# Towards High Quality Mobile Crowdsensing: Incentive Mechanism Design based on Fine-grained Ability Reputation

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***Abstract*—Mobile crowdsensing has become an efficient paradigm for performing large-scale sensing tasks. Many quality-aware incentive mechanisms for mobile crowdsensing have been proposed. However, most of them measure the data quality by one single metric from a specific perspective. Moreover, they usually use the real-time quality, which cannot provide sufficient incentive for the workers with long-term high quality. In this paper, we refine the generalized data quality into the fine-grained ability requirement. We present a mobile crowdsensing system to achieve the fine-grained quality control, and formulate the problem of maximizing the social cost such that the fine-grained ability requirement of all sensing tasks can be satisfied. To stimulate the workers with long-term high quality, we design two ability reputation systems to assess workers' fine-grained abilities online. The incentive mechanism based on the reverse auction and fine-grained ability reputation system is proposed. We design a greedy algorithm to select the winners and determine the payment based on the bids and fine-grained ability reputation of workers. Through both rigorous theoretical analysis and extensive simulations, we demonstrate that the proposed mechanisms achieve computational efficiency, individual rationality, truthfulness, whitewashing proof, and guaranteed approximation. Moreover, the designed mechanisms show prominent advantage in terms of social cost and average ability achievement ratio.**

***Index Terms*—mobile crowdsensing; incentive mechanism; quality-aware; reputation system**

## I. Introduction

Nowadays, human-carried device (e.g., smart phone, tablet computer, miniature camera) becomes almost indispensable to our lives. These mobile devices are integrated with a variety of embedded sensors such as camera, light sensor, GPS, accelerometer, digital compass, gyroscope, microphone, and proximity sensor. These sensors can collectively monitor diverse human activities and the surrounding environment, thus promoting the emergence of mobile crowdsensing. Comparing with the traditional sensor networks, mobile crowdsensing has a huge potential due to the prominent advantages, such as wide spatio-temporal coverage, low cost, good scalability, and pervasive application scenarios [1, 2]. Mobile crowdsensing can be applied in various domains, such as Sensorly [3] for constructing cellular/WiFi network coverage maps, Nericell [4] and VTrak [5] for providing traffic information, as well as Ear-Phone [6] and NoiseTube [7] for creating noise maps. The participation in mobile crowdsensing will incur the cost of workers, such as consumption of battery, memory, computing power and data traffic. Moreover, there are potential privacy threats to smartphone users by sharing their sensory data with location tags or identities. Therefore, the incentive mechanism, which computes payoff for users to compensate their cost, is a necessary component of mobile crowdsensing systems.

Data quality is the main concern of mobile crowdsensing systems. The requesters of some crowdsensing/crowdsourcing marketplaces, such as MTurk [8], can specify that workers who work on their tasks must first complete a qualification test. However, this will incur the extra cost of workers.

To stimulate the workers to submit the high quality sensory data, quality-aware incentive mechanism design has attracted a lot of attentions in recent years [9-15]. However, most of the existing quality-aware incentive mechanisms take a single metric as the rough representation of data quality, e.g., position accuracy [16], contribution for truth discovery [17], compatibility of workers [18], task coverage [19], etc. Actually, the data quality can be assessed from many aspects. For example, in image acquisition crowdsensing [10, 20], the generalized data quality can be assessed by position accuracy, timeliness, number of submitted images, resolution, image accuracy, accuracy of image labeling, etc. Thus, to achieve high quality, the workers should be selected based on the fine-grained quality requirement.

Moreover, most of the existing quality-aware incentive mechanisms select the workers based on the instantaneous quality of workers, i.e., the quality at present time. However, the workers' quality is often time varying. A mature mobile crowdsensing system usually expects a stable crowd of workers, and the incentive mechanism is expected to be able to stimulate the workers with long-term high quality. Reputation system uses the visible histories to create an incentive to reliably perform up to the worker's abilities. Thus workers with long-term high abilities will be drawn to participate in the mobile crowdsensing. Reputation system has been designed for many systems, including E-commerce websites such as eBay [21], online advice communities such as stack exchange [22], web search such as Google, and social news such as Reddit [23].

In this paper, we aim to design truthful incentive mechanism for the multi-round mobile crowdsensing systems based on

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the integrated solution of reverse auction and fine-grained ability reputation system. We consider that the sensing tasks in each round of crowdsensing have the fine-grained ability requirement. Two fine-grained ability reputation systems are proposed to collect, maintain, and disseminate the reputation of workers. The winners are selected based on the bids and ability reputation of workers. Before starting the next round of crowdsensing, the ability reputation of workers is updated by the reputation system. The objective of our incentive mechanism is maximizing the social welfare such that the fine-grained ability requirement of all tasks can be satisfied. The whole process is illustrated by Fig.1.

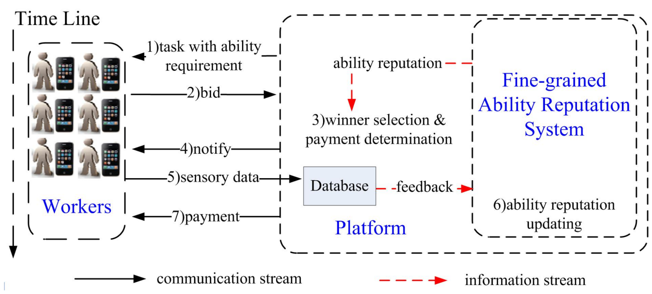



Fig. 1. Mobile crowdsensing process based on reverse auction and fine-grained ability reputation system

The problem of designing truthful incentive mechanism for the mobile crowdsensing system based on the fine-grained ability reputation system is very challenging. First, the problem of social welfare maximization usually can be solved directly by the polynomial time reduction from *Weighted Set Cover* (*WSC*) problem [24] or *Weight Set Multi-Cover* (*WSMC*) problem [24], thus the approximation algorithm can be applied. However, in our setting, each task has a requirement with multiple fine-grained abilities, and the existing approximation algorithm cannot be applied straightforwardly. Second, a worker may acquire a new identity and start over with a clear reputation in order to hide history records. Thus the designed reputation system should be whitewashing proof. Moreover, if the platform is unable to assess the abilities of workers, the external raters can be recruited. The external raters may take a strategic behavior by submitting dishonest ability score of workers to maximize their rewards. Finally, the workers may take a strategic behavior by submitting dishonest bid price to maximize their utilities.

The main contributions of this paper are as follows:

- We present a mobile crowdsensing system based on the ability reputation to achieve the fine-grained quality control, and formulate the *Social Optimization Ability Coverage* (*SOAC*) problem to minimize the social cost when satisfying the overall ability reputation requirement of all tasks.
- We propose two ability reputation systems to quantify workers' fine-grained ability online without extra qualification test. *Beta-distribution*-based ability reputation system considers that the value of workers' ability reputation follows *beta-distribution*, and treats the historical ability and current ability equally. In *peer-prediction*-based [25] ability reputation system, a set of external raters are recruited to assess the abilities of workers. The *logarithmic reward rule* [26] is used to guarantee the truthfulness of raters.
- We propose the *Incentive Mechanism based on the Fine-grained Ability Reputation* (*FAR*). We show that the proposed mechanism achieves the properties of computational efficiency, individual rationality, whitewashing proof, truthfulness and low approximation.

The rest of the paper is organized as follows. We review the state-of-art research in Section II. Section III formulates the system model and lists some desirable properties. Section IV presents the *Beta-distribution*-based ability reputation system and *peer-prediction*-based ability reputation system. Section V presents detailed design and analysis of incentive mechanisms. Performance evaluation is shown in Section VI. We conclude this paper in Section VII.

## II. Related Work

### A. Quality-aware Incentive Mechanism Design

Many quality-aware incentive mechanisms have been proposed for mobile crowdsensing systems. Jin *et al.* proposed *QoI-SRC* and *QoI-MRC* Auction Models [9], which take into consideration the *Quality of Information* (*QoI*). Gu *et al.* studied the problem of stimulating workers to provide high-quality data for multimedia crowdsensing enabled learning system [10]. Xiong *et al.* proposed an incentive mechanism, which ensures that users submit high-quality data and services [11]. Zhao *et al.* studied the problem of data quality and privacy preserving under untruthful reporting [12]. Wang *et al.* studied the problem of measuring workers' long-term quality and proposed *MELODY* [13]. Wen *et al.* proposed an incentive mechanism based on a *Quality Driven Auction* [14], where the workers are paid off based on the quality of sensed data instead of working time. Jin *et al.* designed an incentive mechanism based on reverse combinatorial auctions and incorporated the *QoI* of workers into the incentive mechanism [15]. Xu *et al.* took the accuracy of truth discovery as the quality of workers [17]. They designed the incentive mechanism to achieve the accuracy requirement of tasks, where the payment to the workers is determined based on workers' contribution to truth discovery. Xu *et al.* stated that choosing the compatible users can improve the quality of mobile crowdsensing service, and proposed truthful incentive mechanisms where each task needs to be performed by a group of compatible users [18]. Gao *et al.* designed the worker recruitment algorithm for the workers with unknown sensing quality and cost using multi-armed bandits [27]. Wang *et al.* studied the worker recruitment problem under the scenario where both the workers' objective ability and their subjective collaboration likelihood have an impact on the data quality of cooperative tasks, and developed an algorithm based on multi-armed bandits to find the optimal group of workers [28].

However, the quality-aware incentive mechanisms mentioned above take a single metric as the rough representation of data quality. Different from these prior work, this paper values the quality of workers based on the fine-grained ability assessment from multiple dimensions. Moreover, we utilize the reputation systems to stimulate the workers with long-term high quality.

### B. Reputation based Incentive Mechanism Design

Reputation system has been widely used as the incentives to the workers of crowdsensing system. Gan *et al.* proposed an incentive mechanism to solve the problem of multi-resource sharing based on users' reputation [29]. Pouryazdan *et al.* focused on the scenario where data authenticity and user reliability cannot be guaranteed, and designed a cooperative games to enable the users to join an alliance based on static reputation and dynamic reputation [30]. Some studies used a combination of monetary incentives and reputation incentives [31], [32]. Different from [31], [32], we determine workers' monetary rewards based on their reputation directly. Moreover, our reputation system guarantees the truthful reporting of external raters if the platform is unable to assess workers' abilities.

Table I illustrates the major differences of related work and our incentive mechanism.

## III. System Model

In this section, we model the mobile crowdsensing system as a reverse auction, and present some desirable properties.

### A. System Model

We consider a mobile crowdsensing system consisting of a platform resided in the cloud and a set $W = \{1, 2, ..., n\}$ of $n$ workers, who are interested in performing the mobile crowdsensing tasks. The mobile crowdsensing is launched round by round. Without loss of generality, we consider that the platform publicizes a set $T = \{t_1, t_2, ..., t_m\}$ of $m$ sensing tasks at current round. Each task $t_j \in T$ is associated with the ability reputation requirement $\mathbf{Q}_j = (q_j^1, q_j^2, ..., q_j^l)$ on the workers, where $q_j^k \in [0, 1]$ represents the minimal reputation requirement of ability $k \in \{1,2,...,l\}$ for performing task $t_j$. We consider that there are total $l$ different abilities in the mobile crowdsensing system and denote the ability set by $\Omega = \{1, 2, ..., l\}$. Here, ability $k$ means the $k$-th ability in ability set. The required abilities are determined by the specific sensing tasks. For example, the image crowdsensing system [10, 20] collects the suitable images from the workers to the training dataset for the machine learning algorithms. Since the valid images with high quality are expected, the validity, sharpness, contrast and pixel of submitted images are crucial. Thus, the validity, sharpness, contrast and pixel can be viewed as the ability reputation requirement of image crowdsensing tasks with multiple dimensions. Specifically, if the task has no requirement for some abilities, the platform simply sets the ability reputation requirement as zero. Each task $t_j \in T$ also has an overall ability reputation requirement $\mathbf{D}_j = (d_j^1, d_j^2, ..., d_j^l)$, which means that the reputation summation of ability $k$ of all winners of task $t_j$ should be no less than $d_j^k$, $k \in \Omega$. Let $\mathbf{Q}$ and $\mathbf{D}$ be the ability reputation requirement and overall ability reputation requirement for all tasks, respectively. We denote any worker $i$'s ability reputation by $\mathbf{P}_i = (p_i^1, p_i^2, ..., p_i^l)$, $p_i^k \in [0, 1]$, which is maintained by the ability reputation system deployed in the platform, where $p_i^k$ is the reputation of $k$-th ability of worker $i$.

Each worker $i \in W$ submits a bid $B_i = (T_i, b_i)$ to the platform, where $T_i \subseteq T$ is the task set he/she is willing to perform, and $b_i$ is worker $i$'s bid price to perform the tasks in $T_i$. Each worker $i$ also has a cost $c_i$. We consider that $c_i$ is the private information and is known only to worker $i$.

Given the task set $T$ and the bid profile $\mathbf{B} = (B_1, B_2, \ldots, B_n)$, the platform calculates the winning set $S \subseteq W$ and payment profile $\mathbf{r} = (r_1, r_2, \ldots, r_n)$, and notifies winners of the determination. The winners perform the sensing tasks. After the platform receives winners' sensory data, each worker $i$ is paid $r_i$ by the platform. Finally, the ability reputation of workers is updated.

We define the utility of any worker $i$ as the difference between the payment and its real cost:

$$u_i = r_i - c_i \tag{1}$$

Specially, the utility of the losers would be zero because they are paid nothing in our designed mechanisms and there is no cost for sensing.

Since we consider the workers are selfish and rational individuals, each worker can behave strategically by submitting a dishonest bid price to maximize its utility.

To prevent monopoly, we assume that all sensning tasks still can be completed if any worker does not participate in the auction. This assumption is reasonable for crowdsensing systems as shown in [1, 11].

The utility of the platform is:

$$u_0 = V(S) - \sum_{i \in S} r_i \tag{2}$$

where $V(S)$ is the value of the platform obtained if all of the tasks can be completed by the winners with abilities no less than the overall requirement.

We define the social welfare as the total utilities of the platform and all workers:

$$u_{social} = u_0 + \sum_{i \in W} u_i = V(S) - \sum_{i \in S} c_i \tag{3}$$

The objective of our incentive mechanism is maximizing the social welfare subject to the constraint that each task in $T$ can be completed with ability reputation no less than the overall requirement.

Note that the problem of maximizing the social welfare is equivalent to the problem of minimizing the social cost (total cost of winners) since the value of $V(S)$ is constant under the constraint of overall requirement. We call this problem as the *Social Optimization Ability Coverage* (*SOAC*) problem, which can be formulated as follows:

$$\min \sum_{i \in W} c_i \cdot x_i \tag{4}$$

$$s.t. \quad \sum_{i \in W} p_i^k \cdot x_i \geq d_j^k,\ \forall t_j \in T_i,\ \forall k \in \Omega \tag{4-1}$$

$$p_i^k \geq q_j^k x_i,\ \forall i \in W,\ \forall t_j \in T_i,\ \forall k \in \Omega \tag{4-2}$$

TABLE I
COMPARISON OF RELATED WORKS

| Related Work | Criterion of Quality | Incentive Method | Payment Determination | Multi-dimensional quality | Individual Rationality | Truthfulness | Whitewashing Proof | Approximation |
|---|---|---|---|---|---|---|---|---|
| [9][10][13] [14] [15] | Data Quality | Reverse Auction | Data Quality | No | Yes | Yes | No | Yes |
| [11] | Data Quality | Secure Multi-Party Sorting | Data Quality | No | No | No | No | No |
| [12] | Data Quality | Truth Discovery and Quality Evaluation | Data Quality | No | No | No | No | No |
| [17] | Probability of Truth | Reverse Auction | Probability of Truth | No | Yes | Yes | No | Yes |
| [18] | Compatibility | Reverse Auction | Marginal cost | No | Yes | Yes | No | No |
| [27] | Data Quality and Cost | Multi Armed Bandits | Worker's Cost | No | Yes | No | No | No |
| [28] | Ability and Collaboration Likelihood | Multi Armed Bandits | Worker's Cost | No | Yes | No | No | No |
| [29] | Shared Resources | VCG Auction | Reputation | No | Yes | Yes | No | No |
| [30] | Collaborative Reputation | Coalition Game | Collaborative Reputation | No | Yes | Yes | No | No |
| [31] | Data Quality | Reverse Auction | Data Quality | No | Yes | Yes | No | No |
| [32] | Worker's Effort | Contribution Quantification | Worker's Effort | No | No | No | No | No |
| *FAR* | Fine-grained Ability Reputation | Reverse Auction | Ability Reputation | Yes | Yes | Yes | Yes | Yes |

$$x_i \in \{0,1\}, \ \forall i \in W \tag{4-3}$$

where $x_i$ is the binary variable for each worker $i \in W$. $x_i = 1$ if $i$ is a winner; $x_i = 0$ otherwise.

The constraint (4-1) ensures that the total ability reputation of all winners for any task is no less than the corresponding overall requirement. Constraint (4-2) ensures that each winner satisfies the minimal ability reputation requirement of tasks it performs.

### *B. Desirable Properties*

Our objective is to design an incentive mechanism satisfying the following desirable properties:

- **Computational Efficiency:** An incentive mechanism is computationally efficient if the winner set $S$, the payment profile $\mathbf{r}$, and the ability updating can be computed in polynomial time.
- **Individual Rationality:** Each worker will have a non-negative utility while reporting the true cost, i.e., $u_i \geq 0$, $\forall i \in W$.
- **Whitewashing Proof:** No worker can get more utility through rejoining with a new identity.
- **Truthfulness:** An incentive mechanism is truthful if reporting the true cost is a weakly dominant strategy for all workers. In other words, no worker can improve its utility by submitting a false cost, no matter what others submit.
- **Approximation:** The goal of the mechanism is to minimize the social cost. We attempt to find the algorithm with low approximation ratio if the problem is NP-hard.

The importance of the first two properties is obvious, because they together assure the feasibility of the incentive mechanism. The third property is necessary to prevent the malicious workers from resetting their ability reputation. Truthfulness is indispensable for guaranteeing the compatibility. Being truthful, the incentive mechanisms can eliminate the fear of market manipulation and the overhead of strategizing over others for the workers. The last property can measure the performance of incentive mechanism.

We list the frequently used notations in Table II.

TABLE II
FREQUENTLY USED NOTATIONS

| Notation | Description |
|---|---|
| $W, n, i$ | work set, number of workers, worker $i$ |
| $T, m, t_j$ | task set, number of tasks, task $j$ |
| $\Omega, l$ | ability set, number of abilities, ability $k$ |
| $\mathbf{Q}, \mathbf{Q}_j$ | ability reputation requirement, ability reputation requirement of task $j$ |
| $q_j^k$ | ability reputation requirement of ability $k$ in task $j$ |
| $\mathbf{D}, \mathbf{D}_j$ | overall ability reputation requirement, overall ability reputation requirement of task $j$ |
| $d_j^k$ | overall ability reputation requirement of ability $k$ in task $j$ |
| $\mathbf{P}_i$ | worker $i$'s ability reputation |
| $p_i^k$ | worker $i$'s reputation of ability $k$ |
| $\mathbf{B}, B_i$ | bid profile, bid of worker $i$ |
| $b_i, c_i$ | bid price of worker $i$, cost of worker $i$ |
| $T_i$ | task set of worker $i$ |
| $\mathbf{r}, r_i$ | payment profile, payment to worker $i$ |
| $S, V(S)$ | winner set, value of platform from winners |
| $u_0, u_i$ | utility of platform, utility of user $i$ |
| $u_{social}$ | social welfare |

## IV. Fine-grained Ability Reputation System

In this section, we present two different ability reputation systems. The first is *beta-distribution* based ability reputation system, where the ability assessment is executed by the platform. This reputation system considers that the value of workers' ability reputation follows *beta-distribution*, and treats the historical ability and current ability equally. The second is *peer-prediction* [17] based ability reputation system, where the ability assessment is executed by the third party (e.g., a set of external raters) recruited by the platform. This reputation system can assign different weights to the historical ability and current ability, thus the ability updating rule with more resilience can be applied. Overall, *beta-distribution* based ability reputation system is suitable for the mature mobile crowdsensing system, which can assess workers' abilities by itself and has long-term stable workers. While *peer-prediction* based ability reputation system is suitable for the immature mobile crowdsensing system that cannot assess workers' abilities by itself or the workers are unstable.

### A. Ability Reputation System based on Beta-distribution

The beta probability density function is a natural method to construct reputation system [33]. It provides a sound mathematical basis for combining feedback and for expressing reputation ratings. *Beta-distribution* can be used to represent posteriori probabilities, so we can construct ability reputation system based on *beta-distribution*, and assess and update worker's abilities according to his\her historical ability and sensory data at current round. We consider a random variable $A_i^k$ of any worker $i$ for ability $k$ follows the *beta-distribution*. Then the probability density function of $a_i^k$ with parameters $\alpha_i^k$ and $\beta_i^k$ can be expressed as:

$$f(a_i^k|\alpha_i^k,\beta_i^k) = \frac{\Gamma(\alpha_i^k+\beta_i^k)}{\Gamma(\alpha_i^k)\Gamma(\beta_i^k)}(a_i^k)^{\alpha_i^k-1}(1-a_i^k)^{\beta_i^k-1} \quad (5)$$

where $\Gamma$ is gamma function.

The expectation value of random variable $A_i^k$ is:

$$E(A_i^k) = \frac{\alpha_i^k}{\alpha_i^k+\beta_i^k} \quad (6)$$

In our ability reputation system, $\alpha_i^k$ is the number of positive feedback of worker $i$ for ability $k$, and $\beta$ is the number of negative feedback of worker $i$ for ability $k$. We use the expectation value as the ability reputation, i.e., $p_i^k = E(A_i^k)$. Then the main work of *beta-distribution* based ability reputation system is designing the rules to maintain the values of $\alpha_i^k$ and $\beta_i^k$. We give the rules of system initialization, new worker initialization, and ability reputation updating as follows. Fig. 2 illustrates when these rules are applied in the multi-round mobile crowdsensing system.

- System initialization

Before starting the first bound of mobile crowdsensing, the platform needs to initialize the ability reputation of workers in the system. If there are some priori knowledge for ability $k$ (e.g. historical data), we can initialize workers' ability reputation based on the prior distribution $Beta(\alpha_H^k,\beta_H^k)$, where

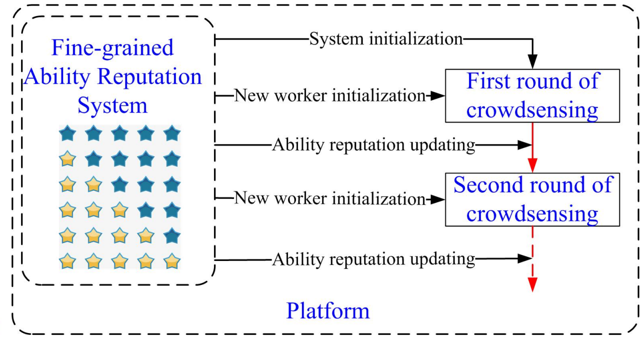



Fig. 2. Illustration for rules of reputation system

$\alpha_H^k$ and $\beta_H^k$ are the parameters of prior distribution. Specifically, if there is no priori-knowledge, we set $\alpha_i^k$=$\beta_i^k$=$\alpha_H^k$=$\beta_H^k$=1, which means that all workers have the same ability reputation of 0.5. For any worker $i$ and ability $k$, the system initialization rule is as follows:

$$\begin{cases} \alpha_i^k=\alpha_H^k,\ \beta_i^k=\beta_H^k, & \text{with priori knowledge} \\ \alpha_i^k=\beta_i^k=\alpha_H^k=\beta_H^k=1, & \text{without priori knowledge} \end{cases} \quad (7)$$

- New worker initialization

If a new worker arrives at some time (any round of crowdsensing), we initialize his/her ability reputation as the minimum of those of all workers in the system to achieve the property of whitewashing proof before participating in the mobile crowdsensing. For any new worker $i$, the new worker initialization rule for all abilities is as follows:

$$\alpha_i^k=\alpha_{i'}^k,\ \beta_i^k=\beta_{i'}^k,\ i' = \arg\min_{i''\in W} E(A_{i''}^k) \quad (8)$$

- Ability reputation updating

After the winners submit the sensory data, the platform needs to update workers' ability reputation based on the submitted data. Let $p'^k_i$ be the actual ability $k$ of worker $i$. We consider the following two cases:

(1) Worker $i$ is an old worker, i.e., this is not the first time to perform tasks. For every task $t_j \in T_i$, if the actual ability can satisfy the ability reputation requirement of task, we increase the number of positive feedbacks of this ability. Otherwise, we increase the number of negative feedbacks of this ability. The ability reputation updating rule for any ability $k$ of old worker $i$ is as follows:

$$\begin{cases} \alpha_i^k = \sigma*\alpha_i^k+1,\ \beta_i^k = \sigma*\beta_i^k, & p'^k_i \geq q_j^k > 0 \\ \alpha_i^k = \sigma*\alpha_i^k,\ \beta_i^k = \sigma*\beta_i^k+1, & p'^k_i < q_j^k \end{cases} \quad (9)$$

where $\sigma$ is the forgetting factor to adjust the weight of historical ability reputation.

(2) Worker $i$ is a new worker, i.e., this is the first time to perform tasks. Note that worker $i$ is with the minimal ability reputation of all workers. For every task $t_j \in T_i$, if the actual ability can satisfies the ability reputation requirement of task, we increase the number of positive feedback of ability $k$ based on the prior distribution $Beta(\alpha_H^k,\beta_H^k)$ to make worker $i$ be a normal worker. Otherwise, we increase the number of negative

feedbacks of this ability. The ability reputation updating rule for any new worker $i$ is as follows:

$$\begin{cases} \alpha_i^k = \sigma * \alpha_H^k + 1, \ \beta_i^k = \sigma * \beta_H^k, & p'^k_i \geq q_j^k > 0 \\ \alpha_i^k = \sigma * \alpha_i^k, \ \beta_i^k = \sigma * \beta_i^k + 1, & p'^k_i < q_j^k \end{cases} \tag{10}$$

### *B. Ability Reputation System based on Peer-prediction*

Different from *beta-distribution*-based ability reputation system, the ability assessment in *peer-prediction*-based ability reputation system is executed by a number of external raters. In our model, the platform recruits a number of raters to assess the abilities of workers. Then the platform updates the abilities of workers and rewards the raters based on the reported score. The process of rating can be modeled as a *simultaneous reporting game*. We consider that the raters are selfish, and each rater can behave strategically by submitting a dishonest score to maximize its reward. Thus we need to ensure the truthfulness of raters.

In this section, we use the *peer-prediction* [25], which is an effective way to elicit and convey private information, to construct the ability reputation system. Without loss of generality, we consider that the scores of ability are discretized by $g = 1, 2, ..., G$. We assume that the platform has the prior probability $\Pr^0_{i,k}(g) > 0$ assigned to the ability $k$ of worker $i$ being score $g$. The prior probability can be obtained by the common knowledge or the previous results of rating [12]. Obviously, $\sum\limits_{g=1}^{G} \Pr^0_{i,k}(g) = 1$. The raters score the abilities based on the prior probability and the sensory data.

Let $I$ be the set of raters, where $|I| \geq 3$. Each rater has a perception of workers' any ability it is scoring now, which is called signal. The rater does not know any other rater's signal. Let $\Delta = \{\delta_1, \delta_2, ..., \delta_G\}$ be the set of possible signals of all workers' abilities, and let $\Delta^e_{i,k}$ be the random signal received by any rater $e \in I$. Let $\chi^e_{i,k}$ be the score that rater $e$ reports. Conditional on the prior probability $\Pr^0_{i,k}(g)$, raters' signals are independent and identically distributed. The distribution is represented by function $f_{i,k}(\delta_v|g) = \Pr^0_{i,k}(\Delta^e_{i,k} = \delta_v|g)$, where $f_{i,k}(\delta_v|g) > 0$ for all $\delta_v \in \Delta$ and $g$, and $\sum_{v=1}^{G} f_{i,k}(\delta_v|g) = 1$ for all $g$. We assume that this function $f_{i,k}(\delta_v|g)$ is common knowledge [25]. Furthermore, we assume that the conditional distribution of signals is different for different values of $g$ [25], so that the signals are informative about the abilities. For convenience, we consider that $\delta_v, \Delta^e_{i,k}, \chi^e_{i,k}$ are normalized in $[0, 1]$.

To assign rewards to rater $e$, we need to design a reward rule. For each possible reported score $\chi^e_{i,k}$ of $\Delta^e_{i,k}$, the reward rule is a function $R(\delta_v|\chi^e_{i,k})$, which assigns a reward to each possible value of $\delta_v$.

**Definition 1.** *A reward rule is strictly proper if the rater maximizes his expected reward by reporting the true beliefs.*

*We use the following logarithmic reward rule:*

$$R(\delta_v|\chi^e_{i,k}) = \ln f_{i,k}(\delta_v|\chi^e_{i,k}) = \ln[\Pr^0_{i,k}(\Delta^e_{i,k} = \delta_v|\chi^e_{i,k})] \tag{11}$$

The *logarithmic reward rule*, which is proven to be *strictly proper* [34], rewards the rater the log of the probability it assigned to the signal that actually occurred.

In the *peer-prediction*, a reference rater $w(e)$ is randomly chosen for rater $e$. We apply the *logarithmic reward rule* to *peer-prediction*:

$$R(\chi^{w(e)}_{i,k}|\chi^e_{i,k}) = \ln[\Pr^0_{i,k}(\Delta^{w(e)}_{i,k} = \chi^{w(e)}_{i,k}|\Delta^e_{i,k} = \chi^e_{i,k})] \tag{12}$$

**Theorem 1.** *For any reference rater $w(e)$ of each rater $e$, truthful reporting is a strict Nash Equilibrium of the simultaneous reporting game with reward rule $R(\chi^{w(e)}_{i,k}|\chi^e_{i,k})$ for each ability $k$ of worker $i$.*

The proof of Theorem 1 will be given in Appendix A for a better flow of the paper.

Note that the expected reward given in (A.1) is always negative. We add a suitably large constant $\phi$ to convert this to a positive reward. It is easy to see that such convert does not alter the property of truthful reporting. Overall, the reward of each rater $e$ for any ability $k$ of worker $i$ is:

$$R(\chi^{w(e)}_{i,k}|\chi^e_{i,k}) + \phi \tag{13}$$

The workflow of *peer-prediction*-based ability reputation system is illustrated in Fig. 3.

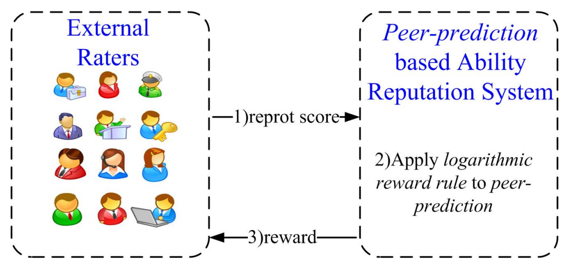



Fig. 3. Illustration for *peer-prediction*-based ability reputation system

Next, we give the rules of system initialization, new worker initialization, and ability reputation updating as follows:

- System initialization

In system initialization, the platform sets each worker's every ability as a constant, i.e.,

$$p_i^k = p_H^k, \ \forall i \in W, \ \forall k \in \Omega \tag{14}$$

where $p_H^k$ is calculated from statistical date, $0 \leq p_H^k \leq 1$.

- New worker initialization

Similar to *beta-distribution*-based ability reputation system, we initialize new worker $i$'s ability reputation as the minimal of those of all workers in the system:

$$p_i^k = \min_{i' \in W} p_{i'}^k, \ \forall k \in \Omega \tag{15}$$

- Ability reputation updating

After receiving the reported scores from raters, the platform updates workers' ability reputation as follows:

$$p_i^k = \sigma * p_i^k + (1 - \sigma) \frac{\sum\limits_{e \in I} \chi^e_{i,k}}{|I|}, \ \forall k \in \Omega \tag{16}$$

## V. Incentive Mechanism based on Fine-grained Ability Reputation

In this section, we present the incentive mechanism, *FAR*, based on the ability reputation of workers.

### A. Mechanism Design

First, we attempt to find an optimal algorithm for the *SOAC* problem given in (4). Unfortunately, as the following theorem shows, the problem is NP-hard.

**Theorem 2.** *The SOAC problem is NP-hard.*

The proof of Theorem 2 is given in Appendix B.

Since the problem is NP-hard, it is impossible to compute the winner set with minimum social cost in polynomial time unless P=NP. In fact, there is no $(1-\varepsilon)\ln n$ approximate polynomial time algorithm for *WSC* problem [24]. In addition, we cannot use the off-the-shelf *VCG* mechanism [24] since the truthfulness of *VCG* mechanism requires that the social cost is exactly minimized. We design our reverse auction, which follows a greedy approach. For the sake of brevity, we only give the incentive mechanism using *beta-distribution*-based ability reputation system, termed *FAR-Beta*, which is illustrated in Algorithm 1.

First, If it is the first round of crowdsensing, we initialize workers' ability reputation based on (7). If there are new workers, we initialize new workers' ability reputation based on (8).

Then we remove the tasks that cannot satisfy the ability reputation requirement from the task subset $T_i$ of any worker $i \in W$ (Lines 7-12). We denote the filtered task subset of worker $i$ as $T'_i$. The workers are sorted according to the effective ability unit cost, which is defined as $\frac{b_i}{\sum_{t_j \in T'_{i'}} \sum_{k \in \Omega} \min\{d'^k_j, p^k_i\}}$ for any worker $i \in W$. We iteratively select the worker with minimum effective ability unit cost over the unselected worker set $W \backslash S$ as the winner until the winners' accumulated ability reputation can fulfil the ability reputation requirement of each task in $T$.

In payment determination, for each winner $i \in S$, we execute the winner selection over $W' \backslash \{i\}$ and denote the winner set as $S'$. We compute the maximum price that worker $i$ can be selected instead of each worker in $S'$. We will prove that this price is a critical value for worker $i$ later.

Finally, we execute the ability reputation updating based on (9) or (10) for $\forall i \in W$ and $\forall k \in \Omega$.

The incentive mechanism using *peer-prediction* based ability reputation system, termed *FAR-Peer*, is similar to Algorithm 1. The difference is that the rules of system initialization, new worker initialization, and ability reputation updating are based on (14), (15), and (16), respectively. In addition, the reward of any rater $e$ for any worker $i$ and ability $k$ is calculated by (13).

**Algorithm 1** **FAR-Beta**

**Input:** task set $T$, bid profile $\mathbf{B}$, worker set $W$, ability reputation requirement $\mathbf{Q}$, overall ability reputation requirement $\mathbf{D}$

**Output:** winner set $S$, payment $\mathbf{r}$

//System Initialization

1: **if** this is the first round of crowdsensing **then**

2:   system initialization based on (7) for $\forall i \in W$ and $\forall k \in \Omega$;

//New Worker Initialization

3: **for each** $i \in W$ **do**

4:   **if** $i$ is a new worker **then**

5:     new worker initialization based on (8) for $\forall k \in \Omega$;

//Winner Selection

6: $S \leftarrow \emptyset$, $\mathbf{D}' \leftarrow \mathbf{D}$;

7: **for each** $i \in W$ **do**

8:   $T'_i \leftarrow T_i$;

9:     **for each** $t_j \in T_i$ **do**

10:       **for each** $k \in \Omega$ **do**

11:         **if** $p^k_i < q^k_j$ **then**

12:           $T'_i \leftarrow T'_i \backslash \{t_j\}$;

13: **while** $D' \neq 0$ **do**

14:   $i \leftarrow \arg\min_{i' \in W \backslash S} \frac{b_{i'}}{\sum_{t_j \in T'_{i'}} \sum_{k \in \Omega} \min\{d'^k_j, p^k_{i'}\}}$;

15:   $S \leftarrow S \cup \{i\}$;

16:   **for each** $t_j \in T'_i$ **do**

17:     **for each** $k \in \Omega$ **do**

18:       $d'^k_j = d'^k_j - \min\{d'^k_j, p^k_i\}$;

//Payment Determination

19: **for each** $i \in W$ **do** $r_i \leftarrow 0$;

20: **for each** $i \in S$ **do**

21:   $W' \leftarrow W \backslash \{i\}$, $S' \leftarrow \emptyset$, $D'' \leftarrow D$;

22:   **while** $D'' \neq 0$ **do**

23:     $i_g \leftarrow \arg\min_{g \in W' \backslash S'} \frac{b_g}{\sum_{t_j \in T'_g} \sum_{k \in \Omega} \min\{d''^k_j, p^k_g\}}$;

24:     $S' \leftarrow S' \cup \{i_g\}$;

25:     $r_i \leftarrow \max\{r_i, \frac{\sum_{t_j \in T'_i} \sum_{k \in \Omega} \min\{d''^k_j, p^k_i\}}{\sum_{t_j \in T'_g} \sum_{k \in \Omega} \min\{d''^k_j, p^k_g\}} b_{i_g}\}$;

26:     **for each** $t_j \in T'_{i_g}$ **do**

27:       **for each** $k \in \Omega$ **do**

28:         $d''^k_j = d''^k_j - \min\{d''^k_j, p^k_{i_g}\}$;

//Ability Reputation Updating

29: ability reputation updating based on (9) or (10) for $\forall i \in W$ and $\forall k \in \Omega$;

### B. Mechanism Analysis

In the following, we present the theoretical analysis, demonstrating that *FAR* can achieve the desired properties of computational efficiency, individual rationality, whitewashing proof, truthfulness, and guaranteed approximation. All proofs will be given in the appendixes.

**Lemma 1.** *FAR is computationally efficient.*

**Lemma 2.** *FAR is individually rational.*

**Lemma 3.** *FAR is whitewashing proof.*

Before analyzing the truthfulness of *FAR*, we first introduce the Myerson's Theorem [35].

**Theorem 3.** *([35, Theorem 2.1]) An auction mechanism is truthful if and only if:*

- *The selection rule is monotone: If worker $i$ wins the auction by bidding $b_i$, it also wins by bidding $b'_i < b_i$;*
- *Each winner is paid the critical value: Worker $i$ would not win the auction if it bids higher than this value.*

**Lemma 4.** *FAR is truthful.*

Before providing the approximation analysis of *FAR*, we first give the following transform of the *SOAC* problem defined in (4):

We transform $m$ tasks with $l$ dimensions of overall ability reputation requirement into $m \times l$ tasks, each of which has one dimension of overall ability reputation requirement. The same transformation is applied for $T'_i$, where $T'_i$ is the filtered task subset of worker $i$ in *FAR*. The question is that finding a subset of workers to complete all tasks such that each task's one dimension of overall ability reputation requirement can be satisfied. Obviously, The *SOAC* problem is equivalent to this problem.

For the sake of brevity, we still use the notations of $T$, $T'_i$, and $t_j$ to denote the task set, the filtered task subset of worker $i$, and task $j$, respectively. We define $d^j$ as the overall ability reputation requirement of $t_j$. Then the *SOAC* problem can be re-expressed as follows:

$$\min \sum_{i \in W} c_i \cdot x_i \tag{17}$$

$$s.t. \quad \sum_{i \in W} p_i^j \cdot x_i \geq d_j, \ \forall t_j \in T'_i \tag{17-1}$$

$$x_i \in \{0, 1\}, \ \forall i \in W \tag{17-2}$$

Then, we provide our analysis about the approximation ratio of *FAR* using the dual fitting method [36]. The normalized primal linear program **P** has been formulated in (17). The dual program **DP** is formulated in (18).

$$\textbf{DP}: \quad \max \sum\nolimits_{t_j \in T} d_j y_j - \sum\nolimits_{i \in W} z_i \tag{18}$$

$$s.t. \quad \sum\nolimits_{t_j \in T'_i} (p_i^j y_j) - z_i \leq b_i, \ \forall i \in W \tag{18-1}$$

$$y_j \geq 0, \ \forall t_j \in T \tag{18-2}$$

$$z_i \geq 0, \ \forall i \in W \tag{18-3}$$

We define any task as alive at any iteration in winner selection if its overall ability reputation requirement is not fully satisfied. We define that task $t_j$ is covered by $T'_i$ if $t_j \in T'_i$ and $t_j$ is alive when worker $i$ is selected. The coverage relationship is represented as $t_j \prec T'_i$. Moreover, we define the minimum ability reputation as $\Delta v$. Suppose when worker $i$ is selected, the residual overall ability reputation requirement is $(d^{1^*}, d^{2^*}, ..., d^{m \times l^*})$ and $T'_i$ is the $i_j$-th set that covers $t_j$, the corresponding normalized effective ability unit cost in terms of unit ability reputation can be represented as:

$$\lambda(t_j, i_j) = \frac{b_i \Delta v}{\sum_{t_j \in T'_i} \min\{d^{j*}, p_i^j\}} \tag{19}$$

We assume that $t_j$ is covered by $h_j$ sets. Then we have $\lambda(t_j, 1) \leq ... \leq \lambda(t_j, h_j)$. We then define two constants $\Psi = \frac{1}{\Delta v} \sum_{t_j \in T'_i} d^j$ and $\varepsilon = \max p_i^j \cdot |T'_i| \cdot b_i, \ i \in W, \ t_j \in T$.

**Lemma 5.** *The following pairs $(y_j, z_i)$, $t_j \in T$, $i \in W$ are feasible to the dual program* ***DP***.

$$y_j = \frac{\lambda(t_j, h_j)}{2\varepsilon H_n \Delta v}, \ \forall t_j \in T,$$

$$z_i = \begin{cases} \dfrac{\sum_{t_j \prec T_i} \left(\min\{d^{j*}, p_i^j\}(\lambda(t_j, h_j) - \lambda(t_j, i_j))\right)}{2\varepsilon H_\Psi \Delta v}, & i \in S \\ 0, & i \notin S \end{cases}$$

where $H_n = 1 + \frac{1}{2} + ... + \frac{1}{n}$, $H_\Psi = 1 + \frac{1}{2} + ... + \frac{1}{\Psi}$.

**Lemma 6.** *FAR can approximate the optimal solution within a factor of $2\varepsilon H_\Psi$, where $H_\Psi = 1 + \frac{1}{2} + ... + \frac{1}{\Psi}$.*

The above lemmas together prove the following theorem.

**Theorem 4.** *FAR is computationally efficient, individually rational, whitewashing proof, truthful and $2\varepsilon H_\Psi$ approximate.*

## VI. Performance Evaluation

We have conducted thorough simulations to investigate the performance of *FAR*.

### A. Simulation Setup

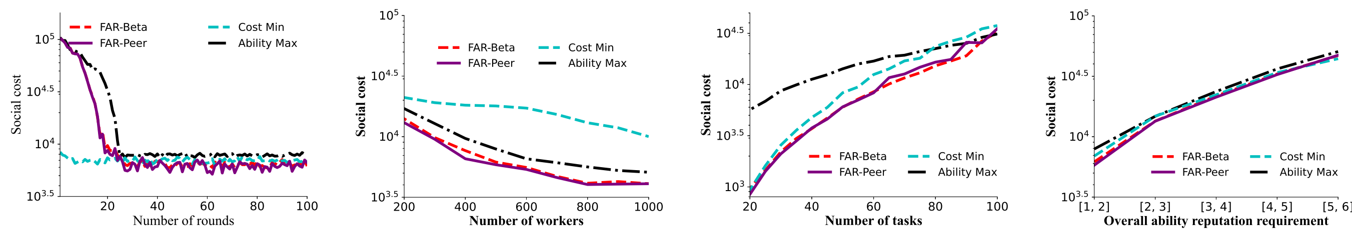
We compare *FAR* with two benchmark mechanisms:

- **Cost Min:** This mechanism selects the winner with minimal cost greedily until all tasks' ability reputation requirement is satisfied. This mechanism is truthful.
- **Ability Max:** This mechanism selects winner with maximal marginal ability greedily until all tasks' ability reputation requirement is satisfied. This mechanism is untruthful. For the sake of simplicity, Ability Max only uses the Beta-distribution reputation system.

For our simulations, we set four different abilities. We use the normalized pixel of the image data from ImageNet [37] consisting of 150,000 photographs as one of workers' actual abilities. We select 1000 images from dataset and use each one's relative pixel to the maximal pixel as the ability. The other three actual abilities are uniformly distributed in [0, 1]. The cost of each bid of workers is selected randomly from the auction dataset [38], which contains 5017 bid prices for Palm Pilot M515 PDA from eBay. The set $l = 4$, $n = 500$, $m = 100$, $\sigma = 0.9$ as the default setting. The overall ability reputation requirement is uniformly distributed in [1, 2], and the ability reputation requirement is uniformly distributed in [0.1, 0.3]. We will vary the value of key parameters to explore the impacts of these parameters. All the simulations were run on a Windows 10 machine with Intel(R) Xeon(R) CPU and 128 GB memory. Each measurement is averaged over 100 instances after 100 rounds of mobile crowdsensing.

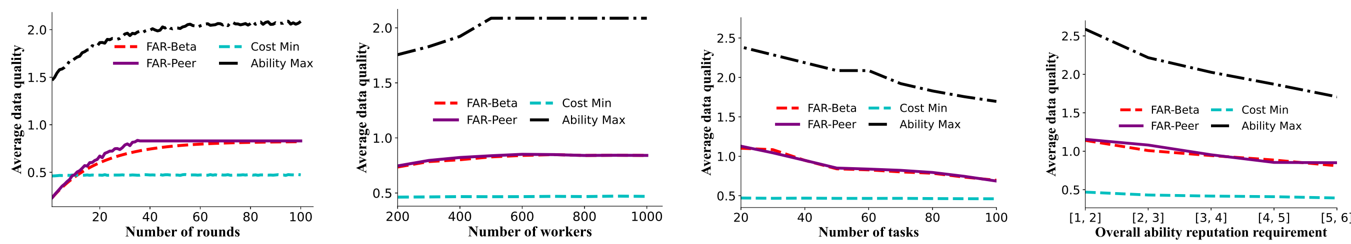
### B. Social Cost

Fig. 4 depicts the social cost of all mechanisms. We can see that the social cost of *FAR-Beta*, *FAR-Peer*, and *Ability-Max* decreases with the increase of rounds. This is because these three mechanisms select winners based on the ability reputation of workers, which is refined with increasing rounds. The social cost of *Cost Min* does not change almost because it does not care the ability reputation of workers when it selects workers. The social cost of all mechanisms decreases with the increase of the number of workers. This is because they can select workers with lower cost. As shown in Fig. 4(c) and Fig. 4(d), the social cost of all mechanisms is getting higher when the number of tasks increases or the overall ability requirement increases. This is because the platform needs to find more workers to meet the ability reputation requirement of tasks.



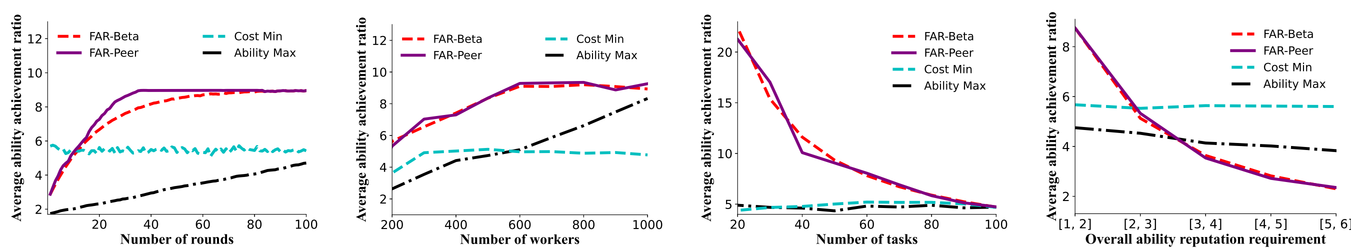

(a) (b) (c) (d)

Fig. 4. Social cost: (a) Social cost versus number of rounds. (b) Social cost versus number of workers. (c) Social cost versus number of tasks. (d) Social cost versus overall ability reputation requirement.




(a) (b) (c) (d)

Fig. 5. Average data quality: (a) Average data quality versus number of rounds. (b) Average data quality versus number of workers. (c) Average data quality versus number of tasks. (d) Average data quality versus overall ability reputation requirement.




(a) (b) (c) (d)

Fig. 6. Average ability achievement ratio: (a) Average ability achievement ratio versus number of rounds. (b) Average ability achievement ratio versus number workers. (c) Average ability achievement ratio versus number of tasks. (d) Average ability achievement ratio versus overall ability reputation requirement.

Overall, we can see that the social cost of *Cost Min* is always larger than *FAR-Beta* and *FAR-Peer*. This is because the ability of workers selected by *Cost Min* cannot be guaranteed, thus it needs to select more workers to finish the tasks. The social cost of *Ability Max* is the highest since it does not consider the cost of workers when it selects winners. For all cases, the social cost of *FAR-Beta* is 79.16% and 77.82% of social cost of *Cost Min* and *Ability Max*, respectively. The social cost of *FAR-Peer* is 80.67% and 79.30% of social cost of *Cost Min* and *Ability Max*, respectively.

### *C. Average Data Quality*

Then we measure the average data quality of mechanisms. The average data quality represents the average actual ability of winners, which can be calculated as:

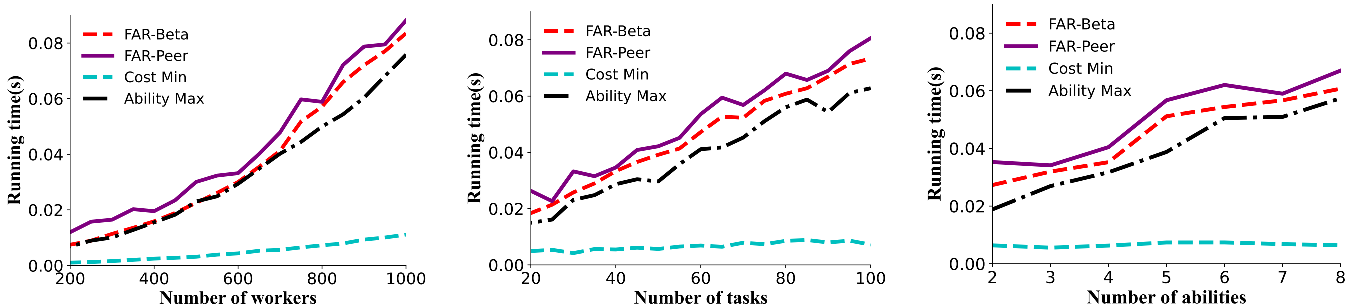
$$\frac{\sum\limits_{i\in S}\sum\limits_{k\in\Omega} p'^{k}_{i}}{l\times|S|} \tag{20}$$

We can see from Fig. 5 that the average data quality of mechanisms except *Cost Min* increases first with the increase of number of rounds. These mechanisms can refine workers' ability reputation round by round, and they can select workers with more ability when the number of rounds increases. The average data quality of *FAR-Beta*, *FAR-Peer* and *Ability Max* becomes stable later because the ability reputation of workers does not change after a certain number of rounds.

The average data quality of *FAR-Beta*, *FAR-Peer* and *Ability Max* increases slightly with the increase of the number of workers, because they can select workers with higher ability. However, the average data quality of *Cost Min* does not change with the number of workers since it does not care the ability reputation of workers when it selects workers.

The average data quality of mechanisms except *Cost Min* decreases with the increase of number of tasks and overall ability requirement. This is because the mechanisms need to find more workers to finish the tasks from fixed number of workers. Thus the average data quality will decrease.

We can see that the average data quality of *Ability Max* is always higher than other mechanisms because it always select the workers with the maximum ability reputation. However, *Ability Max* is untruthful and always outputs high social cost.




(a) (b) (c)

Fig. 7. Running time: (a) Running time versus number of workers. (b) Running time versus number of tasks. (c) Running time versus number of abilities.

### D. Average Ability Achievement Ratio

Then we measure the average ability achievement ratio, which is defined as:

$$\frac{\sum\limits_{t_j\in T}\sum\limits_{k\in\Omega}\sum\limits_{i\in S}\frac{p'^k_i}{d^k_j}}{l\times m} \tag{21}$$

The average ability achievement ratio represents the average ratio of winners' actual ability to the overall ability reputation requirement for each task.

We can see from Fig. 6 that the average ability achievement ratio is always more than one. This is because each winner may perform multiple tasks, and the accumulation of all winners' ability reputation is always greater than tasks' overall ability reputation requirement.

The average ability achievement ratio of *FAR-Beta*, *FAR-Peer* and *Ability Max* gets higher first, and then tends to be stable. This is because that ability reputation of workers is refined round by round and becomes stable after a certain number of rounds.

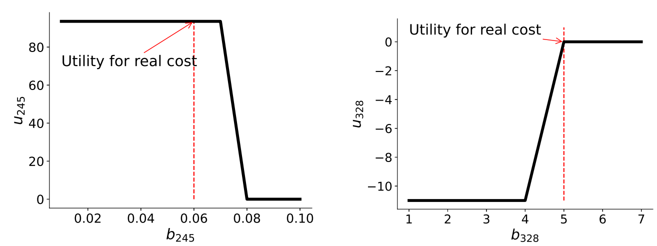
The average ability achievement ratio of *FAR-Beta* and *FAR-Peer* decreases with the increase of the number of tasks and overall ability requirement because the mechanisms need to find more workers to finish the tasks from fixed number of workers.

For all cases, the average ability achievement ratio of *FAR-Beta* is 146.32% and 217.16% of those of *Cost Min* and *Ability Max* on average, respectively. The average ability achievement ratio of *FAR-Peer* is 150.89% and 223.93% of those of *Cost Min* and *Ability Max* on average, respectively.

### E. Running Time

Fig. 7 depicts the running time of all mechanisms. It is not hard to get that the time complexity of *Ability Max* and *Cost Min* is $O(n^3ml)$ and $O(n^3)$, respectively. Thus *Cost Min* is faster than other three mechanisms. It can be seen from Fig. 7 that the running time of *FAR-Beta*, *FAR-Peer* and *Ability Max* increases with increasing number of workers, tasks and abilities. This result is consistent with our analysis of time complexity. The running time of *Cost Min* only depends on the number of workers and is stable in Fig. 7 (b) and (c). *FAR-Beta* and *FAR-Peer* are computationally efficient, and can be terminated within 0.082 seconds with 1000 workers, 100 tasks and 4 abilities.

### F. Truthfulness

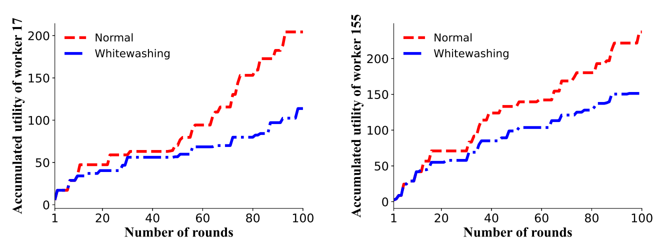



(a) (b)

Fig. 8. Truthfulness of *FAR-Beta*. (a) Utility of winner 245 with cost 0.06. (b) Utility of loser 328 with cost 5.

For the sake of brevity, we only verify the cost-truthfulness of *FAR-Beta* by randomly picking a winning worker (ID=245) and a losing worker (ID=328) and allowing them to bid prices that are different from their true cost. We illustrate the results in Fig. 8. We can see that winner 245 obtains its maximum utility if it bids truthfully ($b_{245} = c_{245} = 0.06$) and loser 328 obtains nonnegative utility if it bids truthfully ($b_{328} = c_{328} = 5$).

### G. Whitewashing proof




(a) (b)

Fig. 9. Whitewashing proof of *FAR*. (a) Accumulated utility of worker 17 in *FAR-Beta*. (b) Accumulated utility of worker 155 in *FAR-Peer*.

We first verify the whitewashing proof of *FAR-Beta* by randomly picking a worker (ID = 17) and allowing it to rejoin with a new identify in round 10. We illustrate the results in Fig. 9(a). We can see that worker 17 will obtain lower utility in the next rounds if he rejoins with a new identity. The whitewashing proof of *FAR-Peer* is also illustrated in Fig. 9(b).

### H. Summary

Based on our simulations, we have the following summary:

- The designed incentive mechanisms show prominent advantage in terms of social cost after 20 rounds of reputation updates. In all cases, the social cost of *FAR-Beta* is 79.16% and 77.82% of social cost of *Cost Min* and *Ability Max*, respectively. The social cost of *FAR-Peer* is 80.67% and 79.30% of social cost of *Cost Min* and *Ability Max*, respectively.
- Our incentive mechanisms can stimulate the workers to contribute more ability reputation. In our simulations, the average ability achievement ratio of *FAR-Beta* is 146.32% and 217.16% of those of *Cost Min* and *Ability Max* on average, respectively. The average ability achievement ratio of *FAR-Peer* is 150.89% and 223.93% of those of *Cost Min* and *Ability Max* on average, respectively.
- The designed incentive mechanisms are computationally efficient, and can be terminated within 0.082 seconds with 1000 workers, 100 tasks and 4 abilities.
- *FAR* is truthful and whitewashing proof.

## VII. Conclusion and Future Work

In this paper, we have presented a mobile crowdsensing system based on the ability reputation to achieve the fine-grained quality control. We have formulated the *SOAC* problem to minimize the social cost when satisfying the overall ability reputation requirement of all tasks. To stimulate the workers with long-term high quality, we have proposed two ability reputation systems. *Beta-distribution* based ability reputation system considers that the value of workers' ability reputation follows *beta-distribution*, and treats the historical ability and current ability equally. In *peer-prediction* based ability reputation system, a set of external raters are recruited to assess the abilities of workers. The *logarithmic reward rule* is used to guarantee the truthfulness of raters. The incentive mechanism based on the reverse auction and fine-grained ability reputation system has been proposed. We have designed a greedy algorithm to select the winners and determine the payment based on the bid and fine-grained ability reputation of workers. Through both rigorous theoretical analysis and extensive simulations, we demonstrate that the proposed mechanisms achieve computational efficiency, individual rationality, truthfulness, whitewashing proof, and guaranteed approximation. Moreover, our algorithm shows prominent advantage in terms of social cost.

The possible weakness of the proposed mechanisms is that the ability reputation updating only depends on the ability reputation calculated in the last round. This means that our ability reputation systems regard all history abilities with equal importance. If a very few bad abilities appear in history, the ability reputation of current round will be affected, and it is hard to apply anomaly detection algorithm [39, 40] as the data preprocessing for removing the outliers in advance. On the other hand, the history abilities of workers may follow some patterns. For examples, ability change periodically due to the periodic behavior of workers and ability mutation due to the sensing device replacement. Learning the patterns of history abilities can help to improve the accuracy of workers' reputation. Thus, one of our future work is to explore the details of history abilities (e.g., outliers and patterns) rather than updating the ability reputation based on the ability reputation of the last round straightforwardly. Moreover, the prediction-based methods [41, 42] also can be applied to estimate the abilities of workers.

## References

[1] J. Xu, J. Xiang, D. Yang, "Incentive Mechanisms for Time Window Dependent Tasks in Mobile Crowdsensing," *IEEE Transactions on Wireless Communications*, vol. 14, no.11, pp. 6353-6364, 2015.
[2] I. Kamil and S. Ogundoyin, "A lightweight CLAS scheme with complete aggregation for healthcare mobile crowdsensing," *Computer Communications*, vol. 147, pp. 209-224, 2019.
[3] Sensorly. http://www.sensorly.com.
[4] P. Mohan, V. Padmanabhan, and R. Ramjee, "Nericell: Rich monitoring of road and traffic conditions using mobile smartphones," in *Proc. ACM SenSys*, 2008, pp. 323–336.
[5] A. Thiagarajan et al., "Vtrack: Accurate, energy-aware road traffic delay estimation using mobile phones," in *Proc. ACM SenSys*, 2009, pp. 85–98.
[6] R. Rana, C. Chou, S. Kanhere, N. Bulusu, and W. Hu, "Earphone: An end-to-end participatory urban noise mapping," in *Proc. ACM/IEEE IPSN*, 2010, pp. 105–116.
[7] N. Maisonneuve, M. Stevens, M. Niessen, and L. Steels, "Noisetube: M easuring and mapping noise pollution with mobile phones," in *Proc. IEEE Information Technologies in Environmental Engineering*, 2009, pp. 215–228.
[8] https://www.mturk.com/
[9] H. Jin, L. Su, D. Chen, K. Nahrstedt, and J. Xu, "Quality of Information Aware Incentive Mechanisms for Mobile Crowd Sensing Systems," in *Proc. ACM MobiHoc*, 2015.
[10] Y. Gu, H. Shen, G. Bai, T. Wang, and X. Liu. "QoI-aware incentive for multimedia crowdsensing enabled learning system," *Multimedia Systems*, vol.26, no.1, pp. 3-16, 2020.
[11] J. Xiong, X. Chen, Q. Yang, L. Chen, and Z. Yao, "A Task-Oriented User Selection Incentive Mechanism in Edge-Aided Mobile Crowdsensing," *IEEE Transactions on Network Science and Engineering*, vol. 7, no. 4, pp. 2347-2360, 2020.
[12] C. Zhao, S. Yang, and J. Mccann, "On the Data Quality in Privacy-Preserving Mobile Crowdsensing Systems with Untruthful Reporting," *IEEE Transactions on Mobile Computing*, vol. 20, no. 2, pp. 647-661, 2021.
[13] H. Wang, S. Guo, J. Cao, and M. Guo, "MeLoDy: A long-term dynamic quality-aware incentive mechanism for crowdsourcing," in *Proc. IEEE ICDCS*, 2017, pp. 933-943.
[14] Y. Wen, J. Shi, Q. Zhang, X. Tian, Z. Huang, H. Yu, Y. Cheng, and X. Shen, "Quality-driven auction based incentive mechanism for mobile crowd sensing," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 9, pp. 1–1, 2014.
[15] H. Jin, L. Su, D. Chen, K. Nahrstedt, and J. Xu, "Quality of information aware incentive mechanisms for mobile crowd sensing systems," in *Proc. ACM MobiHoc*, 2015, pp. 167–176.
[16] J. Li, Z. Cai, M. Yan, Y. Li, "Using crowdsourced data in location-based social networks to explore influence maximization," in *Proc. IEEE INFOCOM*, 2016, pp. 1-9
[17] L. Jiang, X. Niu, J. Xu, D. Yang and L. Xu, "Incentive Mechanism Design for Truth Discovery in Crowdsourcing with Copiers," *IEEE Transactions on Services Computing*, doi:10.1109/TSC.2021.3075741.
[18] J. Xu, Z. Rao, L. Xu, et al, "Incentive Mechanism for Multiple Cooperative Tasks with Compatible Users in Mobile Crowd Sensing via Online Communities," *IEEE Transactions on Mobile Computing*, vol. 19, no.7, pp. 1618-1633, 2020.
[19] J. Xu, C. Guan, H. Dai, D. Yang, L. Xu, and J. Kai, "Incentive Mechanisms for Spatio-temporal Tasks in Mobile Crowdsensing," in *Proc. IEEE MASS*, 2019.
[20] B. Guo, H. Chen, Q. Han, Z. Yu, D. Zhang and Y. Wang, "Worker-Contributed Data Utility Measurement for Visual Crowdsensing Systems," *IEEE Transactions on Mobile Computing*, vol. 16, no. 8, pp. 2379-2391, 2017.
[21] http://www.ebay.com
[22] http://www.stackexchange.com
[23] http://www.reddit.com

[24] U. Feige, "A threshold of ln n for approximating set cover." *Journal of the ACM*, vol. 45, no.4, pp. 634–652, 1998.
[25] N. Miller, P. Resnick, and R. Zeckhauser, "Eliciting Informative Feedback: The Peer-Prediction Method," *Management Science*, vol. 51, no. 9, pp. 1359-1373, 2009.
[26] Bickel, and J. Eric, "Some Comparisons among Quadratic, Spherical, and Logarithmic Scoring Rules," *Decision Analysis*, vol.4, no. 2, pp. 49-65, 2007.
[27] G. Gao, J. Wu, M. Xiao and G. Chen, "Combinatorial Multi-Armed Bandit Based Unknown Worker Recruitment in Heterogeneous Crowdsensing," in *Proc. IEEE INFOCOM*, 2020, pp. 179-188.
[28] H. Wang, Y. Yang, E. Wang, W. Liu, Y. Xu and J. Wu, "Combinatorial Multi-Armed Bandit Based User Recruitment in Mobile Crowdsensing," in *Proc. IEEE SECON*, 2020, pp. 1-9.
[29] X. Gan, Y. Li, W. Wang, L. Fu, and X. Wang, "Social Crowdsourcing to Friends: An Incentive Mechanism for Multi-Resource Sharing," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 3, pp. 795-808, 2017.
[30] M. Pouryazdan, and B. Kantarci, "TA-CROCS: Trustworthiness-Aware Coalitional Recruitment of Crowd-Sensors," in *Proc. IEEE GLOBECOM*, 2018, pp. 1-7.
[31] J. Wang, J. Tang, D. Yang, E. Wang, and G. Xue, "Quality-Aware and Fine-Grained Incentive Mechanisms for Mobile Crowdsensing," in *Proc. IEEE ICDCS*, 2016, pp. 354-363.
[32] D. Peng, F. Wu, and G. Chen, "Data Quality Guided Incentive Mechanism Design for Crowdsensing," *IEEE Transactions on Mobile Computing*, vol. 17, no. 2, pp. 307-319, 2018.
[33] J. Audun, and I. Roslan "The Beta Reputation System," in *Proc. Bled Electronic Commerce Conference*, 2002, pp. 324-337.
[34] T. Gneiting, and R. Adrian "Strictly Proper Scoring Rules, Prediction, and Estimation," *Journal of the American Statistical Association*, vol. 102, no. 477. pp. 359-378, 2007.
[35] R. Myerson, "Optimal Auction Design," *Discussion Papers*, vol. 6, no.1, pp. 58–73, 1978.
[36] S. Rajagopalan, and V. Vazirani, "Primal-dual RNC approximation algorithms for (multi)-set (multi)-cover and covering integer programs," in *Proc. FOCS*, 1993, pp. 322-331.
[37] http://image-net.org/challenges/LSVRC/2012
[38] http://www.modelingonlineauctions.com/datasets
[39] S. Devlin, R. Gnanadesikan and J. Kettenring, "Robust estimation and outlier detection with correlation coefficients," *Biometrika*, vol. 62, no. 3, pp. 531-545, 1975.
[40] M. Hubert, M. Debruyne and P. Rousseeuw, "Minimum covariance determinant and extensions," *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 10, no. 3, e1421, 2018.
[41] E. Wang, Y. Yang, J. Wu, W. Liu and X. Wang, "An Efficient Prediction-Based User Recruitment for Mobile Crowdsensing," *IEEE Transactions on Mobile Computing*, vol. 17, no. 1, pp. 16-28, 2018.
[42] E. Wang, M. Zhang, X. Cheng, Y. Yang, W. Liu, H. Yu, L. Wang and J. Zhang, "Deep Learning-Enabled Sparse Industrial CrowdSensing and Prediction," *IEEE Transactions on Industrial Informatics*, doi: 10.1109/TII.2020.3028616.


## Appendix A
## Proof of Theorem 1

Assume that rater $w(e)$ reports honestly: $\chi_{i,k}^{w(e)}(\delta_v) = \delta_v$ for all $\delta_v \in \Delta$. Since $\Delta_{i,k}^{e}$ is stochastically relevant for $\Delta_{i,k}^{w(e)}$, and $w(e)$ reports honestly, $\Delta_{i,k}^{e}$ is stochastically relevant for $w(e)$'s report as well. Given that $\Delta_{i,k}^{e} = \delta^*$, rater $e$ chooses $\chi_{i,k}^{e} \in \Delta$ in order to maximize the expected reward:

$$\sum_{v=1}^{G} R(\chi_{i,k}^{w(e)}|\chi_{i,k}^{e}) Pr(\Delta_{i,k}^{w(e)}{=}\delta_v|\Delta_{i,k}^{e} = \delta^*) \tag{A.1}$$

Since $R$ is a *strictly proper* scoring rule, (A.1) is uniquely maximized by reporting $\chi_{i,k}^{e} = \delta^*$, i.e., truthful reporting is a best response strategy. Thus, given that reference rater $w(e)$ reports truthfully, rater $e$'s best response strategy is to report truthfully as well.

## Appendix B
## Proof of Theorem 2

We consider a special case of the *SOAC* problem, where $q_j^k = d_j^k = \delta$ for all $t_j \in T$ and all $k = 1, 2, ..., l$, where $\delta$ is a sufficiently small positive constant. This means that, in this special case, any task $t_j \in T$ can be completed if any worker $i \in W$ with $t_j \in T_i$ is selected. In this way, the problem can be simplified as selecting a subset $S \subseteq W$ with minimum total cost such that the workers in $S$ can complete all tasks in $T$ without considering the ability reputation requirement. Since each worker can bid for a subset of $T$ with a cost, this special problem is actually an instance of the *Weighted Set Cover* (*WSC*) problem, which can be formulated as follows:

$$\min \sum_{i \in S} c_i \tag{B.1}$$

$$s.t. \;\; T \subseteq \bigcup\nolimits_{i \in S} T_i \tag{B.2}$$

Since the *WSC* problem is a well-known NP-hard problem, the *SOAC* problem is NP-hard.

## Appendix C
## Proof of Lemma 1

For Algorithm 1, new worker initialization (Lines 3-5) takes $O(n^2 l)$. Removing the tasks that cannot satisfy the ability reputation requirement from workers' task set (Lines 7-12) takes $O(nml)$. Finding the worker with minimum effective ability unit cost takes $O(nml)$, where computing the value of $\sum_{t_j \in T'_{i'}} \sum_{k \in \Omega} \min\{d'^k_j, p^k_{i'}\}$ takes $O(ml)$. Hence, the while-loop (Lines 13-18) takes $O(n^2 ml)$. In each iteration of the for-loop (Lines 20-28), a process similar to Lines 13-18 is executed. Thus, the for-loop takes $O(n^3 ml)$. The ability reputation updating (Line 29) takes $O(nl)$. Hence the time complexity of *FAR-Beta* is bounded by $O(n^3 ml)$.

For *FAR-Peer*, the ability reputation updating will take $O(nl|I|)$. Generally speaking, $|I|$ is much less than $n^2 m$. Hence the time complexity of *FAR-Peer* is also $O(n^3 ml)$.

## Appendix D
## Proof of Lemma 2

Let $i_g$ be worker $i$'s replacement which appears in the $i$-th place in the sorting over $W \backslash \{i\}$. Since worker $i_g$ would not be at $i$-th place if $i$ is considered, we have $\frac{b_i}{\sum_{t_j \in T'_i} \sum_{k \in \Omega} \min\{d'^k_j, p^k_i\}} \le \frac{b_{i_g}}{\sum_{t_j \in T'_{i_g}} \sum_{k \in \Omega} \min\{d'^k_j, p^k_{i_g}\}}$.
Hence, we have

$$\begin{aligned} b_i &\le \frac{\sum_{t_j \in T'_i} \sum_{k \in \Omega} \min\{d'^k_j, p^k_i\}}{\sum_{t_j \in T'_{i_g}} \sum_{k \in \Omega} \min\{d'^k_j, p^k_{i_g}\}} b_{i_g} \\ &= \frac{\sum_{t_j \in T'_i} \sum_{k \in \Omega} \min\{d''^k_j, p^k_i\}}{\sum_{t_j \in T'_{i_g}} \sum_{k \in \Omega} \min\{d''^k_j, p^k_{i_g}\}} b_{i_g} \end{aligned}$$

where the equality relies on the observation that $d'^k_j = d''^k_j$ for every $g \le i$, which is due to the fact that $S = S'$ for every $g \le i$.
This is sufficient to guarantee $b_i \le \max_{g \in W \backslash S'} \frac{\sum_{t_j \in T'_i} \sum_{k \in \Omega} \min\{d''^k_j, p^k_i\}}{\sum_{t_j \in T'_{i_g}} \sum_{k \in \Omega} \min\{d''^k_j, p^k_{i_g}\}} b_{i_g} = r_i$.

## Appendix E
## Proof of Lemma 3

Consider that any worker $i \in W$ launches the whitewash attack by rejoining the system with a new identity $i'$. We have $T_{i'} = T_i$, $b_{i'} = b_i$, and $c_{i'} = c_i$. Moreover, since worker $i'$ is initialized with minimal ability reputation in the whole system based on the new worker initialization in both *beta-distribution*-based ability reputation system and *peer-prediction*-based ability reputation system, we have $p^k_{i'} \le p^k_i, \; \forall k \in \Omega$. We consider the following two cases:
(1) $i \notin S$
We have

$$\frac{b_{i'}}{\sum_{t_j \in T'_{i'}} \sum_{k \in \Omega} \min\{d'^k_j, p^k_{i'}\}} \le \frac{b_i}{\sum_{t_j \in T'_i} \sum_{k \in \Omega} \min\{d'^k_j, p^k_i\}}$$

This means that the new identity will push worker $i$ backwards in the sorting of winner selection, and $i'$ still loses the auction. Nothing happens.
(2) $i \in S$
We further consider the following two cases:
(2.1) $i'$ loses the auction
Since *FAR* is individually rational. We have $u_{i'} = 0 \le u_i$.
(2.2) $i'$ wins the auction

According to the payment rule of Algorithm 1, we have

$$\begin{aligned} r_{i'} &= \max_{g\in W\setminus S'} \frac{\sum_{t_j\in T'_{i'}} \sum_{k\in\Omega} \min\{d''^k_j, p^k_{i'}\}}{\sum_{t_j\in T'_{i'_g}} \sum_{k\in\Omega} \min\{d''^k_j, p^k_{i'_g}\}} b_{i'_g} \\ &\le \max_{g\in W\setminus S'} \frac{\sum_{t_j\in T'_i} \sum_{k\in\Omega} \min\{d''^k_j, p^k_i\}}{\sum_{t_j\in T'_{i_g}} \sum_{k\in\Omega} \min\{d''^k_j, p^k_{i_g}\}} b_{i_g} = r_i \end{aligned}$$

where the inequation relies on the fact that $p^k_{i'} \le p^k_i,\ \forall k \in \Omega$ and $i_g = i'_g$ for all $g \in W\setminus S'$.
Thus we have $u_{i'} = r_{i'} - c_{i'} \le u_i = r_i - c_i$.

## Appendix F
## Proof of Lemma 4

Based on Theorem 3, it suffices to prove that the selection rule of *FAR* is monotone and the payment $r_i$ for each $i$ is the critical value. The monotonicity of the selection rule is obvious as bidding a lower price cannot push worker $i$ backwards in the sorting.
We next show that $r_i$ is the critical value for worker $i$ in the sense that bidding higher $r_i$ could prevent worker $i$ from winning the auction. Note that $r_i = \max_{g\in\{1,2,\dots,L\}} \frac{\sum_{t_j\in T'_i} \sum_{k\in\Omega} \min\{d''^k_j, p^k_i\}}{\sum_{t_j\in T'_{i_g}} \sum_{k\in\Omega} \min\{d''^k_j, p^k_{i_g}\}} b_{i_g}$. If worker $i$ bids $b_i \ge r_i$, it will be placed after $L$ since $b_i \ge \frac{\sum_{t_j\in T'_i} \sum_{k\in\Omega} \min\{d''^k_j, p^k_i\}}{\sum_{t_j\in T'_{i_L}} \sum_{k\in\Omega} \min\{d''^k_j, p^k_{i_L}\}} b_{i_L}$ implies $\frac{b_i}{\sum_{t_j\in T'_i} \sum_{k\in\Omega} \min\{d''^k_j, p^k_i\}} \ge \frac{b_{i_L}}{\sum_{t_j\in T'_{i_L}} \sum_{k\in\Omega} \min\{d''^k_j, p^k_{i_L}\}}$. Hence, worker $i$ would not win the auction because the first $L$ workers have met the overall ability reputation requirement for each task in $T$.

## Appendix G
## Proof of Lemma 5

Suppose for any worker $i \in W$, there are $s_i$ tasks in $T'_i$. We reorder these tasks in the order in which they are fully covered.
If $i \notin S$, then we have $z_i = 0$. Suppose when the last unit ability reputation requirement of $t_j$ is covered, the residual overall ability reputation requirement is $\{d^{1+}, d^{2+}, \dots, \mathrm{d}^{|T|+}\}$, then the residual overall ability reputation requirement of living tasks contained by $T'_i$ are represented as $\sum_{k=j}^{s_i} \min\{d^{k+}, p^k_i\}$. We have

$$\lambda(t_j, h_j) \le \frac{b_i \Delta v}{\sum_{k=j}^{s_i} \min\{d^{k+}, p^k_i\}}$$

Therefore, we have

$$\begin{aligned} \sum_{j=1}^{S_i} (v_i(t_j) y_j) - z_i &\le \sum_{j=1}^{S_i} \frac{v_i(t_j) b_i}{2\varepsilon H_\Psi \sum_{k=j}^{s_i} \min\{d^{k+}, p^k_i\}} - 0 \\ &\le \frac{b_i}{H_\Psi}\left(1 + \frac{1}{2} + \dots + \frac{1}{\Psi}\right) \le b_i \end{aligned}$$

If worker $i \in S$, then we assume that when worker $i$ is selected as a winner, $s'_i$ tasks in $T'_i$ already been fully covered. We have

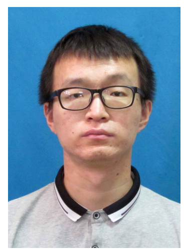
$$\begin{aligned} &\sum_{j=1}^{S_i} (p^j_i y_j) - z_i \\ =&\frac{\sum_{j=1}^{s_i} (\lambda(t_j,h_j) p^j_i)}{2\varepsilon H_\Psi \Delta v} - \frac{\sum_{j=s'_i+1}^{s_i} \min\{d^{j*}, p^j_i\}\left(\lambda(t_j,h_j) - \lambda(t_j,i_j)\right)}{2\varepsilon H_\Psi \Delta v} \\ =&\frac{\sum_{j=1}^{s'_i} (\lambda(t_j,h_j) p^j_i)}{2\varepsilon H_\Psi \Delta v} + \frac{\sum_{j=s'_i+1}^{s_i} \min\{d^{j*}, p^j_i\}\lambda(t_j,i_j)}{2\varepsilon H_\Psi \Delta v} \\ &+ \frac{\sum_{j=s'_i+1}^{s_i} p^j_i - \min\{d^{j*}, p^j_i\}\lambda(t_j,h_j)}{2\varepsilon H_\Psi \Delta v} \\ \le&\frac{\sum_{j=1}^{s'_i} (\lambda(t_j,h_j) p^j_i)}{2\varepsilon H_\Psi \Delta v} + \frac{\sum_{j=s'_i+1}^{s_i} \min\{d^{j*}, p^j_i\}\lambda(t_j,i_j)}{2\varepsilon H_\Psi \Delta v} \\ =&\sum_{j=1}^{s'_i} \frac{p^j_i b_i}{2\varepsilon H_\Psi \sum_{k=j}^{s_i} \min\{d^{k*}, p^k_i\}} + \frac{b_i}{2\varepsilon H_\Psi} \\ \le&\frac{b_i}{H_\Psi}\left(\frac{1}{s_i} + \dots + \frac{1}{s_i - s'_i + 1} + 1\right) \le b_i \end{aligned}$$

Hence, the pairs $(y_j, z_i),\ t_j \in T,\ i \in W$ are feasible to the dual program **DP**.

## Appendix H
## Proof of Lemma 6

By substituting the dual solution given in Lemma 4 into (18), we have

$$\begin{aligned} &\sum_{t_j\in T} d^j y_j - \sum_{i\in W} z_i \\ =&\frac{\sum_{i\in S}\sum_{t_j\prec T'_i}\left(\min\{d^{j*}, p^j_i\}\left(\lambda(t_j,h_j) - \lambda(t_j,i_j)\right)\right)}{2\varepsilon H_\Psi \Delta v} \\ &+ \frac{\sum_{t_j\in T} d^j \lambda(t_j,h_j)}{2\varepsilon H_\Psi \Delta v} \\ =&\frac{\sum_{i\in S}\sum_{t_j\prec T'_i} \min\{d^{j*}, p^j_i\} \frac{b_i \Delta v}{\sum_{t_j\in T'_i} \min\{d^{j*}, p^j_i\}}}{2\varepsilon H_\Psi \Delta v} \\ =&\frac{\sum_{i\in S} b_i}{2\varepsilon H_\Psi} \le OPT \end{aligned}$$



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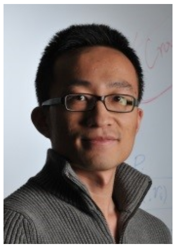

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