DATA: A Double Auction Based Task Assignment Mechanism in Crowdsourcing Systems

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***Abstract*—With the increasing number of smartphone users, mobile phone sensing applications have been regarding as a promising paradigm which makes use of the smartphones to access the ubiquitous environment data. In this work, we study the sensing task auction problem where there are multiple tasks and smartphone users. The most significant challenge of this problem is how to design a truthful auction mechanisms, which is crucial for auction mechanism design. Thus, we address this challenge by proposing DATA, which is a truthful double auction mechanism for sensing tasks allocation. Different from the existing designs, we are the first to design double auction mechanism for solving mobile phone sensing problem. Besides, we further take the relationship between the utility of task demanders and the number of users that are assigned to do the tasks into consideration, and assign a set of smartphone users to a winning demander which can maximize the winning demander's utility. At last, we conduct extensive simulations to study the performances of the proposed auction mechanism, and the simulation results corroborate our theoretical analysis.**

***Index Terms*—Double auction, Truthful, Task assignment, Mobile sensing, Crowdsourcing**

I. Introduction

With the fast development of embedded micro powerful processors and wireless communication technology, smartphones and some intelligent mobile devices are rapidly becoming the crucial central computing device in our daily lives [11]. In accordance with the Moore's Law, embedded sensors (such as *compass, camera, accelerometer, GPS, proximity sensor, gyroscope, etc.*), storage capacities and computing capabilities are becoming powerful [8]. By equipping with such smart sensors and mobile operating system (*e.g. Android, IOS, Windows Phone, etc.*), the mobile devices are programmable and thus making the computing ubiquitous. It has been estimated that the number of smartphones is expected to hit 10 billions by 2016.

In recent years, mobile phone sensing applications have been regarding as a promising paradigm which makes use of the smartphones to access the ubiquitous environment data. As we have mentioned above, various smart sensors embedded in mobile phones can provide us with a huge number of useful sensed data. Instead of traditional artificial data collecting methods, mobile phone sensing appears as a more effective and cheap way to gather information. Comparing with the static wireless sensor mote, mobile sensing by using smartphones offers many advantages over wireless sensor networks.

Crowdsourcing emerged as a distributed problem solving method, which introduces a large amount of volunteers to solve a complex problem [2], [5]. Nowadays, crowdsourcing has received wide attention due to it offers a cheap and scalable way for accessing information. Owing to the widespread use of smartphones, we have a better choice for collecting information and solving problem. Smartphone users everywhere can opportunistically contribute to complex information gathering through mobile sensing. In consideration of the mobile sensing potential, many researchers have designed numerous crowdsourcing systems. For instance, Thiagarajan *et al.* from MIT propose a VTrack [16] crowdsourcing system for estimating the travel time in urban area to relieve the traffic delay with the built-in GPS. Kumar Rana *et al.* [14] implements a *Ear-Phone* system for urban noise mapping on Nokia N95 (Symbian) platform. The Ear-Phone can monitor the environmental noise pollution in urban areas through crowdsourcing data collection. Another similar system NoiseTube [15] which introduces a crowdsourcing approach for measuring and mapping urban noise pollution by using smartphones. Pothole Patrol (P^2) [4] proposed by Eriksson *et al.* investigates an application of mobile sensing to detect and report the surface conditions of roads in Boston area through using a collection of sensor-equipped vehicles.

Although many crowdsourcing systems based on mobile sensing have been proposed, these studies all assume that mobile phone users are willing to upload their sensed data to cloud platform. Unfortunately, this assumption is not always hold in reality. For example, owing to the limitation of devices' battery resource, most of the users have no incentive in participating in mobile phone sensing [19]. Thus, incentive should be considered as a major issue in the mechanism designing procedure.

As we know, a mobile crowdsourcing system consists of a platform, which usually resides in the cloud, and many smartphone users, which can upload their sensed data through wireless communication (*e.g.* 3/4G, WiFi, *etc.*) [19]. Many non-interference task demanders can publish their sensing tasks through this crowdsourcing platform with some money, and many smartphone users can get payment from platform by collaboratively accomplish the assigned task. How to ensure the truthfulness of smartphone users in crowdsourcing system plays an important role in problem solving [3].

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Fig. 1: Double auction model in crowdsourcing system.

To tackle the above challenges, we propose a Double Auction based Task Assignment (DATA) mechanism in crowdsourcing systems to ensure the truthfulness of each participator. Auction served as a fair and effective way to allocate scarce resources [10]. Double auction has been widely used in resource allocation topics, such as spectrum allocation [6], [17], [18], [20]. Double auction [12], in which the crowd mobile users could gain utilities to upload their useful sensed data while task demander could better complete the complex task, encourages more users take part in mobile sensing. Comparing with the traditional one-to-many single-sided auction, a well-designed double auction mechanism can eliminate the collusion or market manipulation. The platform acts as auctioneer in the double auction model. As shown in Figure 1, the platform runs the double auction to enable multiple task publishers (*a.k.a demanders*) and smartphone users to trade.

The DATA mechanism generally makes the following contributions:

- To the best of our knowledge, we are the first to solve task assignment issue in crowdsourcing systems by introducing double auction model with performance guarantee.
- Through theoretical analysis, we prove that the DATA mechanism achieves three essential economic properties (*truthfulness, individual rationality, budget balance*).
- We consider the relationship between the utility of task demanders and the number of users that are assigned to achieve the tasks in this paper, and make sure that the set of smartphone users assigned to a winning demander can maximize his utility.

The rest of paper is organized as follows: Section II introduces the preliminaries and our design objectives. Section III proposes our algorithm design. In section IV, we prove the correctness, effectiveness, and economic properties of our design. Section V evaluates the performance of our approach, and we conclude the paper in Section VI.

II. Preliminaries

In this section, we first give a detailed formulation of our system model, then we will review the double auction mechanism design, and discuss essential economic properties required to implement the double auction. These economic properties can also be considered as the design targets of our mechanism.

A. System Model

We consider the crowdsourcing auction system that consists of a platform, a set of demanders who want to buy the sensing data and a set of smartphone users to provide sensing service. Our auction system is running in cycles, and the platform plays a role of auctioneer. In each round of our auction, the demanders first submit their **sensing tasks** and the **bids** they want to pay for the platform. After collecting all the sensing tasks from demanders, the platform publishes them to the smartphone users. Then, smartphone users read the tasks' description, and submit their **reserve prices** for selling their sensing data to the platform if they are interested in participating in the sensing tasks. After receiving the responds from all the interested smartphone users, the platform executes an allocation mechanism to choose a set of winning smartphone users and sensing tasks, and computes the payment or charge for each winner. At last, the winning smartphone users send their sensed data to the demanders and the demanders send the payments in back. Then, this round of crowdsourcing auction process is finished.

Assume there is a set of demanders $\mathcal{D} = \{d_1, d_2, ..., d_m\}$, and a set of interested smartphone users $\mathcal{U} = \{1, 2, ..., n\}$. Each demander d_j has one sensing task t_j, and willing to pay no more than v_j for each smartphone user. Each user i has an associated cost (*e.g.* battery cost, computing cost, *etc.*) c_i to do the sensing tasks, which is a privacy value of user i. User i bids b_i to the platform, where b_i is the reserve price for user i who wants to sell his sensed data. Suppose P_i^u is the payment for each smartphone user i, then the utility of user i is

$$u_i = \begin{cases} P_i^u - c_i & \text{if user } i \text{ wins the auction} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

In most of the sensing tasks, such as traffic condition monitoring, the more users involved in sensing task, the better of the sensing results. Thus, the utility of demander d_j will be increased with the number of smartphone users who provide sensing service for him. Nevertheless, more users joining in task t_j means more pays. After the number of users reaches to a fixed value, the utility of demander d_j will be decreased with the increase of users. According to this observation, we assume that the utility of demanders and the number of users follow the following equation. Then, we can easily get that the utility of demander d_j is

$$u_{d_j} = \delta ln N_j - P_j^d N_j \quad (2)$$

where δ is a constant coefficient, N_j is the number of users who provide sensing service for t_j, and P_j^d is the payment from demander for each smartphone user providing sensed data for d_j.

TABLE I: Some symbols used in this paper.

Symbol	Symbol Meaning
$\mathcal{D}$	The set of demanders in the crowdsourcing system
$\mathcal{U}$	The set of smartphone users in the crowdsourcing system
d_j	The j-th demander in $\mathcal{D}$
t_j	Sensing task from the j-th demander in $\mathcal{D}$
v_j	The true valuation of the j-th demander for each smartphone user
c_i	The sensing cost of smartphone user i
b_i	The reserve price from user i
P_i^u	The payment for each smartphone user i
P_j^d	The payment from demander for each smartphone user providing sensed data for d_j
u_i	The utility of user i
u_{d_j}	The utility of demander d_j
N_j	The number of smartphone users who provide sensing service for t_j

B. Problem Formulation and Design Targets

As we have mentioned above, due to the fairness and effectiveness of double auction, we intrinsically select the this model as crowdsourcing system task assignment problem solving method. In this paper, we will study the double auction based task assignment issue. All the task demanders can be regarded as the service buyers, while all smartphone users can be regards as sellers. Assuming that each demander has one task to be done, and each smartphone user can bid for one interested task. Since most of the crowdsourcing tasks are similar, thus we can also assume that all the tasks are homogeneous.

The objective of our work is to design a double auction mechanism for crowdsourcing system task assignment problem which satisfies the essential economic properties. We will introduce these properties in the following [1], [9]:

1) ***Truthfulness:*** Truthful is also called *Strategy-proof*. Truthfulness is often seemed as the most important properties for an auction. In a double auction, if no buyer or seller can improve its own utility by bidding an untruthful price, we say that the auction is **truthful**. In our model, truthfulness means no matter how other players bid, neither smartphone user i nor task demander d_j can improve its own utility u_i or u_{d_j} by changing bids. In other words, the utility of demander and smartphone user will be maximized when they bid v_j and b_i respectively. Thus we can conclude that in a truthful auction, bidding truthfully is the ***dominant strategy*** for each player. This property ensures all players have no incentive to be selfish, and the auctioneer can allocate smartphone users to demanders who value the sensing task most.
2) ***Individual Rationality:*** We say a double auction is **individual rational** if no winning demanders pays more than its bid to each phone user ($P_j^d \leq v_j$), and no winning smartphone user is paid less than its bid b_i (in other words $P_i^u \geq b_i$). For each truthful participator, this property guarantees non-negative utilities. It is consistent with thought of incentive mechanism design.
3) ***Ex-post Budget Balance:*** A double auction is **ex-post budget balance** if the auctioneer's utility ϕ is no less than 0. The utility for auctioneer ϕ can be calculated as

$$\phi = \sum_{j=1}^{m} P_j^d N_j - \sum_{i=1}^{n} P_i^u \tag{3}$$

This property ensures that the platform in our crowdsourcing system has incentives to set up the double auction.

However, some researchers have demonstrated that the impossibility of having an efficient, individual rational, incentive compatible and budget-balanced mechanism [7], [13]. Thus our aim is to design a highly efficient double auction based task assignment mechanism.

In order to facilitate reading, we summarize some symbols used in this paper in Table I.

III. OUR MECHANISM DATA: DESIGN DETAILS

In this section, we propose DATA, a **D**ouble **A**uction based **T**ask **A**ssignment mechanism in crowdsourcing system with the goal of allocating smartphone users to task demanders efficiently while achieving three economic properties at the same time.

To solve the task assignment issue in crowdsourcing system and ensures truthful property, the proposed DATA mechanism mainly consists of three key steps: 1) *Bidding and Bids Sorting Procedure*; 2) *Task demanders and Smartphone users Matching Procedure*; 3) *Pricing Procedure*;

Now, we will give a detailed description of these three steps.

(1) Bidding and Bids Sorting Procedure:

At the beginning of double auction, all the participators including task demanders and smartphone users will submit their bids *privately* to the auctioneer. Recall that the task demander acts as the *buyer* in double auction model, and smartphone user plays as the *service seller* in auction model. The auctioneer in our model is the platform, after receiving the sealed-bid from demanders and smartphone users, the platform will execute a sorting process.

The platform firstly sorts the receiving bids from the task demanders. Remember that each demander d_j has a true valuation v_j for each phone user work for him. DATA sorts the demanders' bids in a non-increasing order:

$$\mathcal{V} : v_1 \geq v_2 \geq ... \geq v_m \tag{4}$$

Then the platform in DATA will sort the smartphone users' bids b_i in a non-decreasing order:

$$\mathcal{B} : b_1 \leq b_2 \leq ... \leq b_n \tag{5}$$

After sorting the sealed bids submitted from participators, the bidding and bids sorting procedure is finished. Figure 2 illustrates the bids sorting procedure in DATA.

(2) Task Demanders and Smartphone Users Matching Procedure:

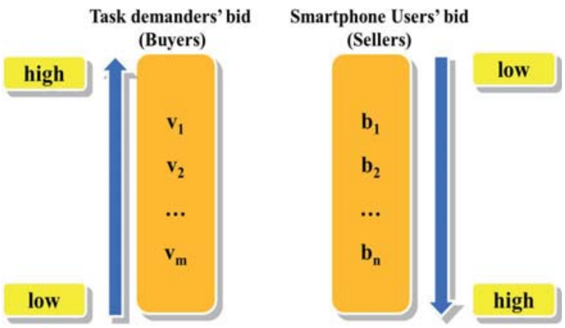

Fig. 2: Bids Sorting Procedure in DATA.

After the bidding and sorting process, we now have two ordered sets. In the task demanders and smartphone users matching procedure, our aim is allocate the user to the most appropriate task demander for achieving the auction efficiency. Meanwhile, we should judiciously design the allocation and matching mechanism to realize the essential economic properties. Recall that the calculation of best participators number for each demander's task is also one of the targets of DATA mechanism design.

The auctioneer first computes the best participators number $N_j (j = 1, 2, ..., m)$ for each sensing task t_j. Since we have defined the utility of demander d_j satisfied the equation (2), we can easily calculate the best participators number for each sensing task through derivation of N_j. Thus, the equation (2) can be reconsidered as

$$\frac{d(u_{d_j})}{d(N_j)} = \frac{\delta}{N_j} - P_j^d \tag{6}$$

As we known, the most appropriate smartphone user number N_j for each task t_j can make the utility for demander d_j maximized. Therefore, we can easily get that

$$N_j = \frac{\delta}{P_j^d} \tag{7}$$

Next, we will give the detailed description of task demanders and smartphone users matching procedure. In order to ensure truthfulness of our mechanism, we choose the classic ***secondary price clearing*** rule. The detailed proof can be referred to section IV. The auctioneer first test the demander with the highest bid v_1. If we calculate the best number of this demander's sensing task is N_1, then we will compare the bid of $(N_1 + 1)$-th smartphone user $b_{(N_1+1)}$ and v_1. If $v_1 \geq b_{(N_1+1)}$ holds, we say the first demander with highest bid wins. Next, we discuss the demander with second highest bid v_2. Assume the best number of this demander's sensing task is N_2, we will compare the bid of $(N_1 + N_2 + 1)$-th smartphone user $b_{(N_1+N_2+1)}$ and v_2 in the similar way. If $v_2 \geq b_{(N_1+N_2+1)}$ still holds, the second demander in demander set also wins. Otherwise, the matching procedure terminated.

The whole details are depicted in *Algorithm 1*.

(3) Pricing Procedure:

Algorithm 1 Matching and Allocation Algorithm

Input:
Sensing task set $\mathcal{T} = \{t_1, ..., t_m\}$, demanders' bid set $\mathcal{V} = \{v_1, ..., v_m\}$, users' bid set $\mathcal{B} = \{b_1, ..., b_n\}$;

Output:
Task assignment X ;

Sorting the demanders' bid in decreasing order, where
$$v_1 \geq v_2 \geq ... \geq v_m$$
Sorting the users' bid in increasing order;
$$b_1 \leq b_2 \leq ... \leq b_n$$
for $i = 1$ to m **do**
  for $j = 1$ to n **do**
    Set $x_{i,j} = 0$; //$x_{i,j} = 1$ means that smartphone user j is successfully allocated to task demander i
for $i = 1$ to $m - 1$ **do**
  Set $N_{sum} = 0$;
  for $k = 1$ to i **do**
    Set the payment of t_k is $p_k = v_{i+1}$;
    Compute N_k which is the optimal number of users for task t_k;
    $N_{sum} = N_{sum} + N_k$;
  if $N_{sum} \leq n$ and $b_{(N_{sum}+1)} \leq v_i$ **then**
    Set $j = 1$;
    for $k = 1$ to i **do**
      for $l = 1$ to N_k **do**
        Set $x_{k,j} = 1$, $j = j + 1$;
  else
    Return X;
Return X;

To maintain truthfulness, individual rationality and ex-post budget balance, DATA charges each winning task demander and smartphone user by the uniform bidding price. Suppose there are k demanders win in the auction, then we can get that:

$$P_i^u = b_{(N_1+N_2+...+N_k+1)} = b_{(1+\sum_{j=1}^{k} N_j)} \tag{8}$$

$$P_i^d = \max(P_i^u, v_{k+1}) \tag{9}$$

In other words, DATA pays each winning smartphone user by the bid of losing user with the highest bid, and charges each winning task demander is $\max(P_i^u, v_{k+1})$.

IV. Theoretical Analysis and Proofs of our DATA Mechanism

In this section, we prove that the proposed DATA double auction mechanism satisfies all the essential economic properties.

It is straightforward to show that DATA is individual rational and ex-post budget balance. Thus, we will only focus on the truthfulness of DATA mechanism in the following.

Theorem 1: DATA is individual rational and ex-post budget balance.

To prove the truthfulness, we should show that for any smartphone user i or task demander d_j, none of them can improve its utility by bidding untruthfully. That is to say, bidding truthfully is the dominant strategy for each of the participators.

We first introduce two lemmas. By using these two lemmas, we can easily prove the truthfulness.

Lemma 2: Given the demanders' bids set $\mathcal{V}$ and the smartphone users' bids set $\mathcal{B}$, if demander d_j wins the double auction by bidding v_j, then this demander will also win the auction by bidding $v' > v_j$.

Proof: Recall that all the bids in the set $\mathcal{V}$ are sorted in a descending order. Thus, demander d_j's position in sorted bids set $\mathcal{V}$ will not decrease when it bids a higher value v'. We can easily conclude that both the $(k+1)$-th bid of demanders and bid $b_{(1+\sum_{j=1}^{k} N_j)}$ are unchanged when winner d_j increases his bid. Then, we get that d_j will also win the auction. So the lemma holds. ■

It has been proven that an auction mechanism is truthfulness if the allocation mechanism is bid-monotone and the payment is bid-independent for each winner. Next, we will show that the payment for each winning demander is bid-independent in DATA.

Lemma 3: Given the demanders' bids set $\mathcal{V}$ and the smartphone users' bids set $\mathcal{B}$, if demander d_j wins the double auction by bidding v_j and v', then the charge for this demander will be the same.

Proof: As we have mentioned above, the pricing of each winning demander is only depend on $(k+1)$-th demander's bid and one user's bid $b_{(1+\sum_{j=1}^{k} N_j)}$. Since bidding v_j and v' both win in the auction, thus the charge for this demander will be the same. So the lemma holds. ■

According to lemma 1 and 2, we can get that:

Theorem 4: DATA is truthful for demanders.

we can prove that DATA is bid-monotone and bid-independent for the smartphone user side by the similar way. Then, we can also get that:

Theorem 5: DATA is truthful for smartphone users.

V. Simulation Results

The main purpose of our extensive simulations section is to examine the performance of the DATA mechanism. We first start by describing our simulation setup. Then, we study the setting variance impact on the performance of the DATA mechanism.

A. Simulation Setup

In our simulations, we assume the bids of task demander are randomly distributed in interval $(0, 200]$, and the bids from smartphone users are uniformly distributed in interval $(0, 100]$. In the evaluation section, we will first keep the number of smartphone users unchanged, and study the number of task demanders impact on payment and average success ratio. Then, we also keep the number of task demander unchanged, and give the number of smartphone users impact on payment and average success ratio. By default, all the simulation results are averaged over **1000 runs**.

Two metrics evaluated in the simulation are listed as follows:

- ***Payment***: For each task demander, the final payment is the charge for demander if it wins in the auction. For smartphone user, the payment is the money pay for each user who wins the auction.
- ***Average Success Ratio***: The ratio between successful bidders and total number of bidders in the auction.

B. Performance analysis

Although we have proved the truthfulness, individual rationality, and budget balance properties in Section IV. We will give the DATA mechanism's efficiency in this part.

In Figure 3, we plot the clearing price for both task demander and smartphone user. We first fix the number of smartphone users and vary the number of task demanders. When the number of task demanders increases, both the charge for task demanders and payment of smartphone users are also increased. This is because more task demanders take part in auction means more smartphone users have opportunities win the auction. Recall that all the smartphone users' bid are sorted in an ascending order, thus the payment for smartphone user is increased. At the same time, more task demanders makes a fierce auction competition, so it is not hard to observe that the charge for demanders will also be increased according to our matching rule.

Figure 4 plots the success ratio when number of task demanders varies. Based on the above analysis, more demanders provide more opportunities to smartphone users, so it is obvious that ratio value will be increased. However, with the increasing number of demanders, the denominator value will get larger. Thus, the ratio value for demanders will experience a degradation.

Due to the page limits, the detailed analysis of Figure 5 and 6 will not be presented. We can easily get the results through the similar analysis method.

VI. Conclusion

In this paper, we have studied a crowdsourcing auction system that exists multiple task demanders and smartphone users. Considering the relationship between the utility of demanders and the number of users assigned to them, we have designed a double auction mechanism which can maximize the winning demanders revenue. We have proved that the auction mechanism we proposed is economic-robust, in particularly truthfulness.

Several interesting questions are left for future research. The first one is to study the case that the sensing tasks are location-based when we assign users to tasks. The second one is to consider the sensing task are heterogeneous for smartphone users, where each smartphone user only interested in part of the published tasks.

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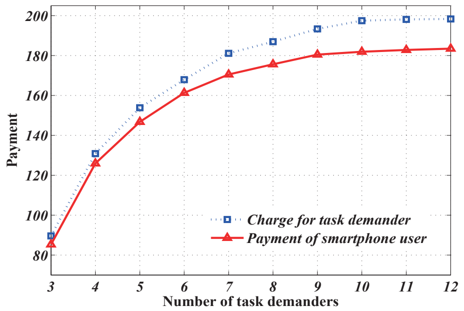

Fig. 3: The payment performance when number of task demanders varies.

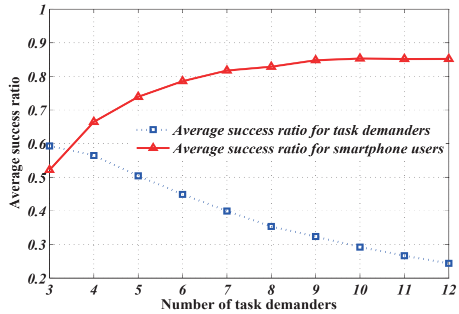

Fig. 4: The success ratio when number of task demanders varies.

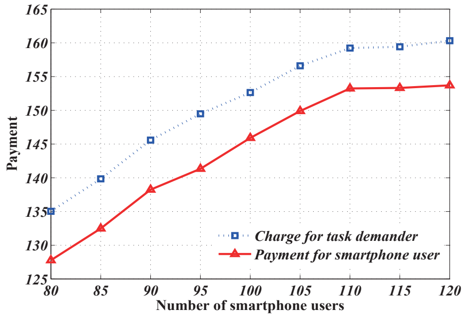

Fig. 5: The payment performance when number of smartphone users varies.

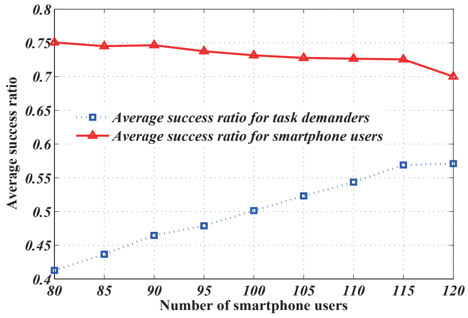

Fig. 6: The success ratio when number of smartphone users varies.

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