Hindawi
Wireless Communications and Mobile Computing
Volume 2019, Article ID 8603526, 14 pages
https://doi.org/10.1155/2019/8603526

Research Article

Designing Incentive Mechanisms for Mobile Crowdsensing with Intermediaries

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Received 19 September 2018; Accepted 13 December 2018; Published 1 January 2019

Academic Editor: Patrick Seeling

In the past decade, with the rapid development of wireless communication and sensor technology, ubiquitous smartphones equipped with increasingly rich sensors have more powerful computing and sensing abilities. Thus, mobile crowdsensing has received extensive attentions from both industry and academia. Recently, plenty of mobile crowdsensing applications come forth, such as indoor positioning, environment monitoring, and transportation. However, most existing mobile crowdsensing systems lack vast user bases and thus urgently need appropriate incentive mechanisms to attract mobile users to guarantee the service quality. In this paper, we propose to incorporate sensing platform and social network applications, which already have large user bases to build a three-layer network model. Thus, we can publicize the sensing platform promptly in large scale and provide long-term guarantee of data sources. Based on a three-layer network model, we design incentive mechanisms for both intermediaries and the crowdsensing platform and provide a solution to cope with the problem of user overlapping among intermediaries. We theoretically prove the properties of our proposed incentive mechanisms, including incentive compatibility, individual rationality, and efficiency. Furthermore, we evaluate our incentive mechanisms by extensive simulations. Evaluation results validate the effectiveness and efficiency of our proposed mechanisms.

1. Introduction

Nowadays smartphones have become indispensable elements for communication and entertainment in our daily lives. The power of smartphone owes greatly to the rapid development of sensor technology. More and more embedded sensors have been integrated into smartphone system, such as GPS, gyroscope, accelerometer, digital compass, microphone, and camera [1, 2]. These sensors provide rich possibilities of smartphone functionality and bring emerging sensing paradigms, which have attracted attentions from both industry and academia.

In the past decade, many efforts on system works have been made to dig the potential of sensor-equipped smartphones. The concept of mobile crowdsensing has been applied to many domains. Taking environment monitoring and transportation, for example, there appeared noise monitoring system [3], air pollution monitoring system [4], traffic congestion monitoring [5, 6], parking lots locating [7], and dynamic driving planning [8, 9]. The system works mentioned above effectively tackle the technical matters. However, one of the realistic challenges encountered by the above systems is how to attract enough number of participants and maintain user stickiness in order to guarantee service quality. First, as human-involved applications, the reliability and accuracy of mobile crowdsensing systems are affected by human factors, such as dynamic joining and leaving, inaccurate or even corrupted sensing, and environment changing due to user mobility. Thus, mobile crowdsensing systems rely on a large and active user community to guarantee adequate

level of service quality. Second, the large user community should be accessed quickly as soon as possible. Mass-oriented applications like mobile crowdsensing applications all face a difficult cold set-up period and need to gradually gather users and effectively turn them into loyal ones. Applications failing to go through this period would not prevail, even if they are of high quality.

Unfortunately, according to [10], nowadays, mobile crowdsensing applications have rarely scaled up to more than 1000 participants. Thus, the key problem we face is (i) how to make mobile crowdsensing application prevalent and (ii) how to shorten the hard cold setup time.

Sensing service would bring cost to the smartphone users, including battery power, computing power, and bandwidth. Counting merely on users' voluntary contributions would impair the users' loyalty and jeopardize the reliability and validity of the system in the long run. To the best of our knowledge, Lee et al. [11] made the first try to address the incentive mechanism for user participation. They designed an incentive mechanism named Reverse Auction based Dynamic Price (RADP) to minimize the cost, while stabilizing the participation level. Yang et al. [12] considered incentive mechanisms under two system models: the platform-centric model and the user-centric model. Luo et al. [13] proposed an all-pay auction to achieve profit maximization of sensing platform. In the above incentive mechanism, generally there are two roles in the system, including a sensing platform and a number of smartphone users. The sensing platform launches the sensing tasks and provides payments (monetary or nonmonetary) to incentivize smartphone users to perform sensing tasks.

The above ubiquitous structure faces three obstacles for mobile crowdsensing applications to scale up. First, it takes a lot of time for the application developers to handle the heterogeneity of software platforms (e.g., Android, iOS, and Windows Phone), and even different versions of each platform. Second, there already appeared many mobile crowdsensing systems. To participate in one of them, a user should install and run the specific application and then directly transmit the sensed data to its central server(s). It is impossible for a smartphone to install all kinds of applications, and thus it can only be accessed by a few applications. Third, the increasing of network bandwidth demand hinders the scale of mobile crowdsensing systems.

Our proposed strategy to overcome the defects mentioned above is to let the crowdsensing platform cooperate with existing applications with large user bases, such as Facebook, Instagram, and Flickr. It is quite common for the applications that may have their own APIs to access the devices' sensor units. Thus, they could act as intermediaries between the mobile sensing platform and a great number of users. With the necessary information provided by the sensing platform, the intermediaries can process sensing data into the format required by some specific crowdsensing application and then send them to the platform.

Intermediary applications' participation changes the existing two-layer network model to a three-layer network model. In the two-layer model, interactions happen only between smartphone users and sensing platform directly. In our proposed model, interactions occur in two places. One is between the intermediary applications and the sensing platform. The other is between every intermediary application and its smartphone user community. For the altering of system model, we must rethink and redesign appropriate incentive mechanisms in mobile crowdsensing systems.

Based on our survey of the state-of-the-art literature, this is the first work on designing incentive mechanism for mobile sensing system with intermediaries. The benefits brought by the participation of intermediaries are summarized as follows:

(i) Sensing platforms do not need to be in the face of the heterogeneity of software platforms directly. Dealing with the transmission interfaces under cooperation protocols is much easier than developing different versions for every software platform.

(ii) Intermediaries have established stable trust relationship with their own large and active user community. Their participation could effectively publicize their cooperating partners, i.e., mobile crowdsensing systems among their users, and more likely enlarge user community of mobile sensing systems in a short time as well as in the long run.

(iii) Intermediaries can incentivize "lazy" users as much as possible. "Lazy" user here means the one that has no time or no interest to download specific sensing applications or to learn how to perform the sensing task. There exists considerable quantity of them in practice. With the help of the intermediary applications, "lazy" users could authorize their intermediary to fetch proper sensing tasks, finish them automatically, and get paid. Thus, "lazy" users may have higher motivations to be involved in crowdsensing.

However, the participation of intermediaries obviously complicates the system model and brings challenges for both mechanism design and analysis. Here, we summarize the main research challenges as follows.

(i) Both the intermediaries and smartphone users are rational and selfish. They may misreport their costs to improve their utilities. The incentive mechanism should prevent both the intermediaries and smartphone users from strategic misbehaviours, which has not been simultaneously considered in the existing work for mobile crowdsensing.

(ii) Intermediaries' participation may enlarge the gap between possible solution results and theoretical optimal result, compared with the way of interacting with smartphone users directly. Limiting the gap within an acceptable level but not damaging the truthfulness of the whole mechanism is difficult, but necessary to avoid the situation, in which the costs exceed the benefits.

(iii) The auction between the platform and the intermediaries is a reverse multiunit auction with multisupply. The mathematical formalization of its allocation

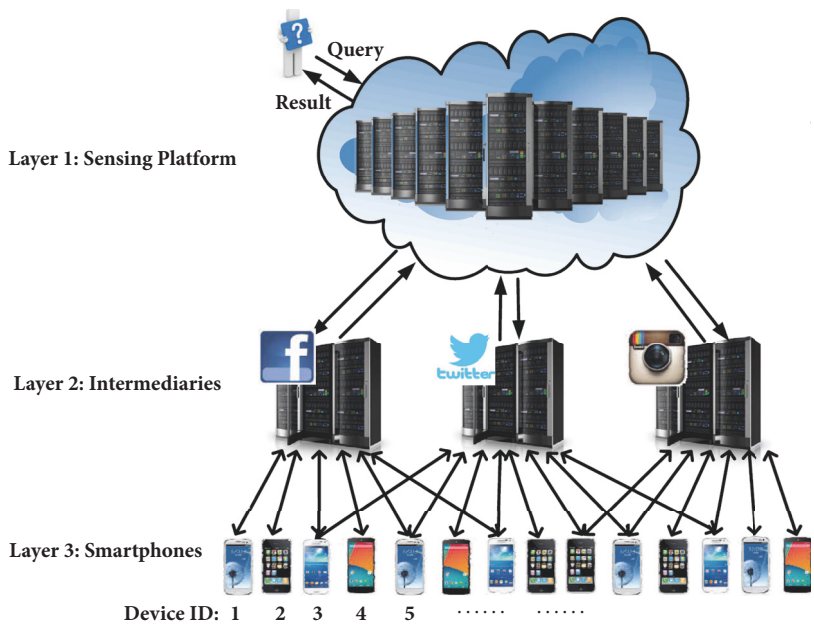

Figure 1: A three-layer network scenario.

problem is a variation of knapsack problem, which is a well-known NP-complete problem. Furthermore, our mechanism should meanwhile eliminate the duplication effectively. The users of different popular intermediaries are much likely to overlap, but the platform does not want to receive duplicated data from the same users.

The key contributions of our work are summarized as follows.

(i) We are the first to introduce intermediaries to mobile sensing system. We model the system as a three-layer network model and design incentive mechanisms for both intermediary and sensing platform.

(ii) We begin with considering the setting without user overlapping and then further improve our design to be applicable to the setting with user overlapping.

(iii) We theoretically prove the following properties of proposed mechanisms: individual rationality, incentive compatibility, and computational efficiency.

(iv) We evaluate the performance of our mechanisms by extensive simulations. Our evaluation results show that the gap between our mechanisms' results and theoretical optimal results is small.

The rest of the paper is organized as follows. In Section 2, we introduce the system model. The detailed mechanism design is elaborated in Section 3. We give formal theoretical proof for the economic properties in Section 4. Section 5 shows the numerical results to verify our design. We summarize related work in Section 6 and conclude this paper in Section 7.

2. Technical Preliminaries

In this section, we would like to illustrate our system model and settings and introduce several important concepts from mechanism design domain.

2.1. System Model. In this paper, we consider a crowdsensing system as shown in Figure 1. There are three main roles in the system, including *sensing platform*, *intermediaries*, and *smartphone users*. We model it as a three-layer network.

To be specific, our system consists of one sensing platform, a set $I = \{1, 2, \ldots, N\}$ of N intermediaries, and a number of smartphone users. For each intermediary $i \in I$, there are N_i smartphone users associated with it. Let u_j^i denote the j-th user of intermediary i. We note that the users of different intermediaries can overlap, which is revealed in Figure 1.

To address the problem of users' overlapping, we assume that intermediaries could access the smartphones' unique device ID. According to our survey, IMEI number is a very good and primary source to get the device ID. It is dependent on the device hardware; thus it is unique for every device. Besides, it is permanent till the lifetime of the device even if the device is rooted or factory reset. The applications require the permission to get the device IMEI. Also, there are some alternatives to device IMEI, such as the WLAN MAC address string and the Bluetooth Address string, each of which has its own advantages and disadvantages. However, the details of the choice of device identifier are not within the scope of this paper.

When the sensing platform receives a task, denoted as $T(D, M)$, from platform users, it can recruit a team of intermediaries, initialize an auction to collect needed data,

and then send the analyzed result back to the platform users. M denotes the number of data items needed. D contains data specifications, including data location and sensing time. In this work, we have not taken the budget of the sensing platform into consideration yet. The characterization of the tradeoff between the budget and the percentage of completed tasks is one of our main future researches.

The platform collects data from multiple intermediaries. Every intermediary may provide multiple available pieces of data. Thus, the auction between platform and intermediaries is a *reverse multiunit* (the platform buys multiple copies of data from multiple intermediaries) auction with *multisupply* (each intermediary can provide multiple pieces of data for the platform).

When the platform conducts an auction and announces the mechanism $\mathbb{M}$, each intermediary I_i would conduct a *contingent downstream auction* to calculate a bid strategy profile β_i based on her N_i available users' bids. Every smartphone user can only provide one piece of data, (i.e., it is meaningless for one smartphone user to provide duplicated data for the same task). Thus, the auction between an intermediary and her smartphone users is a *reverse multiunit* (an intermediary collects multiple data from multiple smartphone users) auction with *unit-supply* (a smartphone user can only provide a piece of data)

Besides the bidding strategy β_i, every intermediary $I_i \in I$ should also submit a list of user IDs $l_i = (id_j^i)_{j \in W_i}$. The content in the user ID list is decided according to the *contingent downstream auction*'s outcome.

For a given bidding profile $\mathbf{B} = (\beta_1, \ldots, \beta_i, \ldots, \beta_N)$ from the intermediaries, the mechanism $\mathbb{M}(\mathbf{B})$ determines a participation level vector $\chi(\mathbf{B}) = (x_1, \ldots, x_i, \ldots, x_N)$ and payment vector $\rho(\mathbf{B}) = (p_1, \ldots, p_i, \ldots, p_N)$, where x_i means the number of pieces of data selected from intermediary I_i and p_i means the payment to intermediary I_i. Next, the platform announces to each intermediary its participation level x_i and payment p_i. Based on the upstream auction's outcome, intermediaries submit data collected from their users to the platform and accordingly get paid by the platform.

Every smartphone user u_j^i is characterized by a perceived cost $c_j^i > 0$ per piece of data contributed. The cost is private information of each user, as it depends on various factors inherent to the device and the user. In our mechanism, every user would submit a bid b_j^i to its intermediary. The bid b_j^i can be interpreted as user u_j^i's minimum requested compensation per piece of data contribution. Here, b_j^i may not equal c_j^i unless truthfulness can be achieved in the auction. The payment p_j^i to user u_j^i is determined by the intermediary I_i she belongs to.

The utility of a smartphone user is defined as the difference between the payment from the corresponding intermediary and the cost induced by performing the sensing task. We can define the utility for u_j^i as

$$U_j^i = \begin{cases} p_j^i - c_j^i, & \text{if } \mathrm{u}_\mathrm{j}^\mathrm{i} \text{ is a winner;} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

The utility U_i of an intermediary is defined as the difference between the payment from the platform and the prices paid in downstream auction.

$$U_i = p_i - \sum_{j \in M_i} p_j^i. \tag{2}$$

The objective of this work is to design a truthful mechanism under the following constraints:

(1) The platform must collect at least M pieces of data.

(2) The platform must solve the problem of user overlapping; i.e., every piece of collected data comes from a distinguished smartphone.

(3) Ex-post Budget Balance: the utility of each intermediary $U_i \geq 0$, $(i = 1, 2, \ldots, N)$.

(4) Individual rationality: the utility of each smartphone user $U_j^i \geq 0$, $(i = 1, 2, \ldots, N; j = 1, 2, \ldots, N_i)$.

Here, we briefly review some important solution concepts and economic properties we would like to achieve in our mechanism.

Definition 1 (dominant strategy [14]). A dominant strategy of a player is one that maximizes her utility regardless of what strategies the other players choose. Specifically, a_i is player i's dominant strategy if, for any $a_i' \neq a_i$ and any strategy profile of the other players a_{-i}, $u_i(a_i, a_{-i}) \geq u_i(a_i', a_{-i})$.

Definition 2 (truthfulness/incentive compatibility [15]). A mechanism (f, p) is truthful/incentive compatible if, for every player i with true valuation v_i, $v_i(f(v_i, v_{-i})) - p(v_i, v_{-i}) \geq v_i(f(v_i', v_{-i})) - p(v_i', v_{-i})$. Intuitively, player i would prefer to tell the true valuation v_i rather than giving a cheating one v_i' to get a higher utility.

Definition 3 (individual-rationality [16]). An auction is individual rational if no buyer is charged more than her bid and no seller is paid less than her ask. It means that each player can always achieve at least as much expected utility from faithful participation as without participation, which guarantees the validness of the auction result.

For readers' convenience in later sections, we list key notations in Table 1.

3. Auction-Based Incentive Mechanism Design

In this section, we present our auction-based incentive mechanism design in detail. To facilitate readers' understanding, we would clarify the algorithms used and details of our design for intermediary (Section 3.1) and platform (Sections 3.2 and 3.3) at first. Then we prove theoretically the properties our mechanism achieved in Section 4.

3.1. Design of Intermediary Mechanism. As mentioned above, the auction between every intermediary $I_i \in I$ and its smartphone users $u_j^i \in W_i$ is a *reverse multiunit* auction with *unit-supply*.

Table 1: Key notations in this paper.

Sym	Meaning	Sym	Meaning
P	The sensing platform	I	The set of all intermediaries
I_i	The i-th intermediary	N	The number of intermediaries
N_i	Number of I_i' smartphones	u_j^i	j-th user of i-th intermediary
T	Task launched by platform	M	The number of data needed
D	The data specification	$\mathbb{M}(\mathbf{B})$	Platform mechanism
$\chi(\mathbf{B})$	platform allocation scheme	x_i	I_i' participation level
$\rho(\mathbf{B})$	platform payment scheme	p_i	payment to I_i
β_i	I_i' bidding strategy	l_i	I_i' sorted smartphone ID list
id_j^i	j-th id in l_i	p_j^i	payment to u_j^i
c_j^i	u_j^i' true cost per data	b_j^i	u_j^i' bid
U_i	I_i' utility	U_j^i	u_j^i' utility

Upon the platform's announcing of the task $T(D, M)$ and mechanism $\mathbb{M}$, each intermediary I_i first finds out the smartphones who can provide the qualified data according to the data specification D and then conduct a *contingent downstream auction* to calculate her bid strategy $\beta_i(k)$ ($k = 1, 2, \ldots, \min(N_i, M)$), in which $\beta_i(k)$ represents the average bid for k pieces of data. Every contingent downstream auction follows the same principle; i.e., to select k winners, the intermediary I_i sorts b_j^i ($j = 1, 2, \ldots, N_i$) in increasing order, and the selected first k users are winners, with a payment to each equalling to the $(k + 1)$-th bid, which is called *Generalized Secondary Price Auction*. Thus, the kth item in the strategy profile is $\beta_i(k) = b_{k+1}^i$, *i.e.*, the $(k + 1)$-th smallest bid.

Generally, the intermediaries always operate to maintain their own services and could also leverage existing optimization algorithms to reduce the overhead of data collection and transmission. Thus, we here consider that the main cost for an intermediary to complete sensing tasks comes from the payment to the smartphones users.

3.2. Platform Mechanism Design without User Overlapping. In this section, we first consider a simple setting without the problem of user overlapping and then improve our mechanism to deal with it.

3.2.1. Overview. Upon receiving a sensing task $T(D, M)$ from platform users, the platform conducts an auction to complete the task. As mentioned before, the auction between platform and intermediaries is a *multiunit* reverse auction with *multiunit* supply. Given a bidding profile of intermediaries $\mathbf{B} = (\beta_1, \ldots, \beta_i, \cdots \beta_N)$, the mechanism $\mathbb{M}(\mathbf{B})$ consists of computing a participation level vector $\chi(\mathbf{B}) = (x_1, \ldots, x_i, \ldots, x_N)$, and payment vector $\rho(\mathbf{B}) = (p_1, \ldots, p_i, \ldots, p_N)$ for each intermediary.

3.2.2. Allocation Scheme. Given $\mathbf{B} = (\beta_1, \ldots, \beta_i, \ldots, \beta_N)$ without user overlapping, the allocation problem of multiunit reverse auction between the platform and the intermediaries could be characterized as the following optimization problem. Here, $X_{k,i} = 1$ iff I_i's participation level $x_i = k$; otherwise, $X_{k,i} = 0$.

$$\text{Obiective} \quad \min \sum_{i \in I} \sum_{k=1}^{\min(M,N_i)} \beta_i(k) X_{k,i} \tag{3}$$

$$\text{Subject to} \quad \sum_{i \in I} \sum_{k=1}^{\min(M,N_i)} k X_{k,i} \geq M \tag{4}$$

$$\sum_{k=1}^{\min(M,N_i)} X_{k,i} \leq 1, \quad \forall i \in I \tag{5}$$

$$X_{k,i} \in \{0, 1\}, \quad \forall i \in I, \quad 1 \leq k \leq \min(M, N_i) \tag{6}$$

Without user overlapping, data items offered from different intermediaries would come from different data sources. According to the intermediary mechanism above, different data item options provided by the same intermediary have part of the same data sources. Data item options from the same intermediary could be regarded as a group, and thus at most one option in each group could be chosen. We note that the problem formulated above can be reduced to the grouping knapsack problem, which is a well-known NP complete problem.

Efficient solutions ask for more insights into bidding strategies' structure. Thus, before conducting allocation, we would process raw bids to satisfy a tailored supermodular property. The traditional definition of supermodular is as follows: $V : R_+ \longrightarrow R_+$ is supermodular if $V(x + 1) - V(x) \leq V(y + 1) - V(y)$ $\forall x \leq y$. The profiles of bidding strategies computed by the above Generalized Secondary Price Auction do not guarantee satisfying the supermodular property. Therefore, we give a tailored supermodular definition for our proposed mechanism.

Definition 4 (tailored supermodular). $V(k)$ satisfies tailored supermodular if $\exists$a monotone increasing nature number sequence $(x_1, x_2, \ldots, x_n)$, assume $x_0 = 0$ and $V(0) = 0$, and then $(V(x_{i+1}) - V(x_i))/(x_{i+1} - x_i) \leq (V(x_{k+1}) - V(x_k))/(x_{k+1} - x_k)$ for $\forall i \leq k$ $(k = 1, 2, \ldots, N)$.

Input:
The raw bidding strategy of I_i:
$\beta_i(k)(k = 1, 2, .., \min(M, N_i))$,
Sorted ID list $l_i = \{id_i^1, \cdots, id_i^{\min(M,N_i)}\}$;
Output:
The processed bidding strategy of I_i:
$\beta_i = \{P_i^j = (p_j, q_j, S_j)\}, j = 1, 2, \cdots, \min(M, N_i)$
1 Calculate the k-th data's marginal cost:
$MC_i^k = \beta_i(k) \times k - \beta_i(k-1) \times (k-1)$;
2 Initialize the output: $P_i^j = (p_j, q_j, S_j) = (MC_i^j, 1, \{id_i^j\}), j = 1, 2, \cdots, \min(M, N_i)$;
3 $x \longleftarrow 1, y \longleftarrow 2, flag \longleftarrow false$;
4 **while** $!flag$ **do**
5 $\quad flag \longleftarrow true$;
6 $\quad$ **while** $y \le length(\beta_i)$ **do**
7 $\quad\quad$ **if** $p_x > p_y$ **then**
8 $\quad\quad\quad$ merge P_i^y into P_i^x:
$$\left(\frac{p_x \times q_x + p_y \times q_y}{q_x + q_y}, q_x + q_y, S_x \cup S_y\right);$$
9 $\quad\quad\quad$ $flag \longleftarrow false$;
10 $\quad\quad$ **else**
11 $\quad\quad\quad$ $x \longleftarrow y, y \longleftarrow y + 1$;
12 **return**
$\beta_i = \{P_i^j = (p_j, q_j, S_j)\}, j = 1, 2, \cdots, \min(M, N_i)$;

Algorithm 1: Intermediary I_i' bidding preprocessing.

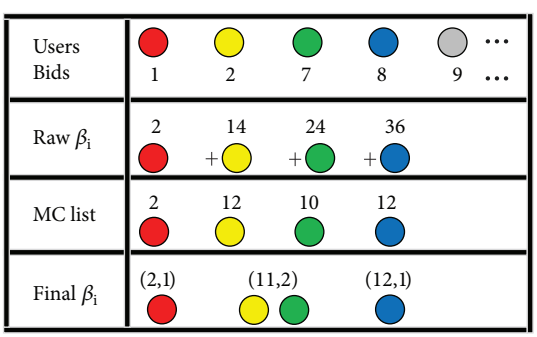

Figure 2: A toy example of bidding preprocessing.

We now give the way (Algorithm 1) for processing the bidding strategy β_i ($i \in I$) to match the tailored supermodular fashion.

Here, we give a toy example to illustrate the key idea of Algorithm 1.

Figure 2 shows five smartphone users denoted by different colored circles belonging to one intermediary along with their own bids. In the first pass, we execute Generalized Secondary Price Auction to get the raw bidding strategy β_i ($1 \times 2 = 2$, $2 \times 7 = 14$, $3 \times 8 = 24$, $4 \times 9 = 36$). In the second pass, we calculate the marginal cost of every data according to formula in Line 1 in Algorithm 1 ($2 - 0 = 2, 14 - 2 = 12, 24 - 14 = 10, 36 - 24 = 12$). In Algorithm 1, $P_i^j = (p_j, q_j, S_j)$ means the average marginal cost for the next q_j data is p_j with their IDs in set S_j. In the final pass, we scan the marginal cost list one by one (Line 4 to Line 11). We find that the second item "12" is larger than the third item "10"; thus we merge them together (Line 8) ($(12 + 10)/(1 + 1) = 11, 1 + 1 = 2$). After the above procedure, the final bidding strategy β_i is monotone increasing by the value of the item's first component ($2 \le 11 \le 12$). The nice marginal increasing property of processed bidding strategies greatly facilitates the platform mechanism design which we would expatiate on later.

Input:
Task T(D,M);
Intermediaries' biddings $\mathbf{B} = \{\beta_i\}, i = 1, 2, \cdots, N$:
$P_i^j = (p_j, q_j, S_j)$ denotes the j-th bidding in β_i
Output:
Intermediaries' participation level vector
$\chi(\mathbf{B}) = \{x_i\}, i = 1, 2, \cdots, N$
1 $S_{candi} \longleftarrow \emptyset, S_{final} \longleftarrow \emptyset, num \longleftarrow 0$;
2 $x_i \longleftarrow 0, \forall i = 1, 2, \cdots, N$;
3 Add the first item of every intermediary's bidding into S_{candi};
4 **while** $num < M$ **do**
5 $\quad$ Choose the item P= (p, q, S) with the smallest p in S_{candi}, assume denoted as $P_s^t = (p_t, q_t, S_t)$;
6 $\quad S_{final} \longleftarrow S_{final} \cup \{S_t\}$;
7 $\quad x_s \longleftarrow x_s + q_t$;
8 $\quad num \longleftarrow num + q_t$;
9 $\quad$ add the next item in bidding β_s to the S_{candi};
10 **return** *Intermediaries' participation level vector*
$\chi(\mathbf{B}) = \{x_i\}, i = 1, 2, \cdots, N$

Algorithm 2: Allocation scheme $\chi(\mathbf{B})$.

Given the tailored supermodular property held by processed intermediaries' bidding strategy, the winner determination $\chi(\mathbf{B})$ is shown in Algorithm 2.

The idea behind Algorithm 2 is as follows. In each step, the first unchosen item in every intermediary would form the candidate set (Line 3 and Line 9). The platform keeps choosing the bid item with the smallest p component in candidate set until the number of effective data units in chosen set exceeds M (Lines 4 to 9).

To help illustrate the main idea of Algorithm 2 intuitively, we give the following toy example (see Figure 3). In this specific setting, there are two intermediaries, I_1 and I_2. Their smartphone users are denoted by different colored circles in Figure 3. Each item of their biddings has three components: bid per data, data quantity, and effective data provider set ($Pk_j^i = (p, q, S)$). The candidate set (S_{candi}) contains data packages that are likely to be chosen in the next step while the chosen set (S_{final}) consists of data packages that have already been chosen. M indicates the number of data units needed at least. Initially, we group the first item of every intermediary's bidding into the candidate set (Line 3). When the number of effective data units in chosen set has not exceeded M, we should keep choosing operation among the candidate set. In every step, the item which has the smallest p component would leave the candidate set for the chosen set (Line 6). Meanwhile, the chosen item's corresponding intermediary

Input:
Intermediaries' biddings: $\mathbf{B} = \{\beta_i\}, i = 1, 2, \cdots, N$;
Participation vector $\chi(\mathbf{B}) = \{x_i\}, i = 1, 2, ..., N$
Output:
Intermediaries' payment:
$\rho(\mathbf{B}) = \{p_i\}, i = 1, 2, \cdots, N$
// `Find the smallest losing bids of each intermediary and stores in an array minLoserBid;`
for $i = 1 : N$ **do**
  minLoserBid(i) = the smallest losing bid of intermediary i;
Find the two smallest ones from minLoserBid, denoted as s_1, s_2 $(s_1 \leq s_2)$;
for $i = 1 : N$ **do**
  if $minLoserBid(i) == s_1$ **then**
    $p_i \longleftarrow s_2 \times x_i$;
  else
    $p_i \longleftarrow s_1 \times x_i$;
return payment vector $\rho(\mathbf{B}) = \{p_i\}, i = 1, 2, \cdots, N$;

Algorithm 3: Payment scheme $\rho(\mathbf{B})$.

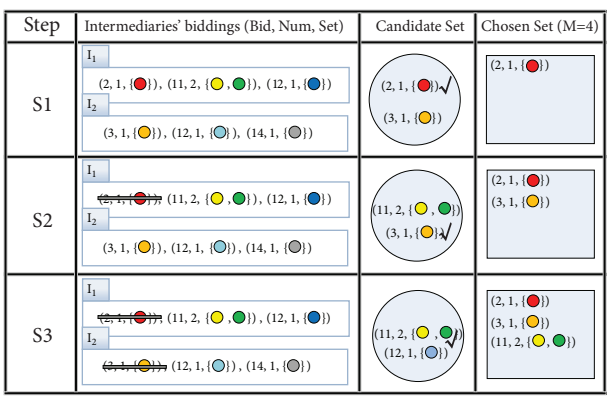

Figure 3: A toy example of winner determination.

would contribute the next item to the candidate set (Line 9) and its participation level would be updated (Line 7).

3.2.3. Partial Uniform Payment Scheme. The platform's payment scheme $\rho(\mathbf{B})$ is shown in Algorithm 3. In partial uniform payment scheme, a winning intermediary would be paid the same amount of money for each data contribution. Its unit reward is determined by the other's lowest losing bid. Different intermediaries can have different unit rewards. Taking the scenario in Figure 3, for example, intermediary I_1 would be paid the lowest losing bid of intermediary I_2 per unit of data ($p_1 = 12 \times 3 = 36$), while intermediary I_2 would be paid the lowest losing bid of the intermediary I_1 per unit of data ($p_2 = 12 \times 1 = 12$).

3.3. Duplication Elimination. In this section, we deal with the problem of user overlapping mentioned in Section 2.1 in order to improve the mechanism design in Section 3.2.

Input:
All intermediaries' sorted ID lists $\{l_i\}, i = 1, 2, \cdots, N$;
Output:
Duplication ID Set
$Dup : \{(id, \{(x_1, y_1), (x_2, y_2), \cdots\}), \cdots\}$;
1 Build 3-tuple (id, i, j) for every item in $\{l_i\}$ $(i = 1, 2, \cdots, N)$: (id, i, j) denotes the number id user is j-th user in intermediary i;
2 Put all 3-tuple (id, i, j) in one array Arr and sort it by the id field in increasing order;
3 $x \longleftarrow 0, y \longleftarrow 1, Dup \longleftarrow \emptyset$;
4 **while** $y < len\ (Arr)$ **do**
5 **if** $Arr[x].id == Arr[y].id$ **then**
6 **if** $!Dup.contain(id))$ **then**
7 $Dup.Add((id, \{(Arr[x].i, Arr[x].j), (Arr[y].i, Arr[y].j)\}))$;
8 **else**
9 $Dup[id].append((Arr[y].i, Arr[y].j))$;
10 $y \longleftarrow y + 1$;
11 **else**
12 $x \longleftarrow y, y \longleftarrow y + 1$;
13 **return** Duplication ID Set Dup;

Algorithm 4: Duplication identification.

Given the bidding profile of intermediaries $\mathbf{B} = (\beta_1, \ldots, \beta_i, \ldots, \beta_N)$, our duplication elimination would be conducted before bidding preprocessing (Algorithm 1) and contains two steps: duplication identification and bid adjustment.

We design Algorithm 4 for duplication identification. The main idea of Algorithm 4 is as follows. First, according to all intermediaries' bidding profile, we construct 3-tuples for every item in every intermediary's sorted ID list, composed of an ID number, the corresponding intermediary, and the ID location in the intermediary (Line 1). We assume ID numbers here are all integer and sort all tuples by the ID value in increasing order (Line 2). Here, tuples with the same ID number are adjacent in tuple array (Arr). Then with the help of two scanning cursors (x and y) in tandem, we find out all duplication ID numbers including the intermediary and corresponding location they appear (Dup) (Line 3 to Line 11).

After finding out the set of duplicated user IDs, we propose two policies to eliminate duplication.

(i) KickOut: in the platform view, overlap behaviours are discouraged because they would bring about computation overhead to eliminate their effect. Thus, kicking out the repeated users directly and notifying the intermediaries of repetition message along with trading result could be a reasonable punishment to restrain overlap behaviours and reduce possible user overlap in the long term.

(ii) Assign: considering some overlap behaviours are unintentional and KickOut policy may waste valuable data sources, another alternative is to delay the punishment and assign each repeated user to an intermediary. The assignment rules are as follows: if we could infer that the user submits different bids in different intermediaries, assign it to the intermediary with the smallest bid; otherwise, assign it randomly to an intermediary. The way of inferring the users'

bid could be regarded as the reverse process of Generalized Secondary Price Auction. If there is a tuple (id, i, j), the user id bid in intermediary i is $\beta_i(j-1)$ (average bid for $j-1$ pieces of winning data task of I_i).

Following KickOut policy or Assign policy, the previous intermediary bidding $\mathbf{B} = (\beta_1, \ldots, \beta_i, \ldots, \beta_N)$ needs adjustment. Assuming tuple (id, i, j) denotes that the i-th intermediary does not get the user id, the bidding strategy β_i should be adjusted in the following way: $\beta_i(j-1) \longleftarrow \beta_i(j), \beta_i(j) \longleftarrow \beta_i(j+1), \cdots$ until the end of bidding.

After duplication identification and bidding adjustment, we could continue conducting mechanism design in Section 3.2 including bidding preprocess, allocation, and payment.

4. Theoretical Analysis

In this section, we give formal theoretical proofs for the economic properties of our proposed mechanisms, including incentive compatibility, individual rationality, and computing efficiency.

4.1. Properties of Intermediary Mechanism. In intermediary mechanism, the smartphone users have strong motive to misreport their cost, i.e., declare a higher cost than the actual one to obtain higher utility. Thus intermediaries need incentive mechanism which is *individually rational* (i.e., it motivates users to participate) and *incentive compatible* (i.e., it motivates truthful cost reporting by users).

This is a single parameter mechanism design, in which each bidder has only one private value. Single-parameter mechanism design relies on Myerson's well-known characterization. For the original version being a forward-auction version, we here modify it to be compatible with reverse auction scenario.

Theorem 5. *In single parameter domains, an auction mechanism is truthful iff*

***(i) The selection rule is monotone**: if user i wins the auction by bidding b_i, it also wins by bidding $b_i' \leq b_i$;*

***(ii) Winners are paid threshold payments**: User i would not win the auction if it bids higher than this value.*

It is obvious to see above *Generalized Secondary Price Auction* is truthful (i.e., $b_j^i = c_j^i$) by checking Theorem 5. Verification of smartphones' individual-rationality is obvious in intermediary mechanism; thus here we omit it.

4.2. Properties of Platform Mechanism. In this section, we prove the properties of the platform mechanism, including incentive compatibility, individual rationality, and efficiency and analyze the task completion situation.

Theorem 6. *The incentive mechanism conducted by the platform is incentive compatible such that each intermediary's best bidding strategy is true result computed by Generalized Secondary Price Auction.*

Proof. Generally, an intermediary has no idea about which group of other intermediaries' users shows in the same trading. Since intermediaries could do nothing to identify user overlapping. The possible intermediaries' manipulation only refers to misreporting bidding strategy $\{\beta_i\}$ $(i = 1, 2, \ldots, N)$. After duplication elimination and bidding preprocessing (Algorithm 1), every bidding strategy β_i $(i = 1, 2, \ldots, N)$ would be transformed into the following style: (b_k^i, q_k^i), denoting that the unit marginal cost of q_k^i more data is b_k^i (here we omit the corresponding user ID set for there does not exist user overlapping yet).

The cheating on the bidding strategy β_i $(i = 1, 2, \ldots, N)$ has two outcomes. If the cheating bid that happens belongs to the overlap user kicked out in duplication elimination process, the cheating actually has no effect on the final trading results. Otherwise, the cheating bid would be reflected on the first field b_k^i of the transformed bid (b_k^i, q_k^i). In the following analysis, we would assume the possible cheating happens directly on the first field b_k^i of the transformed bid.

To prove the incentive compatibility, we need to show, for any $i = 1, 2, \ldots, N$, true valuation $\{(\widetilde{b}_1^i, q_k^i), \ldots, (\widetilde{b}_k^i, q_k^i), \ldots\}$ weakly dominates any other $\{(b_1^i, q_k^i), \ldots, (b_k^i, q_k^i), \ldots\}$.

First, we only replace b_k^i with $\widetilde{b}_k^i$ $(b_{k-1}^i \leq \widetilde{b}_k^i \leq \widetilde{b}_{k+1}^i)$ and prove the new strategy $\{b_1^i, \ldots \widetilde{b}_k^i, \ldots\}$ weakly dominates the previous strategy $\{b_1^i, \ldots b_k^i, \ldots\}$. Assuming by previous strategy I_i wins x_i data tasks and by new strategy, I_i wins x_i^*, we discuss three possible cases.

(1) Case 1: $x_i = x_i^*$. Intermediary I_i wins the same data tasks on both strategies. By the Partial Uniform Payment Scheme (Algorithm 3), its payment is determined by other intermediaries' bids. Thus, Intermediary I_i utilities are the same for both strategies.

(2) Case 2: $x_i < x_i^*$. Intermediary I_i wins more data tasks by new strategy. Based on payment scheme above, its added reward would be more than its marginal cost of additional tasks collection. Therefore, I_i could improve or at least keep the same utility by adopting the new strategy.

(3) Case 3: $x_i > x_i^*$. It means adopting new strategy would make I_i win less data tasks. b_k^i is winning bid but $\widetilde{b}_k^i$ is not. Both b_k^i and $\widetilde{b}_k^i$ are larger than b_j^i $(j = k+1, k+2, \ldots)$; thus b_j^i $(j = k+1, k+2, \ldots)$ are not winning bids. Therefore, $x_i = x_i^* + q_k^i$. According to Partial Uniform Payment Scheme, in original strategy, the added reward paid to I_i is less than the marginal cost of additional q_k^i data tasks $(\widetilde{b}_k^i \times q_k^i)$.

Second, we show that for any strategy $\{b_1^i, \ldots b_k^i, \ldots\}$ could be adjusted step by step to the true evaluation $\{(\widetilde{b}_1^i, q_k^i), \ldots, (\widetilde{b}_k^i, q_k^i), \ldots\}$ in the following way: $\{b_1^i, \ldots b_k^i, \ldots b_K^i\} \longrightarrow \{b_1^i, \ldots b_k^i, \ldots \max(\widetilde{b}_K^i, b_K^i)\} \longrightarrow \cdots \longrightarrow \{b_1^i, \ldots \max(\widetilde{b}_k^i, b_k^i), \ldots\} \longrightarrow \cdots \longrightarrow \{\widetilde{b}_1^i, \ldots\} \longrightarrow \cdots \longrightarrow \{\widetilde{b}_1^i, \widetilde{b}_2^i, \ldots\} \longrightarrow \cdots \{\widetilde{b}_1^i, \ldots, \widetilde{b}_K^i\}$. In every step, the new strategies dominate the previous ones. Thus $\{(\widetilde{b}_1^i, q_k^i), \ldots, (\widetilde{b}_k^i, q_k^i), \ldots\}$ dominates $\{(b_1^i, q_k^i), \ldots, (b_k^i, q_k^i), \ldots\}$. □

Theorem 7. *The incentive mechanism conducted by platform is individual rational; in other words, any intermediary will be paid more reward than its true cost.*

Proof. Suppose $\tilde{b}_j^i$ is a winning bid from I_i and $\tilde{b}_m^i$ is the highest winning bid of I_i; we have $\tilde{b}_j^i \leq \tilde{b}_m^i$. If $\tilde{b}^*$ is the lowest losing bid among all intermediaries, $\tilde{b}_m^i < \tilde{b}^*$ holds. If p_i is the corresponding unit reward, we have $\tilde{b}^* \leq p_i$ based on winner determination and payment mechanism. To sum up, $\tilde{b}_j^i < p_i$ holds. □

Theorem 8. *Given task $T(D, M)$, the number of data units collected by the platform incentive mechanism would be in the range of $[M, 2M)$.*

Proof. The lower bound is guaranteed by the winner determination algorithm (Line 4 in Algorithm 2). In terms of upper bound, in intermediary mechanism, every intermediary would be restricted to contribute at most M units of data. In bidding preprocessing algorithm (Algorithm 1), some bids would be packaged but one package still does not exceed M units of data. Thus, during winner determination, the worst case is that we have chosen $M - 1$ units of data; however the next candidate is a package with M units of data so that the final winner set contains $2M - 1$ units of data. □

In terms of social cost, our mechanism does not achieve social efficiency in theory, but still keeps social cost low enough. On the platform, we assign the overlapping user to the intermediary with that user's lowest bid, i.e, minimize the true cost as much as possible. After duplication elimination, the platform assigns the data tasks to those who could complete them at the least cost. By motivating intermediaries to bid truthfully and selecting at least M lowest biddings, the platform mechanism indeed minimizes social cost as much as possible in reverse auction scenario.

4.3. Time Complexity. In this section, we analyze the running time of the platform mechanism. In duplication identification (Algorithm 4), constructing array Arr takes $O(\sum_{i=1}^{N} N_i)$; sorting array Arr takes $O(\log(\sum_{i=1}^{N} N_i))$; scanning array Arr and building duplication set takes $O(\sum_{i=1}^{N} N_i)$. Computation overhead for bidding adjustment based on duplication set depends on the number of intermediaries affected. For every effected intermediary, the corresponding bidding adjustment takes $O(N_i)$. For intermediary I_i's bidding preprocessing (Algorithm 1), marginal cost calculation takes $O(N_i)$, and bidding adjustment also takes $O(N_i)$. Thus, the whole bidding preprocessing takes $O(N \max(N_i)\ (i = 1, 2, .., N))$. To speed up the computing, we could assign one intermediary's bidding preprocessing to one child process and let all processes execute concurrently. The complexity of winner determination (Algorithm 2) is $O(M \log N)$. Partial uniform payment scheme (Algorithm 3) takes $O(N)$ time.

5. Evaluation

In this section, we evaluate the performance of our proposed mechanism. Our evaluation consists of the following aspects: task completion and its distribution, platform total payment, intermediary revenue and its distribution, and social cost.

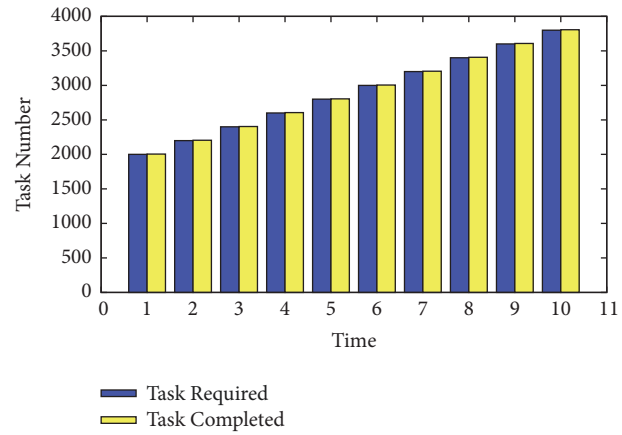

Figure 4: Task required vs. Task completed.

5.1. Setting. In our evaluation, the proposed mechanism has four parameters: intermediary number, task number, user overlapping rate, and total user number. All intermediaries' user numbers follow the Zipf distrubution. All user bids are randomly generated following the normal distribution in the range of (0,2). All user identification numbers (ID) are positive integer. As mentioned in our model, intermediaries have large user base; thus in our evaluation, every intermediary's user number is larger than task number.

For user duplication, to simplify but not harm generality, a user belongs to at most two intermediaries. User overlap rate here means the ratio of the overlap user number to the total user number. For example, considering 2 intermediaries each with 20 users, if without user overlapping, we have $2 * 20 = 40$ valid users. However, if the user overlap rate is 0.1, then we only have $40 * (1 - 0.1) = 36$ valid users. In other words, the number of users who have two intermediaries is 4 and that of users who have one intermediary is 32 ($32 + 4 * 2 = 40$). Thus, the user overlapping rate ranges from 0 to 0.5.

Every data point in the following figures is the average result of 100 executions.

5.2. Task Completion. Theorem 8 shows the proposed mechanism is not exact: given task $T(D, M)$, the number of data units collected by the platform incentive mechanism would be in the range of $[M, 2M)$. In our experiments, we execute the proposed mechanism with different task number settings (all other parameters remain unchanged) and compare the final collected task number with the required task number. As shown in Figure 4, the deviation between the number of collected tasks and required ones is quite small. Thus, although the theoretical upper bound of proposed mechanism is double required task, the collected task numbers are very close to the lower bound at most time in practice.

5.3. Intermediary Participation and Revenue Distribution. In this part, we choose a setting with 0.1 overlap rate, 2000 tasks, and 100 intermediaries with fixed smartphone users following Zipf distribution. Then we simulated the proposed mechanism 100 times, where each time we generate bids

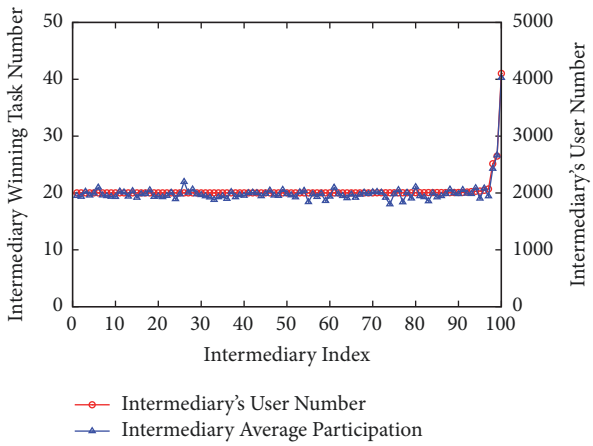

Figure 5: Winner distribution among intermediaries.

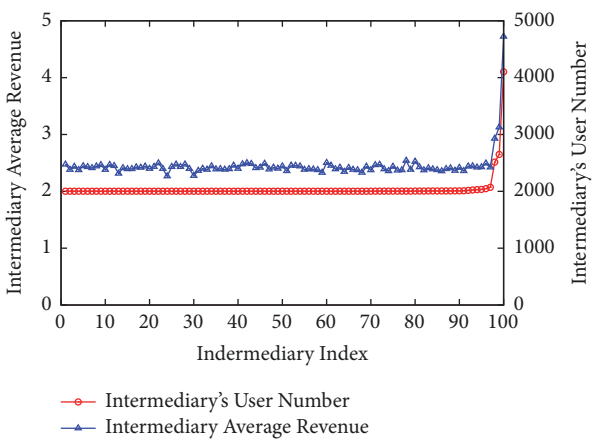

Figure 6: Revenue distribution among intermediaries.

randomly following normal distribution in range of (0, 2). We calculate every intermediary's average number of winning task and revenue. Figures 5 and 6 show that intermediaries with more users win more tasks and gain more revenue. Besides, it is noticed that the tasks are distributed quite equally, which reveals that the proposed mechanism achieves some degree of fairness to attract and keep more participants.

5.4. Platform Payment. The most significant difference between our mechanism and the previous works is the intermediaries' participation. Compared with the way of interacting with smartphone users directly, intermediaries' participation would increase the platform total payment because we would pay price to guarantee trufulness of both smartphones and intermediaries. Besides the proposed mechanism, we also simulate the mechanism where the platform accesses directly all valid users and carries out Generalized Secondary Price Auction mentioned in Section 3.1. Figures 7 and 8 show the following:

(1) Both the platform payment and the payment gap between two models grow with the increase of task number and overlap rate and the decrease of intermediary number; i.e., a greatly competitive market with large gap between supply and demand helps lower the payment and payment gap.

(2) The payment gap is quite close to the intermediaries' total revenue in all settings; i.e, the intermediaries gain profit from the platform overpayment.

(3) With the increment of intermediary number, intermediary total revenue is smaller than payment gap at first but becomes larger than that later. The turning point is around 20 intermediaries.

5.5. Social Cost. Besides platform payment, intermediaries' participation also increases social cost, i.e., the aggregation of all smartphone winners' sensing cost equal to the sum of their bids in the proposed mechanism. Experimental settings are similar to those above. As shown in Figure 9, the social cost grows with the increase of task number and overlap rate and the decrease of intermediary number. Similarly, a greatly competitive market with large gap between supply and demand helps lower the social cost. Furthermore, the social cost gap is relatively small which reveals that the proposed mechanism achieves social efficiency to a certain extent.

6. Related Works

In recent years, the concept of mobile crowdsensing has been widely applied into various application domains. Rana et al. [3] and Dutta et al. [4] adopted mobile devices to monitor urban air pollution. PEIR [17] is a crowdsensing application that generates personal environmental impact report. TrafficSense [5] is a piggyback crowdsenisng system that utilizes smartphone sensors to monitor road and traffic conditions. ParkNet [7] and ParkSense [8] are two different mobile systems that can help drivers to find on-street parking space. GreenGPS is a crowdsensing-based navigation service that utilizes crowdsensing data to construct fuel efficient maps. Zhou et al. [18] relied on the collaborative effort of crowdsensing users to predict the bus arrival time. Azizyan et al. [19] proposed a logical localization system based on ambient fingerprintings. The problem of indoor physical localization has also been widely studied, *e.g.*, [20–23]. Jigsam [24] leverages smartphone sensors to automatically construct indoor floorplans. Moazzami et al. [25] presented ORBIT, a smartphone-based platform for data-intensive embedded sensing applications. Jayarajah et al. [26] proposed LiveLabs deployed across small areas to collect real-time attributes which can be used to test new mobile sensing experiments. Song et al. [27] proposed a real-time projector-camera fnger system based on the crowdsensing, in which user can interact with a computer by bare hand touching on arbitrary surfaces. Yang et al. [28] considered designing incentive mechanisms for motivating private cars in a local region to collect data for HD map producers. However, most of these systems only work on a small scale of participants. To enable the accessibility of mobile crowdsensing systems in a larger participant scale motivates this work.

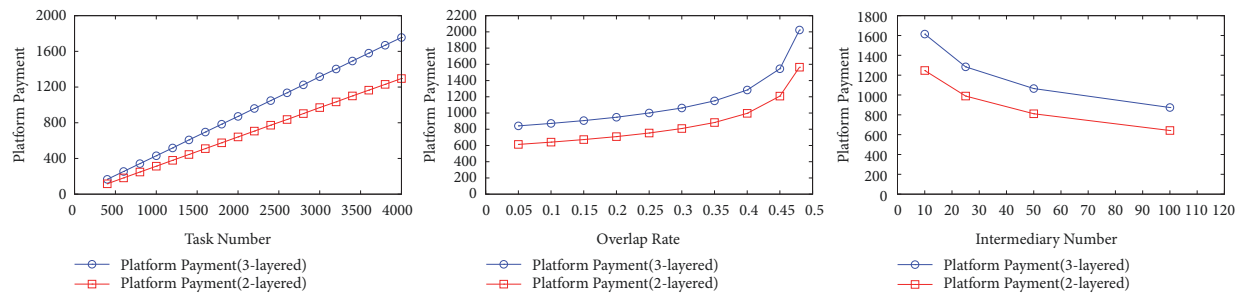

Figure 7: Influential factors of platform payment under two models.

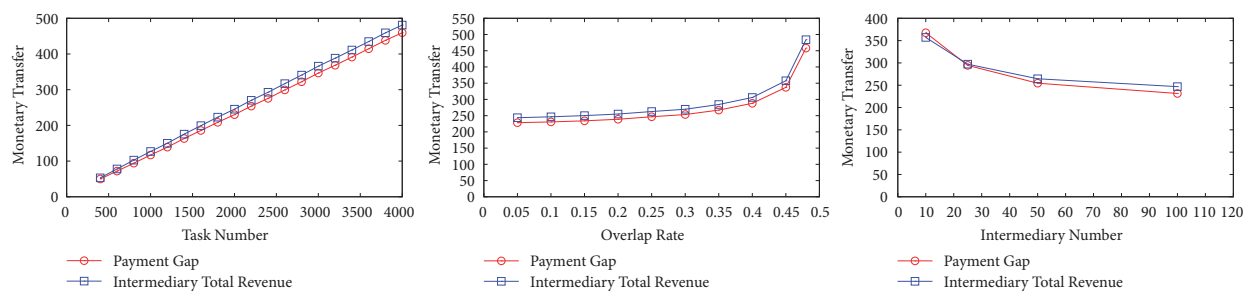

Figure 8: Influential factors of platform payment gap and intermediaries' total revenue.

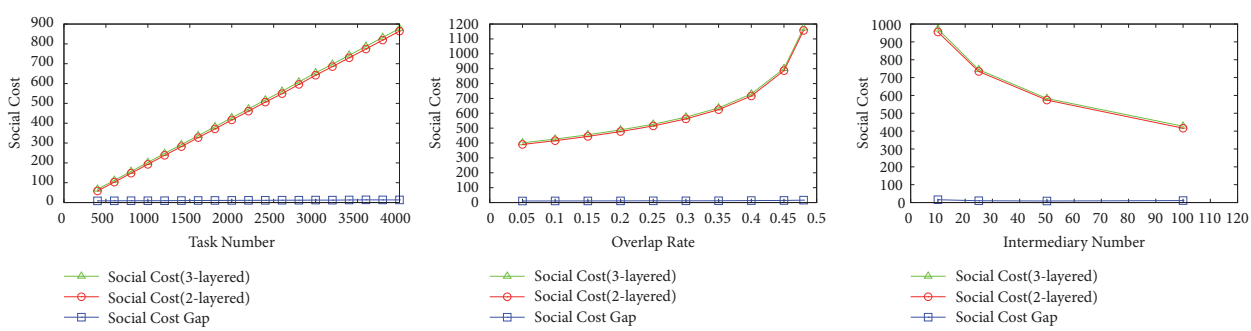

Figure 9: Influential factors of social cost and social cost gap under two models.

Many researchers have adopted market economy or game theory in order to attract more users to engage in the emerging sensing paradigms. Lee and Hoh [11] studied the user participation problem and proposed an incentive mechanism to maintain a large number of participants. Yang et al. [12] considered designing incentive mechanisms for both platform-centric and user-centric models. Koutsopoulos [29] studied the design of optimal frugal mechanism for crowdsensing. Zhao et al. [30] studied the online incentive mechanism design with budget constraint. Gao et al. [31] considered incentivizing users' long-term participation and proposed a Lyapunov-based VCG mechanism. Zhang et al. [32] studied three different models of crowdsensing and designed incentive mechanisms for them, respectively. Wei et al. [33] proposed truthful online double auctions for dynamic mobile crowdsensing. Zhang et al. [34] proposed a multi-market dynamic double auction mechanism for proximity-based mobile crowdsensing. Chen et al. [35] took the concept of network effects into consideration of designing incentive mechanisms. Li et al. [36] studied a new MCS architecture which leverages the cached sensing data to fulfill partial sensing tasks in order to reduce the size of selected participant set. Hu et al. [37] proposed a truthful incentive mechanism based on reverse auction to stimulate enough vehicles to participate in crowdsensing. Yang et al. [38] integrated quality estimation and monetary incentive and proposed a quality-based truth estimation and surplus sharing method for crowdsensing. Zheng et al. [39] studied a budget feasible and strategy-proof incentive mechanism for weighted coverage maximization in mobile crowdsensing. Zhu et al. [40] proposed a greedy discrete particle swarm optimization with genetic algorithm operation to solve the multitask allocation problem. Peng et al. [41] incorporated the consideration of data quality into the design of incentive mechanism for crowdsensing by offering each participant a reward based on her effective contribution. Some researchers also proposed preserving privacy in mobile crowdsensing. Lin et al. [42] designed two frameworks for privacy-preserving auction-based incentive mechanisms that

also achieve approximate social cost minimization. Chen et al. [43] proposed an approach called P^3 to preserve the privacy of the mobile nodes in a mobile crowd sensing system, leveraging node mobility. Xiong et al. [44] proposed a privacy preserving data aggregation scheme, where the mediator and sensing users may not be fully trusted. Lv et al. [45] investigated the possibilities and limitations of incentive trees via an axiomatic approach by defining a set of desirable properties. Zhang et al. [46] aimed to design an auction-based incentive tree to offer rewards to users for both participation and solicitation. Zhang et al. [47] designed a reward mechanism based on the incentive tree and proved that this mechanism satisfies several economic properties. However, these existing works only considered a two-layer crowdsensing architecture, consisting of a sensing platform and many smartphone users, which has critical drawbacks that prevent the sensing systems from scaling up. In contrast to these works, we consider a three-layer architecture by cooperating the sensing platform with certain popular applications that have large user bases. This work is based on the preliminary version [48] which appeared in IEEE IWQoS 2017.

7. Conclusion and Future Work

With the development of emerging mobile crowdsensing paradigm, data source shortage has become the bottleneck of most state-of-the-art mobile crowdsensing systems. Thus, we had proposed to cooperate with applications with large user base (act as intermediaries) to help to incentivize more users to be involved in crowdsensing. Our incentive mechanisms are based on a three-layer network model. We had designed auction-based mechanisms and identified the unique the problem of user overlapping, which had not been considered in existing incentive models, and had provided an effective solution to deal with it. Our incentive mechanisms are individual rational, incentive compatible, and computationally efficient and achieve quite low social cost. We have evaluated our mechanisms with extensive evaluations. Evaluation results have validated the effectiveness and efficiency of our proposed mechanisms.

Mobile crowdsensing has become a promising paradigm in collecting and using sensing data. However, how to ensure the data quality has become a tricky problem for us to discuss. This will be the essential direction for us to explore in the future.

(1) In our evaluation, we pay the participants for their consumptions of physical resources based on their bids and default that the participants would provide the data of high quality. If we consider that the participants cannot guarantee the quality of the sensing data they promised, continuous low-quality data could be harmful to the availability and accuracy of crowdsensing platform, and thus the quality of service cannot be guaranteed. To solve the issue of data quality, we consider two possible approaches to penetrate into in the future. First, it is a feasible and effective method to incorporate the level of data quality as an index into our mechanism. We can pay the participants as how much they contribute to motivate the participants to submit sensory data. Thus, it is a key issue to estimate the quality of sensory data and to reward each participant based on the estimated value. Second, we can also integrate quality estimation and monetary incentives together, by using a learning-based method to quantify the data quality and long-term credits of users, and by sharing the surplus earned by the sensing platform with users depending on each user's contribution. We can also reject low-credit users sensory data to improve data quality.

(2) We can also assume the possibility that a participant may fail to complete the task for some reason with a certain probability into consideration. We must make sure that our mechanism has fault tolerance capability for each sensing task under unreliable circumstances. To solve this problem, we can design a reverse auction mechanism to simulate the strategic interaction between the platform and the participants. The new auction mechanism aims to decrease the social cost and to guarantee the tasks to be completed as much as possible.

We aim to solve the problems and continue to optimize our mechanism in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

The opinions, findings, conclusions, and recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agencies or the government.

Conflicts of Interest

The authors declare that there are no conficts of interest regarding the publication of this paper.

Acknowledgments

This work was supported in part by the National Key R&D Program of China 2018YFB1004703 and in part by China NSF grants 61672348, 61672353, and 61472252.

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