An Efficient and Truthful Online Incentive Mechanism for a Social Crowdsensing Network

Lu Fang[1], Tong Liu[1,2,3,4(✉)], Honghao Gao[1], Chenhong Cao[1,3], Weimin Li[1], and Weiqin Tong[1,3,4]

[1] School of Computer Engineering and Science, Shanghai University, Shanghai, China
{shanhefl,tong_liu,gaohonghao,caoch,wmli,wqtong}@shu.edu.cn
[2] Shanghai Key Laboratory of Data Science, Shanghai, China
[3] Shanghai Institute for Advanced Communication and Data Science, Shanghai University, Shanghai, China
[4] Shanghai Engineering Research Center of Intelligent Computing System, Shanghai, China

Abstract. Crowdsening plays an important role in spatiotemporal data collection by leveraging ubiquitous smart devices equipped with sensors. Considering rational and strategic device users, designing a truthful incentive mechanism is a crucial issue. Moreover, another key challenge is that there may not exist adequate participating users in reality. To encourage more users to participate, the social relationship among them can be leveraged, as users may be significantly influenced by their social friends. In this paper, we assume recruited users to diffuse uncompleted sensing tasks to their friends, and propose an efficient and truthful online incentive mechanism for a such social crowdsensing network. Specially, we model the time-varying social influence of a user by extending two metrics of node centrality used in social networks. In order to maximize the accumulated social welfare achieved by the network, we design a user selection algorithm and a payment determination algorithm respectively, in which payments given to participants not only depend on data qualities but also related with social influences. We theoretically prove that our mechanism achieves properties of computational efficiency, individual rationality, and truthfulness. Extensive simulations are conducted, and the results show the superiority of our mechanism.

Keywords: Crowdsensing · Incentive mechanism · Truthfulness · Social influence

1 Introduction

In recent years, mobile smart devices like smartphones have been widespread in urban life, which are embedded with various sensors such as camera, microphone,

H. Gao et al. (Eds.): CollaborateCom 2020, LNICST 349, pp. 49–63, 2021.
https://doi.org/10.1007/978-3-030-67537-0_4

and accelerometer. Spatiotemporal sensing data can be collected over time in a large urban area by a mass of distributed mobile smart devices, which is referred as mobile crowdsensing. Some practical applications have been implemented based on mobile crowdsensing, such as passenger flow monitoring and environmental noise mapping. Providing sufficient incentives to participate device users is a crucial issue in mobile crowdsensing, in order to compensate their costs incurred by sensing, especially when rational and strategic users are considered. A number of incentive mechanisms [3,4,8] have been proposed, in which different facets of a crowdsensing network are taken into consideration, such as the quality or spatiotemporal coverage of sensing data and the dynamic arrivals of users and requests.

Most of these incentive mechanisms assume there are adequate participants in a crowdsensing network. However, it is not always true in reality. According to the statistics data published by TalkingData [1], the ratios of active users in May, 2019 in two popular traffic-monitoring applications, Tencent map and Google map, are only 2.99% and 0.48% respectively.

To solve the problem of insufficient participating users in a crowdsensing network, some researchers have tried to employ the social relationship among users to attract more participants. Incentive mechanisms with considering the social influences of users have been proposed in recent works [5,6,9,10,12–15]. Specially, in [10] and [9], the in-degree and out-degree of a user in a social network are calculated to measure the social influence of the user. Bayesian game and Stackelberg game are respectively employed to model the crowdsensing system. Social-aware incentive mechanisms are proposed in [15] and [6], where rewards given to participants depend on their social friends, to stimulate them attracting more users. Xu *et al.* [14] propose a two-tiered architecture, in which agents are selected as middlemen, who are employed to recruit their social neighbors as participants. However, most of these works ignore the social influence of a user is time-varying, which is related with the locations and reliability of his/her social friends.

In this work, we consider the problem of designing an incentive mechanism for strategic and unreliable users in a social crowdsensing network, aiming to maximize the social welfare of the network accumulated over time and guarantee the truthfulness of users. To be specific, we consider the quality of sensing data collected by different users are discrepant, which is decided by the reliability of each user. Moreover, we also consider some users in the network are inactive in sensing. Thus, participants are recruited not only for collecting sensing data but also for stimulating their inactive friends to become active. By taking advantage of the social network among users, we assume that uncompleted sensing tasks can be informed to the friends by a recruited user, and more users will be influenced by their social friends to participate in sensing.

Although some incentive mechanisms taking social influences of users into account have been designed in previous works, there still exist several challenges to overcome. *Firstly*, the social influence of a user is hard to be measured in a real-time crowdsensing network, which is not only determined by his/her centrality in the social network, but also related with the reliability of his/her social friends and the locations they may appear. *Secondly*, users can dynamically become active or inactive over time, which is unknown in advance to the platform. However, the platform should select participants and pay them incentives in real time, to support spatiotemporal data collection with high quality-of-service. *Thirdly*, there exists an inherent tradeoff between selecting users with high reliability and selecting users with high social influences. High-quality sensing data can be collected by users with high reliability on condition that there are sufficient users participating in sensing. *Last but not least*, we consider users are rational and strategic, who will not perform tasks with negative rewards and may submit false information for maximizing their own utilities.

To meet the challenges, we propose an efficient and truthful online incentive mechanism for a social crowdsensing network, which comprises of a user selection algorithm and a payment determination algorithm. Firstly, we measure the time-varying social influence of an active user by extending two metrics of node centrality used in social networks. Then, we model the interactions between users and the platform as a repeated reverse auction. In each auction, the platform collects the bids of active users and then greedily selects participants with high reliability, large social influences, and low costs one by one. Inactive users may be stimulated by selected users and then turn into active, if they are social friends of selected users. After receiving sensing data from selected users, the platform will provide incentives to them according to their data qualities and social influences. Finally, we theoretically prove that our proposed incentive mechanism achieves the properties of computational efficiency, individual rationality, and truthfulness.

The rest of the paper is organized as follows. We review the state-of-art related works in Sect. 2. Section 3 presents the network model and the formulated problem. In Sects. 4 and 5, we describe our proposed incentive mechanism in details and theoretically analyze the properties achieved by our mechanism, respectively. We present the simulation results in Sect. 6, and conclude this paper in Sect. 7.

2 Related Work

A lot of efforts [3,4,8] have been paid to design incentive mechanisms for mobile crowdsensing, encouraging rational smart device users to participate in sensing. To attract more users, social networks are also extensively introduced in mobile crowdsensing. In [2], rewarding social influences of participants in crowdsourcing systems are firstly put forward.

In [10] and [9], authors use the in-degree and out-degree of a user in a social network to measure the network effect of the user, which can quantify the influence of his/her behavior on social friends. Specially, a Bayesian game-based social-aware incentive mechanism is proposed in [10] for a crowdsensing system, in which the platform has incomplete information of users. And a two-stage Stackelberg game-based incentive mechanism are proposed for a crowdsensing system in [9], with analyzing the participation level and social influence of users. Yang *et al.* [15] propose a social-aware incentive mechanism in which the incentive given to a user depends on his/her social friends. Thus, users are motivated to drive social friends to provide high-quality services, with the objective to achieve higher utilities. In [5], a VCG-based incentive mechanism for multi-resource sharing in crowdsourcing is proposed, engaging users with low cost and high reputation as participants, in which the reputation of each user is updated according to his/her social influence. In all the above related works, an offline crowdsensing system is considered.

Differently, some other works consider an online crowdsensing system with tasks or users arriving in real time. Jiang *et al.* [6] consider time-sensitive tasks arriving to the platform in real time. In order to stimulate users to spread sensing tasks as soon as possible, extra rewards are paid to users for attracting others and the rewards are decreasing with the participating time of the attracted users. In [13], Xu *et al.* initially select participants according to their numbers of common social friends between participating users and their social friends via a greedy hill-climbing algorithm. Then, reverse auction is employed for selecting more users and providing incentives. [14] proposes a two-tiered crowdsourcing architecture, in which agents are recruited as middlemen between the platform and users. Agents are selected according to their time coverage and social influences which are measured by the similarity of interests between the agents and their social neighbors. Sun *et al.* [12] propose an incentive mechanism with considering the heterogeneity of users in social networks. To ensure users to participate in sensing continuously, participants are selected based on their social states and current workloads.

In these works, different metrics in social networks are employed to measure the social influences of users to provide social-aware incentives to participants. However, most of works ignore that the social influence of a user is time-varying, not only determined by the social network, but also related to the reliability and locations of his/her social friends.

3 Network Model and Problem Formulation

In this section, we first introduce the model of a social crowdsensing network considered in this work, and then mathematically formulate the problem of incentive mechanism design and user selection in such a network.

3.1 Network Model

In this work, we firstly consider a typical crowdsensing network, which comprises of a central platform located at the cloud and a plenty of mobile smartphone users distributed in an urban area. In such a crowdsensing network, a mass of fine-grained spatio-temporal sensing data could be collected for applications like real-time environment monitoring. For convenience, we divide time into equal-interval time slots (e.g., 20 min), and the set of time slots is denoted by

$\mathcal{T} = \{t_1, t_2, \cdots, t_s, \cdots\}$. We consider several points of interest (POIs) in an urban area need recruit smartphone users nearby (e.g., within 500 m) to collect sensing measurements continuously. We denote the set of POIs as $\mathcal{L} = \{l_1, l_2, \cdots, l_K\}$, where K is the number of POIs in the urban area. Moreover, the task of collecting measurements around POI l_k in time slot t_τ is denoted by φ_k^τ. Each measurement collected for task $\varphi_k^\cdot$ is associated with a preliminary value v_k obtained by the platform, which is related to the importance of POI l_k.

We consider there exists a universal set of registered smartphone users, denoted by $\mathcal{U} = \{u_1, u_2, \cdots, u_N\}$, where N represents the number of users. Due to different hardware, the measurements collected by different users may have diverse qualities. We model the qualities of measurements collected by user u_i via considering his/her reliability $q_i \in (0, 1]$, which could be derived from the historical measurements. The larger reliability of user u_i, the higher quality of his/her measurements, as well as the value achieved by the platform. Thus, we calculate the value of the measurement collected by user u_i for task φ_k^* as $q_i \cdot v_k$.

At the beginning of each time slot, *active users* will participate in performing tasks forwardly via a reverse auction with the platform. Specially, if user u_i becomes available in time slot t_τ, he/she will submit a bid $\beta_i^\tau = (\alpha_i^\tau, \Phi_i^\tau, b_i^\tau)$ to the platform. Here, α_i^τ represents the length of time window in which u_i will keep available, and Φ_i^τ is the set of tasks that u_i will perform during time window $[t_\tau, t_\tau + \alpha_i^\tau]$. As energy and bandwidth resources are consumed for doing tasks Φ_i^τ, a certain amount of costs is incurred on user u_i, denoted by c_i^τ. Considering the rationality and selfishness of users, b_i^τ is the bidding price claimed by u_i to the platform for completing tasks Φ_i^τ, which may be unequal to c_i^τ. In addition, the set of active users in time slot t_τ is represented by $\mathcal{U}^\tau \subseteq \mathcal{U}$.

To indicate whether a user is selected or not in time slot t_τ, we define an index vector $\mathbf{I}^\tau = [I_1^\tau, I_2^\tau, \cdots, I_N^\tau]$, in which $I_i^\tau \in [0, 1], \forall u_i \in \mathcal{U}^\tau$. Obviously, $I_i^\tau = 0$ if $u_i \notin \mathcal{U}^\tau$. Specially, $I_i^\tau = 1$ means user u_i is selected by the platform, otherwise u_i is not selected. If user u_i is recruited in t_τ, a certain amount of payment should be provided to u_i by the platform to compensate the cost of the user, which is denoted by p_i^τ. Given the decisions of user selection in period $[t_1, t_{\tau-1}]$, the total value of the measurements collected by these selected users for task φ_k^τ can be calculated as $V_k^\tau = \sum_{t=1}^{\tau-1} \sum_{I_i^t=1 \wedge \varphi_k^\tau \in \Phi_i^t} q_i v_k$. According to the law of diminishing marginal utility [7], we define the utility achieved by collected measurements increases with the total value of the measurements, while the marginal utility decreases. Thus, we define the utility achieved for task φ_k^τ as $\log(1 + V_k^\tau)$. Then, the utility of collected measurements in time slot t_τ is

$$U(\mathbf{I}^\tau) = \sum_{k=1}^{K} \sum_{t=\tau}^{\tau+\max_i\{\alpha_i^\tau\}} \left(\log(1 + V_k^t + \sum_{\varphi_k^t \in \Phi_i^\tau} I_i^\tau q_i v_k) - \log(1 + V_k^t) \right).$$

To promote more users (i.e., *inactive users*) to participate in sensing, the users selected to perform tasks are also responsible for diffusing sensing tasks to their inactive social friends through a social network. In this work, we consider the social network containing all the registered users is represented by a directed graph $G(\mathcal{U}, \mathcal{E})$, in which each node is a user. A directed edge from node u_i to node u_j, denoted by $e_{i,j} \in \mathcal{E}$, means user u_j is a friend or follower of user u_i. In addition, each edge $e_{i,j}$ is associated with a weight $w_{i,j}$, indicating the social influence made by u_i to u_j.

Intuitively, the larger social influence made by a user to his/her social neighbours, the higher effect achieved by the user to diffuse sensing tasks. Here, we employ two metrics, *weighted degree centrality* and *closeness centrality*, to evaluate the social influence made by a user to others. These two metrics are widely used to measure the node centrality in a social network. Generally, given a social network $G(\mathcal{V}, \mathcal{E})$, the weighted degree centrality and the closeness centrality of an arbitrary node $v_i \in \mathcal{V}$ are defined as $\sum_{v_j \in \mathcal{N}(v_i)} w_{i,j}$ and $\frac{|\mathcal{V}|-1}{\sum_{v_j \in \mathcal{V}} d_{i,j}}$, respectively. Here, $\mathcal{N}(v_i)$ is the set of social neighbours of v_i, and $d_{i,j}$ is the shortest distance between v_i and v_j. Obviously, the larger values of these two metrics, the higher centrality a node has.

Inspired by the two metrics of node centrality in social networks, we extend them to evaluate the social influence of each user in our social crowdsensing network. As some measurements have been collected in previous time slots, different POIs have various levels of urgency to collect more measurements at present. Therefore, we also consider various contributions made by different inactive users if they turn into participants, which are highly relevant with the their locations. We denote the probability of an inactive user $u_i \in \mathcal{U} \setminus \mathcal{U}^\tau$ appearing around POI l_k by $o_{i,k} \in [0,1]$, which can be derived from his/her historical trajectories. Considering both the urgency of task φ_k^τ and the probability distribution of the location of inactive user u_i, we define the *potential contribution* of u_i as $O_i^\tau = \sum_{l_k \in \mathcal{L}} (o_{i,k} \cdot e^{-V_k^\tau})$. Intuitively, the less value of task φ_k^τ and the higher probability of u_i appearing around l_k, the more contributions achieved by u_i.

Then, we define two extended metrics to measure the social influence of a recruited user, named as *extended weighted degree centrality* and *extended closeness centrality*, respectively. Specially, given $\mathbf{I}^\tau$, the extended weighted degree centrality achieved by all recruited users is calculated as

$$\omega(\mathbf{I}^\tau) = \sum\nolimits_{u_j \in \bigcup_{I_i^\tau = 1} \mathcal{N}_i^\tau} \max\{I_i^\tau O_j^\tau w_{i,j} | \forall u_i \in \mathcal{U}^\tau\},$$

where $\mathcal{N}_i^\tau$ represents the set of inactive social neighbours of user u_i. Since an inactive user may be influenced by more than one recruited users, we only take the maximal influence into account, to avoid double counting. Note that we take the potential contribution of an inactive user as the auxiliary weight to evaluate the influence of recruited users. In addition, the extended closeness centrality achieved by all recruited users is calculated as

$$\upsilon(\mathbf{I}^\tau) = \sum_{u_i \in \mathcal{U}^\tau} \frac{I_i^\tau \cdot |\mathcal{U} \setminus \mathcal{U}^\tau|}{\sum_{u_j \in \mathcal{U} \setminus \mathcal{U}^\tau} (O_j^\tau)^{-1} d_{i,j}}.$$

Note that the extended closeness centrality of a recruited user is time-varying with the locations of his/her inactive social friends, introduced by taking their potential contributions into consideration. In summary, the utility obtained by the social influences of recruited users also follows the diminishing marginal law, which is defined as

$$W(\mathbf{I}^{\tau}) = \log\left(1 + \omega(\mathbf{I}^{\tau}) + \upsilon(\mathbf{I}^{\tau})\right).$$

3.2 Problem Formulation

In this work, we study the problem of online user selection and payment determination in a social crowdsensing network, aiming to maximize the social welfare of the network accumulated over time and maintain that rational and selfish users are truthful in participating in sensing.

Definition 1 (User Selection Problem). *In each time slot t_τ, a set of active users are selected by the platform to collect sensing data, indicated by $\mathbf{I}^{\tau}$, with the objective that the accumulated social welfare achieved by the crowdsensing network is maximized, i.e.,*

$$\max_{\{\mathbf{I}^{\tau}\}} \sum\nolimits_{\tau=1}^{\infty} [U(\mathbf{I}^{\tau}) + W(\mathbf{I}^{\tau}) - C(\mathbf{I}^{\tau})], \tag{1}$$

where $C(\mathbf{I}^{\tau}) = \sum_{u_i \in \mathcal{U}^{\tau}} I_i^{\tau} c_i^{\tau}$.

Definition 2 (Payment Determination Problem). *An incentive mechanism should be designed to determine the payment p_i^{τ} given to user u_i by the platform in time slot t_τ, if u_i is selected to collect sensing data in t_τ. Moreover, the incentive mechanism should achieve three properties, i.e., computational efficiency, individual rationality, and truthfulness.*

4 Incentive Mechanism Design

In this section, we propose a truthful online incentive mechanism for a social crowdsensing network. In particular, both user selection algorithm and payment determination algorithm are designed, to decide which users are recruited and how many payments are provided to them. In the following, we first present an overview of our proposed incentive mechanism, and then describe the two algorithms in detail, respectively.

4.1 Overview

At the beginning of each time slot, all active users will *firstly* submit bids to the platform. *Then*, after receiving all bids, the platform conducts user selection, to choose participants with high reliability, large social influences, and low costs. *Next*, all selected users are notified to collect sensing data and diffuse a message containing urgent uncompleted tasks to their inactive social friends. *Finally*, the platform will give proper payments to the selected users.

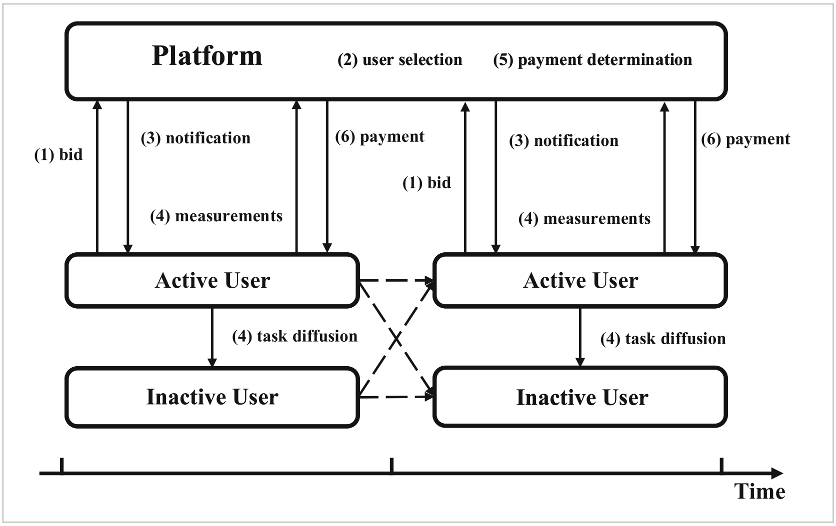

Fig. 1. The interactions between the platform and users in each time slot in the social crowdsensing network.

Note that users can dynamically switch between the active and inactive states. Specially, an inactive user, influenced by an active friend, may turn into active and further diffuse the message containing uncompleted tasks to his/her social friends. Thus, the message can spread to all users quickly through their social relationship (Fig. 1).

4.2 User Selection Algorithm

We first introduce the details of the online user selection algorithm, with assuming all users are truthful (i.e., the bidding price of each user equals to the cost). In each time slot, participating users are selected by the platform one by one. The main idea of this algorithm is to greedily choose the user who achieves the most *per-cost marginal utility.*

Definition 3 (User marginal utility). *Given the set of users already selected by the platform in the current time slot (indicated by* $\mathbf{I}^\tau$*), the marginal utility achieved by user* u_i *if he/she is selected by the platform in the next is defined as*

$$\Delta_i(\mathbf{I}^\tau) = U_i(\mathbf{I}^\tau) + W_i(\mathbf{I}^\tau), \tag{2}$$

where $U_i(\mathbf{I}^\tau)$ *and* $W_i(\mathbf{I}^\tau)$ *are calculated as*

$$U_i(\mathbf{I}^\tau) = U(\mathbf{I}^\tau \wedge I_i^\tau = 1) - U(\mathbf{I}^\tau \wedge I_i^\tau = 0), \tag{3}$$

$$W_i(\mathbf{I}^\tau) = W(\mathbf{I}^\tau \wedge I_i^\tau = 1) - W(\mathbf{I}^\tau \wedge I_i^\tau = 0). \tag{4}$$

Note that $U_i(\mathbf{I}^\tau)$ and $W_i(\mathbf{I}^\tau)$ represent the marginal utility achieved by the collected measurements and the social influences of user u_i, respectively.

At the beginning of each time slot, the platform first collects the bids of all active users, and initializes each element of indicator vector $\mathbf{I}^\tau$ as 0. Then, users are iteratively selected by the platform. In each iteration, the platform aims to find the user with the largest per-cost marginal utility, denoted by u_{i^*}. Specially, the platform calculates the marginal utility $\Delta_i(\mathbf{I}^\tau)$ of each unselected active user u_i. And hence the user $u_{i^*} = \arg\max_{u_i \in \mathcal{U}^\tau}\{\Delta_i(\mathbf{I}^\tau)/b_i^\tau | I_i^\tau = 0\}$ is selected as a participant (i.e., $I_{i^*}^\tau = 1$), unless the utility of his/her measurements is lower than his/her bidding price (i.e., $U_{i^*}(\mathbf{I}^\tau) < b_{i^*}^\tau$). The user selection iteration ends when the marginal utility of any unselected user is less than his/her bidding price, i.e., $\max_{u_i \in \mathcal{U}^\tau}\{\Delta_i(\mathbf{I}^\tau)/b_i^\tau | I_i^\tau = 0\} < 1$. Finally, the user selection algorithm outputs the indicator vector $\mathbf{I}^\tau$.

4.3 Payment Determination Algorithm

In order to ensure the strategic users honestly report their bids, we design a payment determination algorithm based on the rule of critical payment [11]. According to [11], to determine the payment given to a selected user u_{i^*}, we need to obtain the critical bid of u_{i^*} firstly. The critical bid is defined as the bid that makes the bid of user u_{i^*} fail (i.e., u_{i^*} can not be selected if the per-cost marginal utility of bid $\beta_{i^*}^\tau$ is less than the per-cost marginal utility of its critical bid), and the highest payment is achieved by u_{i^*} at the same time.

In what follows, we show how to find the critical bid of user u_{i^*}. We first initialize a virtual set of unselected users by excluding u_{i^*}, i.e., $\mathcal{U}' \triangleq \mathcal{U}^\tau \setminus \{u_{i^*}\}$, and a virtual user selection result $\mathbf{I}' \triangleq \mathbf{I}^\tau$. Moreover, the payment given to u_{i^*} is initialized as 0. Then, we virtually perform the user selection process as described in the previous subsection. In each iteration, user $u_{j^*} = \arg\max_{u_j \in \mathcal{U}'}\{\Delta_j(\mathbf{I}')/b_j^\tau | I_j' = 0\}$ is virtually selected (i.e., $I_j' = 1$), as long as $U_{j^*}(\mathbf{I}^\tau) \geq b_{j^*}^\tau$. We compare $\Delta_{i^*}(\mathbf{I}' \wedge I_{i^*}' = 1)/b_{i^*}^\tau$ and $\Delta_{j^*}(\mathbf{I}' \wedge I_{j^*}' = 1)/b_{j^*}^\tau$. When there exists $\Delta_{i^*}(\mathbf{I}' \wedge I_{i^*}' = 1)/b_{i^*}^\tau \geq \Delta_{j^*}(\mathbf{I}' \wedge I_{j^*}' = 1)/b_{j^*}^\tau$, user u_{i^*} would be selected instead of user u_{j^*}, if u_{i^*} were in the set of unselected users. Then, the payment given to u_{i^*} can be updated according to the per-utility cost of u_{j^*} as

$$p_{i^*|j^*}^\tau \triangleq \min\left(b_{j^*}^\tau \cdot \frac{\Delta_{i^*}(\mathbf{I}' \wedge I_{i^*}' = 1)}{\Delta_{j^*}(\mathbf{I}' \wedge I_{j^*}' = 1)}, U_{i^*}(\mathbf{I}' \wedge I_{i^*}' = 1)\right).$$

After all iterations, the critical bid of user u_{i^*} is obtained, which makes u_{i^*} achieve the highest payment. Thus, the payment given to user u_{i^*} can be calculated as

$$p_{i^*}^\tau = \max_{\left\{j^* | \frac{\Delta_{i^*}(\mathbf{I}' \wedge I_{i^*}' = 1)}{b_{i^*}^\tau} \geq \frac{\Delta_{j^*}(\mathbf{I}' \wedge I_{j^*}' = 1)}{b_{j^*}^\tau}\right\}} (p_{i^*|j^*}^\tau).$$

Note that if $U_{i^*}(\mathbf{I}' \wedge I_{i^*}' = 1)/b_{i^*}^\tau \geq 1$ after the iteration process of virtual user selection ends, which indicates there is no critical bid of user u_{i^*}, we set $p_{i^*}^\tau = \max\left(p_{i^*}^\tau, U_{i^*}(\mathbf{I}' \wedge I_{i^*}' = 1)\right)$.

5 Mechanism Analysis

In the following, we theoretically analyze that our mechanism can achieve the three desired properties, i.e., computational efficiency, individual rationality, and truthfulness.

Theorem 1. *Our incentive mechanism is computationally efficient. Specially, the computation complexity of the user selection algorithm and the payment determination algorithm is at most $O(N^2)$.*

Proof. First we prove that the user selection algorithm has polynomial-time computation complexity. The complexity for calculating the per-cost marginal utility $\frac{\Delta_i(\mathbf{I}^\tau)}{b_i^\tau}$ of all users in user selection algorithm is $O(|\mathcal{U}^\tau|)$. The operation of finding the user with largest per-cost marginal utility in current time slot is $O(|\mathcal{U}^\tau|)$. There are at most N bids in time slot t_τ because each user can only submit at most one bid in his/her active time window. So we have $|\mathcal{U}^\tau| \leq N$ and the operation analysed above will repeat at most N times. Then, it is easy to compute the total computation complexity of user selection algorithm which is at most $O(N^2)$.

Then we prove that the payment determination has polynomial-time computation complexity. The complexity for calculating the per-cost marginal utility $\frac{\Delta_i(\mathbf{I}^\tau)}{b_i^\tau}$ of all users in payment determination algorithm is $O(|\mathcal{U}^\tau|)$. The operation of choosing the user with highest per-cost marginal utility is $O(|\mathcal{U}^\tau|)$. There are at most N bids in time slot t_τ because each user can only submit at most one bid in his/her active time window. So we have $|\mathcal{U}^\tau| \leq N$ and the operation analysed above will repeat at most N times. So, it is easy to compute the total computation complexity of payment determination algorithm which is at most $O(N^2)$.

Theorem 2. Our mechanism guarantees that each user in the social crowdsensing network is individually rational.

Proof. Users are individual rational means each participating user will have a non-negative utility: $p_i^\tau - c_i^\tau \geq 0$. So we should prove that for each bid β_i^τ of participating users, the corresponding payment p_i^τ satisfies $p_i^\tau - c_i^\tau \geq 0$.

Since the payment of a selected user u_{i^*} for his/her bid $\beta_{i^*}^\tau$ is determined by two values which are $U_{i^*}(\mathbf{I}^{'})$ and $b_{j^*}^\tau \frac{\Delta_{i^*}(\mathbf{I}^{'})}{\Delta_{j^*}(\mathbf{I}^{'})}$ according to payment determination algorithm. So we should prove that these two values are both not less than the bidding price $b_{i^*}^\tau$ of $\beta_{i^*}^\tau$.

First of all, it is obviously that we have $\frac{U_{i^*}(\mathbf{I}^{'})}{b_{i^*}^\tau} \geq 1$ if u_{i^*} with bid $\beta_{i^*}^\tau$ is the m-th user selected in time slot t_τ. According to the judgement condition in payment determination algorithm, if there exists a m-th or m'-th ($m' > m$) selected user u_{j^*} and $\frac{\Delta_{i^*}(\mathbf{I}^{'})}{b_{i^*}^\tau} - \frac{\Delta_{j^*}(\mathbf{I}^{'})}{b_{j^*}^\tau} \geq 0$ when u_{i^*} does not participate in time slot t_τ, we will update the payment of u_{i^*} with bid $\beta_{i^*}^\tau$.

Next, we move the per-cost marginal utility of user u_{j^*} to the right side of the inequation above and multiply $b_{i^*}^{\tau}$ on both sides of the inequation. Now we have $\Delta_{i^*}(\mathbf{I}') \geq \frac{\Delta_{j^*}(\mathbf{I}')}{b_{j^*}^{\tau}} b_{i^*}^{\tau}$, then we have $b_{j^*}^{\tau} \frac{\Delta_{i^*}(\mathbf{I}')}{\Delta_{j^*}(\mathbf{I}')} \geq b_{i^*}^{\tau}$ since $\frac{\Delta_{j^*}(\mathbf{I}')}{b_{j^*}^{\tau}}$ is a positive number.

As the prove process shown above, we have $p_{i^*}^{\tau} = \min(b_{j^*}^{\tau} \frac{\Delta_{i^*}(\mathbf{I}')}{\Delta_{j^*}(\mathbf{I}')}, U_{i^*}(\mathbf{I}')) \geq b_{i^*}^{\tau}$, i.e., in the payment determination algorithm, we have $p_{i^*}^{\tau} - b_{i^*}^{\tau} \geq 0$. Due to the rationality of users, the real cost $c_{i^*}^{\tau}$ of each user must lower than or equal to his/her bidding price $b_{i^*}^{\tau}$. Thus, we successfully prove that users in our crowdsensing system are individual rational.

According to [11], our mechanism can achieve truthful if and only if it satisfies the following two conditions: (1) the user selection algorithm is monotonic, and (2) each selected user is paid the critical value. We first give the specific definitions of the two conditions in our crowdsensing network as follows.

- *The user selection algorithm is monotonic*, if user u_i with bid $\beta_i^{\tau} = (\alpha_i^{\tau}, \Phi_i^{\tau}, b_i^{\tau})$ selected as a participant will be still selected, if the user reports bid $\widetilde{\beta_i^{\tau}} = \left(\widetilde{\alpha_i^{\tau}}, \widetilde{\Phi_i^{\tau}}, \widetilde{b_i^{\tau}}\right)$ with $\widetilde{\alpha_i^{\tau}} \geq \alpha_i^{\tau}, \widetilde{b_i^{\tau}} \leq b_i^{\tau}, \Phi_i^{\tau} \subseteq \widetilde{\Phi_i^{\tau}}$.
- *The critical value of a user* indicates that if user u_i submits a bidding price lower than the critical value, u_i will be selected; otherwise, u_i will not be selected.

Theorem 3. Our mechanism guarantees that each user in the social crowdsensing network is truthful, including cost-truthful, time-truthful, and task-truthful..

Proof. We first prove that the user selection rule is monotonic.

Obviously, the $\frac{\Delta_i(\mathbf{I}^{\tau})}{b_i^{\tau}}$ of user u_i with β_i^{τ} at each time slot will increase with the decrease of his/her bidding price b_i^{τ}. If user u_i with bid β_i^{τ} is selected in time slot t_{τ}, u_i can also be selected if he/she submits a lower bidding price.

It is easily found that the $\frac{\Delta_i(\mathbf{I}^{\tau})}{b_i^{\tau}}$ of user u_i will not decrease if user u_i reports a wider active time window (the marginal utility of the measurements and social influence of users will not change when users report wider active time windows according to Eqs. (3) and (4)). So if user u_i is selected by submitting the bid β_i^{τ} in time slot t_{τ}, u_i can also be selected by submitting a bid with wider active time window.

The $\frac{\Delta_i(\mathbf{I}^{\tau})}{b_i^{\tau}}$ of user u_i will increase if it bids a larger task set $\widetilde{\Phi_i^{\tau}} \subseteq \Phi_i^{\tau}$ (Φ_i^{τ} is the real task set that u_i^{τ} can do during his/her active time window this time), so user u_i will submit his/her real task set for maximizing his/her own utility. Therefore, we can easily prove that if user u_i is selected with the bid $\widetilde{\beta_i^{\tau}} = (\alpha_i^{\tau}, \widetilde{\Phi_i^{\tau}}, b_i^{\tau})$ in time slot t_{τ}, u_i can also be selected if he/she submits a bid with a larger task set $\widehat{\Phi_i^{\tau}} \subseteq \Phi_i^{\tau}$ including tasks within his/her ability. Thus, we have proved that the user selection rule of our mechanism is monotonic.

Secondly, we verify that the payment p_i^{τ} computed by payment determination algorithm is the critical value to user u_i with bid β_i^{τ}. If selected user u_i submits a bid $\widetilde{\beta_i^\tau} = (\alpha_i^\tau, \phi_i^\tau, \widetilde{b_i^\tau})$ whose $\widetilde{b_i^\tau} < p_i^\tau$, u_i will obviously be selected in time slot t_τ when $U_i(\mathbf{I}^\tau) \geq \widetilde{b_i^\tau}$, because there exists at least one user u_j who satisfies the inequation $\frac{\Delta_i(\mathbf{I}^\tau)}{\widetilde{b_i^\tau}} \geq \frac{\Delta_j(\mathbf{I}^\tau)}{b_j^\tau}$ and $U_j(\mathbf{I}^\tau) \geq b_j^\tau$ according to payment determination algorithm. Or user u_i must be selected if $U_i(\mathbf{I}^\tau) \geq \widetilde{b_i^\tau}$ when there is no other user u_j has $U_j(\mathbf{I}^\tau) \geq b_j^\tau$ in time slot t_τ. Thus, user u_i with bid $\widetilde{\beta_i^\tau}$ would be selected instead of user u_j with bid β_j^τ. On the contrary, if $\widetilde{b_i^\tau} > p_i^\tau$, user u_i with bid $\widetilde{\beta_i^\tau}$ can not be selected in time slot t_τ since there is no user u_j with $U_j(\mathbf{I}^\tau) \geq b_j^\tau$ satisfies $\frac{\Delta_i(\mathbf{I}^\tau)}{\widetilde{b_i^\tau}} \geq \frac{\Delta_j(\mathbf{I}^\tau)}{b_j^\tau}$ or the bidding price $\widetilde{b_i^\tau}$ is larger than $U_i(\mathbf{I}^\tau)$. Therefore, we prove that p_i^τ is the critical value to user u_i with bid β_i^τ.

6 Performance Evaluation

In this section, we conduct extensive simulations to show the performance achieved by our proposed incentive mechanism, in terms of the social welfare of the system.

6.1 Simulation Setup

We compare our proposed mechanism with the following four baselines.

- *Only-Bid selection Algorithm (OBA)*: Users are selected only based on the marginal utilities of their measurements. Specially, the user with the largest marginal utility of his/her measurements will be selected in each iteration, unless the marginal utility is lower than the bidding price of the user. The selected users will diffuse tasks to their social friends.
- *Only-Social selection Algorithm (OSA)*: Users are selected only based on the marginal utilities of their social influences. Specially, the user with the largest marginal utility of his/her social influence will be selected in each iteration, unless the marginal utility is lower than the bidding price of the user. The selected users will diffuse tasks to their social friends.
- *Random Selection Algorithm (RSA)*: A user is randomly selected in each iteration, as long as his/her marginal utility is not lower than his/her bidding price. The selected users will diffuse tasks to their social friends.
- *No-Social selection Algorithm (NSA)*: Users are selected only based on the marginal utilities of their measurements. Moreover, the selected users in NSA will not diffuse tasks to their social friends.

The default setup is illustrated as follows. The default number of POIs K in the mobile crowdsensing system is 20. The preliminary value of each measurement collected in location l_k, v_k, is uniformly distributed over $[2, 7]$. We set the number of registered users N is 60. The reliability of each user q_i is uniformly sampled in $(0, 1]$. In each time slot, we consider that 20% users randomly become active users, who will submit a bid to the platform. In each bid β_i^τ, the length of active time window α_i^{τ} and the bidding price b_i^{τ} of user u_i are uniformly distributed in $[1, 5]$, respectively. In each time slot during the active time window, a task $\varphi_k^t \in \Phi_i^{\tau}$ is randomly generated in location l_k, which will be performed by u_i if u_i is selected as participant. To simulate the social network, we randomly generate a directed edge between an arbitrary pair of users, to represent they are social friends or not. The weight of the directed edge $w_{i,j}$ (i.e., the social influence from u_i to u_j) follows a uniform distribution $\mathcal{U}(0, 1)$. An inactive social friend of a selected user may turn into active in the next time slot, according to the weight of the edge between them in the social network. The probability of each user appearing in each POI is uniformly sampled in $[0, 1]$. We run 50 time slots in each setting up of our simulations, with each time slot equals to 10 min. All the simulation results are the average of 20 runs under the same setting up.

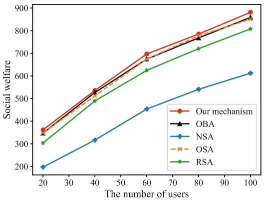

Fig. 2. Social welfare versus number of users

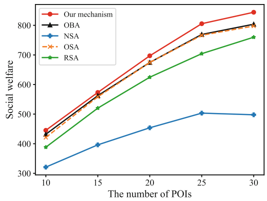

Fig. 3. Social welfare versus number of POIs

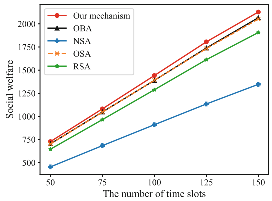

Fig. 4. Social welfare versus number of time slots

6.2 Evaluation Results

We compare the performance achieved by our proposed mechanism and the four baselines, in terms of the social welfare they obtain, i.e., $\sum_{\tau=1}^{|\mathcal{T}|}[U(\mathbf{I}^{\tau}) + W(\mathbf{I}^{\tau}) - C(\mathbf{I}^{\tau})]$. Specially, we vary the number of users, the number of POIs, and the number of time slots, to evaluate the performance of all algorithms under different setups. The evaluation results are shown in Figs. 2, 3, and 4, respectively.

We can easily observe that NSA achieves the worst performance, which is much lower than other algorithms. It is because NSA is the only algorithm without employing recruited users to diffuse sensing tasks to their social friends. This observation validates that leveraging the social relationship among users to attract more participants can make significant improvement to the performance of an incentivized crowdsensing system. Moreover, RSA performs worse than other algorithms except NSA under different setups, which can be seen as the lower bound of all feasible user selection solutions with considering the rationality of users. Furthermore, we can find that our proposed algorithm outperforms OBA and OSA, no matter how the parameters vary. It validates that taking both utilities achieved by measurements and social influences into the consideration of user selection is meaningful. Specially, when there are 30 POIs need to collect sensing data, our proposed mechanism can obtain 4.8% and 5.5% more social welfare than OBA and OSA, respectively.

7 Conclusion

In this paper, we consider the online incentive mechanism design for crowdsensing, in which the social relationship among users is leveraged to attract more participants. We define two novel metrics to evaluate the social influences of users, based on the definitions of node centrality in social networks. In addition, we propose an efficient and truthful online incentive mechanism, consisting of a user selection algorithm and a payment determination algorithm. Users are greedily selected based on their reliability, costs, and social influences. Our proposed mechanism is proved to achieve the desirable properties of computational efficiency, individual rationality, and truthfulness. Finally, we have conducted extensive simulations, and the results demonstrate that our proposed mechanism achieves the most social welfare, compared with baselines.

Acknowledgements. This work is supported by National Key R&D Program of China with No. 2017YFE0117500, NSFC (No. 61802245), the Shanghai Sailing Program (No. 18YF1408200), and STSCM (No. 19511121000). This work is also supported by the Open Project Program of Shanghai Key Laboratory of Data Science (No. 2020090600002).

References

1. TalkingData. http://mi.talkingdata.com/app-rank.html?type=105060
2. Chen, Y., Li, B., Zhang, Q.: Incentivizing crowdsourcing systems with network effects. In: IEEE INFOCOM 2016-The 35th Annual IEEE International Conference on Computer Communications, pp. 1–9. IEEE (2016)
3. Feng, Z., Zhu, Y., Zhang, Q., Ni, L.M., Vasilakos, A.V.: Trac: truthful auction for location-aware collaborative sensing in mobile crowdsourcing. In: IEEE INFOCOM 2014-IEEE Conference on Computer Communications, pp. 1231–1239. IEEE (2014)
4. Feng, Z., et al.: Towards truthful mechanisms for mobile crowdsourcing with dynamic smartphones. In: 2014 IEEE 34th International Conference on Distributed Computing Systems, pp. 11–20. IEEE (2014)
5. Gan, X., Li, Y., Wang, W., Fu, L., Wang, X.: Social crowdsourcing to friends: an incentive mechanism for multi-resource sharing. IEEE J. Sel. Areas Commun. **35**(3), 795–808 (2017)
6. Jiang, L., Niu, X., Xu, J., Wang, Y., Wu, Y., Xu, L.: Time-sensitive and sybil-proof incentive mechanisms for mobile crowdsensing via social network. IEEE Access **6**, 48156–48168 (2018)
7. Kauder, E.: History of Marginal Utility Theory, vol. 2238. Princeton University Press, Princeton (2015)
8. Lin, J., Li, M., Yang, D., Xue, G.: Sybil-proof online incentive mechanisms for crowdsensing. In: IEEE INFOCOM 2018-IEEE Conference on Computer Communications, pp. 2438–2446. IEEE (2018)

9. Nie, J., Luo, J., Xiong, Z., Niyato, D., Wang, P.: A stackelberg game approach toward socially-aware incentive mechanisms for mobile crowdsensing. IEEE Trans. Wirel. Commun. **18**(1), 724–738 (2018)
10. Nie, J., Luo, J., Xiong, Z., Niyato, D., Wang, P., Guizani, M.: An incentive mechanism design for socially aware crowdsensing services with incomplete information. IEEE Commun. Mag. **57**(4), 74–80 (2019)
11. Nisan, N., Roughgarden, T., Tardos, E., Vazirani, V.V.: Algorithmic Game Theory. Cambridge University Press, Cambridge (2007)
12. Sun, J.: An incentive scheme based on heterogeneous belief values for crowd sensing in mobile social networks. In: 2013 IEEE Global Communications Conference (GLOBECOM), pp. 1717–1722. IEEE (2013)
13. Xu, J., Bao, W., Gu, H., Xu, L., Jiang, G.: Improving both quantity and quality: Incentive mechanism for social mobile crowdsensing architecture. IEEE Access **6**, 44992–45003 (2018)
14. Xu, J., Guan, C., Wu, H., Yang, D., Xu, L., Li, T.: Online incentive mechanism for mobile crowdsourcing based on two-tiered social crowdsourcing architecture. In: 2018 15th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON), pp. 1–9. IEEE (2018)
15. Yang, G., He, S., Shi, Z., Chen, J.: Promoting cooperation by the social incentive mechanism in mobile crowdsensing. IEEE Commun. Mag. **55**(3), 86–92 (2017)