Promoting Collaboration in Cross-Silo Federated Learning: Challenges and Opportunities

Chao Huang, Ming Tang, Qian Ma, Jianwei Huang, and Xin Liu

The authors focus on designing effective economic mechanisms to address challenges in the field of cross-silo federated learning.

Abstract

In cross-silo federated learning (FL), companies or organizations collectively train a shared model while keeping the raw data local. The success of cross-silo FL relies on client cooperation, effective communication, and sufficient resource contributions for model training. However, several unique challenges make client collaboration in cross-silo FL difficult. First, as the global model is a public good, clients may choose to free ride on the process instead of actively contributing to the training process. Second, market competition among clients also discourages their collaboration in training, as clients may not want their business competitors to obtain a high-quality model. Third, repeated interactions among clients may further decentivize collaboration, as one can free ride on others' long-term active contributions. This article focuses on designing effective economic mechanisms to address the above challenges. Specifically, we propose an incentive mechanism to address the public good issue, a revenue-sharing mechanism to mitigate business competition, and a cooperative strategy to enable clients' long-term collaboration. Our results provide insights into better design of collaboration mechanism and communication in practical cross-silo applications. We further discuss some future directions and open issues that merit research efforts from the community.

Introduction

Federated learning (FL) is a distributed and privacy-preserving machine learning approach, where a group of clients (e.g., learning agents) collaboratively train a shared model without exchanging private raw data. Clients perform model training using their private data and only need to exchange model updates in the form of gradients or parameters. This exchange relies heavily on digital communications, where the efficiency and reliability of data transmission directly impact the speed and accuracy of the learning process. The clients may further apply techniques, such as differential privacy and homomorphic encryption to the shared model updates to enhance privacy protection. According to the participating clients and training scale, one can categorize FL into two main types: cross-device FL and cross-silo FL.

Cross-Device FL: The participating clients are usually edge devices such as smartphones and wearables. Each client is typically constrained by limited computation and communication resources. This limitation not only restricts their ability to participate in multiple FL rounds but also poses challenges in efficient transmission of model updates. Furthermore, a client typically possesses a relatively limited quantity of local data. Therefore, to achieve success in cross-device FL, substantial participation of edge devices is required, which can range up to millions. The model owner in cross-device FL is the coordinating central server (such as Google).

Cross-Silo FL: The clients are canonically companies or organizations (e.g., data centers, hospitals, and banks) who own the global model themselves. Clients usually have sufficient computation powers and reliable connections (e.g., high-speed wired networks) and are anticipated to engage in the entire training process [1]. The number of clients is small (e.g., ranging from two to around a hundred), and each can have a relatively large amount of local data.

Prior related studies focus on cross-device FL, and interested readers can find an insightful survey in [2]. This article focuses on the relatively under-explored cross-silo FL. There are numerous examples of cross-silo FL in the industry [3]. In the financial sector, SwissRe and WeBank engage in joint FL data analysis to offer personalized reinsurance services. In the healthcare domain, Owkin partners with pharmaceutical institutions to develop graph neural network models for drug discovery. In the transportation industry, organizations possessing traffic data collectively train a model to forecast road traffic. These collaborations require secure and efficient exchange of model data over their networks to ensure data privacy. This necessitates a communication framework that can support reliable transmission of large and complex model updates, often across different geographic locations.

To obtain a good model in cross-silo FL, clients need to provide sufficient resources (e.g., computation capabilities and local data) for model training. This calls for effective mechanisms to incentivize client contribution and collaboration.

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Enhanced collaboration also has a potential to mitigate the communication bottleneck in cross-silo FL by fostering synchronized learning and efficient model exchanges, leading to faster convergence and smaller communication overheads. However, several unique challenges in cross-silo settings make client collaboration difficult.

Public Good Provision: Since the global model is owned and shared by all the clients, it is a public good that one can free-ride on. That is, some clients may contribute little to model training but enjoy the high-quality global model trained by the other clients. It is challenging to address the free rider issue and incentivize clients' contributions to cross-silo FL due to the public good feature. Note that while free-riding can also occur in cross-device FL, its impact is less significant than in cross-silo settings, as edge devices do not own the global model and usually only participate in a few FL rounds.

Business Competition: Cross-silo clients may be business competitors (e.g., banks who compete for the same pool of customers), which may increase the incentives of free riding. That is, clients may have concerns that contributing to FL could benefit their business competitors. It is challenging to promote clients' FL collaboration when business competition is present.

Long-Term Collaboration: Cross-silo clients typically engage in multiple FL processes to dynamically adjust the global model to the time-varying datasets. While this brings an opportunity for long-term collaboration, it also leads to a possibility where clients may free ride on others' long-term active contributions [4]. Furthermore, how cross-silo clients would behave during repeated interactions has not been sufficiently modeled and understood, making a sustainable long-term collaboration challenging.

In this article, we propose to model and analyze the above key challenges in cross-silo FL through a game-theoretical perspective. Our main contributions are as follows:

- We point out the public good feature of the global model and present an incentive mechanism to address the associated free rider issue. We show that our mechanism incentivizes clients' contributions to FL model training.
- We point out potential business competition among cross-silo clients and present a revenue-sharing mechanism to promote collaboration. We show that our mechanism alleviates business competition, promotes client collaboration, and improves the global model accuracy.
- We point out the opportunity for long-term collaboration and present a cooperative strategy to this end. We show that our proposed strategy induces clients to contribute sufficient training resources in the long run.
- We further identify future research directions for client collaboration in cross-silo FL.

While prior work in [1] provided an overview cross-silo FL, their focus is on identifying the key challenges in cross-silo FL and the differences to cross-device FL. This article, however, focuses on the challenges related to collaboration in cross-silo FL and the corresponding potential solutions.

The remainder of this article is organized as follows: We discuss the key challenges and propose mechanisms to address the public good issue, mitigate business competition, and enable long-term collaboration in the next sections. Following that, we discuss future research opportunities and conclude. The codes are available at https://codeocean.com/capsule/4662633/tree.

Public Good Provision

Global Model as a Public Good

In cross-silo FL, organizations contribute various types of resources (e.g., processing capacity and local data) to cooperatively train a global model (e.g., deep neural networks). After training, each organization can obtain a copy of the trained global model and exploit it for its revenue improvement. Unlike conventional types of goods, the trained global model involved in cross-silo FL can be viewed as a public good and has two distinctive features below:

- *Non-rivalrous:* Any organization can "consume" (i.e., have a copy of and exploit) the neural network without affecting the consumption of other organizations.
- *Non-excludable:* No organization can forbid other organizations who have participated in the training process from obtaining and exploiting the trained neural network.

Due to the non-rivalrous and non-excludable features, free rider issues may occur. That is, an organization may contribute few resources but enjoy the high-accuracy neural network resulting from the significant contributions of other organizations.

An Incentive Mechanism for Public Good Provision

To address the free-rider issue due to the public good feature, we proposed an incentive mechanism in [5]. The main idea is to specify clients' training contributions based on their valuation of the global model performance. Based on the design, high-valuation clients are more willing to contribute and pay to incentivize low-valuation clients' participation. The mechanism overcomes the challenge due to the public goods features and can achieve three desired economical properties at Nash equilibrium:

- *Individual rationality:* Each organization can receive a non-negative payoff.
- *Budget balance:* No third-party investment is needed for maintaining collaboration among organizations.
- *Social efficiency:* The sum of all organizations' payoffs is maximized.

Note that it has been proven that there does not exist any public goods mechanism that can simultaneously achieve the above three properties and incentive compatibility (i.e., organizations truthfully report their valuations) [6]. Despite this, with our proposed mechanism, it can be proven that organizations truthfully report their marginal valuations in an indirect fashion.

Figure 1 illustrates our proposed mechanism, which operates in an auction-like fashion and executes in four steps below.

Step 1: Each organization first submits a message profile (γ_n, π_n) to the central server. Here, γ_n is the number of training rounds that organization n expects to have. A positive (or negative) value of π_n indicates the unit monetary transfer per training round that organization n expects to receive from (or pay for) other organizations.

In cross-silo FL, organizations contribute various types of resources (e.g., processing capacity and local data) to cooperatively train a global model (e.g., deep neural networks). After training, each organization can obtain a copy of the trained global model and exploit it for its revenue improvement.

In essence, companies or organizations could potentially act as both collaborators in model training and competitors in the business arena. For one thing, companies collaboratively train FL models, with each gaining benefits from the improved model performance. For another, these companies may also engage in business competition by offering model-related services to customers, rendering the collaboration more difficult.

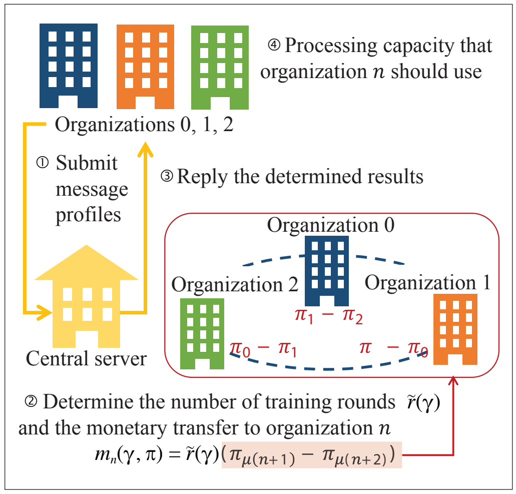

FIGURE 1. An illustration of our proposed incentive mechanism with three organizations. The mechanism achieves social efficiency while satisfying budget balance and individual rationality.

Step 2: Upon receiving the message profiles, the central server processes the submitted profiles. Specifically, it determines the number of training rounds by averaging these values. Then the server further calculates the monetary transfer to each organization.

Step 3: The central server replies to the organizations on the number of training rounds that organizations need to perform as well as the monetary transfer.

Step 4: Each organization computes its processing capacity used for training.

Importantly, in *Step 2*, the monetary transfer that each organization needs to receive or pay is chosen to be the difference between the unit monetary transfers submitted by the next and second next organizations (see highlighted part in Fig. 1 for an example). This makes the organizations at equilibrium pay according to their marginal benefits, which leads to social efficiency.

Results

We further devise a distributed algorithm in [5] that enables the organizations to gradually reach the system equilibrium without knowing the private information of others. This algorithm takes several iterations. In each iteration, each organization greedily optimizes its own payoff with respect to the number of training rounds, given the others' message profiles submitted in the previous iteration. It updates its submitted monetary transfer to motivate its "neighboring" organizations (in terms of organization indices) to reduce the differences in their submitted monetary transfer in the next iteration.

Figure 2 shows the performance of our distributed algorithm with MNIST dataset, which converges to the equilibrium of our proposed incentive mechanism. We consider 10 organizations, where 80 percent of their data samples are non-IID (independently and identically distributed). Each curve corresponds to an organization, and a darker color indicates a higher unit utility of the organization for having a high-accuracy global model. In Fig. 2, our algorithm converges to the equilibrium (which is socially optimal) after around 150 iterations. Moreover, a positive (or negative) value indicates that the associated organization will receive payment (or pay). With the proposed mechanism, despite the public goods feature, an organization with a higher valuation (toward the global model) needs to pay more for motivating other organizations to collaborate, whereas an organization with a lower valuation will be paid a higher amount for its participation.

Discussion

We provided a general approach for addressing the public good issue among organizations in cross-silo FL. The proposed incentive mechanism is not only applicable for incentivizing the organizations' contributions of their computational resources but also can be extended to deal with other resources (e.g., communication resources, datasets). However, there are still many important challenges to be addressed. For example, since organizations are business entities, it is crucial to investigate their potential coalition behaviors. It is also beneficial to extend the mechanism for asynchronous FL scenario in order to characterize the straggler issue and dynamic participation behaviors of organizations. Moreover, it is important to develop efficient and transparent communication protocols in cross-silo FL, as it can help track contributions and usage, potentially mitigating the free-rider problem by providing a clear record of each organization's participation and impact on the model training process.

Business Competition

Business Competition in Cross-Silo FL

Besides the public good issue, the possible business competition makes the collaboration in cross-silo FL even more challenging. In essence, companies or organizations could potentially act as both collaborators in model training and competitors in the business arena. For one thing, companies collaboratively train FL models, with each gaining benefits from the improved model performance. For another, these companies may also engage in business competition by offering model-related services to customers, rendering the collaboration more difficult. To be concrete, companies may be unwilling to use enough data during the training process. The reluctance comes from the concern that contributing many data could lead to the improvement of the global model shared by other clients (who are business rivals), and hence can undermine the contributing client's own market competitiveness.

Revenue Sharing to Mitigate Business Competition

To mitigate business competition, we proposed a revenue-sharing mechanism in [7] that promotes client collaboration. We start with a duopoly case where there are two clients, for example, WeBank and SwissRe. Figure 3 illustrates how clients interact in terms of FL training collaboration, duopoly business competition, and revenue sharing. The interaction consists of five steps elaborated below.

Step 1: Two clients decide whether to participate in FL, and if so, how much local data to use for model training.

Step 2: If clients do not participate in FL, each uses its data to train a local model. If clients participate in FL, each client further fine-tunes the converged global model (e.g., retrain all or part of the model parameters) and obtains a final local model. Fine-tuning is a widely used and effective solution to improve local model performance when clients have non-IID data.

Step 3: Each client utilizes its own final model to provide model-related service (e.g., disease screening by hospitals). Then, each client decides the unit price it needs to charge if customers decide to purchase the service.

Step 4: Given the clients' provided services and prices, individual customers in the market decide whether to purchase the service. If so, each customer further decides from which one of the two clients to purchase service.

Step 5: Clients share revenues generated from selling services to the customers.

The revenue sharing in *Step 5* is the key to mitigating business competition and promoting collaboration, as it can better align clients' conflicting objectives arising from business competition. A key challenge in *Step 5* is to design a mechanism that appropriately reallocates the revenues to the competing clients. To this end, we propose a revenue-sharing mechanism using Shapley-value-based contribution evaluation. It consists of two phases.

Phase 1: The clients (or a trusted third party) estimate each client's average marginal contribution to the global model accuracy by running a sandbox simulation.

Phase 2: Assign each client an index based on its estimated contribution to the global model, specified by the Shapley value method. Then, each client obtains a share (proportional to the index) of the total revenue.

Results

To demonstrate the effectiveness of our proposed revenue-sharing mechanism, we also study the benchmark case where there is no revenue sharing (i.e., a similar process in Fig. 3 yet with *Step 5* removed). We use the global model accuracy to quantify the effectiveness of our proposed mechanism. The global model accuracy helps indicate how much data clients contribute to FL training.

In our experiments, we use the CIFAR-10 dataset and the two clients have non-IID data. The customers are modeled as a continuum and their valuation toward the clients' services are uniformly distributed. Figure 4 compares our proposed revenue-sharing mechanism with the benchmark case, where the *x*-axis represents clients' unit cost per data sample used for FL, and is assumed to be the same among the two clients. We first observe that the global model accuracy decreases in the unit cost. Clients with a larger cost will contribute less data to FL, leading to a worse global model. Second, we observe that compared to the case without revenue sharing, our proposed mechanism significantly improves the global model accuracy. Without revenue sharing, the clients participate in fierce market competition by lowering their prices to attract more customers, leading to a smaller client profit. This in turns constitutes a smaller incentive to contribute data for FL and hence results in a worse global model. With proper revenue sharing, however, clients align their objectives, avoid fierce price competition, and collaborate to train FL models. This leads to a better global model.

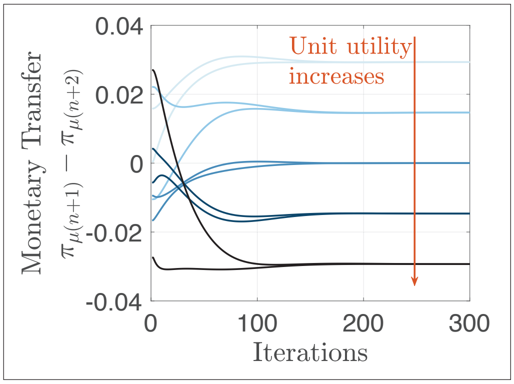

FIGURE 2. Convergence of the monetary transfer submitted by organizations in message profiles.

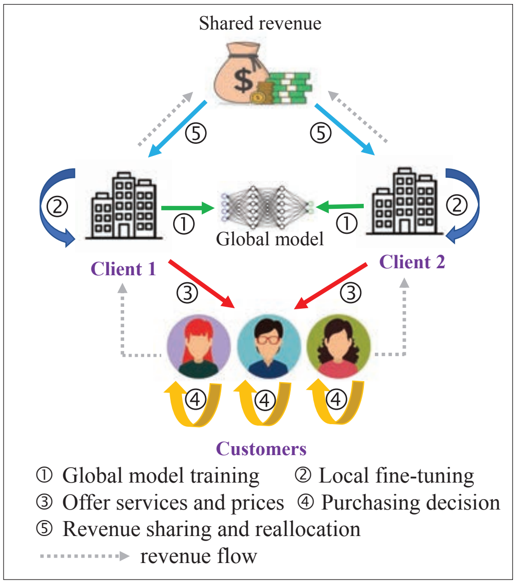

FIGURE 3. An illustration of our revenue-sharing mechanism to mitigate business competition between two clients. The revenue-sharing mechanism better aligns clients' objectives, incentivizes collaboration, and improves the global model accuracy.

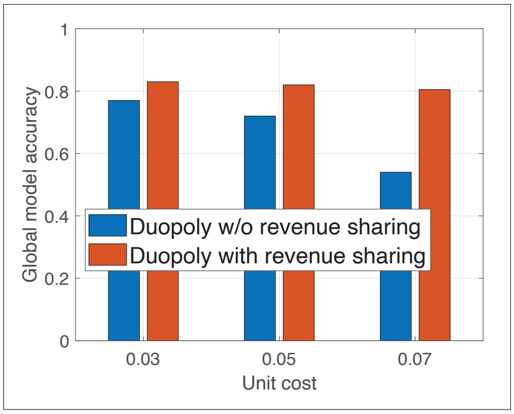

FIGURE 4. Equilibrium results of the global model accuracy.

Discussion

The study of business competition in the context of cross-silo FL is still in its initial phases, with many critical challenges unaddressed. For instance, the study of more intricate customer behaviors, for example, multi-homing in which a customer purchases services from multiple clients,

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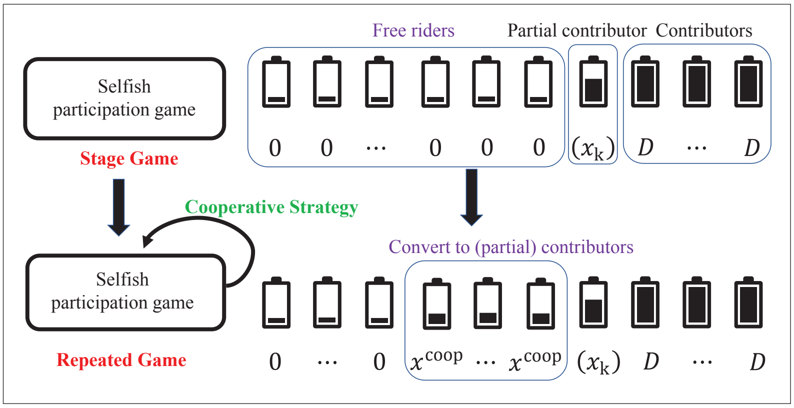

FIGURE 5. An illustration of our cooperative strategy to enable long-term collaboration among clients. Our strategy converts free-riders to contributors and leads to more data contribution at equilibrium.

is important and interesting. It is also a promising avenue to consider that clients provide complementary (instead of substitutable) services In addition, one may extend the mechanism to an oligopoly scenario with more than two competing clients. Note that this can bring communication challenges, which demand improved solutions for data synchronization and conflict resolution in model training among multiple clients.

Long-Term Collaboration

Long-Term Collaboration in Cross-Silo FL

In cross-silo FL, the training process may require clients' active long-term participation. For example, the MELLODDY project serves as a long-term endeavor characterized by collaborations among ten organizations. [8]. One motivating factor stems from the temporal variability of clients' local data. For instance, hospitals continually receive new patients and update treatment data. This dynamic nature of data not only requires clients to engage in multiple FL processes but also presents significant communication challenges. Ensuring the continuous, secure, and efficient exchange of up-to-date model updates and data insights is crucial for adapting the global model to reflect the evolving datasets. Consequently, clients must maintain robust and reliable communication channels that can handle the frequent and potentially large-scale data transmissions inherent in these long-term FL collaborations.

However, as mentioned earlier, clients may free-ride on the global model. This is detrimental, as free riding would lead to a bad global model, decentivizing clients to form long-term FL training collaboration.

A Repeated Game-Theoretical Cooperative Strategy

To promote cross-silo clients' long-term collaboration, we need to understand how clients would behave when they are involved in repeated interactions. To this end, we model the clients' long-term interactions as a repeated game consisting of an infinite number of stage games, where each stage game corresponds to one cross-silo FL process (see also Fig. 5). In the following, we analyze the stage game, and then propose a cooperative strategy to enable clients' collaboration in the repeated game.

In the stage game, each client strategically decides the quantity of local data for FL training to optimize its individual payoff. By analyzing the equilibrium of this game, we show that clients can be categorized into up to three groups: free riders who contribute no data, a partial contributor (if existent) who contributes a portion of its local data, and full contributors who contribute all local data for model training.

In the repeated game, we analyze the equilibrium and find that there can exist equilibrium where clients contribute little to the long-term FL collaboration. While our approach above may be a solution to each stage game, it does not take into account the dynamic interactions among organizations in the long term. To address this issue, we present a cooperative strategy in [9] to minimize the number of free riders. The key idea is to enforce punishment whenever clients deviate from the cooperative strategy. For example, if some client does not follow the agreed cooperative strategy, the other clients would play punishment strategies so that the deviating client would be punished and worse off. We show that at the subgame perfect Nash equilibrium (SPNE) of the repeated game, some free riders in the stage game will be converted to either full contributors or partial contributors (see Fig. 5 for an example), demonstrating the effectiveness of our proposed cooperative strategy.

Results

We propose a distributed algorithm that converges to the SPNE of the repeated game. The server first computes the minimum number of free riders under the subgame perfect Nash equilibrium (SPNE). Then, it determines the maximum number of local data that converted contributors can use via solving an optimization problem.

In our experiments, we consider 100 clients whose data are uniformly randomly sampled from MNIST. We consider two benchmarks: a free rider detection method called DAGMM [10], and a contract-based mechanism [11]. Figure 6 plots at SPNE, how the total number of contributed training data changes with the available number of data D of each client. Figure 6 shows that our method induces a larger amount of total training data compared with the other two benchmarks. The key reason is that our cooperative strategy helps convert free riders into contributors in the long run. We can further show that our method induces a much smaller number of free-riders than the benchmarks when each client has enough local data.

Discussion

The discussion of client's long-term cooperation in cross-silo federated learning is at its infant phase, with many intriguing future challenges to be solved. One important direction is to derive the cooperative strategy under the imperfect information case, in which the strategies of clients (regarding data contributions) are unknown to others. It is also interesting to study the incomplete information case, in which the client information (e.g., valuation toward the global model accuracy) is private to each client and unknown to other clients.

Future Directions and Open Issues

There are many interesting unaddressed challenges regarding the collaboration in cross-silo FL, and we discuss some of them below.

Mechanism Design with Data Quality

There have been some recent research efforts on mechanism design in cross-silo FL. Most of these studies either focused on the ideal IID data scenario or the more realistic non-IID scenario. However, the important issue of data quality is under explored. Here, data quality corresponds to the conditions of data based on factors such as the correctness of labels.

To make the collaboration mechanisms usable in practical cross-silo settings, it is important to incorporate the important feature of data quality. Recent studies (e.g., [12]) have theoretically and empirically quantified how data quality affects cross-silo FL. The authors in [13] presented an algorithm to estimate data quality during FL training. These approaches can be integrated into our mechanisms to better incentivize contribution in cross-silo FL. We believe that more research efforts should be given to practical scenarios incorporating both data quality and data non-IIDness and how they jointly affect the mechanism design.

Market Entry

Market entry is an important aspect of business strategy formulation, particularly in the context of emerging technologies (e.g., cross-silo FL). However, the research of market entry in cross-silo FL remains under-explored, offering promising future directions for academic and commercial endeavors alike.

In practice, market entry in cross-silo FL involves understanding various factors that can influence the success of an organization. These factors include, but are not limited to, data availability, market size, growth potential, and competitive landscape (e.g., [14]). By examining these factors, organizations participating in cross-silo FL can make informed decisions about whether to enter the competitive market, and how best to position themselves for success. We believe that more research efforts should be devoted along this line.

Coalition

In practical cross-silo FL, companies may choose to form coalitions due to two reasons. Consider a scenario where multiple banks compete to offer finance-related services to prospective customers. First, when faced with limited data resources, the banks can establish a coalition and jointly train a model. This can yield an enhanced model, and improve the quality of their services (e.g., [15]). Second, the banks may be strategic in forming a coalition that maximizes their market competitiveness. For example, smaller banks could form a business coalition, which can potentially outperform larger counterparts and amplify their market influence. To our best knowledge, there is no prior work along the latter and more research efforts are needed.

Nash Bargaining

In many cross-silo settings, there may not be a neutral third party (e.g., government) who designs and enforces the collaboration mechanism. Instead, companies or organizations in many cases need to negotiate binding agreements/contracts themselves on how to contribute and collaborate. To our best knowledge, there is no prior work along this important line, which however, could provide insights into and improve practical client collaboration. The authors believe that Nash Bargaining can be a promising solution to this problem.

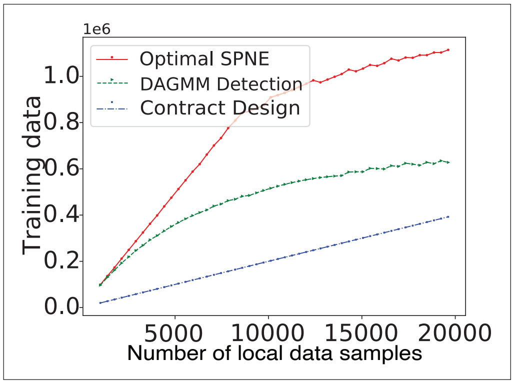

FIGURE 6. Total contributed data points at equilibrium.

The success of cross-silo FL requires clients to collaborate and contribute sufficient training resources for model training. This is challenging, as clients tend to free ride on the global model, which can be escalated when business competition is present.

Conclusion

The success of cross-silo FL requires clients to collaborate and contribute sufficient training resources for model training. This is challenging, as clients tend to free ride on the global model, which can be escalated when business competition is present. We first propose an incentive mechanism to encourage clients' contribution and mitigate free riding. Next, we devise a revenue-sharing mechanism to alleviate business competition. We further propose a cooperative strategy to enable clients' long-term collaboration. Our results provide insights into the design and implementation of collaboration mechanisms in practical cross-silo applications. Finally, we discuss open issues that deserve future study.

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Biographies

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