hardware parameters of each participant: $H(i) = c_i, f_i, \xi, B, \rho_i, h_i, N_0$. If i obtains benefits in FL as U_i, then only when $U_i \geq Cost_i$, members will join the federation and keep active. Therefore, the requester must pay the basic cost of FL for each member $\Sigma Cost_i$. The basic cost calculation algorithm is as followed:

Algorithm 2 Basic Cost Calculation

Input: User i, Number of iterations $iteration_i$, Size of data set Num_i, Size of i's intermediate parameter δ_i, Total times of communication in FL *total*
Output: Basic Cost of user i $Cost_i$
1: Initialize $c_i, f_i, \xi, B, \rho_i, h_i, N_0 = H(i), Cost_k = 0, Cost_i = 0$
2: Each data provider *i* executes:
3: for round t = 0; t < *total*; t++ **do**
4:   **for** round k = 0; k < $iteration_i$; k++ **do**
5: $Cost_k \leftarrow Cost_k + f(Num_i)$
6:   **end**
7: end
8: $Cost_i \leftarrow Cost_i + Cost_k + g(\delta_i)$
9: Upload $Cost_i$ to the blockchain
10: return $Cost_i$ to requester
11: Requester executes:
12: Aggregate all users' cost: $Cost = \Sigma Cost_i$

3.3 Shapley Value and Smart Contract

Shapley Value is a way of calculating the data's contribution to the model. If the data of participant i is D_i; X_j is the eigenvalue vector of the j-th feature; S is a subset of the entire feature space, $|S|$ is the number of features in the subset; k is the number of features. The Shapley value calculation method is defined as:

$$\tau_j = \sum_{S \subseteq x1, x2, \ldots, x_k \backslash x_j} \frac{|S|!(k - |S| - 1)!}{k!} \left(val\left(S \cup x_j\right) - val(S) \right) \tag{2}$$

The contribution of data to the model is $\tau_{D_i} = \sum_{j=1}^{n} \tau_j$. The relative contribution of each member is $p_i = \frac{\tau_{D_i}}{\sum \tau_D}$. If the model creates income M, participant i will get $p_i * M$. The Smart Contract consists of the whole procedure of B-LSP and a business contract which contains the members' quotations, winners, extra bonus, and basic costs.

Table 2. Commercial contract content

Participant type	Name	Winner	Quotation	Basic cost	Allocation ratio	Extra bonus
Requester	*name*	No	*Volume*	$\Sigma Cost_i$	P	*None*
Participants	*name*	Yes	*Volume*	$Cost_i$	P_i	V

4 Theoretical Analysis

By combining blockchain and game theory, B-LSP can give more data security and traceability than many existing solutions. Table 3 compares the advantages of B-LSP to other game theory models. Now, let's pay more attention on the profit analysis.

First, we consider no cost for members in FL. If the extra bonus for the winner is V, the income of the collaborative model used once is M, then member i can get benefits $p_i * M$. The member's revenue in FL can be expressed as:

$$U_i = \begin{cases} V + M * P_i, \ i \, wins \, bonus \\ M * P_i, \ i \, loses \, bonus \end{cases} \tag{3}$$

we can deduct from this formula that if $M * P_i \geq 0$ (the utility of each member is more than zero), it will satisfy the individual rational assumptions in economics, then members will be willing to join the federation [12].

The B-LSP determine the extra bonus for the winner using the requester's own hardware parameters:

$$\mathrm{V} = \begin{cases} f\left(Num_i - Separate_k\right) + g\left(Num_i - Separate_k\right), \ i \, and \, others \, in \, different \, layer \\ f\left(Num_i - Num_j\right) + g\left(Num_i - Num_j\right), \ i \, and \, others \, in \, the \, same \, layer \end{cases} \tag{4}$$

from the equation, we can know that $0 \leq \mathrm{V} \leq f(Interval) + g(Interval)$ which means requester can control the amount of V.

Second, let's consider about cost. The cost of requester can be expressed as: $Cost_r = V + \Sigma Cost_i$. Assume the requester's expected revenue from the collaborative model is W, the income for the model used once by requester is r, the income of the model used once by others is M, and the requester can get $p * M$ per time. If there are k members, the requester's revenue can be expressed as:

$$U_r = W - V - \sum_{train} \left[f(Num) + g(\delta)\right] \tag{5}$$

$$W = \begin{cases} \sum_1^{\infty} r - \sum_1^{k} (f(Num) + g(\delta)), \ requester\ use \\ \sum_1^{\infty} p * M + \sum_1^{\infty} r, others\ use \end{cases} \tag{6}$$

Due to the individual rationality, the requester's income must be more than zero. It's obvious that $\sum_1^{\infty} p * M + \sum_1^{\infty} r \geq 0$ which means $\sum_1^{\infty} r - \sum_1^{k} (f(Num) + g(\delta)) \geq 0$ is the key for requester to initiate a FL job.

Table 3. The advantage of B-LSP than other methods

Methods	Controllability	Stability	Security	Traceability
B-LSP	✓	✓	✓	✓
Stackelberg	✓	✓	×	×
Cournot	✓	✓	×	×
Leader price	✓	✓	×	×

5 Conclusion and Outlook

The B-LSP help members in getting benefits and requesters in controlling their costs and FL model quality. Through B-LSP, all members can gain greater benefits than the existing widely used Stackelberg model and all members can be continually rewarded. The B-LSP mechanism in this article is a continuous, multi-party, fair and effective incentive mechanism for FL.

The basic cost of FL is defined in this article as computing and communication energy cost. As a result, the remainder of this article will concentrate on fundamental cost accounting and data value appraisal in FL. Furthermore, how to assess the model's value should also be studied in the future.

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