A Double Auction Mechanism for Mobile Crowd Sensing with Data Reuse

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Abstract—Mobile Crowd Sensing (MCS) is a new paradigm of sensing, which can achieve a flexible and scalable sensing coverage with a low deployment cost, by employing mobile users/devices to perform sensing tasks. In this work, we propose a novel MCS framework with data reuse, where multiple tasks with common data requirement can share (reuse) the common data with each other through an MCS platform. We study the optimal assignment of mobile users and tasks (with data reuse) systematically, under both information symmetry and asymmetry, depending on whether the user cost and the task valuation are public information. In the former case, we formulate the assignment problem as a generalized Knapsack problem and solve the problem by using classic algorithms. In the latter case, we propose a truthful and optimal double auction mechanism, built upon the above Knapsack assignment problem, to elicit the private information of both users and tasks and meanwhile achieve the same optimal assignment as under information symmetry. Simulation results show by allowing data reuse among tasks, the social welfare can be increased up to 100% ~ 380%, comparing with those without data reuse. We further show that the proposed double auction is not budget balance for the auctioneer, mainly due to the data reuse among tasks. To this end, we further introduce a reserve price into the double auction (for each data item) to achieve a desired tradeoff between the budget balance and the social efficiency.

I. INTRODUCTION

A. Background and Motivations

The proliferation of mobile devices (e.g., smartphones) with rich embedded sensors has led to a novel sensing paradigm known as Mobile Crowd Sensing (MCS) [1], where mobile users/devices are employed to perform different sensing tasks. By crowdsourcing the sensing capabilities of massive powerful mobile devices, this new sensing paradigm can achieve a high sensing coverage with a low deploying cost, hence has attracted a wide range of applications in environment, infrastructure, and community monitoring (e.g., [2]–[12]).

A typical MCS framework mainly consists of the following three parts [1]: (i) a set of task planners, who initiate sensing tasks with specific data requirements, (ii) a set of mobile users, who report their capabilities and interests for performing different tasks, and (iii) an MCS platform, who collects the information of tasks and users, and assigns tasks to users carefully. When a user is assigned with a task, he performs the task accordingly using his device resource (e.g., CPU cycles and energy for sensing and processing data, bandwidth and energy for sending data to the task planner), which will incur a certain cost on the user. Meanwhile, the user can obtain a certain reward from the task planner via the platform according to a certain pre-defined payment rule.

Some prior works (e.g., [13]–[19]) have studied the general MCS model with multiple tasks and multiple users from different aspects, such as how to assign tasks to users efficiently, how to determine the rewards for users and the payments from tasks properly, and so on. Most of the existing works (i.e., [13]–[18]) focused on the MCS model without data reuse among tasks, where the same data required by multiple tasks cannot be shared (reused) among tasks and has to be sensed distinctly for each task. In practice, however, it is highly likely that different tasks require (hence can reuse) some common data [19]. For example, the weather data at a particular time and location may be required by the weather app (task 1), the travel app (task 2), and the road navigation app (task 3). Thus, without data reuse, it is likely to cause duplicated data sensing and processing, leading to resource waste and performance degradation. For this purpose, some practical MCS platforms such as PRISM [20] and Medusa [21] have allowed task planners to define data requirements in a standard language, such that the common data (requirement) of different tasks can be identified and reused potentially.

In [19], Jiang et al. studied the MCS model with data reuse among tasks, which allows multiple tasks with the common data requirement to share the common data with each other. They proposed a randomized auction mechanism, which is truthful in expectation and approximately optimal in term of social welfare. In this work, we consider a similar MCS model which allows data reuse among tasks, but our purpose is to design a mechanism which is strictly truthful and optimal.
B. Model and Problem

In this work, we study a general multi-task multi-user MCS model with data reuse, where different tasks can have common data requirements and reuse the common data. Specifically, each task is associated with a set of data items that it requires, and the overlap of different tasks’ data sets is the common data requirement of those tasks. Each user is associated with a set of data items that he can sense, and such a sensing capability depends on factors such as location, device capability, budget constraint, and so on.

Figure 1 illustrates such an MCS model with common data requirement (and data reuse) among tasks. Each blue circle denotes a particular data item (e.g., specific information at a particular time and location), and the dash line between a user and a data item denotes that the user can sense the data item. Each ellipse denotes the data items interested and required by each task. Obviously, tasks 1 and 2 require the common data set \{1, 2, 3\}, hence can potentially reuse those data items \{1, 2, 3\}. It is easy to see that our model generalizes the traditional model without data reuse in [13]–[18], as it can degenerate to the traditional model by simply viewing each common data required by multiple tasks as multiple virtual data, each associated with a particular task.

In such an MCS model, we are interested in the following Task-Data-User Assignment (TDU-A) problem:

- **How to assign different users to sense different data of different tasks, aiming at maximizing the social welfare, taking the data reuse among tasks into consideration?**

The social welfare is defined as the difference between the total valuation of all completed tasks and the total sensing cost of all employed users. More specifically, a task is completed if and only if all of its required data items have been sensed successfully, and the completion of a task will generate a certain valuation for the task planner. A user will incur certain sensing cost when he is scheduled to sense a data item, and each user is associated with a budget, denoting the maximum sensing cost that the user can afford.

Solving the above problem is challenging due to the following reasons. First, from the technical perspective, a simplified version of the problem (with a single user) is a Knapsack problem [22] (which is NP-hard), where the total user budget can be viewed as the knapsack capacity, and the sensing cost for each data item can be viewed as the weight of the item. Besides, involving the intermediate layer of data (between tasks and users) will further complicate the problem. Second, from the economic perspective, users may not be willing to report their sensing costs and budgets truthfully, and task planners may not be willing to report their valuations truthfully. Hence, a well-designed incentive mechanism (e.g., VCG auction [23]) is necessary for eliciting the private information of both users and task planners and making the assignment.

C. Solution and Contributions

We will solve the problem under both information symmetry and asymmetry, depending on whether the user sensing cost and budget and the task valuations are public information. In the former case, all information are public and can be observed by the platform. We formulate the assignment problem as a generalized Knapsack problem and solve the problem by using classic algorithms. In the latter case, the sensing cost and budget are private information of each user, and the task valuation is private information of each task planner, both of which cannot be observed by the platform. We propose a truthful double auction with the platform as the auctioneer and users and task planners as bidders, which can elicit the private information of users and task planners credibly, and meanwhile achieve the same optimal social welfare as under information symmetry.

We further show that the proposed double auction is not budget balance for the auctioneer (platform), in the sense that the total payment from all task planners may be smaller than the total reward to all employed users. This implies that the platform may need additional budget for organizing such an auction, which is not desirable in practice. To avoid this, we further introduce a reserve price to restrict the minimum payment (of tasks) for each data item. We show that a desired tradeoff between the budget balance and the social efficiency can be achieved by turning the reserve price finely.

In summary, the main results and key contributions of this work are summarized as follows.

- **Novel MCS Model:** We study a novel MCS model which allows multiple tasks to reuse the common data. Comparing with the existing models without data reuse, this new model can reduce the duplicated data sensing and processing, hence increase the social efficiency.

- **Truthful and Optimal Auction Design:** We study the optimal assignment problems under both information symmetry and asymmetry. In particular, we propose a truthful and optimal double auction under information asymmetry, which can elicit the private information of users/tasks credibly and achieve the same optimal social welfare as under information symmetry.

- **Performance Evaluations:** Simulation results show by allowing data reuse among tasks, the social welfare can be increased up to 100% ∼ 380%, comparing with those without data reuse. We further compare our approach with that in [19], and show that our proposed double auction (which is provably optimal) has an average of 10% performance gain over the randomized auction in [19] (which is approximately optimal).

- **Observations and Insights:** We show that allowing data reuse among tasks will reduce the competition of tasks, hence reduce the payments of task planners. This may lead to the undesired outcome of budget unbalance for the platform. We further show that a well-designed reserve price can achieve a desired tradeoff between the budget balance and the social efficiency.

The rest of the paper is organized as follows. In Section II we present the system model. In Section III and IV we analyze the problem under information symmetry and asymmetry,
respectively. We present the simulation results in Section VI and finally conclude in Section VII.

II. SYSTEM MODEL

A. Network Model

We consider a multi-task multi-user MCS model, consisting of a set $\mathcal{I} = \{1, \ldots, I\}$ of mobile users, a set $\mathcal{J} = \{1, \ldots, J\}$ of tasks, and a set $\mathcal{K} = \{1, \ldots, K\}$ of target data items. Each data item corresponds to a specific information at a particular location and time.[1] Each task $j \in \mathcal{J}$ is associated with a data requirement, i.e., a set $\mathcal{K}_j \subseteq \mathcal{K}$ of data items that it requires. Each user $i \in \mathcal{I}$ is associated with a sensing capability, i.e., a set $\mathcal{S}_i \subseteq \mathcal{K}$ of data items that he can sense. Note that different tasks may have common data requirement, i.e., $\mathcal{K}_{j1} \cap \mathcal{K}_{j2} \neq \emptyset$, and can reuse the common data potentially.

In the example of Figure I, we have: $I = 3$ users, $J = 2$ tasks, and $K = 12$ target data items. The data requirements of both tasks are $\mathcal{K}_1 = \{1\text{-}7\}$ and $\mathcal{K}_2 = \{1\text{-}3, 8\text{-}11\}$. The sensing capabilities of three users are $\mathcal{S}_1 = \{1, 4\text{-}7\}$, $\mathcal{S}_2 = \{1\text{-}3, 5, 8\}$, and $\mathcal{S}_3 = \{2, 3, 10\text{-}12\}$. Obviously, tasks 1 and 2 can reuse the common data set $\mathcal{K}_1 \cap \mathcal{K}_2 = \{1, 2, 3\}$.

The system operates in the following way. First, each task planner publishes the sensing task on the platform, indicating the data requirement and task valuation (under certain incentive mechanism). Each user reports the sensing interest on the platform, indicating the sensing capability, sensing cost, and sensing budget (under certain incentive mechanism). Then, based on the information reported by task planners and users, the platform decides the task-data-user assignment, aiming at maximizing the social welfare.

B. User Model

Each user $i \in \mathcal{I}$ is associated with (i) a sensing capability $\mathcal{S}_i \subseteq \mathcal{K}$, denoting the set of data items that he can sense, and (ii) a sensing cost vector $c_i = (c_{i,k}, k \in \mathcal{S}_i)$, denoting the cost for sensing each data item in $\mathcal{S}_i$. Each user may have different sensing costs for different data items, due to, for example, the different distances to those data items or the different capabilities for processing different data. Moreover, each user $i$ is associated with a sensing budget $C_i > 0$, capturing the maximum resource that can be used for sensing. Such a budget may depend on factors such as the user’s own service requirement and resource availability. For example, a user with a heavy burden of service or a low available device resource may assign a low budget for sensing.

Let $x_{i,k} \in \{0, 1\}$ denote whether a user $i \in \mathcal{I}$ is scheduled to sense a data item $k \in \mathcal{S}_i$, and $x_i = (x_{i,k}, k \in \mathcal{S}_i)$ denote the sensing scheduling vector of user $i$. Then, we have the following budget constraint for user $i$:

$$\sum_{k \in \mathcal{S}_i} x_{i,k} \cdot c_{i,k} \leq C_i$$

Given the feasible scheduling vectors of all users, i.e., $x = (x_i, i \in \mathcal{I})$, the total incurred sensing cost on all users is:

$$C(x) = \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{S}_i} x_{i,k} \cdot c_{i,k}.$$  \hspace{1cm} (2)

C. Data Model

A data item is sensed successfully, if and only if it is sensed by at least one user. Let $\mathcal{I}_k \equiv \{i \in \mathcal{I} \mid k \in \mathcal{S}_i\}$ denote the set of users that can sense a data item $k$, and $y_k \in \{0, 1\}$ denote whether a data item $k \in \mathcal{K}$ is sensed successfully. Then,

$$y_k = \max\{x_{i,k}, \forall i \in \mathcal{I}_k\}.$$  \hspace{1cm} (3)

The system operates in the following way. First, each task planner publishes the sensing task on the platform, indicating the data requirement and task valuation (under certain incentive mechanism). Each user reports the sensing interest on the platform, indicating the sensing capability, sensing cost, and sensing budget (under certain incentive mechanism). Then, based on the information reported by task planners and users, the platform decides the task-data-user assignment, aiming at maximizing the social welfare.

D. Task Model

Each task $j \in \mathcal{J}$ is associated with (i) a data requirement $\mathcal{K}_j \subseteq \mathcal{K}$, denoting the set of data items that it requires, and (ii) a task valuation $v_j > 0$, denoting the value of task for the task planner when the task is completed. A task $j$ is completed if and only if all of its required data items in $\mathcal{K}_j$ have been successfully sensed by at least one user. Let $\mathcal{I}_k \equiv \{i \in \mathcal{I} \mid k \in \mathcal{S}_i\}$ denote the set of users that can sense a data item $k$, and $y_k \in \{0, 1\}$ denote whether a data item $k \in \mathcal{K}$ is sensed successfully. Then, for each task $j \in \mathcal{J}$, we have the following completion indicator:

$$z_j = \min\{y_k, \forall k \in \mathcal{K}_j\}.$$  \hspace{1cm} (4)

In the example of Figure I, we have: (i) $\mathcal{I}_1 = \{1, 2\}$ and $\mathcal{K}_1 = \{1\text{-}7\}$, (ii) $\mathcal{I}_2 = \{2, 3\}$ and $\mathcal{K}_2 = \{1\text{-}3, 8\text{-}11\}$, (iii) $\mathcal{I}_3 = \{1\}$ and $\mathcal{K}_3 = \{1\}$. Each task planner in the above example has a sensing capability of one of the three users. For convenience, we denote $z_j = (z_{j,k}, k \in \mathcal{K}_j)$ as the sensing indicators of all data items.

E. Problem Formulation

The social welfare $W(x, z)$ is defined as the difference between the total valuation $V(z)$ of all completed tasks and the total sensing cost $C(x)$ of all employed users, i.e.,

$$W(x, z) = V(z) - C(x).$$  \hspace{1cm} (6)

Our purpose is to decide the best task-data-user assignment $\{x, y, z\}$ that maximizes the social welfare, taking the potential data reuse among tasks and the budget constraints of
users into considerations. Specifically, we can formulate the joint task-data-user assignment problem (A1) as follows.

\[ \text{A1:} \quad \max_{x, y} V(z) - C(x) \]
\[ \text{s.t.} \quad (1)(3)(4), \quad \forall i \in I, j \in J, k \in K; \]
\[ \text{var.} \quad x_{i,k} \in \{0,1\}, \quad \forall i \in I, k \in K; \]
\[ z_j \in \{0,1\}, \quad \forall j \in J; \]
\[ y_k \in \{0,1\}, \quad \forall k \in K. \]

Here \( y = (y_k, k \in K) \) is an intermediate variable indicating whether a data item is sensed successfully, which connects the tasks and users. It is easy to see that Problem P1 is a binary integer linear programming problem.

However, solving the Problem A1 is challenging due to the following reasons. First, it is a generalized Knapsack problem, as a simplified version of the problem (with a single user) is a Knapsack problem [22] (which is NP-hard), where the total user budget can be viewed as the knapsack capacity, and the sensing cost for each data item can be viewed as the weight of the item. Second, it involves an intermediate data layer in the assignment of users and tasks, leading to a three-layer model, which makes the problem even more complicated and challenging. Third, it requires the complete information of the whole system, including the data requirements and valuations of all tasks as well as the sensing capabilities, sensing costs, and budgets of all users. However, such information can be private information in practice, and task planners or users may not be willing to report their private information truthfully. Hence, we need to design a proper incentive mechanism to elicit such private information.

In what follows, we first solve Problem A1 under information symmetry where all information is public information (Section III). Then we study Problem A1 under information asymmetry where the above mentioned information is private information of task planners and users (Section IV).

### III. Information Symmetry

In this section, we consider the information symmetry scenario, where all information is public information and can be observed by the platform. Hence, the key problem is to solve the optimal task-data-user assignment by the Problem A1.

We first show that the Problem A1 is a Knapsack problem [22]. To show this, we consider a simplified model with \( J \) tasks, each requiring a distinct data item, and \( I = 1 \) user who can sense all data items. Then the problem becomes the following: select the tasks (or data items) to be completed within the user budget. Let us view the user budget as the knapsack capacity, the sensing cost for each data item as the weight of the item, and the valuation of each data item (task) as the valuation of the item. It is easy to see that the problem in this simplified model is exactly a Knapsack problem. Thus, the general case of Problem A1 is a generalized Knapsack problem. Note that there are many efficient algorithms for solving Knapsack problems, either optimally or sub-optimally [22]. Due to space limit, we will not go into the details of these algorithms in this work.

We further notice that it is still challenging to apply the classic algorithms to solve the Problem A1, mainly due to the min and max operations in the equality constraints (3) and (4). Hence, it is necessary to transform these constraints into other equivalent forms. Formally,

**Lemma 1.** The equality constraint in (3) is equivalent to the following constraints:

\[ y_k \geq x_{i,k}, \quad \forall i \in I_k, \quad \text{and} \quad y_k \leq \sum_{i \in I_k} x_{i,k}. \]

**Lemma 2.** The constraint in (4) can be relaxed to the following constraints without affecting the optimal solution:

\[ z_j \leq y_k, \quad \forall k \in K_j. \]

Based on the above lemmas, we can transform the Problem A1 into the following equivalent Problem A2.

\[ \text{A2:} \quad \max_{x, y} V(z) - C(x) \]
\[ \text{s.t.} \quad (1)(7)(8), \quad \forall i \in I, j \in J, k \in K; \]
\[ \text{var.} \quad x_{i,k} \in \{0,1\}, \quad \forall i \in I, k \in K; \]
\[ z_j \in \{0,1\}, \quad \forall j \in J; \]
\[ y_k \in \{0,1\}, \quad \forall k \in K. \]

**Theorem 1.** Problem A1 and Problem A2 are equivalent.

This theorem can be proved by the above two lemmas directly. Moreover, by transforming the Problem A1 into an equivalent and solvable Problem A2, we can adopt the classic algorithms for Knapsack problems directly into our problem. For notational convenience, we denote the optimal solution of the Problem A2 (or A1) by \( \{x^o, y^o, z^o\} \).

### IV. Information Asymmetry

In this section, we consider the information asymmetry scenario, where the data requirement and valuation of a task are the private information of the task planner, and the sensing capability, sensing cost, and budget are the private information of each user, both of which cannot be observed by the platform. Hence, the key problem is to design a truthful mechanism to elicit the private information of task planners and users, and meanwhile to achieve the optimal task-data-user assignment as under information symmetry.

#### A. Double Auction Framework

Inspired by the VCG mechanism [23], we propose a VCG-based double auction mechanism for eliciting the private information of users and task planners. In the proposed double auction, the MCS platform acts as the auctioneer employing mobile users (bidders on one side) for sensing different data items and selling the sensed data items to the required tasks (bidders on the other side). Different from a traditional VCG mechanism where the private information often resides on one side (either sellers or buyers) of the market, in our model the private information resides on both the user side (sellers) and the task plan side (buyers).

\[ ^3 \text{The auctioneer can also be acted by any other third-party network node.} \]
A typical VCG auction framework mainly consists of an assignment rule (e.g., for deciding the assignment of buyers and sellers) and a payment rule (e.g., for deciding the payments of buyers)\cite{23}. The payment rule is carefully designed such that bidders will report the private information truthfully. In our double auction framework, due to the two-sided private information, we need to design not only a payment rule (for deciding the payments of task planners), but also a reward rule (for deciding the rewards for users). The payment rule is used to guarantee the truthful information disclosure of task planners, while the reward rule is used to guarantee the truthful information disclosure of users.

Before presenting the detailed double auction rule, we first provide some important notations. Denote

\[ t_j \triangleq \{ K_j, v_j \} \quad \text{and} \quad t_i \triangleq \{ S_i, c_i, C_i \} \]

as true information of task \( j \in J \) and user \( i \in I \). Denote

\[ b_j \triangleq \{ \bar{K}_j, \bar{v}_j \} \quad \text{and} \quad b_i \triangleq \{ \bar{S}_i, \bar{c}_i, \bar{C}_i \} \]

as the reported information (bids) of task \( j \in J \) and user \( i \in I \), respectively. For convenience, we further denote \( b_{\text{TASK}} \triangleq (b_j, j \in J) \) and \( b_{\text{USER}} \triangleq (b_i, i \in I) \) as the bids of all task planners and users, respectively. Obviously, if the proposed auction is truthful, we will have: \( b_j = t_j \) and \( b_i = t_i \).

With a little abuse of notations, we denote

\[ x(\cdot) \triangleq (x_i(\cdot), i \in I) \quad \text{and} \quad z(\cdot) \triangleq (z_j(\cdot), j \in J) \]

as the assignment rule, where \( x(\cdot) \) is the user scheduling rule and \( z(\cdot) \) is the task completion rule. We further denote

\[ p(\cdot) \triangleq (p_j(\cdot), j \in J) \]

as the payment rule for task planners, where \( p_j(\cdot) \) denotes the payment of each task planner \( j \in J \). Similarly, we denote

\[ r(\cdot) \triangleq (r_i(\cdot), i \in I) \]

as the reward rule for users, where \( r_i(\cdot) \) denotes the reward for each user \( i \in I \). Based on the above, we can write such an auction mechanism as follows:

\[ \Omega \triangleq \{ x(\cdot), z(\cdot), p(\cdot), r(\cdot) \}. \]

Note that \( x(\cdot), z(\cdot), p(\cdot), \) and \( r(\cdot) \) are all functions of \( b_{\text{USER}} \) and \( b_{\text{TASK}} \), hence can also be written as \( x(b_{\text{USER}}, b_{\text{TASK}}), z(b_{\text{USER}}, b_{\text{TASK}}), p(b_{\text{USER}}, b_{\text{TASK}}), \) and \( r(b_{\text{USER}}, b_{\text{TASK}}) \).

**B. Truthful Double Auction**

Now we provide the detailed assignment rule, payment rule, and reward rule for our proposed double auction \( \Omega \), based on the key idea of VCG auction\cite{23}.

**Definition 1 (Assignment Rule).** The assignment rule \( x(b_{\text{USER}}, b_{\text{TASK}}) \) and \( z(b_{\text{USER}}, b_{\text{TASK}}) \) is given by:

\[ x(b_{\text{USER}}, b_{\text{TASK}}) = x^*(b_{\text{USER}}, b_{\text{TASK}}) \]

and

\[ z(b_{\text{USER}}, b_{\text{TASK}}) = z^*(b_{\text{USER}}, b_{\text{TASK}}), \]

where \( \{ x^*(b_{\text{USER}}, b_{\text{TASK}}), z^*(b_{\text{USER}}, b_{\text{TASK}}) \} \) is the optimal solution to Problem A2 by replacing the true information \((t_i, i \in I)\) and \((t_j, j \in J)\) with the reported bids \( b_{\text{USER}} \) and \( b_{\text{TASK}} \).

**Definition 2 (Payment Rule).** The payment rule \( p(b_{\text{USER}}, b_{\text{TASK}}) \) for task planners is given by:

\[ p(b_{\text{USER}}, b_{\text{TASK}}) = (p^*_j(b_{\text{USER}}, b_{\text{TASK}}), j \in J), \]

where the payment of task planner \( j \) is

\[ p^*_j(b_{\text{USER}}, b_{\text{TASK}}) \triangleq W^*_j(b_{\text{USER}}, b_{\text{TASK}}) - \sum_{l \in J \setminus \{ j \}} z^*_{l}(b_{\text{USER}}, b_{\text{TASK}}) \cdot v_l + \sum_{i \in I \setminus \{ j \}} \sum_{k \in S_i} x^*_{i,k}(b_{\text{USER}}, b_{\text{TASK}}) \cdot c_{i,k}, \]

and \( W^*_j(b_{\text{USER}}, b_{\text{TASK}}) \) is the maximum social welfare (defined on bids \( b_{\text{USER}} \) and \( b_{\text{TASK}} \)) excluding task planner \( j \).

**Definition 3 (Reward Rule).** The reward rule \( r(b_{\text{USER}}, b_{\text{TASK}}) \) for users is given by:

\[ r(b_{\text{USER}}, b_{\text{TASK}}) = (r^*_i(b_{\text{USER}}, b_{\text{TASK}}), i \in I), \]

where the reward to user \( i \) is

\[ r^*_i(b_{\text{USER}}, b_{\text{TASK}}) \triangleq \sum_{j \in J} z^*_j(b_{\text{USER}}, b_{\text{TASK}}) \cdot v_j - \sum_{l \in I \setminus \{ i \}} \sum_{k \in S_l} x^*_{l,k}(b_{\text{USER}}, b_{\text{TASK}}) \cdot c_{l,k} - W^*_i(b_{\text{USER}}, b_{\text{TASK}}), \]

and \( W^*_i(b_{\text{USER}}, b_{\text{TASK}}) \) is the maximum social welfare (defined on bids \( b_{\text{USER}} \) and \( b_{\text{TASK}} \)) excluding user \( i \).

It is easy to prove that the double auction \( \Omega \) defined on Definition 1–3 is truthful and optimal (i.e., achieving the same optimal social welfare as under information symmetry).

**Theorem 2.** The double auction mechanism \( \Omega \) given by (13)–(16) is truthful and optimal.

The proof for truthfulness is standard and can be referred to our technical report [23]. The optimality can be easily shown by Definition 1, together with the truthfulness.

**C. Budget Balance**

Now we discuss the budget balance property of the proposed auction, which is important for incentivizing the auctioneer (platform) to organize such an auction.

Specifically, an auction is said to be (weakly) budget balance, if the total payment collected from the task planners is no smaller than the total reward assigned to the users, hence the platform will not lose money by organizing such an auction\cite{23}. Therefore, budget balance is a highly desirable property for

\[ \text{Specifically, } W^*_i(b_{\text{USER}}, b_{\text{TASK}}) \text{ is the maximizer of Problem A2, by replacing the true information } (t_i, i \in I) \text{ and } (t_j, j \in J) \text{ with the reported bids } b_{\text{USER}} \text{ and } b_{\text{TASK}}, \text{ and meanwhile excluding task planner } j. \]

\[ \text{An auction is said to be strictly budget balance, if the total payment collected from the task planners equals the total reward assigned to the users.} \]
our auction, otherwise the platform may lose the interest of organizing such an auction.

Unfortunately, our proposed double auction is not budget balance, mainly due to the data reuse among tasks. Specifically, the data reuse among tasks reduces the competition among tasks, hence potentially reduces the payments of task planners (which is a common result in VCG), leading to the undesired budget imbalance. This can be shown by the following simple example: (i) Two tasks requiring a same data item with \(v_1 = 0.5\) and \(v_2 = 0.6\), and (ii) One user can sense the data with cost \(c = 0.2\). According to the assignment rule in (13) and (14), the user will be scheduled the data item and both tasks will be completed, hence the maximum social welfare is \(0.5 + 0.6 - 0.2 = 0.9\). According to the reward rule in (16), the user will receive a reward of \(0.5 + 0.6 - 0 - 0 = 1.1\). According to the payment rule in (15), task 1 will be charged a payment of \(0.4 - 0.6 + 0.2 = 0\), and task 2 will be charged a payment of \(0.3 - 0.5 + 0.2 = 0\). This coincides with the common results in classic VCG mechanisms, where a task not generating harmful impact to the rest of the market often does not need to pay money. Obviously, in this example, the platform loses a total money of 1.1.

To this end, we introduce a reserve price for each data item in the proposed double auction, which denotes the minimal price for each data item. Let \(\pi_k \geq 0\) denote the reserve price for each data item \(k \in K\). Then, for each task planner \(j \in J\), his minimum payment (if task \(j\) is completed) can be calculated by:

\[
P_j = \sum_{k \in K_j} \pi_k.
\]

Based on the above, we propose the following new payment rule \(p^*(b_{user}, b_{task})\) for task planners.

**Definition 4** (Payment Rule with Reserve Price). The new payment rule \(p^*(b_{user}, b_{task})\) for task planners is given by:

\[
p^*(b_{user}, b_{task}) = \left(p^0_j(b_{user}, b_{task}), j \in J\right),
\]

where the payment of task planner \(j\) is

\[
p^0_j(b_{user}, b_{task}) \triangleq \max \left\{ p^*_j(b_{user}, b_{task}), p_j \right\},
\]

where \(p^*_j(b_{user}, b_{task})\) is given in Definition 3.

We will show that the double auction \(\Omega^\dagger\) with the reserve price given in (18) is still truthful, but may be not optimal.

**Theorem 3.** The double auction mechanism \(\Omega^\dagger\) given by (13)(14)(16)(18) is truthful (but not optimal).

The proof for truthfulness is still standard and can be referred to our technical report [25]. The impact of the reserve price on optimality can be shown as follows. With the reserve price, some task planners, i.e., those with a valuation lower than the minimum payment given in (17), will decide to not join the auction. Hence, the maximum social welfare may be reduced. Therefore, there is a tradeoff between the social efficiency and the budget balance. A larger reserve price may lead to a better budget balance, but to a worse social efficiency. We will show the impacts of reserve price on the budget balance and the social efficiency via simulations.

V. Simulation Results

Now we provide simulation results to evaluate the performance of our proposed double auction mechanism.

A. Simulation Setup

To compare our proposed double auction with the randomized auction in [19], we consider a similar simulation setting as in [19], with \(I = 8\) tasks, \(I = 8\) users, and \(K \in \{5, 10, 15, 20\}\) target data items. Each data item is location-based and distributed in an area of 10km\(\times\)10km randomly and uniformly. Each user is associated with a random location and can sense the data items within a distance of 5km to his location. Each task requires 5 data items randomly picked from the whole target data set. The sensing cost \(c_{i,k}\) of each user \(i\) for each data item \(k\) is selected from \([0, 1]\) randomly and uniformly, and the total sensing budget \(C_i\) of user \(i\) is selected from \([0, 5]\) randomly and uniformly. The valuation \(v_{j,k}\) of each task \(j\) for each data item \(k\) that it requires is selected from \([0, 1.5]\) randomly and uniformly, and the total valuation \(v_j\) of task \(j\) is the sum of valuations on all required data items.

B. Social Welfare Gain

We first illustrate the social welfare gain due to data reuse among tasks, comparing with those without data reuse.

Figure 2 shows the maximum social welfare without data reuse and with data reuse among tasks, under different number of data items. For the case with data reuse, we further compare the social welfare gains achieved by our proposed double auction (which is provably optimal) and by the randomized auction in [19] (which is approximately optimal). We can see that the social welfare increases with the number of data items without data reuse, while decreases with the number of data items with data reuse. The reason is as follows. With a smaller set of data items, tasks are more likely to require the same data item. Hence, with data reuse, they can potentially reuse a larger set of common data items, resulting in a lower sensing cost and hence a higher social welfare; without data reuse, however, the competition among tasks become more intensive (as the common data has to be sensed distinctly for each task), leading to a potentially lower social welfare.

Figure 3 further shows the social welfare gain due to data reuse among tasks, comparing with those without data reuse. We can see that the social welfare gain can be up to 380% ~ 100% by our proposed double auction, and 370% ~ 80% by the randomized auction in [19], when the number of data items changes from 5 to 20. That is, we propose a double auction has an average of 10% performance gain over the randomized auction in [19]. When the number of data items is very large, there will be no common data requirement among tasks (hence no data reuse), and thus the social welfare gain due to data reuse will go to zero, which implies that the social welfare with and without data reuse are same.
C. Platform Budget

We now illustrate the impacts of the reserve price on the platform budget and the social welfare. We will show that a well-designed reserve price can achieve a desired tradeoff between budget balance and social efficiency.

Figure 4 shows the social welfare and the platform budget under different reserve prices. For clarity, we also present the total task payment and the total user reward in the figure, and the platform budget is just the difference between the total task payment and user reward. We can see that the social welfare always decreases with the reserve price, while the platform budget first increases and then decreases with the reserve price. The reason is as follows. Note that a task planner will leave the auction, if his task valuation is lower than the minimum payment defined in (17), i.e., the sum of reserve price on all required data items. Thus, with the increasing of the reserve price, more task planners are likely to leave the auction, resulting in a lower social welfare. Moreover, when the reserve price increases from a small level, most task planners still stay in the auction, and hence the platform budget increases due to the increased payment from task planners; when the reserve price increases from a high level, many task planners leave the auction, hence the platform budget decreases due to the decreased number of task planners. Besides, when the reserve price is very large (e.g., 1.5 in the figure), almost all of the task planners will leave the auction, leading to a zero social welfare and a zero platform budget.

Figure 4 also shows the minimum reserve price that achieves the platform budget balance, i.e., that leading to a zero budget for the platform (i.e., 0.38 in the figure). We can see that under such a reserve price (which achieves the strict budget balance), the social welfare loss is less than 2%, comparing with the maximum social welfare under the zero reserve price.

VI. CONCLUSION

In this work, we consider a novel MCS framework, where different tasks may have the common data requirement and can reuse the common data through a MCS platform. We study the optimal assignment among mobile users and sensing tasks (with data sharing) under both information symmetry and asymmetry. In particular, we propose a truthful and optimal double auction mechanism under information asymmetry. We further introduce a reserve price to achieve a desired tradeoff between the budget balance and the social efficiency. There are several interesting directions for future research. First, it is meaningful to consider more practical valuation model for tasks and cost model for users. Second, it is also important to study the approximate algorithm for solving the inherit NP-hard assignment problem.

REFERENCES

[1] H. Ma, D. Zhao, and P. Yuan, “Opportunities in mobile crowd sensing,” IEEE Communications Magazine, 52(8):29-35, 2014.
[2] WeatherLab, [http://www.weatherlab.com/](http://www.weatherlab.com/)
[3] OpenSense Project, [http://www.nano-tera.ch/projects/401.php](http://www.nano-tera.ch/projects/401.php/)
[4] Intel Urban Atmospheric, [http://www.urban-atmospheres.net](http://www.urban-atmospheres.net/)
[5] OpenSignal, [http://opensignal.com](http://opensignal.com/)
[6] NoiseTube, [http://www.noisetube.net](http://www.noisetube.net/)
[7] Sensorly, [http://www.sensorly.com](http://www.sensorly.com/)
[8] Waze: Free GPS Navigation with Turn by Turn, [https://www.waze.com](https://www.waze.com/)
[9] Mobile Millennium, [http://traffic.berkeley.edu](http://traffic.berkeley.edu/)
[10] B. Hull, V. Bychkovsky, Y. Zhang, et al., “CarTel: A Distributed Mobile Sensor Computing System,” in Proc. ACM SenSys, 2006.
[11] SpotSwitch, [http://spotswitch.com](http://spotswitch.com/)
[12] S. Mathur, T. Jin, N. Kasturirangan, et al., “ParkNet: Drive-by Sensing of Road-side Parking Strategies,” in Proc. ACM MobiSys, 2010.
[13] L. Duan, et al., “Incentive mechanisms for smartphone collaboration in data acquisition and distributed computing,” IEEE INFOCOM, 2012.
[14] D. Yang, et al., “Crowdsourcing to smartphones: incentive mechanism design for mobile phone sensing,” in Proc. ACM MobiCOM, Aug. 2012.
[15] T. Luo and C.-K. Tham, “Fairness and social welfare in incentivizing participatory sensing,” in Proc. IEEE SECON, June 2012.
[16] Z. Feng, et al., “TRAC: truthful auction for location-aware collaborative sensing in mobile crowdsourcing,” in Proc. IEEE INFOCOM, Apr. 2014.
[17] C. Jiang, L. Gao, L. Duan, and J. Huang, “Economics of Peer-to-Peer Mobile Crowdsensing,” in Proc. IEEE GLOBECOM, 2015.
[18] L. Gao, F. Hou, and J. Huang, “Providing long-term participation incentive in participatory sensing,” in Proc. IEEE INFOCOM, Apr. 2015.
[19] C. Jiang, L. Gao, L. Duan, and J. Huang, “Exploiting Data Reuse in Mobile Crowdsensing,” in Proc. IEEE GLOBECOM, 2016.
[20] T. Das, et al., “PRISM: platform for remote sensing using smartphones,” in Proc. ACM MobiSys, June 2010.
[21] M.-R. Ra, et al., “Medusa: a programming framework for crowd-sensing applications,” in Proc. ACM MobiSys, June 2012.
[22] H. Kellerer, U. Pferschy, and D. Pisinger, Knapsack Problems, Springer 2004.
[23] N. Nisan and A. Ronen, “Computationally feasible VCG mechanisms,” J. Artif. Intell. Res., vol. 29, pp.19-47, May 2007.
[24] L. Breslau, et al., “Web caching and Zipf-like distributions: evidence and implications,” in Proc. IEEE INFOCOM, Mar. 1999.
[25] Online Technical Report, url: [https://www.dropbox.com/s/iu4jqcecx9quw/AppendixCS.pdf?dl=0](https://www.dropbox.com/s/iu4jqcecx9quw/AppendixCS.pdf?dl=0)
Online technical report for “A Double Auction Mechanism for Mobile Crowd Sensing with Data Reuse” submitted to IEEE GLOBECOM 2017. Outline of the report:

- A: Proof for Lemma 1
- B: Proof for Lemma 2
- C: Proof for Theorem 1
- D: Proof for Theorem 2
- E: Proof for Theorem 3

APPENDIX

A. Proof for Lemma 1

Proof. We consider two cases: (i) \( x_{i,k} = 0, \forall i \in I_k \), and (ii) there exists at least one \( i \in I_k \) with \( x_{i,k} = 1 \). In the first case, we have \( y_k = 0 \) by both (3) and (7). In the second case, we have \( y_k = 1 \) by both (3) and (7). Hence, (3) and (7) are equivalent with each other.

B. Proof for Lemma 2

Proof. We consider two cases: (i) \( y_k = 1, \forall k \in K_j \), and (ii) there exists at least one \( k \in K_j \) with \( y_k = 1 \). In the first case, we have \( z_j = 1 \) by (4). It is easy to check that the optimal \( z_j \) under the constraint (8) is also \( z_j = 1 \) due to the definition of \( V(z) \) in (5). In the second case, we have \( z_j = 0 \) by both (4) and (8). Hence, relaxing (4) to (8) does not affect the optimal solution.

C. Proof for Theorem 1

Proof. By Lemma 1 and Lemma 2 we can prove the theorem directly.

D. Proof for Theorem 2

Proof. Proof for Truthfulness: It is easy to see that the payment rules given by (15) and (16) follow the basic principle of VCG mechanism [23], where each bidder (task planner or user) is charged by his critical bid, i.e., the harm they cause to other bidders. According to the classic results in [23], each bidder will report his private information truthfully.

Proof for Optimality: Based on the above, each bidder will report his private information truthfully. Thus, the assignment rule given by (13) and (14) is optimal, that is, it maximizes the social welfare.

E. Proof for Theorem 3

Proof. Similar as the proof for Theorem 2, we can easily find that the payment rules given by (16) and (18) follow the basic principle of VCG mechanism [23], where each bidder (task planner or user) is charged by his critical bid, i.e., the harm they cause to other bidders. Thus, by the classic results in [23], each bidder will report his private information truthfully.