A Fairness-aware Incentive Scheme for Federated Learning

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ABSTRACT

In federated learning (FL), data owners "share" their local data in a privacy preserving manner in order to build a federated model, which in turn, can be used to generate revenues for the participants. However, in FL involving business participants, they might incur significant costs if several competitors join the same federation. Furthermore, the training and commercialization of the models will take time, resulting in delays before the federation accumulates enough budget to pay back the participants. The issues of costs and temporary mismatch between contributions and rewards have not been addressed by existing payoff-sharing schemes. In this paper, we propose the Federated Learning Incentivizer (FLI) payoff-sharing scheme. The scheme dynamically divides a given budget in a context-aware manner among data owners in a federation by jointly maximizing the collective utility while minimizing the inequality among the data owners, in terms of the payoff gained by them and the waiting time for receiving payoffs. Extensive experimental comparisons with five state-of-the-art payoff-sharing schemes show that FLI is the most attractive to high quality data owners and achieves the highest expected revenue for a data federation.

CCS CONCEPTS

• **Information systems** → **Incentive schemes**; • **Security and privacy**; • **Computing methodologies** → *Artificial intelligence*;

KEYWORDS

federated learning; incentive mechanism design

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1 INTRODUCTION

In traditional machine learning, the training dataset is usually stored in a central entity. Data need to be first collected from the data sources in order to facilitate learning. The rapid development of artificial intelligence (AI) has benefited from large-scale training data in real-world application. As AI becomes increasingly ubiquitous, nations are increasingly concerned about AI governance and privacy protection. They instituted new legislations such as the General Data Protection Regulation (GDPR) [2] for these purposes. These new laws can potentially limit the development of AI in the long run. Federated Learning (FL) [16] has been proposed to enable AI to continue developing in this new regulatory landscape.

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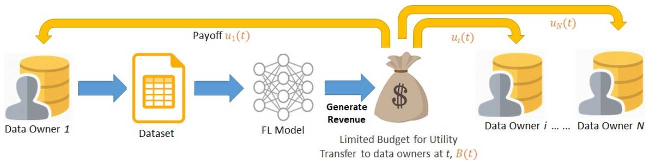


Figure 1: The transfer of utility in FL.

FL focuses on data integration methods which comply with privacy and security laws [22]. Under federated learning, *data owners* employ privacy protection techniques such as homomorphic encryption [19], secret sharing [5] and differential privacy [20] to contribute model parameters trained on their own datasets to a *federation*. The federation then combines these local model parameters using techniques such as Federated Averaging [16] and federated transfer learning [9] in order to train more effective collectively machine learning model. This allows the learning process to leverage the computational power of the data sources to train the model in a process similar to crowdsourcing [7]. Recently, Google has released the Tensorflow Federated[1] toolkit to support the development FL applications. The technology has been applied to improve Google's keyboard query suggestions by leveraging millions of mobile phone users in a privacy-preserving manner.

For a federation, data owners' continued participation in the federated learning process (through sharing of encrypted model parameters) is key to its long-term success. Existing federated learning platforms such as Tensorflow Federated and the Federated AI Technology Enabler (FATE)[2] assume that the federation already has a readily available group of participating data owners and do not provide any incentive mechanism to motivate participation. Such an assumption may not hold in practice, especially when data owners are companies rather than individuals.

The contributions by data owners to a federation are used to build a machine learning model which, in turn, can be used to generate revenue. Thus, the federation can allocate part of the revenue to data owners as incentives (Figure 1). The research question here is how to quantify the payoff for each data owner in order to achieve long-term systemic wellbeing. In order to address this problem, a payoff-sharing scheme developed specially for federated learning is needed. In game theoretic research, a number of payoff-sharing schemes exist. Standard coalition games with transferable utility [8]. Auctions, lotteries, and reputation can also be used to incentivize participation [14]. Payoff-sharing games such as the Labour union game and the Shapley game share payoff among players according to their marginal contribution in a coalition[3, 10].

In FL, participants need to incur some cost for contributing to the FL models with their local datasets. This cost might not be significant in scenarios involving only individual users (e.g., [16]). However, when companies from the same business sector join FL, contributing their data to train a federated model which is subsequently shared with potential competitors can incur significant opportunity costs to a company [12, 23]. From our anecdotal experience, companies are generally reluctant to join FL under such conditions without a satisfactory compensation arrangement. Even when costs are accounted for, there is another problem. The training and commercialization of the models will take time. Thus, there will be some delays before the federation has enough budget to pay back the participants. This temporary mismatch between contributions and rewards has not been accounted for by existing payoff-sharing schemes.

In order to sustain long-term stability in a data federation and attract more high quality data owners over time, a fair incentive mechanism suitable for the federated learning context is needed [22]. For this purpose, we propose a dynamic payoff-sharing scheme - Federated Learning Incentivizer (FLI). It is a polynomial time algorithm that can compute solutions for payoff-sharing by instalment in order to achieve fair treatment among data owners. It dynamically divides a given budget among data owners in a federation by jointly maximizing the collective utility generated while minimizing the inequality among the data owners in terms of the payoff and the waiting time for receiving the full payoff. Once the cost incurred by a data owner is fully compensated, FLI continues to pay the data owner following the baseline payoff-sharing scheme adopted by the federation (which are explained in more detailed in the Related Work section).

We make the following contributions in this paper:

(1) We model and describe the problem of motivating participation by high quality data owners with incentives in the context of federated learning.
(2) We provide a real-time algorithm to jointly achieve three fairness criteria (1. contribution fairness, 2. regret distribution fairness, and 3. expectation fairness), which are important to federated learning; and account for the interest of both the federation and the participating data owners.
(3) We have extensive experimental comparisons with five existing payoff-sharing schemes show that FLI is the most attractive to high quality data owners and least attractive to low quality data owners, and achieves the highest expected revenue, thereby sustaining the long-term wellbeing of a data federation.

To the best of our knowledge, this paper is the first to study the issue of motivating continued participation by businesses into FL, considering more factors than just their contributions. It provides a framework to sustain participation by business data owners into FL to empower privacy-preserving AI.

2 RELATED WORK

The problem studied in this paper is related to the field of distributed welfare games [15]. In a typical distributed welfare game, each player can select a subset of resources to generate welfare. The resulting welfare may depend on the subset of players who chose this resource, and the welfare generated at

[1] https://www.tensorflow.org/federated
[2] https://github.com/WeBankFinTech/FATE

each resource is distributed among players who select it at the same time. Research in this field mainly focused on designing efficient schemes to fairly form coalitions by players in a distributed manner to reach (approximate) Nash equilibria.

Similar research problems have also been studied under the topic of cost-sharing games. Most existing works in this field investigate how to design cost-sharing mechanisms in the context of congestion games in order to achieve efficient resource utilization [13, 21]. Other approaches design scheduling rules to address similar problems in this domain [6].

The research most closely related to our problem comes from the topic of profit-sharing games. In general, there are three categories of widely used profit-sharing schemes:

(1) Egalitarian: any unit of utility produced by a data federation is divided equally among the data owners who help produce it.
(2) Marginal gain: the payoff of a data owner in a data federation is the utility that the team gained when the data owner joined.
(3) Marginal loss: the payoff of a data owner in a data federation is the utility that the team would lose if the data owner were to leave.

In general, a participant i's share of payoff from a total budget $B(t)$ in a given round of profit-sharing t, denoted as $\hat{u}_i(t)$, is computed as:

$$\hat{u}_i(t) = \frac{u_i(t)}{\sum_{i=1}^{N} u_i(t)} B(t) \tag{1}$$

where $u_i(t)$ is i's share of $B(t)$ among the peers computed following a given scheme.

Equal division is an example of egalitarian profit-sharing [24]. Under this scheme, the available profit-sharing budget, $B(t)$, at a given round t is equally divided among all N participants. Under the Individual profit-sharing scheme [24], each participant i's own contribution to the collective (assuming the collective only contains i) is used to determine his share of the profit. The Labour Union game [10] profit-sharing scheme determines i's share of $B(t)$ based on his marginal contribution to the utility of the collective formed by his predecessors F (i.e. each participant's marginal contribution is computed based on the sequence they joined the collective).

The Shapley game profit-sharing scheme [3] is also a marginal contribution-based scheme. Unlike the Labour Union game, Shapley game aims to eliminate the effect of the participants joining the collective in different sequences in order to more fairly estimate their marginal contributions to the collective. Thus, it averages the marginal contribution for each i under all different permutations of the i joining the collective relative to other participants. [11] computes a Shapley value to split rewards among data owners. Such computations tend to be expensive.

These schemes are useful as baseline approaches to help a federation evaluate the contribution from a data owner. However, none of them accounts for the fairness of distributing profit over time with multiple contributions to a federation.

3 THE FLI SCHEME

In this section, we introduce the federated learning system model and derive the FLI payoff-sharing scheme.

3.1 Modelling Contribution

We assume that the data federation follows synchronous mode of model training commonly adopted by federated learning [4] in which data owners share their model parameters in rounds. In round t, a data owner i can contribute his local model trained on a dataset to a federation. The federation is able to assess the contribution of i's data contribution to the federation following one of the profit-sharing schemes discussed in the previous section as the FLI baseline scheme.

To do so, a federation can run a sandbox simulation to estimate the effect of a data owner's contribution on model performance. The outcome is recorded by a variable $q_i(t) \geqslant 0$, which denotes the expected marginal revenue the federated model can gain with i's latest contribution. FLI is fully decoupled from how such a contribution score is produced. Thus, we do not focus on the exact mechanism by which $q_i(t)$ is produced, and treat it as an input for FLI.

3.2 Modelling Cost

Let $c_i(t)$ be the cost for i to contribute $d_i(t)$ to the federation. There can be multiple ways to compute $c_i(t)$. Although it is possible to build computational models based on market research, a more practical solution is still auction-based self-report. A procurement auction [17] can be used to estimate the cost when $c_i(t)$ is privately known. Specifically, the federation can ask each data owner to request a payment for the data contribution, and then select which data owner shall be allowed to join the federation.

In this case, the delayed payment scheme can be separated from the procurement auction where $c_i(t)$ can be interpreted as the payment to data owner i determined by the auction. This way, a clear separation of concern between the auction stage and the proposed incentive scheme can be achieved. Since this paper focuses on developing the framework of incentive design for federated learning, we leave the topic of computing $c_i(t)$ to be treated in another work, and assume that this value is available here.

3.3 Modelling Regret

For each data owner i, the federation keeps track of the payoff gained from contributing data to the federation over time. As this value represents the difference between what the data owner has received so far and what he is supposed to receive, we refer to this term as *regret*, $Y_i(t)$. The dynamics of $Y_i(t)$ can be regarded as a queueing system:

$$Y_i(t+1) \triangleq \max[Y_i(t) + c_i(t) - u_i(t), 0]. \tag{2}$$

where $u_i(t)$ is the payoff to be transferred to i by the federation. A large value of $Y_i(t)$ indicates that i has not been adequately compensated.

3.4 Modelling Temporal Regret

In some cases, the cost $c_i(t)$ may be too large to be fully covered by a single payment of $u_i(t)$ due to budget limitation in the federation. In such cases, the federation needs to compute instalments to be paid out to the data owners in multiple rounds. Their share of the current payout budget, $B(t)$, depends on their regret as well as how long they have been waiting to receive the full payoff.

For this purpose, we complement equation (2) with a *temporal queue*, $Q_i(t)$, with queueing dynamics defined as:

$$Q_i(t+1) \triangleq \max[Q_i(t) + \lambda_i(t) - u_i(t), 0] \tag{3}$$

where $\lambda_i(t)$ is an indicator function:

$$\lambda_i(t) = \begin{cases} \hat{c}_i, & \text{if } Y_i(t) > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

This formulation means that as long as $Y_i(t)$ is not empty, the temporal queue, $Q_i(t)$, will increase. The increment is based on i's average cost of data contribution to the federation, $\hat{c}_i$, through past experience. Both queues decrease by the same amount when the federation pays i.

Equation (3) can be re-expressed as:

$$Q_i(t+1) \geqslant Q_i(t) + \lambda_i(t) - u_i(t). \tag{5}$$

Re-arranging the above inequality and summing both sides of the above inequality over all $t \in \{0, ..., T-1\}$ yields:

$$\sum_{t=0}^{T-1}[Q_i(t+1) - Q_i(t)] \geqslant \sum_{t=0}^{T-1}[\lambda_i(t) - u_i(t)]. \tag{6}$$

Since $Q_i(0) = 0$, the above inequality is simplified as:

$$\frac{Q_i(T)}{T} \geqslant \frac{1}{T}\sum_{t=0}^{T-1}\lambda_i(t) - \frac{1}{T}\sum_{t=0}^{T-1}u_i(t). \tag{7}$$

Based on equation (7), by ensuring that the computed $u_i(t)$ values satisfy the queueing stability requirement of $\frac{1}{T}\sum_{t=0}^{T-1}u_i(t) \geqslant \frac{1}{T}\sum_{t=0}^{T-1}\lambda_i(t)$ for the temporal queue, the profit-sharing approach can ensure that data owners are compensated not only for their data contributions, but also for waiting to receive the full payoff, thereby making it "worth their while" to attract them to the federation.

3.5 The Policy Orchestrator

In order to encourage data owners to continue participating in the federation, the federation needs to ensure that the data owners are treated fairly based on their individual contribution. Here, we define three fairness criteria that are important to the long-term sustainable operation of a federation:

(1) **Contribution Fairness**: a data owner i's payoff shall be positively related to his contribution $q_i(t)$;
(2) **Regret Distribution Fairness**: the difference of the regret and the temporal regret among data owners shall be minimized; and
(3) **Expectation Fairness**: the fluctuation of data owners' regret and temporal regret values shall be minimized.

In order to satisfy all the three fairness criteria, the federation shall maximize a "value-minus-regret drift" objective function over time. The collective utility derived from data owners' contributions is related to two factors: 1) the contribution to the federation by a data owner i ($q_i(t)$) and 2) the payoff that i receives from the federation for the contribution ($u_i(t)$). It is fair that a data owner who make significant contribution to the federation shall receive high payoff:

$$U = \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\{q_i(t)u_i(t)\}. \tag{8}$$

Maximizing U satisfies **Fairness criterion (1)**.

Since $Y_i(0) = 0$ for all i, if we consistently strive to minimize the variation in $Y_i(t)$ over time, the regret must not grow unbounded to drive data owners away. Based on recommendations from the Belmont Report [1], the federation needs to jointly consider the magnitude and distribution of regret among data owners and over time in order to treat them fairly [30]. l_2-norm can capture simultaneously the magnitudes of the regret values and the distribution of regret among data owners. A large l_2-norm value means there are many data owners with none-zero regrets, and/or there are a few data owners with very large regret [25–29]. Both shall be minimized.

Based on the l_2-norm technique, we formulate the Lyapunov function [18] of FLI as:

$$L(t) = \frac{1}{2}\sum_{i=1}^{N}[Y_i^2(t) + Q_i^2(t)]. \tag{9}$$

For simplicity of derivation later, we omit the $\sqrt{\cdot}$ operator in the standard l_2-norm calculation and multiply the whole term with $\frac{1}{2}$. These changes do not alter the desirable properties of l_2-norm for our formulation.

The drift in data owners' regret over time is:

$$\begin{aligned}\triangle &= \frac{1}{T}\sum_{t=0}^{T-1}[L(t+1) - L(t)] \\ &= \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\left[\frac{1}{2}Y_i^2(t+1) - \frac{1}{2}Y_i^2(t) + \frac{1}{2}Q_i^2(t+1) - \frac{1}{2}Q_i^2(t)\right] \\ &\leqslant \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\Bigg[Y_i(t)c_i(t) - Y_i(t)u_i(t) + \frac{1}{2}c_i^2(t) - c_i(t)u_i(t) \\ &+ \frac{1}{2}u_i^2(t) + Q_i(t)\lambda_i(t) \\ &- Q_i(t)u_i(t) + \frac{1}{2}\lambda_i^2(t) - \lambda_i(t)u_i(t) + \frac{1}{2}u_i^2(t)\Bigg].\end{aligned} \tag{10}$$

Since $u_i(t)$ it the control variable here, we extract only terms containing it from equation (10):

$$\triangle \leqslant \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\left\{u_i^2(t) - u_i(t)[Y_i(t) + c_i(t) + Q_i(t) + \lambda_i(t)]\right\}. \tag{11}$$

The regret drift variable $\triangle$ jointly captures the distribution of regret (both $Y_i(t)$ and $Q_i(t)$) among data owners, as well as the fluctuation of regret over time. Minimizing $\triangle$ satisfies **Fairness criteria (2) and (3)**.

By jointly considering collective utility and the distribution of regret, the objective function of a given federation can be defined as "maximizing collective utility while minimizing inequality among data owners' regret and waiting time":

$$\omega U - \triangle \tag{12}$$

which shall be maximized. Here, ω is a regularization term for a federation to control the trade-off between the two objectives. Thus, the objective function of a federation is:

Maximize:

$$\frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\left\{u_i(t)[\omega q_i(t) + Y_i(t) + c_i(t) + Q_i(t) + \lambda_i(t)] - u_i^2(t)\right\} \tag{13}$$

Subject to:

$$\sum_{i=1}^{N}\hat{u}_i(t) \leqslant B(t), \forall t \tag{14}$$

$$\hat{u}_i(t) \geqslant 0, \forall i, t \tag{15}$$

where $\hat{u}_i(t) \leqslant u_i(t)$ denotes the actual instalment payout from the federation to a data owner i in round t, which will be derived in the following section.

3.6 Computing Payoff Weightage

In order to optimize equation (13), we set its first derivative to 0 and solve for $u_i(t)$:

$$\frac{d}{du_i(t)}[\omega U - \triangle] = 0. \tag{16}$$

Solving the above equation yields:

$$u_i(t) = \frac{1}{2}[\omega q_i(t) + Y_i(t) + c_i(t) + Q_i(t) + \lambda_i(t)]. \tag{17}$$

The second derivative of equation (13) is:

$$\frac{d^2}{du_i^2(t)}[\omega U - \triangle] = -1 < 0. \tag{18}$$

Thus, the solution maximizes the objective function.

For contributing $d_i(t)$ amount of data of quality $q_i(t)$ at round t, the data owner i shall receive a total compensation of $u_i(t) = \frac{1}{2}[\omega q_i(t) + Y_i(t) + c_i(t) + Q_i(t) + \lambda_i(t)]$. The federation may need to pay out this in instalments over a period of time if not enough budget, $B(t)$, is available to pay all data owners fully at round t. To share $B(t)$ among the data owners, the computed $u_i(t)$ values are used as weights to divide the budget $B(t)$. The actual payout instalment to i at t, $\hat{u}_i(t)$, is:

$$\hat{u}_i(t) = \frac{u_i(t)}{\sum_{i=1}^{N} u_i(t)} B(t). \tag{19}$$

The FLI payoff-sharing scheme is summarized in Algorithm 1. It accounts for both the magnitude and the temporal aspects of participating in a federation. Data owners who has contributed a large set of high quality data, and who has not been fully compensated for a long time will enjoy a higher share of subsequent revenues generated by the federation.

Algorithm 1 Federated Learning Incentivizer (FLI)

Require: ω and $B(t)$ set by the system administrator; $Y_i(t)$ from all data owners at round t (with $Y_i(t) = 0$ for any i who just joined the federation); and $Q_i(t)$ from all data owners at round t (with $Q_i(t) = 0$ for any i who just joined the federation).

Initialize $S(t) \leftarrow 0$; //to hold the sum of all $u_i(t)$ values.
for $i = 1$ to N **do**
  if $d_i(t) > 0$ **then**
    Compute $c_i(t)$;
    Compute $q_i(t)$;
  else
    $c_i(t) = 0$;
  end if
  $u_i(t) \leftarrow \frac{1}{2}[\omega q_i(t) + Y_i(t) + c_i(t) + Q_i(t) + \lambda_i(t)]$;
  $S(t) \leftarrow S(t) + u_i(t)$;
end for
for $i = 1$ to N **do**
  $\hat{u}_i(t) \leftarrow \frac{u_i(t)}{S(t)} B(t)$
  $Y_i(t+1) \leftarrow \max[0, Y_i(t) + c_i(t) - \hat{u}_i(t)]$;
  $Q_i(t+1) \leftarrow \max[0, Q_i(t) + \lambda_i(t) - \hat{u}_i(t)]$;
end for
return $\{\hat{u}_1(t), \hat{u}_2(t), ..., \hat{u}_N(t)\}$;

The computational time complexity of Algorithm 1 is $O(N)$. Once $Y_i(t)$ and $Q_i(t)$ both reach 0 with no new cost incurred by i, $u_i(t) = \omega q_i(t)$. From then on, i will share future payoffs based on his contribution to the federation assessed using one of the baseline methods (e.g., the Shapley game payoff-sharing scheme). FLI prioritizes compensating the data owners with non-zero regret while taking into account their contributions.

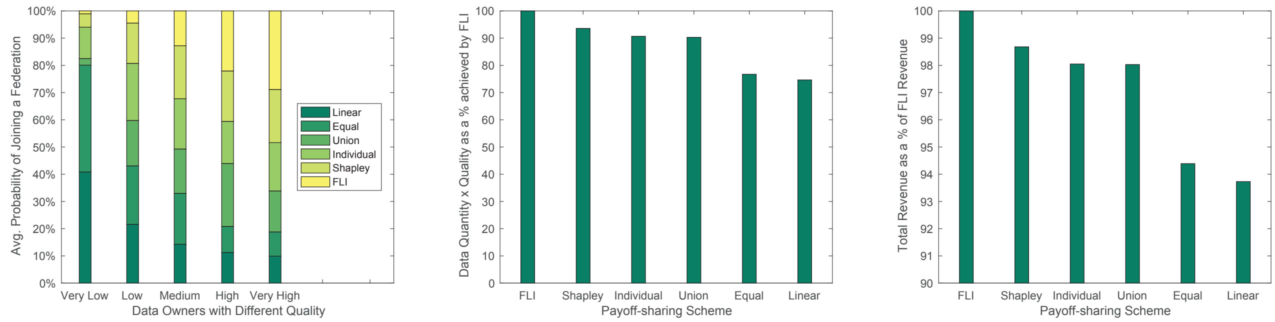
4 EXPERIMENTAL EVALUATION

To complement the analytical results and evaluate the performance of FLI under federated learning settings, we built a simulator which creates data owner agents with diverse characteristics and supports multiple payoff-sharing schemes.

4.1 Experiment Settings

We simulate 6 federations each adopting one of the following 6 payoff-sharing schemes for data owner agents to join:

(1) Linear: a data owner i's share of $B(t)$ is proportional to the total quantity of data contribution weighted by its data quality (this is a baseline payoff-sharing scheme that we designed for experimental comparison purposes only);
(2) Equal: $B(t)$ is equally divided among data owners in this federation [24];
(3) Individual: i's share of $B(t)$ is proportional to his marginal contribution to the revenue of the federation [24];
(4) Union: i's share of $B(t)$ follows the Labour Union game [10] scheme and is proportional to his marginal contribution to the revenue of the federation formed by his predecessors, $v(F \cup \{i\}) - v(F)$;



(a) Data owner agents' final probability of following each scheme (b) $\frac{1}{NT}\sum_i \sum_t d_i(t)\rho_i$ as a percentage of that achieved by FLI (c) Revenue as a percentage of that achieved by FLI

Figure 2: Experiment results.

(5) Shapley: i's share of $B(t)$ follows the Shapley value-based scheme proposed in [11]; and
(6) FLI: data owners receive payoff following FLI ($\omega = 1$).

We simulate 100 self-interested data owner agents in the experiment, each representing a company. Their ρ_i values are randomly initialized following a uniform distribution between 0 and 1 at the beginning of each round of experiment. In each epoch, each agent decides on which federation to join based on the cumulative payoffs received from each federation so far. The probability of an agent joining a federation at t equals to the cumulative payoff it received from this federation divided by total payoff received from all federations. Each agent joins federations following the ϵ-greedy approach, with equal starting probability for all federations.

We follow the decreasing marginal utility assumption to map data quality and quantity to revenue generated by a federation. The revenue function used in the experiment is log-linearly related to the product between the quality and quantity of data contributed to it. It is of the form $\log(1 + \sum_i \sum_t d_i(t)\rho_i)$. In essence, federations are competing for data owner agents. The performance of the schemes is evaluated by the percentage and type of data owner agents who eventually choose to join each of them and the revenue generated. Each round of simulation consists of 1,000 epoches, and we repeat the simulation for 10 rounds with re-initialization to smoothen the effect of randomness.

4.2 Results and Discussion

Figure 2(a) shows different data owner agents' final probability of following each scheme. Data owner agents are divided into five types based on their individual ρ_i values. Agents with ρ_i values belonging to the range of $[0, 0.2)$, $[0.2, 0.4)$, $[0.4, 0.6)$, $[0.6, 0.8)$ and $[0.8, 1]$ are labelled as 'Very Low', 'Low', 'Medium', 'High' and 'Very High' types, respectively. It can be observed that the Medium, Low and Very Low type agents have the smallest probabilities of joining the federation adopting FLI. Shapley and Union follow are similar trend but are less attractive to Very High and High type agents compared to FLI. Individual, Linear and Equal are more attractive to agents with lower data quality than those with higher data quality.

Figure 2(b) shows the total quantity of data received by each federation weighted by data quality ($\frac{1}{NT}\sum_i \sum_t d_i(t)\rho_i$). FLI achieves the best performance, outperforming the second best scheme, Shapley, by around 7%. Individual and Union perform similarly, which is around 10% lower than that achieved by FLI. The performance of Equal is more than 30% lower than that of FLI. Linear fares the worst, under-performing FLI by over 34%.

Figure 2(c) shows the total revenue as a result of the data received by each federation. Similar to the trend shown in Figure 2(b), FLI achieves the highest revenue, followed by Shapley, Individual, Union, Equal, and Linear. As long as the adopted revenue function monotonically increases with data quality and quantity, this performance trend holds.

5 CONCLUSIONS

In this paper, we proposed the FLI payoff-sharing scheme incentivize FL data owners to contribute high quality data to the data federation. Data owners who has contributed a large set of high quality data, and who has not been fully compensated for a long time, will enjoy a higher share of subsequent revenues generated by the federation. A federation following FLI is able to dynamically adjust data owners' shares in order to fairly distribute benefits and sacrifice among them. Analytical evaluation established that FLI is able to produce near-optimal collective utility while limiting data owners' regret. With FLI accounting for the temporary mismatch between contributions and rewards due to the limitations of FL, thereby enabling a healthy FL ecosystem to emerge over time. To the best of our knowledge, FLI is the first incentive mechanism designed for federated learning. It jointly considers factors important to FL, with clear separation of concerns with respect to the delay for the federated model to start generating revenue. In subsequent research, we will study alternative ways to quantify data owners' contribution.

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