Incentive Mechanisms in Federated Learning and Game-theoretical Approach

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***Abstract*—Federated learning or FL represents a new machine learning paradigm, in which it utilizes various resources from participants to collaboratively train a global model without exposing the privacy of training data. The learning performance critically depends on various resources provided by participants and their active participation. Hence, it is essential to enable more participants to actively contribute their valuable resources in FL. In this article, we present a survey of incentive mechanisms for federated learning. We identify the incentive problem, outline its framework, and categorically discuss the state-of-the-art incentive mechanisms in Shapley value, Stackelberg game, auction, contract, and reinforcement learning. In addition, we propose three multi-dimensional game-theoretical models to study the economical behaviors of participants and demonstrate their applicability in cross-silo FL scenarios.**

***Index Terms*—Federated learning, incentive mechanism, performance improvement, cross-silo FL.**

I. Introduction

As a promising distributed learning paradigm, Federated Learning (FL) has been proposed to collaboratively train a global model with plenty of participants who value their data privacy as top priority [1]. FL enables each participant to train a local model with its private data and only exchange model parameters with a server (or other peers) instead of raw data. The unnecessity of uploading training data improves the data privacy for participants. This salient feature accelerates widespread applications of FL in a series of settings. For example, Google applies FL to its product Gboard to improve user experience [1]. Similarly, Apple employs FL to QuickType and "Hey Siri" of iOS13. Some industrial examples include biomedical data analysis in Owkin, finance and insurance data analysis in Swiss Re, and drug discovery in MELLODDY [2].

Incentive design is paramount and indispensable to FL. FL consumes plenty of multi-dimensional resources from participants, such as computation power, network bandwidth, and private data, most of which are constrained in some scenarios like Mobile Edge Computing (MEC). In addition, participants still worry about security and privacy threats in FL, where several attacks have already been reported recently [1]. All these factors hinder the active participation in FL without enough payback. Furthermore, FL training performance in terms of model accuracy and training speed will deteriorate without sufficient training data, communication bandwidth, and computation power provided by participants [3]. In other words, deficient resources might cause FL to malfunction in reality. Therefore, incentive mechanism is required to motivate more clients with high-quality data and sufficient resources to engage in FL, which finally achieves the goal of overall performance improvement.

Fortunately, incentive mechanism has attracted increasing attention and many impressive studies mushroomed in the last two years. Among them, Zhan et al. presented a survey of incentive mechanisms for FL and summarized the existing studies into three categories, i.e., clients' contribution, reputation, and resources allocation [4]. Compared with [4], we provide another valuable survey of incentive design with distinct understanding, comprehensive taxonomy, innovative summary, and insights for future investigation. Furthermore, most previous studies on incentive design focus on cross-device FL which consists of massive resource-constrained nodes with occasional availability, and few literatures except [2] study incentive issue in the cross-silo scenario, where a group of giant organizations trains a model with sufficient communication and computation resources. Our work differs with [2] in the target problem, design goals, and main techniques.

In this article, we first identify the problem of incentive design in FL and highlight that its final goal is to improve the training performance like global model accuracy, training time, etc. Then, we point out three components of incentive mechanism, namely contribution measurement, node selection, and payment allocation, and present a novel taxonomy for further review. Also, we explicitly summarize the existing studies along the roadmap of major related techniques, including Shapley value, Stackelberg game, auction, contract theory, and reinforcement learning. Among them, Shapley value is mostly adopted for contribution measurement, while payment allocation mostly involves Stackelberg game, auction, contract theory, and non-convex optimization. Some cutting-edge techniques, such as reinforcement learning and blockchain, are adopted as auxiliary tools for node selection, contribution evaluation, and robustness improvement. From these results, we pinpoint some insights and opportunities for future investigation.

Following some observations from our survey, we concen-

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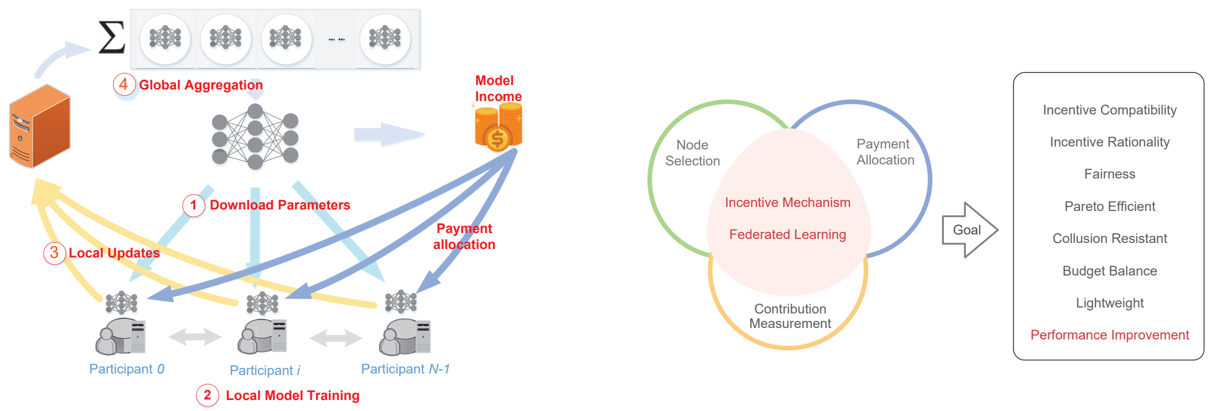


Fig. 1. The system model of FL and its framework of incentive mechanism

trate on the cross-silo FL setting and propose three multi-dimensional game-theoretical models to analyze the economical behaviors of participants and improve the global model accuracy. Specifically, we consider cross-silo FL as a perfectly competitive market and propose the Cournot model, Stackelberg-Cournot (SC) model, and Cournot-Stackelberg (CS) model for equally-dominant, coordinator-dominant, and participant-dominant cases, respectively. Then, we use gradient descent to approximately compute the Nash Equilibrium (NE) solution. We perform extensive experiments on a cluster and the experimental results demonstrate that our proposed models can improve the learning accuracy and system designers can achieve their goals with distinct models.

II. The Incentive Framework and Research Opportunities in FL

A. The Incentive Problem & Framework in FL

FL is a distributed training paradigm that targets minimizing the loss function of global model with many participants in a collaborative way, as shown in Fig. 1. An incentive mechanism aims to motivate more clients to participate in FL training and provide sufficient and various resources. In this article, we argue that the final goal of incentive scheme is to improve the training performance, which makes it different from the incentive design in other scenarios like crowdsensing. Besides this design goal, incentive schemes also aim at the properties of Incentive Compatibility (IC), Individual Rationality (IR), fairness, Pareto efficiency, collusion resistance, etc.

An incentive mechanism for FL includes three major design elements: contribution measurement, node selection, and payment allocation. Contribution measurement endeavors to get the accurate and fair evaluation of contribution to FL training performance for each participant [15]. In FL, contribution comes from not only training data but also many other resources. It is challenging to fairly and efficiently consider these resources together in their contribution evaluation. Node selection is to choose a subset of candidates to join in FL training. In nature, node selection tends to gather sufficient resources from participants with the economical budget constrained by the system designer or model owner. Additionally, node selection should consider different types of resources simultaneously, since a participant with low computing power and sufficient data might delay the training process. How to design an efficient mechanism with the goal of performance improvement and several constraints is one of main challenges for node selection. Payment allocation decides the payment for each participant. The payment, offered by the system designer, model owner [2], or the coordinator server [3], includes money, the usage of global model, and some other reputation rewards. We only consider the payment of currency in this article. Most payment allocation problems are NP-hard, and thus it is critical to efficiently obtain approximate solutions to these problems. Note that these components might be interdependent.

The existing studies of FL incentive schemes can be categorized in terms of application settings (cross-silo FL and cross-device FL), the FL phase (training and prediction), major related techniques (Shapley value, Stackelberg game, contract theory, auction, and reinforcement learning), and the assumption of information symmetry (complete information, weakly complete information, and incomplete information). In Section V, we review state-of-the-art FL incentive mechanisms from a technical perspective, and the skeleton of these techniques is illustrated in Fig. 2.

B. Opportunities & Challenges in Future Investigation

The study of incentive mechanism in FL is still in its infancy, and we point out four directions for future investigation.

(1) We reiterate that incentive mechanism should involve the training performance improvement of FL with several constraints by inspiring more participants. The absence of performance improvement makes incentive mechanisms useless, even though they can motivate massive participants to join in FL.

(2) FL has already found widespread applications in cross-silo settings, making incentive schemes more indispensable. In cross-silo FL, players are a few large and stable companies or organizations with sufficient resources instead of many volatile end users with limited resources. We need to analyze the economical behaviors of large organizations and design appropriate incentive mechanisms for them.

(3) Some comprehensive and lightweight incentive schemes are required for FL in some scenarios like MEC, 5G/B5G, etc., which might introduce additional constraints to the

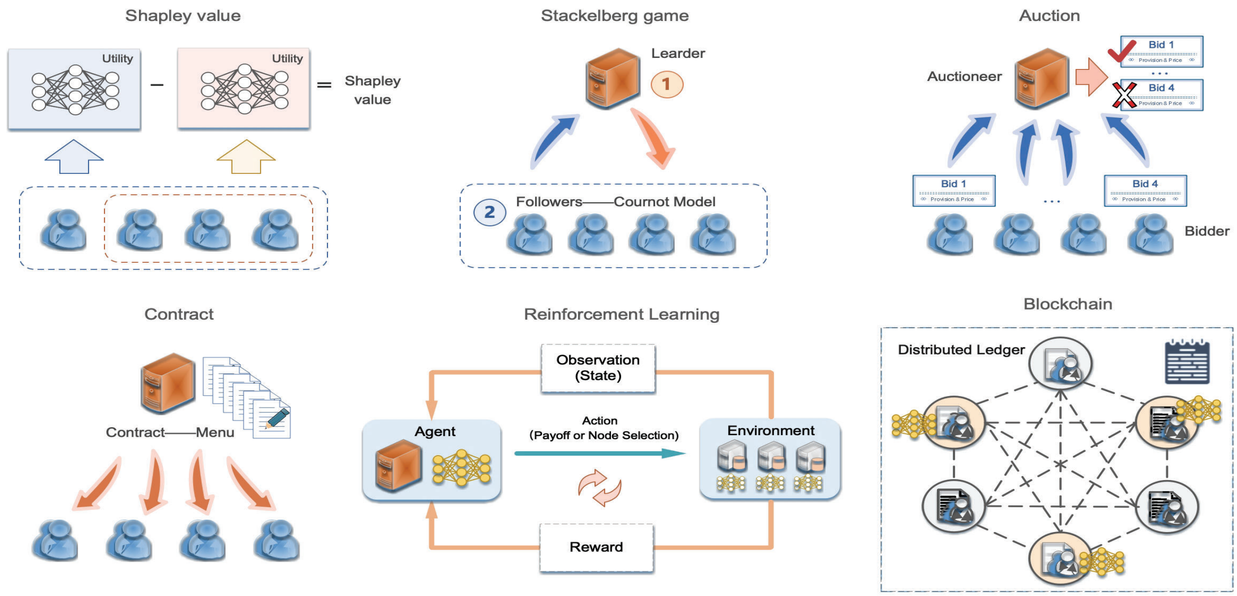


Fig. 2. The skeleton of main techniques for incentive mechanisms in FL

incentive design. For instance, participants in mobile networks appreciate lightweight incentive schemes, since resource-constrained nodes hesitate to perform expensive computation or contribute their network bandwidth.

(4) Some cutting-edge technologies like graph neural networks, generative adversarial networks, and multi-agent reinforcement learning might find their potential applications in the incentive design of FL.

III. The Incentive Design for Cross-silo FL

In this section, we propose an incentive scheme of multi-dimensional game-theoretical models to analyze the economic behaviors of participants in cross-silo FL scenarios, where participants are relatively stable, and the performance impact of each participant is comparatively large. Our proposed scheme aims to motivate fixed participants to provide multiple types of resources as well as to improve the training performance.

A. Multi-dimensional Game Models for Cross-silo FL

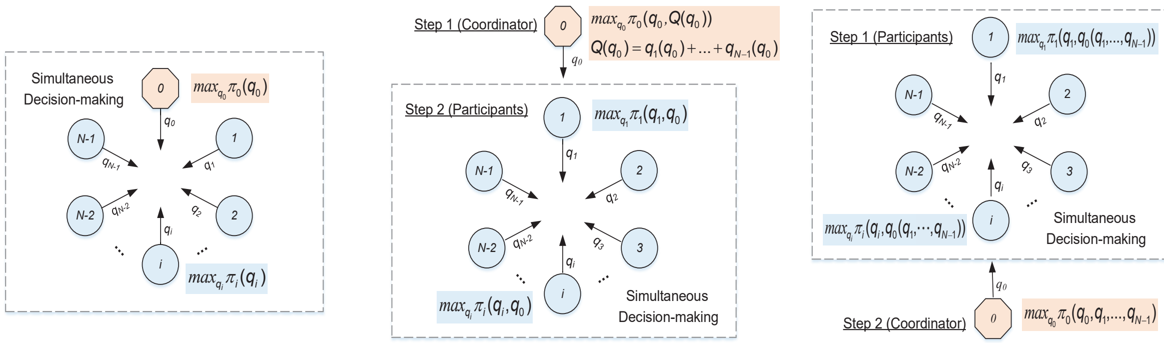
In cross-silo FL, there are two types of players, i.e., one global coordinator (a special participant) and $N-1$ common participants. The coordinator not only performs local training but also orchestrates the training process, and all the players join in FL by considering their resource provisions and others' reactions. According to the procedure of training, cross-silo FL can be categorized into three types, i.e., simultaneous decision-making, coordinator-move-first, and participants-move-first. These three cases are separately formulated by Cournot model, Stackelberg-Cournot (SC) model and Cournot-Stackelberg (CS) model in Fig. 3. Note that players in Cournot model make their decisions simultaneously and independently, while Stackelberg game models a sequential decision-making process. The combination of these two models can properly describe the cross-silo FL. Taking SC model as an example, it formulates the cross-silo FL scenario where powerful Western Union Bank (coordinator) cooperates with many smaller Bank of California (participants) to train a global deep learning model. In SC model, the coordinator first maximizes its profit π_0 by considering others' reactions and the total requirement denoted by the inverse demand function $P(\cdot)$ and then broadcasts its decision q_0. After the declaration of q_0, participants perform Cournot game to make their decisions with fixed external provision q_0. The detailed explanations of the other two models are skipped due to the space limitation.

What is the "common product" in cross-silo FL? We point out that resource provision should be multi-dimensional and consider all the variables related to training performance such as data size, data quality (e.g., label accuracy), CPU/GPU computing power, communication bandwidth, etc. To transform multi-dimensional resource provision variables into a single scalar in our game models, we need to employ a linear utility function, perfect substitution utility function, or Cobb-Douglas utility function, which are separately denoted as $q_i = \alpha_{i,1}q_{i,1} + \cdots + \alpha_{i,M}q_{i,M}$, $q_i = \min\{\alpha_{i,1}q_{i,1}, \cdots, \alpha_{i,M}q_{i,M}\}$, and $q_i = q_{i,1}^{\alpha_{i,1}} q_{i,2}^{\alpha_{i,2}} \cdots q_{i,M}^{\alpha_{i,M}}$, where $q_{i,j}$ is the resource provision of type j for participant i, and variable $\alpha_{i,j}$ is its corresponding weight.

B. Approximate NE Solution with Gradient Descent

NE solution is critical to analyze the economic behaviors of participants, and it enables all the participants to maximize their own profits with rational resource provision. Unfortunately, it is infeasible to get the NE solution manually especially when the number of participants is slightly large. In this article, we borrow the idea of gradient descent and backward induction to obtain the numerical NE solution. Due to the limited space, we only present the approximation algorithm for SC model as an example. This algorithm can fully describe the core idea of gradient descent and backward induction in all three approximation methods.

In Algorithm 1, we first compute the total provision function $Q(q_0)$ as $Q(q_0) = q_0 + q_1(q_0) + \cdots + q_{N-1}(q_0)$, among



(a) Cournot Model (b) Stackelberg-Cournot Model (c) Cournot-Stackelberg Model

Fig. 3. Three multi-dimensional models of cross-silo FL

Algorithm 1: The Approximation Algorithm for SC Model

Input: The inverse demand function $P(\cdot)$ and cost function $C_i(q_i)$

Output: NE solution $(q_0^{[SC]}, q_1^{[SC]}, \cdots, q_{N-1}^{[SC]})$

1 $q_0 = 0$;
2 **while** $q_0 \leq q_0^{max}$ **do**
3 $\quad (q_1, \cdots, q_{N-1}) = Cournot(q_0)$;
4 $\quad Q(q_0) = \sum_{i=0}^{N-1} q_i$;
5 $\quad q_0 = q_0 + \eta$;
6 **end**
7 $q_0 = 0, i = 0$;
8 **while** $(q_0 + \delta) \leq q_0^{max}$ **do**
9 $\quad \gamma = (Q(q_0 + \delta) - Q(q_0))/\delta$;
10 $\quad Q(x) := \gamma(x - q_0) + Q(q_0)$;
11 $\quad (q_0[i], \pi_0[i]) = GetOptimal(x * P(Q(x)) - C_0(x)), x \in [q_0, q_0 + \delta]$;
12 $\quad q_0 = q_0 + \delta$;
13 $\quad i{+}{+}$;
14 **end**
15 $(q_0^{[SC]}, \pi_0^{[SC]}) = GetMax(\pi_0[0], \cdots, \pi_0[i-1])$;
16 $(q_1^{[SC]}, \cdots, q_{N-1}^{[SC]}) = Cournot(q_0^{[SC]})$;

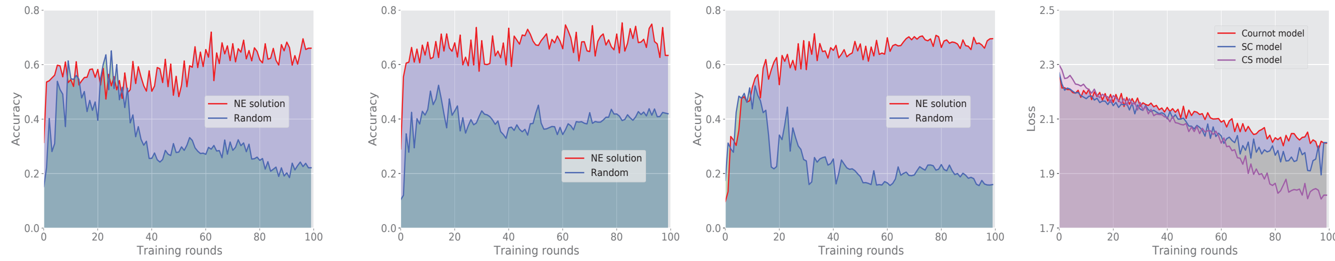
which $q_1(q_0), \cdots, q_{N-1}(q_0)$ are responses to the coordinator q_0 according to Cournot model, and then solve the profit optimization problem (the maximization of obtained payment minus cost) of the coordinator according to backward induction. In details, we sample q_0 and approach function $Q(q_0)$ with a piecewise linear function in a small interval. In the computation of $Q(q_0)$, we play Cournot game with fixed external quantity q_0, which can be further solved by the approximation method of Cournot model. After obtaining the approximate $Q(q_0)$, we can get the optimal strategy q_0 by solving univariate optimization problem (Line 11 in Algorithm 1) in each small interval. When q_0 is computed, $q_1, \cdots, q_{N-1}$ are correspondingly determined as Line 3 in Algorithm 1. In this way, we can obtain the numerical NE strategies of SC model. Note that the computing complexity of this algorithm is not a key issue and can be neglected, since the number of participants in cross-silo FL is not huge, and each player has sufficient computing resource.

IV. Experiments and Evaluations

We implement a cross-silo FL with our proposed models in a HPC cluster of 7 nodes. The specifications of these 7 nodes include Intel Xeon E5 CPU with 4 Cores and Linux Ubuntu 18.04.4 OS. All these nodes are connected by a 10Gbps Ethernet switch. We train a classic CNN model with MNIST dataset in FedML framework. The CNN model has 6 layers with structure similar to [3]. All the results are the average of five trails, and experiments with another dataset CIFAR10 also show similar results. The inverse demand function is $P(Q) = 10Q^{-0.5}$ and the cost function for node i is $c_i(q_i) = a_i q_i$, where the coefficient a_i is randomly chosen from $[4, 4.1]$. The multi-dimensional resources include data size q_1 (the number of data item) and data quality q_2 (the percentage of data item with correct label) in our experiments. Data quality is controlled by randomly choosing data items with a certain percentage for each class and setting them with false labels. We assume a simple linear function $q_i = \alpha_{i1} q_{i1} + \alpha_{i2} q_{i2}$, where $\alpha_{i1} = \alpha_{i2} = 0.5$.

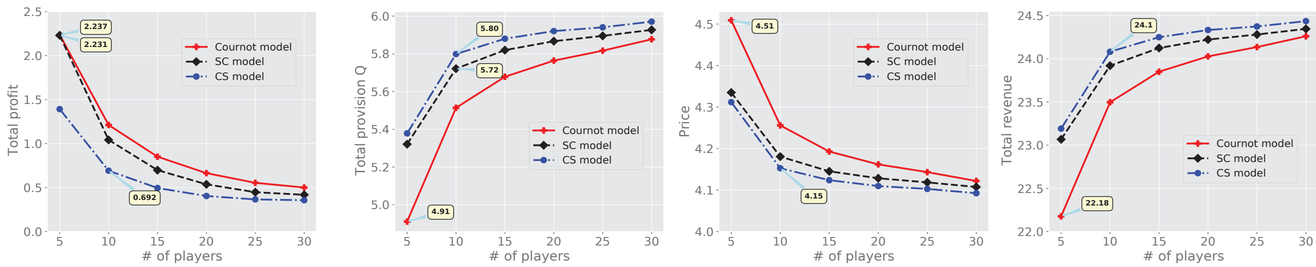
The first group of experiments aims to study the performance improvement of cross-silo FL due to our proposed incentive scheme. The results of training accuracy in three game models are shown in Fig. 4. Since the work [2] only considers a single type of resource and does not target the learning performance, we choose random resource provision with fixed Q as our baseline. From Fig. 4, we can observe that NE solutions of three models achieve better training accuracy than the random baseline. The average improvements are separately 28.1%, 28.3%, and 44.3% after 20 communication rounds. In addition, the accuracy of random schemes might degrade after a few communication rounds. Since we need to set Q in baseline as the NE solution for fairness concern, at least one participant with low data quality exists and lowers the accuracy of global model after the global model starts to learn some trivial details of training data.

The other group of experiments focuses on comparisons of three game models. In Fig. 5, there are several takeaways from our results: (1) the coordinator's profit in SC model is larger than that in Cournot model while the profit of coordinator in CS model is the smallest among three models. This result indicates that the coordinator prefers to choose SC model to maximize its profit when it dominates the incentive model selection; (2) the total provisions Q in SC model and CS model are similar, and both of them are larger than that in Cournot model. It indicates that Stackelberg game incurs much competition among players, which are also proved by the results of participants; (3) The profit of participant in Cournot model dominates the other two models, while the quantity

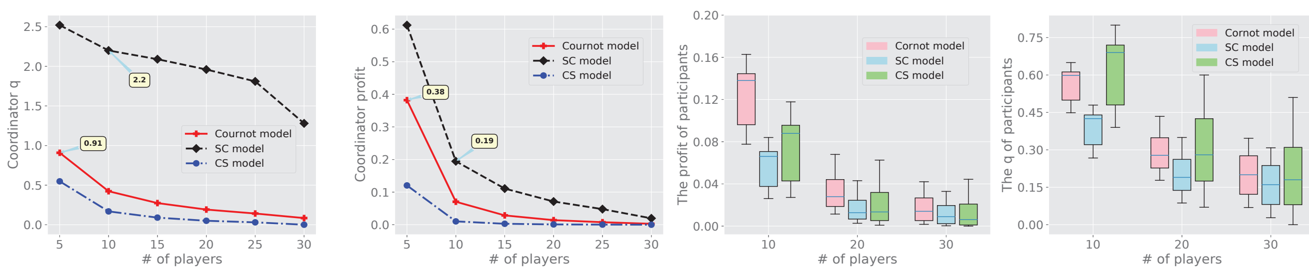


(a) Cournot model (b) SC model (c) CS model (d) Loss

Fig. 4. The accuracy improvement and loss for three proposed models



(a) Total profit (b) Total provision Q (c) Price (d) Total Revenue



(e) Coordinator's provision q_0 (f) Coordinator's profit π_0 (g) Participant's profit (h) Participant's quantity

Fig. 5. The comparisons among our three models

provision of participant in Cournot model lies between SC model and CS model; and (4) system designers can choose distinct models to achieve their goals like large resource quantity Q, the increased profit of coordinator, small total payment, etc.

V. Related Work

1) Shapley Value: Shapley value is adopted by contribution evaluation and payment allocation. Instead of quantifying multi-dimensional resource provisions, Shapley value considers the contribution from the utility or after-effects of recruited resources on the FL training performance. The Shapley value of each participant, referred to as its contribution, is the weighted average of marginal impacts on FL training performance with and without its resource provision in different participant subsets. Unfortunately, the computation complexity of Shapley value is NP-hard and one possible solution is to trade additional storage of local gradients for the calculation of contribution without the need of retraining each model [4].

The disclosure of user privacy is a potential threat to Shapley value in FL, where the direct adoption of Shapley value might reveal feature information or data distribution. One solution is to employ Shapley group value to measure the utility of a subset without revealing the data distribution of any specific participant. Furthermore, some techniques such as differential privacy and homomorphic encryption can be applied to enhance the privacy of FL. It is a promising direction to simultaneously protect user privacy in FL training and Shapley value calculation.

2) Stackelberg Game: Stackelberg game is a sequential game model commonly applied to formulate the interactions between different players in the sell or procurement of common products. In Stackelberg game, a player called leader moves first to declare its decision which optimizes its profit by considering the expected reactions of others. A player who moves after the leader is named as follower, and it observes the action of leader, optimizes its own profit, and responds to the leader. From the definition, we find that Stackelberg model can solve the payment allocation problem from a sequential game perspective.

Some issues require to be tackled when Stackelberg model is adopted in FL settings. (i) *What is the "common product" in FL?* One group of studies relates to training data. Intuitively, the simplest product is local data evaluated by its quantity, and the model owner trades rewards for data [5]. The second type of product is computation or communication resource. For example, Ding considered a multi-dimensional product of computation speed and start-up computation time [6]. (ii)

How to obtain NE solution with incomplete information? For incomplete information and stochastic information scenario, Ding found that the computation complexity of NE solution is increased with additional $N(N-1)$ IC constraints, where N is the total number of players [6]. In [5], Zhan used deep Reinforcement Learning (RL) to dynamically adjust players' strategies and optimize their profits in scenarios with incomplete information and ambiguous contribution. In fact, both heuristic algorithm and RL appeal to approximate NE solution in incomplete information scenarios. (iii) *Does the proposed model relate to the training performance?* [6] provides a performance-aware incentive scheme with Stackelberg game and shows that the optimal recovery threshold of MDS codes should be linearly proportional to the number of players N.

3) Auction: Auction is another efficient mathematical tool for payment allocation and node selection. When applying auction to FL, the model owner or global coordinator serves as a single auctioneer and orchestrates the auction process, while participants serve as bidders and respond to the auctioneer with various local resources and their bids. The winners in auction are chosen as the selected participants for FL training, and their payments are given based on their bids. Auction allows participants to actively report their true bids to maximize their profits, which makes it more fascinating for FL.

It is challenging to apply auction to FL in a computation-efficient way, and [3], [7], [8], and [14] are four representative studies on auction-based incentive schemes. Specifically, Zeng proposed a lightweight and multi-dimensional incentive scheme FMore with procurement auction of $K \leq N$ winners for FL in MEC [3]. In [8], Deng proposed a quality-aware auction scheme in a multi-task learning scenario. They innovatively formulated the winner selection problem as an NP-hard learning quality maximization problem and devised a greedy algorithm to perform real-time task allocation and payment distribution based on Myerson's theorem. Meanwhile, Zhou considered another practical scenario where clients are scheduled at different global iterations to assure the completion of FL job and proposed an auction approach to decompose the goal of social cost minimization into several winner selection problems which are further solved by greedy algorithm [14]. Actually, most of winner selection and payment allocation problems are computationally intractable, and randomized auction can be applied as an approximate solution for FL [7].

4) Contract Theory: Contract theory studies how players achieve optimal agreements with conflicting interests and different levels of information. In incentive mechanisms of FL, the global server/coordinator offers a list of contracts, each of which is a tuple of the quantity of resource provision and the corresponding payment to participants, without being informed about the private cost of participants. Then, each participant proactively picks a specific option designed for its type and performs local training with the chosen resource provision. The technique of contract embodies the self-revealing property which could elicit the optimal provisions from participants with the presence of information asymmetry.

The existing studies can be categorized into two groups, i.e., multi-dimensional contracts and contracts with different assumptions of information asymmetry. The first group of studies considers various resource provisions and applies multi-dimensional contracts to motivate participants in FL. For example, a 3-dimensional contract item might look like (communication bandwidth, computation power, data size, payment), and the coordinator provides a collection of such contract items to participants for their selection. The second group of studies assumes the information asymmetry between the task publisher and participants, since the private information of data size and various resources is unknown to the global coordinator [12].

5) Reinforcement Learning: As a prevalent learning technique, RL approaches to the optimal solution by successive decision-making trials. In FL training, the coordinator modelled as an agent performs the action of node selection or payment allocation to elicit high-quality participants to join in FL training. The agent iteratively makes decisions by trial and error and gets responses from participants (considered as rewards) to achieve the optimal training performance. From this formulation, the incentive process can be properly modeled by RL. Furthermore, we can adopt RL to derive approximation solutions in incentive design, since many incentive problems are NP-hard. In sum, RL can be innovatively applied to incentive design.

The existing studies of incentive schemes with RL can be classified into RL with discrete action space and RL with continuous action space. Most RL-based schemes with discrete action space focus on the node selection problem. The work [9] used the technique of double Deep Q Network (DQN) to select candidates to improve FL learning performance by counterbalancing the data distribution bias. Another example [7] also applied DQN to randomized multi-dimensional auction to improve social welfare in node selection. The other group of studies with continuous decision space mainly concentrates on contribution measurement and payment allocation in FL. For instance, an impressive work [15] proposed a fair and efficient contribution measurement approach with RL in a privacy-preserving manner. Zhan applied PPO algorithm to compute the payment of participant in Stackelberg game with incomplete information in [5].

6) Others: Some other studies include incentive design in cross-silo FL [2], the incentive of predication phase [11], fairness-aware and sustainable incentive design [10], robust and tamper-proof incentive scheme [10], etc. In [11], Weng firstly studied the incentive issue in the predication phase of FL, where the prediction accuracy and privacy are their top priority. In the cross-silo setting, Tang proposed an incentive scheme from a public goods perspective and formulated this problem as a social welfare maximization problem with non-convex objective function [2]. But [2] considers a single-dimensional product and neglects FL training improvement, both of which are the focus of our proposal.

VI. Conclusion

In this article, we provide a survey of incentive mechanism design for FL, from which we figure out four avenues for future investigation. Following two of them, we propose three game-theoretical models with multi-dimensional resource provisions to analyze the economical behaviors for cross-silo

FL. Our proposed models exemplify the multi-dimensional incentive design in a new scenario of cross-silo FL. Our experimental results demonstrate the training accuracy improvement by the proposed game-theoretical models, which conforms to our statement in the survey. The comparison results also imply some future research directions with different design goals in cross-silo FL.

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