Friend-as-Learner: Socially-Driven Trustworthy and Efficient Wireless Federated Edge Learning

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Abstract—Recently, wireless edge networks have realized intelligent operation and management with edge artificial intelligence (AI) techniques (i.e., federated edge learning). However, the trustworthiness and effective incentive mechanisms of federated edge learning (FEL) have not been fully studied. Thus, the current FEL framework will still suffer untrustworthy or low-quality learning parameters from malicious or inactive learners, which undermines the viability and stability of FEL. To address these challenges, the potential social attributes among edge devices and their users can be exploited, while not included in previous works. In this paper, we propose a novel *S*ocial *F*ederated *E*dge *L*earning framework (SFEL) over wireless networks, which recruits trustworthy social friends as learning partners. First, we build a social graph model to find like-minded friends, comprehensively considering the mutual trust and learning task similarity. Besides, we propose a social effect based incentive mechanism for better personal federated learning behaviors with both complete and incomplete information. Finally, we conduct extensive simulations with the Erdos-Renyi random network, the Facebook network, and the classic MNIST/CIFAR-10 datasets. Simulation results demonstrate our framework could realize trustworthy and efficient federated learning over wireless edge networks, and it is superior to the existing FEL incentive mechanisms that ignore social effects.

Index Terms—Social trust, federated edge learning, resource allocation, incentive mechanism

1 Introduction

With the development of the Internet of Things (IoT) and social applications, big data over wireless edge networks has proliferated [1]. Following the Cisco Global Cloud Index (GCI), the annual global data traffic will reach about 20.6 ZB by 2021. To extract valuable knowledge from multi-source heterogeneous edge data, the emerging "edge-AI" or "edge intelligence" paradigm has been widely applied [2], [3], [4]. In edge-AI, over 50 billion edge devices (e.g., mobile phones, micro-servers, and smart vehicles) could be employed for data mining and knowledge discovery over wireless networks. The most well-known of them, named federated edge learning (FEL) framework, was designed by Google in 2016. In FEL, the trained AI sub-models (i.e., weights and gradients) from each device could synthesize a global AI model in the aggregate node (e.g., Base Station). Mobile users will no longer directly share the original raw data, but share the AI model parameters obtained from the data, thus protecting the original data privacy to a certain extent. Meanwhile, FEL will also improve users' QoS (Quality of Service) and relieve the network bandwidth pressure by the local data processing [3].

FEL has the advantages of privacy-preserving, low-cost, and high-efficiency, but the trustworthiness and effective incentive mechanisms of FEL have not been well studied yet [5]. On the one hand, untrustworthy learning participants are likely to upload malicious learning parameters or training models (e.g., poisoning attack), resulting in the unavailability of FEL. So how to establish trust relationships between collaborative learners of FEL becomes a challenge. On the other hand, some existing work assumes that unconditional learning resource sharing will occur between mobile users and their devices [6], [7]. In fact, individual learners will always act as conditional volunteers in real life, which means they are unwilling to contribute any learning resources (i.e., computing, communication, data resources) without proper financial compensation. Meanwhile, In a collaborative environment, selfish learners usually only want to benefit from the contributions of others without making any effort for the group, thus "Tragedy of the Commons" is prone to appear [8] with a low learning quality. How to establish an effective incentive mechanism to stimulate high-quality learning behavior becomes another challenge. Moreover, the above two challenges in FEL are hard to be addressed separately due to their high couplings [9].

Recently, with the great success of social networks, social relationships have been widely established between mobile users and their devices. Trustworthy and efficient multi-resource sharing and utilization can be realized by social networks. Specifically, mobile users can establish trustworthy social relationships through mobile social networks (MSNs), such as Facebook and Twitter. For example, according to Facebook statistics in 2017, there are 2.2 billion social users monthly interacted via Facebook, and each user

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maintains nearly 200 friendships [10]. By granting social attributes to mobile devices and IoT devices, a framework called Social Internet of Things (SIoT) was also proposed to support better mobile and IoT applications and services [11]. So, benefiting from large-scale social networks, mobile users and their belongings can easily obtain assistance from multiple social friends. These trustworthy and familiar social friends could be recruited as potential learners. Besides, the external effects of social networks could regulate learners' learning behaviors through peer social influence and improve personal contribution to collaborative learning. Further, social friends also have enough motivation to provide spontaneous assistance for learning services, so as to avoid spending too many financial incentives to stimulate FEL collaboration. Therefore, by coordinating social networks and the FEL paradigm, two critical coupling challenges in FEL can be well resolved.

There have been some previous works on FEL [6], [7], [12], [13], but the marriage of FEL and social networks has not been well studied. Motivated by this, we propose a *S*ocially-driven trustworthy and efficient *F*ederated *E*dge *L*earning framework (SFEL), which will recruit social friends as trustworthy co-learners. In SFEL, edge devices and their users could interconnect via social networks. It indicates socially-aware resource allocation and user incentives are involved in our SFEL. So, we also investigate a social effect based incentive mechanism with a hierarchical Stackelberg game model. The contributions of our work could be summarized as follows:

- We propose a novel SFEL framework, which realizes a trustworthy and efficient federated edge learning framework over wireless networks.
- We establish a social graph model with social ties in SFEL. It comprehensively considers the mutual trust and learning task similarity, which acts as a criterion for selecting like-minded learning partners.
- We propose a Stackelberg game based social incentive mechanism with both complete and incomplete information to encourage better personal learning behaviors.
- We implement simulations on real-world datasets to show the performance of our framework. And we demonstrate the advancement of our framework compared to the existing ones.

The rest of this paper is organized as follows. We give an overview of the related works in Section 2. We then present our SFEL framework in Section 3. The system model and problem formulation are presented in Section 4. Stackelberg game model analysis with complete and incomplete information are discussed in Sections 5 and 6, respectively. Simulation results show the performance of our framework in Section 7. Finally, we conclude the paper.

2 Related Works

2.1 Federated Learning Over Wireless Edge Networks

The study on wireless federated edge learning is still in the initial stage. The architecture, technologies, standards, real-world case studies of FEL were comprehensively presented in [3]. In terms of FEL algorithm optimization, Wang *et al.* [6] proposed an adaptive control algorithm that achieves the desired trade-off between local update and global parameter aggregation in the resource-constrained edge environment. Zhou *et al.* [14] designed and analyzed a cost-efficient optimization framework named CEFL to coordinate edge-cloud resources with Lyapunov optimization theory, which could optimize the system-wide cost-efficiency of FEL. Besides, a Hierarchical Federated Edge Learning (HFEL) framework was proposed in [15], which jointly optimizes resource allocation and edge association of FEL. In view of the uncertainty of the wireless channel and heterogeneous power constraints in FEL, the authors in [7] comprehensively analyzed and optimized the latencies and energy consumptions of wireless communication models in FEL. The authors in [16] also investigated a bandwidth-limited fading multiple access channel (MAC) in FEL, and implemented distributed stochastic gradient descent (DSGD) over this shared noisy wireless channel. Besides, Sun *et al.* [17] studied non-orthogonal multiple access (NOMA) together with adaptive gradient quantization and sparsification for communication-efficient FEL uplinks.

Some other works focus on the incentive mechanism of FEL. In [12], the authors designed a game-based incentive mechanism for FEL workers to mitigate computing delays, but communication time and energy consumption are not taken into account. And Kang *et al.* proposed an effective incentive mechanism coordinating reputation with contract theory to motivate high-reputation participants in FEL [9]. Besides, Zhan *et al.* investigated the incentive mechanisms for FEL with heterogeneous edge nodes and uncertainty of network bandwidth [18], [19]. Some others studied the data quality-driven incentive mechanisms in FEL. In [20], Jiao *et al.* designed an auction-based incentive mechanism for the FEL to maximize the social welfare of the FEL services market. Besides, a hierarchical incentive mechanism framework with contract theory and coalition game was also proposed in [21]. In general, trustworthy incentive mechanisms are critical to the actual implementation of FEL. Unlike previous works, by introducing social network effects into FEL, our work could simultaneously establish a trust model and offer indirect social incentives for FEL participants.

2.2 Socially-Aware Wireless Edge Networks

Socially-aware collaborative computing, communication, and caching over wireless edge networks has been studied extensively [22], [23], [24], [25], [26]. In specific, the authors in [22] introduced the socially-aware hybrid computation offloading (SAHCO) system, which coordinates MEC (Mobile Edge Computing) offloading and D2D (Device-to-Device) offloading. And Feng *et al.* analyzed the characteristics of evolving wireless social networks for content transmission [23]. Besides, Ma *et al.* proposed a socially-aware caching strategy in the D2D content caching with social relationships [25].

With the popularity of social networks, some studies on the incentive mechanism with the help of social networks have also been conducted. Socially-aware incentive

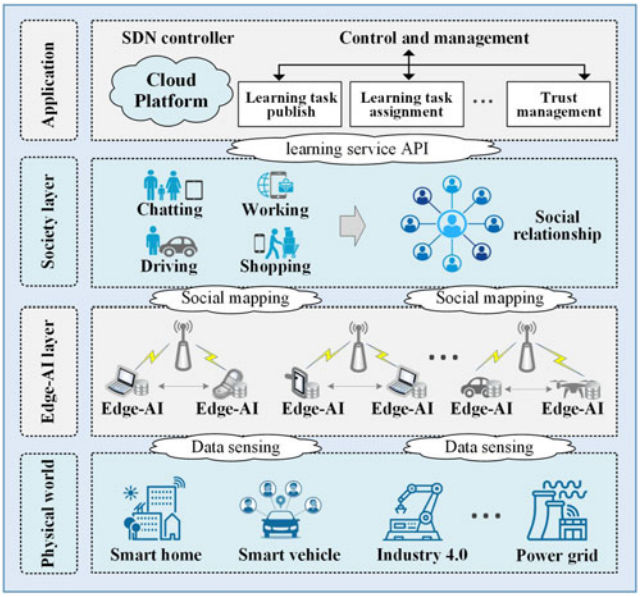


Fig. 1. The social federated edge learning (SFEL) framework.

mechanisms for mobile crowdsourcing (MCS) were discussed in [27], [28], [29]. For instance, Wang *et al.* [27] proposed a dynamic incentive mechanism named SocialRecruiter, to stimulate MCS workers to propagate tasks via social networks. And a socially-aware incentive mechanism with dynamically task pricing and social network effects for vehicular crowdsensing was investigated in [29]. For the D2D resource sharing, Yi *et al.* studied an incentive mechanism for downlink cellular traffic offloading with social-aware D2D content sharing [30]. In terms of specific applications [31], [32], an incentive-based demand response (IBDR) scheme by social-behavioral factors was proposed for smart grid [31]. Besides, Su *et al.* have designed an auction game based incentive scheme for cyber-physical-social systems (CPSS) considering the social behaviors of CPSS users [32]. The socially-aware incentive mechanisms have been extensively studied in wireless edge networks, but how to employ social network effects to appropriately improve the learning performance of FEL has not been fully studied in the aforementioned researches.

3 Social Federated Edge Learning Framework

3.1 Our Proposed SFEL Framework

In Fig. 1, we show our proposed social federated edge learning (SFEL) framework, which includes four layers as follows: the physical world layer, the distributed edge-AI layer, the human society layer, and the application layer.

- *The physical world layer* is composed of widely distributed sensors and actuators over wireless networks. The sensors could collect perceptual data from physical space applications (e.g., smart building, industrial system, and power grid).
- *The distributed edge-AI layer* contains more and more powerful geo-distributed edge devices, such as smartphones, smart vehicles, laptops, and unmanned aerial vehicles (UAV), which offers sensing data locally storage and processing. Distributed AI technologies (e.g., federated edge learning) based data mining and knowledge discovery are implemented in this layer. Compared with the centralized AI, distributed edge-AI will handle learning tasks through the collaboration between edge-AI devices.
- *The human society layer* consists of the Social Internet of Things (SIoT) and social mapping in human society. In this layer, humans could control their edge-AI devices via human-computer interaction (HCI) in daily social behavior (e.g., working, driving, and shopping). Thus, human social attributes could be mapped to their belongings. This layer will bring human social relationships to edge devices, which plays a significant role in trustworthy and collaborative edge-AI.
- *The application layer* includes intelligent SFEL services and applications. These intelligent services and applications are configured and managed via a centralized platform (e.g., cloud platform). And the centralized platform also provides users with the standard APIs (application programming interfaces). Thus, users could publish their learning service requests and tasks with the corresponding payment.

The application layer is the core of the entire framework. It is responsible for centralized management and control of the entire system, including learning task publication, learning task assignment, and trust management between edge-AI devices, etc. The specific interaction process is presented in Section 3.2. The social relationships in the human society layer can be mapped to the edge-AI layer. We will specifically analyze the positive effects of the social attributes on wireless federated edge learning in Section 4.

3.2 Centralized Control/Management Scheme in SFEL

In our SFEL framework, FEL will perform edge learning tasks in distributed wireless edge environments, how to conduct learning tasks according to available edge resources and wireless edge network status is still a challenge. To guarantee the better utilization of distributed edge-AI, centralized control and management are needed. It is highly desirable to employ softwarized networking paradigms (i.e., software defined networks) for centralized control and management of the distributed network nodes and edge devices [33]. Due to the separation of the control plane and the data plane in SDN, the main control and management functions are separated from the distributed base stations (BSs) and integrated into the centralized SDN controller in the cloud platform. Thus the resource utilization of wireless edge networks will be flexible and efficient with the help of the SDN method.

In Fig. 2, we employ a centralized control and management scheme in SFEL. It contains three planes, i.e., device plane, data plane, and control plane. Device plane includes edge-AI devices who are willing to undertake edge learning tasks. Data plane consists of Mobile Edge Computing (MEC) enabled Base Stations (BS). Control

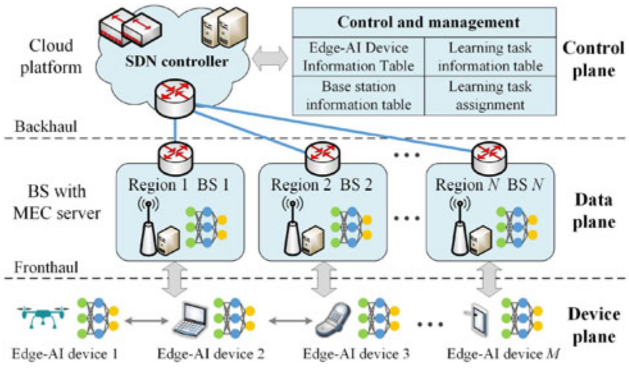


Fig. 2. Centralized control and management in SFEL.

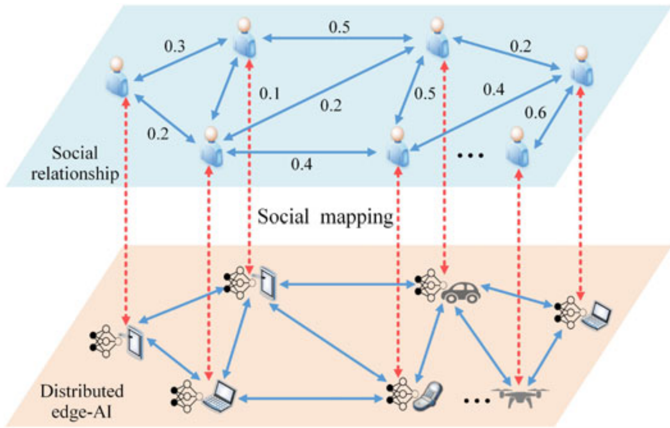


Fig. 3. The social graph model in SFEL.

plane is achieved by the SDN controller deployed in the cloud platform. edge-AI devices communicate with BSs via the wireless links and the distributed BSs are connected to the cloud via high-speed backhaul networks. We bring the SDN method to decouple the control plane from the data plane in our SFEL. In specific, the cloud supports the control/management of our SFEL. The significant control functionalities (e.g., resource allocation and scheduling) are determined by the SDN controller in the cloud. The SDN controller will maintain the edge-AI device information table, the BS information table, and the learning task information table. The edge-AI device information table contains resource information of edge-AI devices (e.g., training data size and CPU cycle) and social relationships. BS information table includes wireless access network information (e.g., communication bandwidth and channel gain). The learning task information table includes the learning task type, task time limit, AI model training accuracy, etc. edge-AI devices periodically upload the device information to the nearby BS. Then the BS integrates multiple edge-AI devices' information and BS information, and periodically transmits to the SDN controller. With the centralized control/management scheme, we conclude the interaction process as three steps:

- *Step 1:* The learning task subscribers (i.e., service requesters) publish their learning tasks to the cloud platform and the SDN controller updates the learning task information table.
- *Step 2:* Potential edge-AI devices upload their information (e.g., learning task attributes) to the nearest BS, then the BS transmits the edge-AI devices information and BS information (e.g., channel status) to the SDN controller.
- *Step 3:* The SDN controller then updates all the information tables, and recruits the corresponding edge-AI devices as the task producers based on the task matching and social trust relationships. Besides, the cloud platform will design the optimal system strategies (e.g., pricing and resource allocation strategies in Sections 5 and 6) to optimize the utilities of all the parties in our framework.

Noticed that, on the cloud management platform, we can implement social trust management, task assignment, as well as the reward-punishment mechanism of SFEL. In order to reduce the malicious learning behavior of malicious attackers, the reward-punishment mechanism is also important in SFEL. The reward-punishment mechanism in the existing system has been studied a lot [34]. Our SFEL can adopt a reward-punishment mechanism based on credit scores, which is designed in our previous work [35]. Specifically, when learning task producers (i.e., edge-AI devices) log on to the platform for the first time, they not only need to update their learning task attributes and social trust relationships but also will be granted an initial credit score at the beginning of logging. After each learning task is completed, the subscribers and the platform will evaluate the quality of their learning service, and give corresponding rewards or punishments, corresponding to the increase or reduction of credit scores. When the credit score is lower than the credit threshold, producers will be kicked out of the service platform. Thus, we could achieve punishment for malicious services, thereby mitigating malicious learning behavior in SFEL.

4 System Model and Problem Formulation

In this section, we mainly analyze the social mapping between the human social layer and the edge smart device layer, as well as the positive effect of social attributes, which is also shown in Fig. 1. We assume the cloud platform will recruit a set of edge-AI devices $\mathcal{M}=\{0,1,2,\ldots,i,\ldots,M\}$ to perform a certain learning task. These edge-AI devices also connect with each other via social links mapped from the human social layer, as shown in Fig. 3.

4.1 Social Graph Model in SFEL

As is shown in Fig. 3, we construct a social graph $\mathcal{G}^{EI}=\{\mathcal{M},\mathcal{E}^{EI}\}$ with social ties to show the social relationships. The underlying reason for employing social ties lies in that pervasive edge devices (e.g., mobile phones, smart vehicles) are owned and controlled by their users. Thus the intrinsic trust model in human social relationships could be exploited to realize the collaboration among their belongs. The vertex set is the same as the edge-AI device set $\mathcal{M}$, and $\mathcal{E}^{EI}=\{(i,j): e^{EI}(i,j)=1, \forall i,j\in\mathcal{M}\}$ is the edge set, where $e^{EI}(i,j)=1$ if and only if edge-AI device i and j have a social tie toward each other. We also define that $Nbr(i)=\{j:(i,j)\in\mathcal{G}^{EI}\}$ as the set of neighbors of edge-AI device i. Besides, the social tie of edge-AI device i on j is represented as ϕ_{ij}, specially, $\phi_{ii} = 0$. We also consider the social influences between device i and j are the same, which is presented as $\phi_{ij} = \phi_{ji}$. The social ties in our framework are not only depended on the mutual trust among devices, but also determined by the learning task similarity.

1) Mutual trust: social interactions could be widely observed in people with social trust, and altruistic behaviour might also occur spontaneously. Thus, mobile devices and their users with social trust are more likely to be selected as learning partners in FEL. For instance, when an edge device owner stays at home or at work, his/her parents, neighbors, and colleagues are pleased to perform collaborative learning tasks. To depict the distinct trustworthy relationships among devices and users, we utilize $J_{ij} \in [0, 1]$ to present the mutual trust in our framework, where 0 shows no trust between edge devices i and j, and 1 shows the strongest trust value. In practical applications, edge device owners can identify their neighbors or colleagues by matching information (e.g., home or work addresses). Besides, they could also detect their social trust with online social networks (e.g., Facebook and WeChat). For instance, authenticated Facebook users could obtain social graph data by the OpenGraph API.

2) Learning task similarity: we also assume that there are multiple federated edge learning tasks as $(task_1, task_2, \ldots, task_k, \ldots, task_N)$. And we believe that resource-constrained edge-AI devices cannot perform all kinds of federated learning tasks. This is because a single edge device (or user) cannot provide all the required raw learning materials (data). The edge-AI devices are also willing to learning with some like-minded learning partners, who could provide the required valuable data for model training. Thus, we define the learning task attributes of edge-AI devices as $\Delta_i = (\lambda_{i1}, \lambda_{i2}, \ldots, \lambda_{ik}, \ldots, \lambda_{iN})$, where $\lambda_{ik} \in (0, 1)$ shows the diversity rating. For instance, learning tasks can be smart healthcare, smart transportation, and so on [3]. A higher rating $\lambda_{ik} \in (0, 1)$ indicates that edge node i can provide more training data in learning task k. In practice, we can detect the learning task attributes of users through their social behaviors. Moreover, we could derive the learning task similarity I_{ij} between edge device i and j with a cosine similarity as

$$I_{ij} = \cos < \Delta_i, \Delta_j > = \frac{\sum_{k=1}^{k=N} \lambda_{ik} \cdot \lambda_{jk}}{\sqrt{(\sum_{k=1}^{k=N} \lambda_{ik}^2) \cdot (\sum_{k=1}^{k=N} \lambda_{jk}^2)}}, \tag{1}$$

where $I_{ij} \in (0, 1)$, $I_{ij} = 0$ shows no learning task similarity between edge devices i and j, and $I_{ij} = 1$ shows the strongest learning task similarity.

In our framework, it is meaningless to select a trustworthy partner with which collaborated learning can be not achieved due to different learning task attributes, and vice versa. Therefore, we combine the mutual trust and learning task similarity to establish social ties ϕ_{ij} in SFEL, which is defined as

TABLE 1
Main Notations Referred in Our Work

Notations	Descriptions
$\mathcal{M}$	The selected edge-AI devices set to perform learning tasks
$\mathcal{G}^{EI}$	The social graph model among edge-AI devices and their owners
c_i	The CPU cycles number required for one sample data training
d_i	The local personal dataset size of device i
δ_i	The local training accuracy of device i
T_i^{com}	The communication time of device i
T_i^{cmp}	The computing time of edge-AI device i
E_i^{com}	The energy consumption of edge-AI device i in the communication process
E_i^{cmp}	The energy consumption of edge-AI device i in the computing process
ϕ_{ij}	The social tie (social influence) of edge-AI device i on j
f_i	The contributed learning resources (CPU cycle frequency) of edge-AI device i
p_i	The unit reward from the service requester for edge-AI device i.
$X(s)$	The probability distributions of in-degrees s in the social structure
$Y(t)$	The probability distributions of out-degrees t in the social structure

$$\phi_{ij} = I_{ij} \times J_{ij}. \tag{2}$$

The social ties not only acts as a criterion for selecting partners, but also show the social influence in the SFEL. The main notations of our work are presented in *Table 1*.

4.2 Federated Edge Learning Model in SFEL

In our SFEL, each edge device i ($\forall i \in \mathcal{M}$) is equipped with a local personal dataset $\mathcal{D}_i$ ($|\mathcal{D}_i| = d_i$). Each data sample is shown as an input-output pair $\{\boldsymbol{m}_l, \boldsymbol{n}_l\}_{l=1}^{d_i}$. The input $\boldsymbol{m}_l$ is a sample vector with various features, and the output $\boldsymbol{n}_l$ is the label value of the input features from users' mobile application [7]. The loss function is discribed as $f_l(\boldsymbol{m}_l, \boldsymbol{n}_l, \boldsymbol{w})$. For instance, $f_l(\boldsymbol{m}_l, \boldsymbol{n}_l, \boldsymbol{w}) = 0.5||\boldsymbol{n}_l - \boldsymbol{w}^T \boldsymbol{m}_l||^2$ in linear regression. So the local average loss function of edge device i is defined as

$$\mathcal{L}_i(\boldsymbol{w}) = \frac{1}{d_i} \sum_{l=1}^{l=d_i} f_l(\boldsymbol{m}_l, \boldsymbol{n}_l, \boldsymbol{w}). \tag{3}$$

In addition, the optimization target of global federated edge learning process could be defined as

$$\min_{\boldsymbol{w}^*} \mathcal{L}_{gobal}(\boldsymbol{w}) = \frac{d_i \sum_{i \in \mathcal{M}} \mathcal{L}_i(\boldsymbol{w})}{\sum_{i \in \mathcal{M}} d_i}. \tag{4}$$

4.2.1 *Local Training on Devices*

Edge device i trains a local model with a local accuracy δ_i ($0 \le \delta_i \le 1$). The accuracy δ_i is defined as inexact accuracy, which is shown as follows:

Definition 1. *(δ-inexact accuracy): For a smooth convex function $\mathcal{L}_i(\boldsymbol{w}_i)$, $\boldsymbol{w}_i^*$ is δ_i-inexact accuracy for local training, if the following holds:*

$$\left\|\nabla\mathcal{L}_i(\boldsymbol{w}_i^*, \boldsymbol{w}^{(t)})\right\| \le \delta_i\left\|\nabla\mathcal{L}_i(\boldsymbol{w}^{(t)}, \boldsymbol{w}^{(t)})\right\|. \tag{5}$$

When $\delta_i = 0$, it shows the local problem has been solved optimally, while $\delta_i = 1$ means no progress at all in the local training [7]. At the t^{th} model training round, we solve the following optimization problem:

$$\boldsymbol{w}_i^{(t)} = \arg\min\mathcal{L}_i(\boldsymbol{w}_i|\boldsymbol{w}_i^{(t-1)}, \nabla\mathcal{L}_i^{(t-1)}(\boldsymbol{w}_i^{(t-1)})). \tag{6}$$

After that, edge devices upload local training model (i.e., weights $\boldsymbol{w}_i^{(t)}$ and gradients $\nabla\mathcal{L}_i{}^{(t)}$) to the BS node for aggregating the global model.

In our SFEL framework, since model information (including weights $\boldsymbol{w}_i^{(t)}$ and gradients $\nabla\mathcal{L}_i{}^{(t)}$) will be exposed or shared among social friends, some malicious edge device nodes will extract original training data through advanced AI attacks such as model reverse attacks or member inference attacks. It will lead to privacy leakage of mobile users. We solve this problem from two aspects. First, we select some edge devices with a higher trust degree for collaborative learning, which can avoid these AI attacks to a certain extent, because we believe that edge devices with a high trust degree are honest but curious (or semi-trusted). Second, we could also employ advanced privacy protection mechanisms (e.g., differential privacy technology) to prevent privacy leakage [36]. Specifically, before uploading the local model, we need to add a certain degree of interference noise (Gaussian noise or Laplacian noise) to the local model. According to the definition of differential privacy, even if a malicious user obtains the disturbed model information, it is difficult for him to extract the original information from it. The standardized differential privacy protection could be realized in our SFEL framework.

4.2.2 Global Updating at BSs

The BS node (or MEC node) collects and aggregates all the sub-models from edge devices

$$\boldsymbol{w}^{(t+1)} = \frac{1}{M}\sum_{i\in\mathcal{M}}\boldsymbol{w}_i^{(t)}, \nabla\mathcal{L}^{(t+1)} = \frac{1}{M}\sum_{i\in\mathcal{M}}\nabla\mathcal{L}_i{}^{(t)}. \tag{7}$$

Then, the MEC node will feed back the global model to the edge device. Interactive learning will be repeated iteratively. Until α-inexact accuracy is realized, i.e., $||\nabla\mathcal{L}(\boldsymbol{\omega}^{(t)})|| \le \alpha||\nabla\mathcal{L}(\boldsymbol{\omega}^{(t-1)})||$, the global learning will finish, where $\alpha \in [0, 1]$ denotes the global model accuracy. We assume the loss function $\mathcal{L}_i$ is convex objective, so the local iterations is general upper bounded to $\mathcal{O}(\log(1/\delta_i))$. It is suitable for various iterative algorithms (e.g., gradient or stochastic descent)[7].

4.2.3 Computation Model of SFEL

In SFEL, the contributed learning resources of devices are represented by the CPU cycle frequency $f_i \in [0, f_i^{\max}]$. Thus, the training time per local iteration of the edge device i is $c_i d_i/f_i$, where c_i indicates the CPU cycles number required for one sample data training. Therefore, the total time of one global model training round at device i is expressed as

$$T_i^{cmp}(\delta_i, f_i) = \mathcal{O}(\log(1/\delta_i))c_i d_i/f_i. \tag{8}$$

Besides, we also depict the energy consumption as the learning cost of edge-AI device i in the training process. The square relationship between computing CPU and the computing energy consumption is defined according to [7]. Because the quadratic function model is a typical model to represent the energy cost in a wireless edge environment, which could be shown as follows:

$$E_i^{cmp}(\delta_i, f_i) = \mathcal{O}(\log(1/\delta_i))\mu_i c_i d_i f_i^2, \tag{9}$$

where μ_i is the coefficient of chipset capacitance at edge-AI device i. In addition, considering $\mathcal{O}(\log(1/\delta_i)) = \omega\log(1/\delta_i)$, without loss of generality, we also normalize ω to 1 by absorbing ω into T_i^{cmp} and E_i^{cmp}.

4.2.4 Communication Model of SFEL

In SFEL, edge-AI devices should periodically communicate with the model aggregation node (i.e., the MEC node) to upload and update trained sub-models. Thus we consider a time-sharing multi-access protocol (e.g., OFDMA) to establish a wireless communication links for edge-AI devices. The transmission rate of edge-AI devices i is defined as $R_i = W\log_2(1 + \frac{P_i H_i}{N_0 W})$, where W represents the transmission bandwidth, H_i indicates the wireless channel gain between device i and the aggregate node, P_i is the transmission power, and N_0 represents the noise power spectrum density.

We assume the data size of the uploading sub-model gradient is β_i. Although the data size β_i of the uploaded gradient is slightly changed over every round of training, we set the update size β_i as an approximate fixed value in the simulations [7], [9], without loss of generality. Thus the communication time of edge-AI device i is discribed as

$$T_i^{com}(P_i) = \beta_i/R_i = \frac{\beta_i}{W\log_2(1 + \frac{P_i H_i}{N_0 W})}. \tag{10}$$

Besides, the energy consumption in communication process mainly results from the transmit power of edge-AI device, which could be expressed as follows:

$$E_i^{com}(P_i) = P_i T_i^{com} = \frac{\beta_i P_i}{W\log_2(1 + \frac{P_i H_i}{N_0 W})}. \tag{11}$$

Noticed that, due to the small data size of the trained AI model and the high transmission rate of wired backhaul networks, we have ignored the transmission delay and energy consumption between the aggregation node and the cloud platform.

4.3 Problem Formulation for SFEL

4.3.1 Utility Function of Edge-AI Devices

Each edge-AI device i will decide its learning resource allocation f_i to optimize its utility, which mainly contains the following several parts:

- Price-based reward: edge-AI device i receives a price-based reward $p_i f_i$ from the service requester, which is proportional to its resource allocation.
- Learning cost: edge-AI device i has a learning cost to perform the federated learning sub-task, which could be represented as the energy consumption during the whole process (computation and communication).
- Social-aware satisfaction: resulting from the social network external effect, the payoff of the edge-AI device is positively influenced by the learning contribution of its friends. Thus, we express the social satisfaction of edge-AI device i associated with its friend j as $\phi_{ij} f_i f_j$, which is a classical assumption in social networks to simulate the interplay of social influence [37].

We employ a proportionality constant $\xi_i > 0$ to show the weight of social-aware satisfaction. Therefore, we could define the utility function of edge-AI devices U_i^{EI} as follows:

$$U_i^{EI}(p_i, f_i) = p_i f_i + \xi_i \sum_{j \in \mathcal{M}} \phi_{ij} f_i f_j - E_i^{com} - E_i^{cmp}(f_i). \tag{12}$$

Specially, we also define social welfare (surplus) as the summation of the utility (payoff) U_i^{EI} of all edge-AI devices.

4.3.2 Utility Function of the Service Requester

We believe that the SFEL service requester expects to complete learning tasks in a shorter time, thus the service requester will set the maximum complete time $T_i^{\max}$ for each edge-AI device. We could define the QoS of each edge-AI device i as $Q_i = T_i^{\max} - T_i^{com} - T_i^{cmp}$. Intuitively, the high-quality learning service means high satisfaction. And we assume the service requester satisfaction is proportional to learning quality. Logarithm utility functions could realize the proportional fairness among users. So we define the satisfaction function S_i [38] as the monotone increasing function of learning quality Q_i, i.e., $S_i = \gamma_i \ln(1 + Q_i(f_i))$, where $\gamma_i > 0$ represents the satisfaction degree parameter. Furthermore, the utility function of the service requester U^{SR} could be expressed as follows:

$$U^{SR}(\boldsymbol{p}, \boldsymbol{f}) = \sum_{i \in \mathcal{M}} \gamma_i \ln(1 + Q_i(f_i)) - \sum_{i \in \mathcal{M}} p_i f_i. \tag{13}$$

4.3.3 Problem and Game Formulation

In the joint optimization problem, we need to maximize the utilities of both parties. To characterize the interactions between the service requester and edge-AI devices, we formulate a two-stage Stackelberg game in SFEL. At stage I, the service requester provides rewards $\boldsymbol{p}$ to motivate edge-AI devices to perform learning sub-tasks. Meanwhile, at stage II, each edge-AI device optimizes its learning resource allocation $\boldsymbol{f}$ to maximize its utility function. Thus, the leader-level and followers-level game could be formulated as follows, respectively

$$\max_{\boldsymbol{p},\, \boldsymbol{f}} \quad U^{SR} = \sum_{i \in \mathcal{M}} \gamma_i \ln(1 + Q_i(f_i)) - \sum_{i \in \mathcal{M}} p_i f_i \quad s.t. \quad p_i^{\min} \le p_i \le p_i^{\max} \quad (p_i \in \boldsymbol{p}) \tag{14}$$

$$\max_{p_i, f_i} U_i^{EI} = p_i f_i + \xi_i \sum_{j \in \mathcal{M}} \phi_{ij} f_i f_j - E_i^{com} - E_i^{cmp} \; s.t. \quad 0 \le f_i \le f_i^{\max} \quad (f_i \in \boldsymbol{f}). \tag{15}$$

To solve the proposed Stackelberg game, we aim to find the Nash equilibrium (NE) and Stackelberg equilibrium (SE) between the leader and followers, which is defined as:

Definition 2. *(NE and SE): Let* $\boldsymbol{p}=\{p_1, p_2, \ldots, p_i, \ldots, p_M\}$ *and* $\boldsymbol{f}=\{f_1, f_2, \ldots, f_i, \ldots, f_M\}$ *show the resource pricing and allocation strategies, respectively. Then,* $\boldsymbol{p}^*$ *and* $\boldsymbol{f}^*$ *denote learning resource pricing and allocation strategies in Stackelberg equilibrium (SE) and Nash equilibrium (NE), respectively, if and only if*

$$U^{SR}(\boldsymbol{p}^*, \boldsymbol{f}^*) \ge U^{SR}(\boldsymbol{p}^*, \boldsymbol{f}), \quad U_i^{EI}(p_i^*, f_i^*) \ge U_i^{EI}(p_i, f_i^*), \quad \forall i \in \mathcal{M}, \tag{16}$$

where $\boldsymbol{p}^*$ *and* $\boldsymbol{f}^*$ *are also the optimal strategies that we define under the game equilibrium. We mainly need to solve the equilibrium strategies in the following paper.*

5 Stackelberg Game Analysis With Complete Information in SFEL

In this section, we analyze our Stackelberg game with complete information. That is, the cloud platform can collect all the system information (e.g., social relationships) to determine the optimal system strategies.

Lemma 1. *Under the given* $\boldsymbol{p}$ *provided by the service requester, the optimal resource allocation strategies* $\boldsymbol{f}^*$ *of edge-AI device i could be described as*

$$f_i^*(p_i) = \min\{\frac{p_i + \xi_i \sum_{j \in \mathcal{M}} \phi_{ij} f_j}{2\omega \log{(1/\delta_i)} \mu_i c_i d_i}, f_i^{\max}\}. \tag{17}$$

Proof: The optimal resource allocation strategies could be obtained by taking the first-order derivative of $U_i^{EI}(f_i)$ with respect to f_i, and setting it is equal to 0, that is

$$\frac{\partial U_i^{EI}}{\partial f_i} = p_i + \sum \xi_i \phi_{ij} f_j - 2\omega \log{(1/\delta_i)} \mu_i c_i d_i f_i = 0. \tag{18}$$

To simplify, we employ $C = 2\omega \log{(1/\delta_i)} \mu_i c_i d_i$. If we have $(p_i + \xi_i \sum \phi_{ij} f_j)/C \ge f_i^{\max}$, then we could obtain $f_i^* = f_i^{\max}$ from Eq. (15). And we have $p_i \ge f_i^{\max} C - \xi_i \sum \phi_{ij} f_j$. By substituting f_i^* into Eq. (13), we then need to maximize $U^{SR}(p_i, f_i^{\max})$, which could be observed as a decreasing function with respect to p_i. So, the optimal pricing $p_i^* = f_i^{\max} C - \xi_i \sum \phi_{ij} f_j$. In general, $p_i^* \le f_i^{\max} C - \xi_i \sum \phi_{ij} f_j$ and $f_i^* \le f_i^{\max}$. The proof has been completed.

Assumption 1. *Similar to [37], [38], we give an assumption of network effects. i.e.,* $C > \sum \xi_i \phi_{ij}$.

Remark. Assumption 1 ensures that all the edge-AI devices have a negative marginal utility when increasing the contribution of learning resources f_i, as presented in Eq. (18). If this assumption does not hold, then all the edge-AI devices can unlimitedly increase the contribution of learning resources without considering learning pricing rewards p_i. Following [37], [38], we have made a similar assumption to ensure that the social-aware learning resource contribution f_i of each edge-AI device is bounded. Based on this assumption, we have the following *Theorem 1*.

Theorem 1. *There exist unique NE learning resource allocation strategies $\boldsymbol{f}^*$ among all the selected edge-AI devices at the stage II.*

Proof: We take the second-order derivative of $U_i^{EI}(f_i)$ with respect to $\boldsymbol{f}^*$, and then we investigate the matrix H

$$H = \begin{vmatrix} \nabla_{11}^2 U_1^{EI} & \nabla_{12}^2 U_1^{EI} & \dots & \nabla_{1M}^2 U_1^{EI} \\ \nabla_{21}^2 U_2^{EI} & \nabla_{22}^2 U_2^{EI} & \dots & \nabla_{2M}^2 U_2^{EI} \\ \vdots & \vdots & \ddots & \vdots \\ \nabla_{1M}^2 U_M^{EI} & \nabla_{2M}^2 U_M^{EI} & \dots & \nabla_{MM}^2 U_M^{EI} \end{vmatrix}. \tag{19}$$

We could obtain $\nabla_{ii}^2 U_i^{EI} = -C$ and $\nabla_{ij}^2 U_i^{EI} = \xi_i \phi_{ij}$. Under *Assumption 1*, we have $-\nabla_{ii}^2 U_i^{EI} > \sum \nabla_{ij}^2 U_i^{EI} > 0$. $-H$ could be proved strictly diagonal dominant and positive definite, while H is diagonally strictly concave, correspondingly. Thus we could prove there exist unique NE learning resource allocation strategies according to [40].

Theorem 2. *Under the optimal response strategies $\boldsymbol{f}^*$, there exists unique SE strategies $\boldsymbol{p}^*$ at stage I.*

Proof: By substituting Eqs. (17) into (13), Then, the optimization problem at stage I can be rewritten as

$$\begin{aligned} \max_{\boldsymbol{p}} U^{SR} = & \sum \gamma_i \ln(1 + T_i^{\max} - \frac{2\omega^2 \log^2(1/\delta_i)\mu_i c_i^2 d_i^2}{p_i + \xi_i \sum \phi_{ij} f_j} \\ & - T_i^{com}) - \sum \frac{p_i^2 + p_i \xi_i \sum \phi_{ij} f_j}{2\omega \log(1/\delta_i)\mu_i c_i d_i} \\ & s.t. \quad p_i^{\min} \le p_i \le p_i^{\max} \quad (p_i \in \boldsymbol{p}). \end{aligned} \tag{20}$$

To simplify, we employ $A = 1 + T_i^{\max} - T_i^{com}$, $B = 2\omega^2 \log^2(1/\delta_i)\mu_i c_i^2 d_i^2$. We observe each term in the second summation of the utility function is a quadratic function (convex). With a negative, the convex function is converted to a concave one. Thus we investigate the first summation. Each term in the first summation is represented as the satisfaction function $S_i(p_i)$. We then take the first-order and second-order derivative of S_i

$$\frac{\partial S_i}{\partial p_i} = \frac{\gamma_i}{p_i + \xi_i \sum \phi_{ij} f_j} \frac{B}{A(p_i + \xi_i \sum \phi_{ij} f_j) - B}, \tag{21}$$

$$\frac{\partial^2 S_i}{\partial^2 p_i} = \frac{-\gamma_i B[2A(p_i + \xi_i \sum \phi_{ij} f_j) - B]}{[A(p_i + \xi_i \sum \phi_{ij} f_j)^2 - B(p_i + \xi_i \sum \phi_{ij} f_j)]^2}. \tag{22}$$

We can observe $A - B/(p_i + \xi_i \sum \phi_{ij} f_j) > 0$ in Eq. (20), i.e., $2A(p_i + \xi_i \sum \phi_{ij} f_j) - B > 0$. Thus, $\nabla_{ii}^2 S_i < 0$. Besides, $\nabla_{ij}^2 S_i = 0$. So, the Hessian matrix of S_i is strictly negative definite, i.e., S_i is a concave function. So U^{SR} is a concave function with regard to $\boldsymbol{p}$. The optimization problem of Eq. (20) must be a convex optimization problem. Moreover, there exist unique SE strategies $\boldsymbol{p}$ at stage I, which completes the proof. Based on *Theorems 1* and *2*, we design a dynamic gradient-based iterative algorithm with the well-performance convergence ability and low algorithm complexity. So it could be easily implemented in the SDN controller, which is shown in *Algorithm 1*.

Algorithm 1. Gradient-Based Iterative Searching Algorithm for NE and SE

Input: c_i, d_i, δ_i, $f_i^{\max}$, $p_i^{\min}$, $p_i^{\max}$, and $\mathcal{G}^{EI}, \forall i \in \mathcal{M}$;
Output: $\boldsymbol{p}^*$, $\boldsymbol{f}^*$, U^{SR}, $\boldsymbol{U}^* = (U_1^{EI}, U_2^{EI}, \dots, U_M^{EI})$;
Initialization: Threshold κ, σ, step size θ, and $n = 0$;
  Select initial input $\boldsymbol{p}^0 = (p_1^0, p_2^0, \dots, p_i^0, \dots, p_M^0)$, $\boldsymbol{f}^0 = (f_1^0, f_2^0, \dots, f_i^0, \dots, f_M^0)$, and $\boldsymbol{f}^1 = (f_1^1, f_2^1, \dots, f_i^1, \dots, f_M^1)$, where $p_i^0 \in [p_i^{\min}, p_i^{\max}]$, $f_i^0, f_i^1 \in [0, f_i^{\max}]$, $\forall i \in \mathcal{M}$;
while $\frac{\|p^{n+1} - p^n\|_1}{\|p^n\|_1} > \sigma$ **do**
  $m = 0$;
  while $\frac{\|\boldsymbol{f}^{m+1} - \boldsymbol{f}^m\|_1}{\|\boldsymbol{f}^m\|_1} > \kappa$ **do**
    for all edge-AI device $i \in \mathcal{M}$ **do**
      Calculate $\boldsymbol{f}^{m+2}$ according to Eq. (17):
      $f_i^{m+2} = \min\{\frac{p_i^n + \xi_i \sum \phi_{ij} f_j^{m+1}}{2\omega \log(1/\delta_i)\mu_i c_i d_i}, f_i^{\max}\}$;
    end for
    $m := m + 1$;
  end while
  $\boldsymbol{f}^*(\boldsymbol{p}^n) := (f_1^m, f_2^m, \dots, f_i^m, \dots, f_M^m)$;
  Updates the learning resource pricing:
  $\boldsymbol{p}^{n+1} = \boldsymbol{p}^n - \theta \nabla U^{SR}(\boldsymbol{p}^n, \boldsymbol{f}^*(\boldsymbol{p}^n))$;
  $n := n + 1$;
end while
Calculate $\boldsymbol{f}^*$, U^{SR}, and $\boldsymbol{U}^* = (U_1^{EI}, U_2^{EI}, \dots, U_M^{EI})$ according to Eqs. (17), (14), and (15);

6 Bayesian Stackelberg Game With Incomplete Information in SFEL

In Section 5, we assume edge-AI devices will send the social information ϕ_{ij} $(\forall j \in \mathcal{M})$ to the SDN controller, so that the cloud platform could determine optimal strategies with the complete social information based on *Algorithm 1*. However, due to social privacy-preserving concerns, the scenario with asymmetric social information is more practical. We assume the specific social information is unknown, while the probability distribution of social information could be acquired via historical interaction information. Thus we extend the original game model to the Bayesian model with incomplete information. In specific, we denote the social coefficient as ϕ_{ij}=λ, thus Eq. (12) could be rewritten as

$$U_i^{EI} = \mathbb{E}(u_i^{EI}) = p_i f_i + \xi_i \lambda \mathbb{E}(F_{-i}) f_i - E_i^{com} - E_i^{cmp}, \tag{23}$$

where F_{-i} represents the summation of $f_j, \forall j \in Nbr(i)$.

The social structure will generate in-degrees and out-degrees for social nodes (edge-AI devices). The in-degree denotes the number of edge-AI devices that a certain device influences (prestige), and the out-degree shows the number of edge-AI devices influences this device (groupness). We employ various in-degrees and out-degrees between edge-AI devices to characterize the underlying social network effects. That is, we assume the in-degree $s \in \Gamma$ and out-degree $t \in \Gamma$, where $\Gamma = \{0, 1, 2, \ldots, \gamma^{\max}\}$. And we define the probability distributions of in-degrees and out-degrees as $X : \Gamma \to [0,1]$ and $Y : \Gamma \to [0,1]$, respectively. Consistency theory derives that $\sum X(s)s = \sum Y(t)t = \bar{t}$. $\bar{t}$ represents the mean level of social network effects. And for edge-AI device i, its randomly selected social neighbours have the in-degree distribution $\bar{X}(s) = \frac{X(s)s}{\sum X(s')s'} = X(s)s\bar{t}^{-1}$ and out-degree distribution $Y(t)$. Thus the utility of edge-AI device i with out-degree t is shown as follows:

$$U_i^{EI} = p_i f_i - E_i^{com} - E_i^{cmp} + \xi_i \lambda t_i Ave(F_{-i}) f_i, \tag{24}$$

where $Ave(F_{-i}) = \sum \bar{X}(s) \sum Y(t) f(s,t)$ shows the mean learning resource of the neighbors of edge-AI device i. In addition, Eq. (13) could be rewritten as follows:

$$\begin{aligned} U^{SR} = &\sum\sum X(s)Y(t)(-p(s,t)f(s,t) \\ &+\gamma \ln(1 + Q(f(s,t)))). \end{aligned} \tag{25}$$

Theorem 3. *There exist unique Bayesian NE resource allocation strategies $f^*(s,t)$ for the edge-AI device with in-degree s and out-degree t, which is described as follows:*

$$f^*(s,t) = \frac{1}{C}[p(s,t) + \frac{\xi\lambda t \bar{p}(s,t)}{C - \xi\lambda\bar{t}}], \tag{26}$$

where $\bar{p}(s,t) = \sum\sum \bar{X}(s)Y(t)p(s,t)$, and $\bar{t} = \sum Y(t)t$.

Proof: We now investigate the second-order derivative of Eq. (23), which is shown as follows:

$$\frac{\partial^2 U_i^{EI}}{\partial^2 f(s,t)} = -C \leq 0. \tag{27}$$

U_i^{EI} is strictly concave. It means a unique Bayesian Nash equilibrium exists. Let the first-order derivative equal to 0, we can obtain the NE strategy, i.e.,

$$f^*(s,t) = \frac{1}{C}[p(s,t) + \xi\lambda t Ave(F_{-i})]. \tag{28}$$

In addition, we could obtain the expression of the average learning resource $Ave(F_{-i})$ from Eq. (29), i.e., $Ave(F_{-i}) = \bar{p}(s,t)/(C - \xi\lambda\bar{t}) \geq 0$. By substituting $Ave(F_{-i})$ into Eq. (28), we could conclude the expression of the optimal learning resource $f^*(s,t)$ as Eq. (26). The proof has been completed

$$\begin{aligned} Ave(F_{-i}) &= \sum\sum \bar{X}(s)Y(t)f(s,t) \\ &= \sum\sum \bar{X}(s)Y(t)\frac{p(s,t) + \xi\lambda t Ave(F_{-i})}{C} \\ &= \frac{\sum\sum \bar{X}(s)Y(t)p(s,t) + \xi\lambda Ave(F_{-i})\sum Y(t)t}{C} \\ &= \frac{1}{C}[\bar{p}(s,t) + \xi\lambda Ave(F_{-i})\bar{t}]. \end{aligned} \tag{29}$$

Theorem 4. *For the service requester, under the optimal response strategies $f^*(s,t)$, there exist unique Bayesian SE strategies $p^*(s,t)$ between the leader and follows.*

Proof: we assume the SDN controller can only get the probability distribution information of out-degrees and in-degrees, while the specific out-degree and in-degree of each device are not known. Thus the unified pricing strategy in the asymmetric Bayesian Stackelberg game must be more practical, i.e., $p(s,t) = \bar{p} = p$. By substituting Eqs. (26) into (25), we can conclude the utility of the leader as Eq. (30)

$$\begin{aligned} U^{SR}(p) = &\sum u^{SR} = \sum Y(t)[-\frac{p^2}{C} - \frac{p^2\xi\lambda t}{C(C - \xi\lambda\bar{t})} \\ &+\gamma\ln(A - \frac{B}{p}\frac{C - \xi\lambda\bar{t}}{C - \xi\lambda\bar{t} + \xi\lambda t})]. \end{aligned} \tag{30}$$

$$\begin{aligned} \frac{\partial u^{SR}(p,\hat{t})}{\partial p} = &Y(\hat{t})[\frac{\gamma B(C - \xi\lambda\bar{t})}{p^2\Pi(C + \xi\lambda\hat{t} - \xi\lambda\bar{t})} \\ &- \frac{p(C + \xi\lambda\hat{t} - \xi\lambda\bar{t})}{C(C - \xi\lambda\bar{t})} - \frac{p(C - \xi\lambda\bar{t}) + p\xi\lambda\hat{t}}{C(C - \xi\lambda\bar{t})}, \end{aligned} \tag{31}$$

$$\begin{aligned} \frac{\partial^2 u^{SR}(p,\hat{t})}{\partial^2 p} = &-Y(\hat{t})[\frac{(C + \xi\lambda\hat{t} - \xi\lambda\bar{t})^2}{C(C - \xi\lambda\bar{t})^2} \\ &+ \frac{\gamma B^2(C - \xi\lambda\bar{t})^2}{p^4\Pi^2(C + \xi\lambda\hat{t} - \xi\lambda\bar{t})^2} + \frac{2\gamma B(C - \xi\lambda\bar{t})}{p^3\Pi(C + \xi\lambda\hat{t} - \xi\lambda\bar{t})}], \\ \Pi = &A - \frac{B(C - \xi\lambda\bar{t})}{p(C - \xi\lambda\bar{t} + \xi\lambda t)}. \end{aligned} \tag{32}$$

We now investigate each term in the above sum utility function. For a certain $\hat{t} \in \Gamma$, $Y(t) = Y(\hat{t})$, we can take the first-order and second-order derivative of the partial utility function $u^{SR}(p,\hat{t})$ as Eqs. (31) and (32). $Ave(F_{-i}) \geq 0$, thus $C - \xi\lambda\bar{t} \geq 0$. So the third term in Eq. (32) is positive and the second-order derivative is negative. In general, the expected utility function U^{SR} is a concave function with regard to p. Meanwhile, p is bounded to $[p^{\min}, p^{\max}]$. The utility optimization problem of Eq. (30) is proved as a convex optimization problem and unique Bayesian SE strategies $p^*(s,t)$ exist. The proof is now complete. And we could obtain the optimal strategies by a multi-round Bayesian Stackelberg game algorithm as shown in *Algorithm 2*.

Algorithm 2. Multi-Round Bayesian Stackelberg Game Algorithm for NE and SE

Input: $\Gamma = \{0, 1, 2, \ldots, \gamma^{\max}\}$, λ, $X(s)$ and $Y(t)$;
Output: $f^*(s,t)$, $p^*(s,t)$, U^{SR}, $U^{EI}(s,t)$
Initialization: Threshold α;
$\widehat{p}(s,t) = \frac{p^{\max}(s,t)+p^{\min}(s,t)}{2}$, $\breve{p}(s,t) = \frac{p^{\max}(s,t)+\widehat{p}(s,t)}{2}$;
while $\widehat{p}(s,t) - \breve{p}(s,t) > \alpha$ **do**
  for all edge-AI devices $\forall s,t \in \Gamma$ **do**
    Calculate $f^*(\widehat{p}(s,t))$ according to Eq. (26);
  end for
  Calculate $U^{SR}(\widehat{p}(s,t), f^*(\widehat{p}(s,t)))$ based on Eq. (25);
  for all edge-AI devices$\forall s,t \in \Gamma$ **do**
    Calculate $f^*(\breve{p}(s,t))$ according to Eq. (26);
  end for
  Calculate $U^{SR}(\breve{p}(s,t), f^*(\breve{p}(s,t)))$ based on Eq. (25);
  if $U^{SR}(f^*, \widehat{p}(s,t)) > U^{SR}(f^*, \breve{p}(s,t))$ **then**
    $p^{\max}(s,t) = \breve{p}(s,t), \forall s,t \in \Gamma$;
  else
    $p^{\min}(s,t) = \widehat{p}(s,t), \forall s,t \in \Gamma$;
  end if
  $\widehat{p}(s,t) = \frac{p^{\max}(s,t)+p^{\min}(s,t)}{2}$, $\breve{p}(s,t) = \frac{p^{\max}(s,t)+\widehat{p}(s,t)}{2}$;
end while
$p^*(s,t) = \widehat{p}(s,t) = \breve{p}(s,t)$ is acquired;
Calculate $f^*(s,t)$, U^{SR}, $U^{EI}(s,t)$ according to Eqs. (26), (25), and (24);

7 Simulation and Discussion

In this section, we conduct extensive simulations to evaluate our optimal system strategies with the Erdos-Renyi random network [41], the real Facebook network [42], and the classic MNIST/CIFAR-10 dataset. The simulations are conducted with an Intel(R) Xeon(R) Silver 4114 CPU @2.20 GHz, 256 G memory, and four GeForce RTX 2080 GPUs. We employ the Tensorflow framework and Gym library to implement the federated edge learning model, and Docker containers are employed to simulate the environment of edge-AI devices in the federated edge learning model.

7.1 Simulation Setup in Our Framework

7.1.1 Edge-AI Parameters

The training size d_i of each edge-AI device is uniformly selected from $25-35$ MB, CPU cycle number of data training c_i is uniformly selected from $10-30$ cycles/bit, and the maximum computing resource $f_i^{\max}$ is uniformly distributed in $1.5-2.5$ GHz. The channel gain H_i between edge-AI devices and the based station is modeled as the path loss model, i.e., $32.44 + 20\log_{10}(d)$, where d is euclidean distance uniformly distributed 0 m to 150 m. The communication bandwidth W is set as 1 MHz and the noise power spectrum density N_0 is set as -174 dBm/Hz. The communication transmit power P_i is uniformly distributed in $100-200$ mW.

7.1.2 ER Network and Facebook Network Parameters

In our work, we mainly analyze the influence of social network externalities. The influence includes two aspects, one is the influence of social connections, and the other is the influence of social tie value. Obviously, when there are more social connections or greater social tie value, the external effects of social networks will be higher. The ER random graph can extensively simulate the influence of social connections. We can build random graphs with different probability connections in the ER model to reflect the influence of social connections. The influence of The social tie value is simulated through the normal distribution parameters. Facebook ego network is a real network topology after desensitization. We mainly use this real network topology to show the feasibility of our framework in real-life. Thus these two networks are representative. In complete information game, we consider the Erdos-Renyi (ER) random network G and Facebook network, where the social tie value ϕ_{ij} follows a consistent normal distribution with mean $\mu_r = \mu_f = 0.5$ and standard deviation $\sigma_r = \sigma_f = 0.15$. The node number of ER random network is set to 100, and the social link probability of it is ranging from 0.1 to 0.9. We also considered an actual network topology. In specific, we consider a Facebook ego network that presents a Facebook user's social friend list with other 228 users. If two users are social friends in the Facebook dataset, a social link will be formed between them. In the incomplete information game, we only know the probability distribution information of the social network topology, i.e., we consider the in-degree and out-degree of edge-AI devices also follow the same normal distribution with mean $\mu_g = [30, 60]$ and standard deviation $\sigma_g = [25, 35]$, and the node number is set to 150.

7.2 Result Analysis of the Complete Information Game With ER Random Network

In Figs. 4a, 4b, 4c, and 4d, we investigate the impact of link probability of ER random network in terms of social welfare, SFEL service requester's utility, resource allocation, and learning service price, respectively. The number of edge-AI devices is set to $N = 100$. For comparative analysis, we also introduced the classic random scheme and uniform scheme, where each edge-AI device randomly/uniformly selects a resource allocation strategy from $[0, f_i^{\max}]$, and the service requester randomly/uniformly selects a learning pricing strategy from $[p_i^{\min}, p_i^{\max}]$. As shown in Figs. 4a and 4b, compared with the classic random and unified scheme, our scheme could achieve greater utility for both edge-AI devices and the service requester whether $G = 0$ or $G \neq 0$.

When $G = 0$, there are no social links between edge-AI devices, thus the social-aware satisfaction in Eq. (5) is equal to 0. In this case, our scheme degenerates into the discussion in [9], [12]. Thus, when $G = 0$, social welfare and SFEL service requester's utility will not change with different link probability values. When $G \neq 0$, it means G is partially connected, and the probability of connection is determined by the probability value of the ER random network model. We can observe that the service requester's utility increases with the link probability in Fig. 4b. It is because the service requester could grant less learning service pricing to edge-AI devices when the link probability increases as shown in

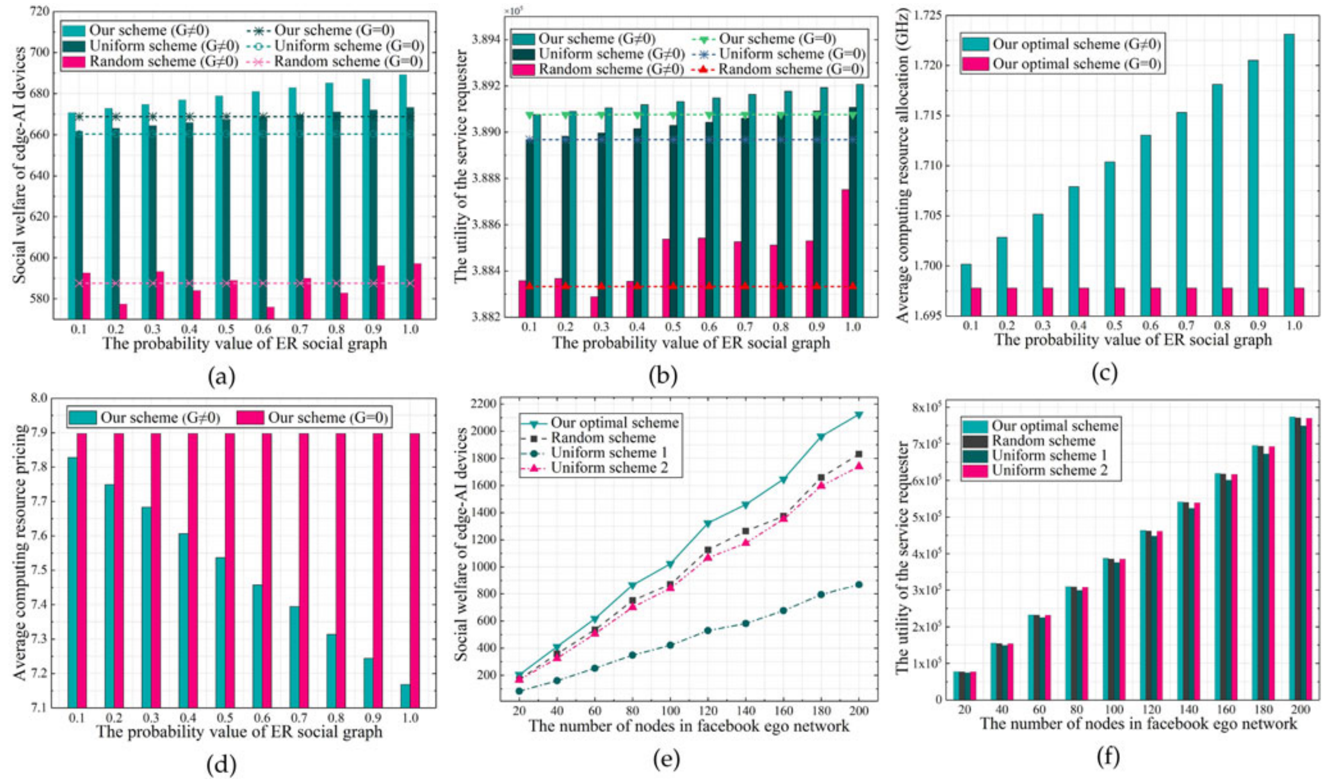


Fig. 4. Simulations of the complete information game: (a) social welfare versus ER graph probability; (b) service requester utility versus ER graph probability; (c) computing resource versus ER graph probability; (d) resource pricing versus ER graph probability; (e) social welfare versus Facebook node number; and (f) service requester utility versus Facebook node number.

Fig. 4d. Meanwhile, with a tighter social link, even if the pricing strategy is low, the resource allocation strategy of edge-AI devices will not decrease but will increase slightly, which is shown in Fig. 4c. For edge-AI devices, as the link probability increases, the peer social effect is getting stronger, and each edge-AI device will obtain more social-aware satisfaction. Thus the social welfare also increases accordingly as shown in Fig. 4a. In summary, apart from increasing the SFEL service requester's utility, the social network effect by G also increases the social surplus of edge-AI devices. Therefore, the introduction of the peer social network effect will not only generate revenue for one party, but brings a win-win situation for both parties in our proposed SFEL framework.

7.3 Result Analysis of the Complete Information Game With Facebook Ego Network

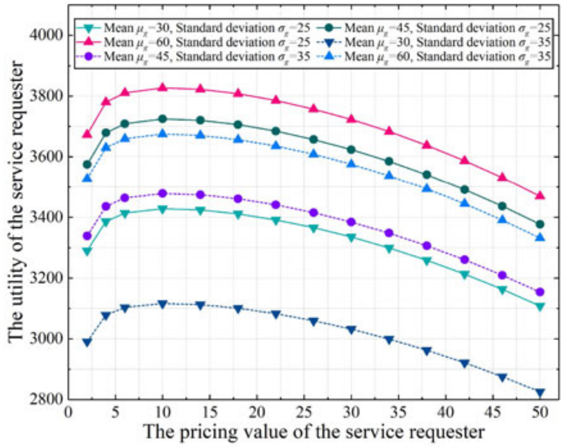
In Figs. 4e and 4f, we study the impact of the number of edge-AI devices on social welfare and the service requester's utility based on the real Facebook Ego Network trace $(N = 228)$. As shown in Fig. 4f, we draw the service requester's utility versus the number of edge-AI devices. We could observe that the service requester's utility under Facebook social information increases with the number N. On the one hand, with the increase of edge devices, the service requester could obtain more local data from edge-AI devices, thus obtaining more valuable learning services. On the other hand, more edge-AI devices also mean a larger probability of recruiting edge-AI devices with strong social ties, thus inducing stronger peer social effects and obtaining more profits for both parties in SFEL. In actual large-scale network topologies, the number of social nodes is often very large, and social links usually take a sparse form. Based on this assumption, the service requester is required to select more influential edge-AI devices with a higher in-degree in social space, which could increase the profits of both parties.

In Fig. 4e, we draw social welfare versus the number N. We observe that social welfare also increases by N. This is because the service requester will provide higher learning service prices and bring higher social welfare for edge-AI devices under a high level of peer social effects when the number N increases.

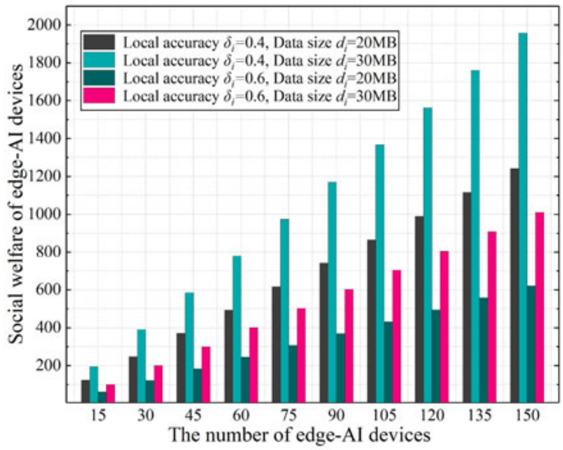
7.4 Result Analysis of the Incomplete Information Game

In Figs. 5a and 5b, we conduct simulations of the incomplete information Bayesian game. The number of edge-AI devices is set to $N = 150$. Specifically, in Fig. 5a, we plot the service requester's utility against the pricing value. As shown in Fig. 5a, the learning pricing of the service requester and its utility are in the form of concave correlation. That is, for the uniform pricing strategy, there is a Bayesian Stackelberg equilibrium point. As μ_g increases, the equilibrium point will move up. This is because a larger μ_g indicates that a large average out-degree and in-degree of edge-AI devices in social space, which also means a larger social network effect. Thus it will directly improve the utility of the service requester and edge-AI devices.

In Fig. 5b, we investigated the influence of learning parameters on the social welfare of edge-AI devices. A smaller δ_i indicates a higher learning accuracy requirement



(a) Service requester utility vs uniform pricing value.



(b) Social welfare vs edge-AI device number.

Fig. 5. Simulations of the incomplete information game.

for learning services, which means that more training iterations need to be performed. This will also consume more energy consumption of edge-AI devices, but it will not reduce the social welfare of edge-AI devices. This is because the pricing rewards of the service requester will also increase accordingly. Thus on the premise of ensuring the quality of learning service, the profits of edge-AI devices are guaranteed. Similarly, when d_i increases, edge-AI devices will also consume more resources, but the revenue could be also made up based on the service requester's pricing rewards. It also shows the availability of our strategies in the proposed SFEL framework.

7.5 Result Analysis With the MINIST/CIFAR-10 Datasets

In Fig. 6, we evaluate the SFEL training of three different models based on two different datasets (i.e., MNIST and CIFAR-10). The models include support vector machines (SVM), fully-connected neural network (FC), deep convolutional neural networks (CNN). SVM and FC are trained on the original MNIST dataset, which includes gray-scale images of 70,000 handwritten digits (training: 60,000 and testing: 10,000). CNN is trained on the CIFAR-10 dataset, which includes 60,000 color images (training: 50,000 and testing: 10,000). SVM outputs a binary label corresponding to whether the number is even or odd. FC performs handwritten digit recognition of gray-scale images. CNN performs object recognition of color images. FC and CNN perform multi-class classification among the 10 different labels from the MNIST and CIFAR-10 datasets, respectively.

In SVM and FC training, the number of edge-AI devices is set to 40. In CNN training, the number of edge-AI devices is set to 10. We mainly compare three situations in terms of learning performance: a) High social effects in SFEL; b) Low social effects in SFEL; c) No social effects in SFEL. As shown in Fig. 4, higher network effects can encourage edge-AI devices to contribute more computing resources. The social network effects only depend on two aspects: 1) the intensity of social connections; 2) the influence of social ties ϕ_{ij}. For the ER random network, as the connection probability increases, the social network effects increase. For the actual Facebook network, as social ties ϕ_{ij} increase, the social network effects increase. Situation a) and situation b) can reflect the impact of different levels of social network effects on learning performance. When the connection probability of ER random network is 0, or social ties in Facebook network are 0, the social network effects are 0. If there are no social network effects in SFEL, our strategy will automatically degenerate into existing research works. In Fig. 6, we draw the global accuracy and loss of the SFEL framework under 3 situations with 3 learning models. It can be seen that social network effects can significantly improve the learning performance of FEL. Under the same circumstances, social network effects can motivate edge-AI devices to contribute more learning resources and regulate the learning behavior of edge-AI devices. Instead of adopting selfish learning strategies, the social welfare of the entire system will be improved. From the perspective of FEL, under the same time conditions, edge-AI devices will converge a higher-precision global learning model, which greatly improves the learning efficiency of FEL.

8 Conclusion

In this paper, we have proposed a novel SFEL framework, which leverages the hidden social effects among edge devices and their users for achieving trustworthy and effective federated edge learning. Besides, we built a social graph model with social ties to find the trustworthy co-learners in SFEL, jointly considering the mutual trust and learning interests. Based on the social ties, we constructed a social effect based incentive mechanism, which encourages a better learning behavior of each learner. The socially-driven incentive mechanism was established by a Stackelberg game model with both complete and incomplete information. Performance evaluation was based on the Erdos-Renyi random network, the real Facebook networks, and the MNIST/CIFAR-10 datasets. Simulation results have proved our optimal strategies are more efficient than existing schemes, and our optimal strategies will bring a win-win situation for both parties in SFEL by social effects. Simulation results also demonstrated that our SFEL framework could improve the performance of wireless federated edge learning.

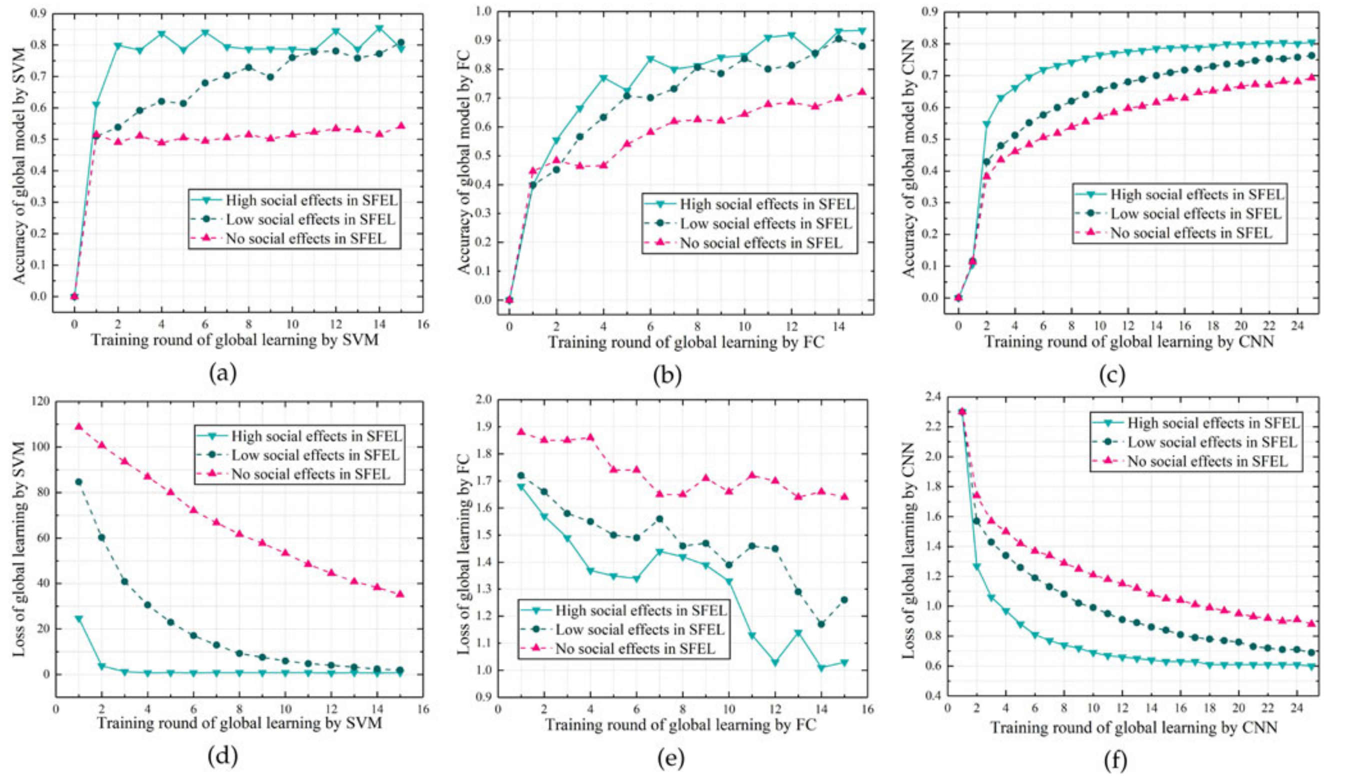


Fig. 6. Simulations with the MNIST/CIFAR-10 datasets: (a) Global model accuracy by SVM versus training round; (b) Global model accuracy by FC versus training round; (c) Global model accuracy by CNN versus training round; (d) Global loss by SVM versus training round (e) Global loss by FC versus training round; (f) Global loss by CNN versus training round.

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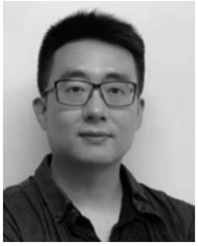

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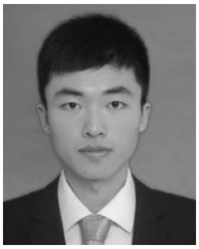

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