Incentive Design for Efficient Federated Learning in Mobile Networks: A Contract Theory Approach

Jiawen Kang, Zehui Xiong, Dusit Niyato, *Fellow, IEEE*, Han Yu, Ying-Chang Liang *Fellow, IEEE* and Dong In Kim, *Fellow, IEEE*

Abstract—To strengthen data privacy and security, federated learning as an emerging machine learning technique is proposed to enable large-scale nodes, e.g., mobile devices, to distributedly train and globally share models without revealing their local data. This technique can not only significantly improve privacy protection for mobile devices, but also ensure good performance of the trained results collectively. Currently, most the existing studies focus on optimizing federated learning algorithms to improve model training performance. However, incentive mechanisms to motivate the mobile devices to join model training have been largely overlooked. The mobile devices suffer from considerable overhead in terms of computation and communication during the federated model training process. Without well-designed incentive, self-interested mobile devices will be unwilling to join federated learning tasks, which hinders the adoption of federated learning. To bridge this gap, in this paper, we adopt the contract theory to design an effective incentive mechanism for simulating the mobile devices with high-quality (i.e., high-accuracy) data to participate in federated learning. Numerical results demonstrate that the proposed mechanism is efficient for federated learning with improved learning accuracy.

Index Terms—Federated learning, contract theory, incentive mechanism, mobile networks.

I. INTRODUCTION

With the rapidly improving computation and communication capabilities of mobile devices, many novel mobile applications based on machine learning techniques, e.g., Google Translate APP, are emerging to bring excellent experience to mobile users [1]. Although the machine learning techniques dramatically enhance the performance of mobile applications, traditional machine learning techniques require mobile devices to directly upload user data with potentially sensitive private information to a central server for model training [2]. This causes not only large computation and storage overhead, but also serious risk of privacy breach due to the centralized entity suffering from single point of failure [3]. To solve these challenges, an emerging distributed machine learning technique named federated learning is introduced to allow mobile devices to jointly train a shared global model in a decentralized manner. The mobile devices only send local model updates trained on their local raw data to a task publisher of federated learning without uploading any raw data, thus decoupling the machine learning from acquiring, storing and training data in a central server [4].

With the significant advantages in privacy protection, federated learning has attracted increasing attention from researchers and developers recently. Google designed a virtual keyboard application named Gboard for smart phones by using federated learning [5]. The authors in [1] further discussed architecture and potential applications about federated learning. The authors in [4] formulated an optimization problem of federated learning over wireless networks to obtain optimal learning time, accuracy level, and energy cost. A deep Q learning algorithm is used to solve the optimal data and energy management problems of federated learning without prior knowledge of network dynamics in [6]. Considering clients with heterogeneous resources, the authors in [7] proposed a client selection scheme for federated learning based on a greedy algorithm.

The aforementioned studies have specifically focused on optimizing the performance of federated learning algorithms, e.g., learning time or energy cost. However, the most existing work made an optimistic assumption that all the mobile devices will unconditionally participate in federated learning when invited [8], [9], which is not practical in the real world due to resource costs incurred by model training [10]. Without well-designed economic compensation, the self-interested mobile devices will be reluctant to participate in federated learning [4], [9]. Moreover, there exist the following information asymmetry issues between the task publisher and the mobile devices. I) The task publisher does not know the amount of available computation resources and the data sizes from mobile devices for model training. II) The local data quality of a mobile device is unknown to the task publisher due to the lack of prior knowledge. As a result, the task publisher may incur a high cost when providing incentives to the mobile devices. Therefore, it is essential for the task publishers to design an efficient incentive mechanism to reduce the impact of information asymmetry [1], [6].

In this paper, to attract mobile devices with high-quality data to join federated learning and overcome the information asymmetry issue, we adopt the contract theory to design an efficient incentive mechanism that maps the contributed resources into appropriate rewards. The data owners (i.e., mobile devices) with larger-accuracy local data and more resource contributions can obtain more rewards from the task

Jiawen Kang, Zehui Xiong, Dusit Niyato and Han Yu are with School of Computer Science and Engineering, Nanyang Technological University, Singapore. Emails: {kavinkang, dniyato, han.yu}@ntu.edu.sg and zxiong002@e.ntu.edu.sg. Ying-Chang Liang is with Center for Intelligent Networking and Communications, University of Electronic Science and Technology of China, China. Email: liangyc@ieee.org. Dong In Kim is with School of Information & Communication Engineering, Sungkyunkwan University, Korea. Email: dikim@skku.ac.kr.

publisher. Each data owner chooses its desired contract item to maximize its profit [10]. The main contributions of this paper are listed as follows:

- We design an effective incentive mechanism using contract theory to stimulate mobile devices to join federated model training under information asymmetry.
- To attract data owners with high-quality data, we define the accuracy-related parameter of local data as the type of the contract model. The higher type data owners that have larger-accuracy local data can receive more rewards.
- We perform the real-world experiments using the well-known digit classification dataset to demonstrate that the proposed mechanism outperforms existing approaches.

The rest of this paper is organized as follows. The problem formulation and solutions for contract theory model are introduced in Section II and Section III, respectively. Numerical results are presented in Section IV followed by the conclusions in Section V.

II. PROBLEM FORMULATION

Similar to that in [4], we consider a universal mobile network with wireless communication infrastructures and a set of mobile devices. These widely distributed communication infrastructures, e.g., base stations, can act as task publishers with federated learning tasks, while the mobile devices are data owner candidates for the learning tasks. The mobile devices equipped with advanced computation and communication functions can not only generate diverse user data from mobile applications, but also collect a lot of sensing data. Each task publisher designs contract items for incentivizing mobile devices with high-quality data to join federated learning. Every data owner iteratively trains a shared global model with local model updates generated using their private local data. Then, all the data owners upload their local model updates to the task publisher for updating the global model. The training process is repeated until the accuracy of the global model achieves a pre-defined, desirable value. More details about the basics of federated learning can be found in [4], [2].

A. Computation Model for Federated Learning

We consider a federated learning task as a monopoly market with a monopolist operator (a task publisher) and a set of mobile devices $\mathcal{N} = \{1, \ldots, N\}$. Each data owner $n \in \mathcal{N}$ with a local training dataset uses a size s_n of its local data samples to participate in the federated learning task. There is an input-output pair in each data sample, in which the input is a sample vector with various data features and the output is the label value for the input generated through mobile apps [4]. The contributed computation resources for local model training, i.e., CPU cycle frequency, from the data owner n is denoted as f_n. The number of CPU cycles for a data owner n to perform local model training using a single data sample [1] is denoted by c_n. Hence, for data owner n, the computation time of a local iteration in local model training is $\frac{c_n s_n}{f_n}$. According to [4], the CPU energy consumption for one local iteration is

$E_n^{cmp}(f_n) = \zeta c_n s_n f_n^2$, where ζ is the effective capacitance parameter of the computing chipset for data owner n.

B. Communication Model for Federated Learning

For a federated learning task, all the participating data owners collaborate to train a shared global model and achieve a global accuracy level of learning by an iterative method with a number of communication rounds (i.e., global iterations). During a global iteration, the data owners send their own local model updates to the task publisher through wireless communications. Each local model update achieves a local accuracy of ε_n corresponding to the local data quality of data owner n. Note that a higher local accuracy leads to fewer local and global iterations [11]. Given the target local accuracy, the number of local iterations is $\log(\frac{1}{\varepsilon_n})$ [4], [11]. The computation time of a local iteration and uplink communication time[2] of a local model update are involved in a global iteration. The computation time of a local iteration by data owner n is denoted by $T_n^{cmp} = \frac{c_n s_n}{f_n}$. For the communication time of local model updates, time-sharing multi-access protocols, e.g., Time-Division Medium Access (TDMA) technology, are taken into consideration in this paper. We consider that the locations of data owners are fixed when transmitting local model parameters. The transmission rate of data owner n is denoted as $r_n = B\ln(1 + \frac{\rho_n h_n}{N_0})$ [4]. Here, B is the transmission bandwidth and ρ_n is the transmission power of the data owner n. h_n is the channel gain of peer-to-peer link between data owner n and the task publisher. N_0 is the background noise. We consider the data size of a local model update σ to be a constant with the same value for all data owners. The transmission time of a local model update with size σ is expressed by $T_n^{com} = \frac{\sigma}{B\ln(1 + \frac{\rho_n h_n}{N_0})}$.

Therefore, the total time of participating in one global iteration for the data owner n is denoted as

$$T_n^t = \log(\frac{1}{\varepsilon_n})T_n^{cmp} + T_n^{com}. \tag{1}$$

According to [4], the energy consumption by data owner n to transmit local model updates in a global iteration is expressed as $E_n^{com} = T_n^{com} \cdot \rho_n = \frac{\sigma \rho_n}{B\ln(1 + \frac{\rho_n h_n}{N_0})}$. Therefore, for a global iteration, the total energy consumption of the data owner n is denoted as follows:

$$E_n^t = \log(\frac{1}{\varepsilon_n})E_n^{cmp} + E_n^{com}. \tag{2}$$

C. Profit Function of the Task Publisher

To attract more data owners with high-quality data (i.e., high-accuracy and reliable local data), we define a parameter about data quality as the type of a data owner n, which is denoted as $\theta_n = \frac{\psi}{\log(\frac{1}{\varepsilon_n})}$. Here, ψ is the coefficient about the number of local model iterations affected by the local data accuracy. The data owners are divided into M types sorted in ascending order of data quality: $\theta_1 < \cdots < \theta_m < \cdots <$

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[1] We consider that each data sample has the same data size.

[2] We consider that the downlink time between the task publisher and the data owners is negligible compared with the uplink time as typically the downlink bandwidth is much larger than the uplink bandwidth.

$\theta_M, m \in \{1, \ldots, M\}$. <mark>A larger θ_m means better data quality with higher accuracy leading to fewer local model iterations [7], [12].</mark> Although the task publisher does not know exactly true type of a given data owner, it has the knowledge of the probability that a data owner belongs to a certain type-m [13] and $\sum_{m=1}^{M} p_m = 1$. The task publisher obtains the distribution of data owner types from previous observations [14].

Due to information asymmetry, the task publisher should design specific contracts for different types of data owners with different levels of data quality to increase its profits. The task publisher offers different resource-reward bundles to the data owners according to their types. For different data owners with different computation resources, i.e., CPU cycle frequency, the task publisher offers the contract $(R_n(f_n), f_n)$ including a series of resource-reward bundles. Here, f_n is the computation resource of type-n a data owner and $R_n(f_n)$ is the corresponding reward for the data owner. The more contributed computation resource leads to faster local model training, thus bringing higher rewards. The data owners choose and sign one of the provided contracts at will and finish the given federated learning task. If a data owner cannot finish the learning task or misbehaves, the task publisher will put the data owner into a blacklist and withhold payment.

For a signed contract $(R_n(f_n), f_n)$, we define the profit of the task publisher obtained from a type-n data owner as $U_{TP}(R_n) = \omega \ln(T_{\max} - T_n^t) - lR_n$, where $\omega > 0$ is the satisfaction degree parameter of task publisher. T_{max} is the task publisher's maximum tolerance time of federated learning, and l is the unit cost about the rewards for the data owners. $[\omega \ln(T_{\max} - T_n^t)]$ is the satisfaction function of the task publisher regarding the total time of one global iteration for type-n data owner. Note that both the higher accuracy (higher type) and larger CPU cycle frequency can improve the profit for the task publisher, i.e., $\frac{\partial U_{TP}}{\partial \varepsilon_n} > 0$, $\frac{\partial U_{TP}}{\partial \theta_n} > 0$ and $\frac{\partial U_{TP}}{\partial f_n} > 0$. Moreover, for the task publisher, more high-type data owners joining the federated learning lead to more profit, but also incur larger reward cost lR_n. Apparently, the task publisher will not accept a negative profit when performing the federated learning task, i.e., $U_{TP}(R_n) \geq 0$. The objective of the task publisher is to maximize its profit in the federated learning task defined as follows:

$$\max_{(R_n, f_n)} U_{TP} = \sum_{n=1}^{N} N p_n \cdot w \ln[T_{\max} - (\frac{\sigma}{B \ln(1 + \frac{\rho_n h_n}{N_0})} + \frac{\psi}{\theta_n} \cdot \frac{c_n s_n}{f_n})] - lR_n. \quad (3)$$

D. Utility Function of Data Owners

The utility function of a type-n data owner for the signed contract $(R_n(f_n), f_n)$ is defined as: $U_D(f_n) = R_n - \mu E_n^t = R_n - \mu \left[\frac{\psi}{\theta_n}\zeta c_n s_n f_n^2 + E_n^{com}\right]$, where μ is a pre-defined weight parameter for energy consumption. We consider that every data owner is self-interested and the valuation of U_D is zero when there is no reward [13]. Intuitively, the higher-type data owners have larger utility since they provide better quality data. The data owner also wishes to minimize energy consumption when performing the federated learning task for maximizing its utility. The overall goal of a type-n data owner

is expressed by

$$\max_{(R_n, f_n)} U_D = R_n - \mu \left[\frac{\psi}{\theta_n}\zeta c_n s_n f_n^2 + \frac{\sigma \rho_n}{B \ln(1 + \frac{\rho_n h_n}{N_0})}\right]. \quad (4)$$

III. Optimal Contract Designing

With information asymmetry, to make contracts feasible, each contract must satisfy the following constraints: i) Individual Rationality (IR) and ii) Incentive Compatibility (IC) in order to ensure that each type of data owners are properly motivated [13].

Definition 1. Individual Rationality: A data owner only participates in the federated learning task when its utility is not less than zero, i.e.,

$$U_D = R_n - \mu \left[\frac{\psi}{\theta_n}\zeta c_n s_n f_n^2 + \frac{\sigma \rho_n}{B \ln(1 + \frac{\rho_n h_n}{N_0})}\right] \geq 0. \quad (5)$$

Definition 2. Incentive Compatibility: To maximize utility, every data owner can only choose the contract designed for itself, i.e., type θ_n instead of any other contracts (R_m, f_m), i.e.,

$$R_n - \mu[\frac{\psi}{\theta_n}\zeta c_n s_n f_n^2 + \frac{\sigma \rho_n}{B \ln(1 + \frac{\rho_n h_n}{N_0})}] \geq R_m - \mu[\frac{\psi}{\theta_m}\zeta c_n s_n f_n^2$$
$$+ \frac{\sigma \rho_n}{B \ln(1 + \frac{\rho_n h_n}{N_0})}], \forall n, m \in \{1, \ldots, N\}, n \neq m. \quad (6)$$

In what follows, for simplicity, we consider $\mu = 1$. Without loss of generality, we consider the transmission bandwidth, transmission power, and the channel gain for all the data owners to be identical due to similar wireless communication environments [4], and thus we have $E_1^{com} = \cdots = E_n^{com} = \frac{\sigma \rho_0}{B \ln(1 + \frac{\rho_0 h_0}{N_0})}, n \in \{1, \ldots, N\}$. For ease of presentation, the optimization problems in (3) and (4) can be reformulated as

$$\max_{(R_n, f_n)} U_{TP} = \sum_{n=1}^{N} N p_n \left[w \ln(T_{\max} - T_n^{com} - \frac{\psi T_n^{cmp}}{\theta_n}) - lR_n\right],$$
s.t.
$$R_n - (\frac{\psi}{\theta_n} E_n^{cmp} + E_n^{com}) \geq 0, \forall n \in \{1, \ldots, N\},$$
$$R_n - (\frac{\psi}{\theta_n} E_n^{cmp} + E_n^{com}) \geq R_m - (\frac{\psi}{\theta_n} E_m^{cmp} + E_m^{com}),$$
$$\forall n, m \in \{1, \ldots, N\}, n \neq m,$$
$$\frac{c_n s_n}{f_n} \leq T_{\max}, \forall n \in \{1, \ldots, N\},$$
$$\sum_{n=1}^{N} N \cdot p_n \cdot R_n \leq R_{\max}, \forall n \in \{1, \ldots, N\}, \quad (7)$$

where R_{max} is the total reward budget of the task publisher. Although the problem in (7) is not a convex optimization problem, its solution can be found by performing the following transformation.

According to the above definitions, we have the following lemmas.

Lemma 1 (Monotonicity). For contract (R_n, f_n) and (R_m, f_m), we have $f_n \geq f_m$ and $R_n \geq R_m$, if and only if $\theta_n \geq \theta_m$, $n \neq m$, and $n, m \in \{1, \ldots, N\}$.

Lemma 2. If the IR constraint of type-1 is satisfied, the other IR constraints will also hold.

Lemma 3. According to the monotonicity in **Lemma 1**, the IC condition can be reduced as the Local Downward Incentive

Constraints (LDIC) that is expressed as $R_n - \frac{\psi}{\theta_n} E_n^{cmp} \geq R_{n-1} - \frac{\psi}{\theta_n} E_{n-1}^{cmp}, \forall n \in \{2, \ldots, N\}$.

The proofs of **Lemma 1**, **2**, and **3** are similar to those in the [12]. Based on the analysis of these lemmas, the optimization problem in (7) is simplified as follows:

$$\max_{(R_n, f_n)} U_{TP} = \sum_{n=1}^{N} N p_n \left[w \ln(T_{\max} - T_n^{com} - \frac{\psi T_n^{cmp}}{\theta_n}) - l R_n \right],$$
$$\text{s.t.}$$
$$R_n - \frac{\psi}{\theta_n} E_n^{cmp} - E_n^{com} = 0, \forall n \in \{1, ..., N\},$$
$$R_n - \frac{\psi}{\theta_n} E_n^{cmp} = R_{n-1} - \frac{\psi}{\theta_n} E_{n-1}^{cmp}, \forall n \in \{2, ..., N\},$$
$$\frac{c_n s_n}{f_n} \leq T_{\max}, \forall n \in \{1, \ldots, N\},$$
$$\sum_{n=1}^{N} N \cdot p_n \cdot R_n \leq R_{\max}, \forall n \in \{1, \ldots, N\}.$$
$$(8)$$

To derive the optimal contracts in the problem (8), we first solve the relaxed problem in (8) without monotonicity constraint. Subsequently, this acquired solution is checked whether it satisfies the monotonicity condition. By using the iterative method on *IC* and *IR* constraints, we can obtain the reward which is expressed as $R_n = E_n^{com} + \frac{\psi E_1^{cmp}}{\theta_1} + \sum_{k=1}^{n} \Delta_k$, where $\Delta_k = \frac{\psi E_k^{cmp}}{\theta_k} - \frac{\psi E_{k-1}^{cmp}}{\theta_k}$ and $\Delta_1 = 0$. By substituting R_n into $\sum_{n=1}^{N} N \cdot p_n \cdot l R_n$, we can obtain

$$\sum_{n=1}^{N} N \cdot p_n \cdot l R_n = N l E_n^{com} + N l \zeta \sum_{n=1}^{N} g_n c_n s_n f_n^2, \quad (9)$$

where $g_n = \begin{cases} \frac{\psi P_n}{\theta_n} + (\frac{\psi}{\theta_n} - \frac{1}{\theta_{n+1}}) \sum_{i=n+1}^{N} p_i, & n < N, \\ \frac{\psi P_N}{\theta_N}, & n = N. \end{cases}$

By substituting (9) into the problem in (8) and also removing all R_n, we can rewrite (8) as

$$\max_{(R_n, f_n)} U_{TP} = \sum_{n=1}^{N} N p_n \left[w \ln(T_{\max} - \frac{\sigma}{B \ln(1 + \frac{\rho_n h_n}{N_n})} - \frac{\psi c_n s_n}{f_n \theta_n}) \right]$$
$$- \frac{N l \sigma \rho_n}{B \ln(1 + \frac{\rho_n h_n}{N_n})} - N l \zeta \sum_{n=1}^{N} c_n s_n g_n f_n^2,$$
$$\text{s.t.}$$
$$\frac{c_n s_n}{T_{\max}} \leq f_n, \forall n \in \{1, \ldots, N\},$$
$$\frac{N \sigma \rho_n}{B \ln(1 + \frac{\rho_n h_n}{N_n})} + N \zeta \sum_{n=1}^{N} c_n s_n g_n f_n^2 \leq R_{\max}, \forall n \in \{1, \ldots, N\}.$$
$$(10)$$

By differentiating U_{TP} with respect to f_n, we can obtain $\frac{\partial^2 U_{TP}}{\partial f_n^2} < 0$, and thus U_{TP} is concave. The summation of concave functions (U_{TP}) is still a concave function, and hence the problem in (10) with affine constraints is a concave optimization problem. With the help of convex optimization tools, e.g., CVX, we can calculate the optimal computation resource, i.e., contributed CPU-cycle f_n^* and the corresponding incentive R_n^* [12]. In addition, the monotonicity can be automatically met when the types of data owners follow uniform distribution. If the distribution of data owners' types is not uniform, we can utilize the infeasible sub-sequence replacing algorithm to meet the final optimal computation resource requirement [12], [15].
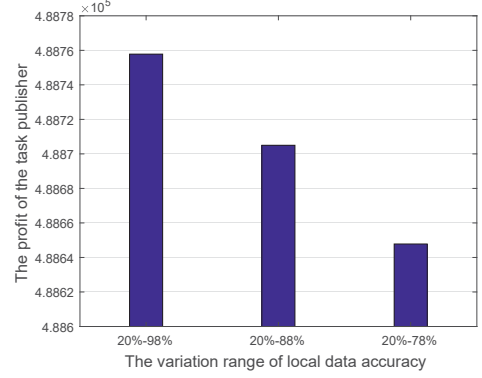

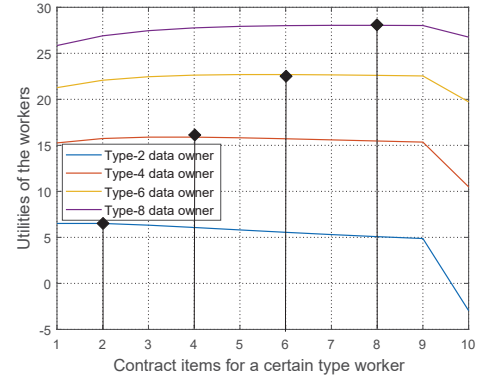Fig. 1: The profit of the task publisher with respect to different accuracy levels of local training data.

Fig. 2: Utilities of data owners with different contract items.

IV. NUMERICAL RESULTS

In the simulation, a well-known digit classification dataset named MNIST is used to evaluate the performance of the proposed incentive schemes. This dataset includes 60,000 training examples and 10,000 test examples, which can be used to perform a digit classification task. We consider a task publisher and 100 data owners in the federated learning tasks. The data owners are randomly assigned a training set following a uniform distribution over 10 classes as their own local training data. The accuracy of local data ranges from 20% to 92%. The CPU cycles of performing a data sample c_n is 5 and the size of data samples s_n is 20. The transmission time T_n^{com} and energy consumption E_n^{com} for transmitting a local model update are 10 and 20, respectively. The maximum tolerance time T_{max} and the total amount of given reward R_{max} of a federated learning task are 600 and 10,000, respectively. Moreover, the data owners are initially classified into 10 types according to accuracy-related parameters of local training data, and the probability for a candidate belonging to a certain type is 0.1 [12].

To show the impacts of the variation range of local training data accuracy on the profit of task publisher, we vary the upper limit of local data accuracy (i.e., a parameter related to the data owner type) from 98% to 78%, respectively. As shown in Fig. 1, the profit of the task publisher decreases with the decrease of the upper limit of local data accuracy. As reducing upper limit of the local data accuracy means that the number of
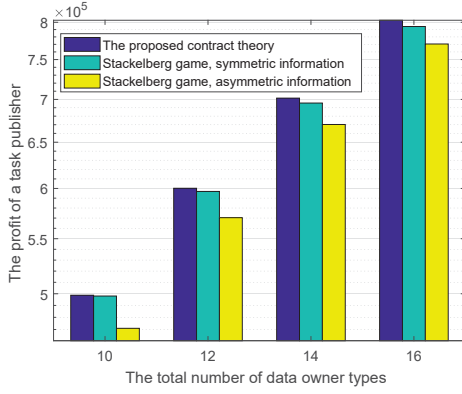
Fig. 3: The profit of a task publisher with respect to different total number of data owner types

high-type data owners is decreasing. Therefore, the low-quality of local training data has a negative impact on the profit of the task publisher. Therefore, the proposed schemes can stimulate data owners with high-quality data to join learning tasks, hence leading to more efficient federated learning.

To validate the feasibility, i.e., IR and IC, of the proposed scheme under information asymmetry, we present Fig. 2 to show the utilities of data owners with types 2, 4, 6 and 8, respectively [15]. From Fig. 2, we observe that all types of data owners can only achieve their own maximum utility when they choose the contract item exactly designed for their types, which explains the IC constraint [12]. Moreover, each data owner can obtain nonnegative utility when selecting the contract item corresponding to its type, which validates the IR constraint.

We compare the profit of the task publisher obtained from the proposed contract theory model, and that from the Stackelberg game model in [15]. Figure 3 shows that the larger total number of data owner types leads to the larger profit of a task publisher. The more data owner types bring more contract item choices to high-type data owners, thus ensuring more efficient federated learning. For a certain number of data owner types, the profit of the task publisher in the proposed contract model is higher than that of the Stackelberg game model [12]. The reason is that, in the monopoly market, the task publisher working as the monopolist only provides limited contract items to the data owners and extracts more profit from the data owners. Nevertheless, in the Stackelberg game model, rational data owners can optimize their individual utilities resulting in less profit for the task publisher. Although the task publisher needs to consider the IR and IC constraints during designing the contract items, these constraints have a small impact on maximizing the utilities of the data owners compared with the Stackelberg game model [16]. As a result, the task publisher can obtain the higher profit than that in the Stackelberg game models [12]. Moreover, the Stackelberg game model with symmetric information has better performance than that of Stackelberg game model with asymmetric information. The reason is that the game leader (the task publisher) in the Stackelberg game with symmetric information can optimize its profit because of knowledge about the actions of followers (data owners), i.e., the symmetric information, and set the utilities of the followers to zero [15].

V. CONCLUSIONS

In this paper, we designed a contract theory-based incentive mechanism to motivate data owners that have high-accuracy local training data to join the learning processes for efficient federated learning. Numerical results have indicated that the proposed incentive scheme can attract more data owners with high-quality local training data to ensure efficient federated learning and also optimize the utilities of both the task publishers and the data owners. For further work, we will consider using blockchains to ensure reliability of local model updates when formulating the incentive mechanism for reliable federated learning in mobile networks [17], [18], [19], [20].

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