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Eliciting Joint Truthful Answers and Profiles from Strategic Workers in Mobile Crowdsourcing Systems

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Abstract—Mobile crowdsourcing has emerged as a promising paradigm that applies the principle of crowdsourcing to perform tasks of mobility requirement. Due to the openness of mobile crowdsourcing, workers may yield low-quality task answers. To alleviate this problem, substantial efforts have been devoted to elicit truthful data from workers. On the other hand, to facilitate task assignment, workers are required to upload the platform their profiles, such as locations and expertise. Therefore, task assignment outcomes and thus mobile crowdsourcing service accuracy is subject to the quality of workers' self-reported profiles. In this paper, we leverage incentive design to motivate workers to honestly reveal both task answers and their profiles. The challenge is to design one incentive payment for truth elicitation in two kinds of submissions. For this, we first derive the sufficient and necessary conditions for answer truthfulness and profile truthfulness separately. We then construct an incentive optimization problem that incorporates these conditions as constraints. Its optimal solution lists the payment to each worker that elicits answers and profiles jointly. Our proposed mechanism, with a formally proved bounded approximation ratio, ensures that truth-telling is a Bayesian Nash equilibrium. We prototype the mechanism and conduct a series of experiments that involve 30 volunteers to validate the efficacy and efficiency of the proposed mechanism.

Index Terms—Mobile crowdsourcing, joint answer and profile truthfulness, incentive mechanism design

1 Introduction

Mobile crowdsourcing facilitates individuals and businesses to outsource their processes and jobs to a large pool of mobile workers who carry out tasks using their sensor-equipped mobile devices. Mobile crowdsourcing has a wide spectrum of potential applications. For example, quite a few research propose to harness the sensing power of distributed mobile devices for spectrum monitoring/sensing of a large geographic area [1], [2], [3], [4]. Under the framework of crowdsourcing, mobile devices are hired to sense the spectrum occupancy/vacancy of their present locations. The aggregated sensing results can produce a real-time fine-grained spectrum usage map over a large geographic area. Mobile crowdsourcing has also gained great interest in the field of wireless signal fingerprinting based indoor/outdoor localization [5], [6], [7], [8]. To reduce the effort of a manual calibration for the site survey, especially in a multi-floor building or a large geographic area, various kinds of crowdsourcing-based indoor localization methodologies have been successfully applied. In addition, many mobile crowdsourcing tasks also exist in commercial crowdsourcing platforms. For example, in Clickworker [9] some tasks hire workers with mobile devices to carry out geolocation-aware image collection, image tagging, road traffic monitoring, etc. In Taskrabbit [10], the platform publishes spatial tasks such as cleaning a house or walking a dog. Typically, these tasks are only accessible by workers nearby.

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In most mobile crowdsourcing systems, the platform assigns tasks to suitable workers based on their self-reported profiles, such as locations and expertise.

A typical workflow can be divided into four stages: task assignment, task execution, answer collection, and answer aggregation/analysis. In general, task assignment problems are formulated to achieve certain optimization goals, e.g., maximizing the number of assigned tasks [11], [12] or minimizing overall cost (time, effort, and computing resources, etc.) incurred to workers [13], [14]. For practical considerations, the problem may further take into account various constraints, such as the maximum distance a worker is willing to travel to perform tasks, a worker's available time duration, and her expected work quality.

Work quality is of essential importance to the success of mobile crowdsourcing tasks because low-quality answers from the crowd would easily deteriorate the accuracy of tasks via aggregation. Low quality is often attributed to workers' deliberate mis-reporting, lack of effort exertion, or free-riders copying results from peers. There have been some prior studies tackling the latter two cases [15], [16]. In this paper, we are interested in defending against more intelligent workers who may game the system through strategically reporting task answers for higher beneficial gain. Our discussion focuses on one of the most typical mobile crowdsourcing tasks–*binary-answer*[1], e.g., if a specific spectrum band is vacant or not in the current location. A task is associated with a ground truth of a binary value. Each worker exerts her effort to derive an answer. To elicit truthful answers from the crowd, some existing solutions resort to economic mechanisms [17], [18], [19], [20], [20], [21], [22], [23]. Incentives are rewarded to

1. Our scheme can be easily extended to tasks with multiple answers.

truthful workers such that truth-telling is a *Nash equilibrium* [24]: no worker receives higher gain by lying, when others respond honestly. Therefore, no one would unilaterally deviate from honest reporting. It is worth noting that workers' truthful answers do not necessarily always coincide with the task ground truth, as workers may be hindered from, for example, the insufficient accuracy of smartphones' built-in GPS module.

Workers may also be deceitful about their self-reported profiles. These profiles are indispensable in task assignments. A strategic worker may fabricate her profile to manipulate task assignment outcomes for their own gain. For instance, a worker in location-based tasks is more likely to be selected if she misreports her position as being closer to the location of interest. To prevent workers from manipulating task assignment outcomes, one of the primary goals of this work is to achieve profile truthfulness. Some prior studies aim at improving *cost truthfulness* [1], [14], [25], [26], [27], [28], [29], [30], i.e., motivating workers to reveal their genuine costs. As cost can be deemed as part of self-reported profiles, cost truthfulness is a special case of profile truthfulness. Our approaches to achieve profile truthfulness need to cover a much wider spectrum of strategic behaviors.

Rather than treating answer misreporting and profile misreporting separately, this paper aims to develop a unified framework that protects two different stages from workers' strategic manipulation simultaneously. To the best of our knowledge, this is the first study to tackle such a combined challenge of misreporting in mobile crowdsourcing. Under the framework of incentive design, there are existing solutions to elicit answer truthfulness [17], [18], [19], [20], [20], [21], [22], [23] and cost truthfulness [1], [14], [25], [26], [27], [28], [29], [30], respectively. However, they are not directly applicable here due to their neglect of the other aspect. We cannot simply apply the above schemes in different stages of mobile crowdsourcing either, i.e., a worker is first paid for answer truthfulness and then paid for cost truthfulness, as the total payment would violate the conditions for each of the two objects. Thus, our goal is to design a unified payment scheme that guarantees both answer and cost truthfulness.

Since a worker's true answers and profile are only known to herself, uncovering the worker's untruthful behavior is hard. Hence, instead of directly detecting if a worker lies or not, we take a proactive approach that focuses on prevention instead of passive detection. To be specific, we propose an incentive mechanism such that honestly providing both answers and profile is a *Nash equilibrium*. While there are various types of incentives to adopt, such as payment, reputation, and social recognition, our design assumes incentives in the form of monetary payment. The salient challenge in this approach is to design one payment to reward a worker for truth elicitation in two kinds of submissions. Our idea is to first derive the sufficient and necessary condition for answer truthfulness and profile truthfulness, separately. We then construct an incentive optimization problem that incorporates these conditions as constraints. Its optimal solution lists the payment to each worker. Since the solution must satisfy the constraints and thus the conditions for truth-telling, the workers are well motivated to behave honestly.

To derive each worker's sufficient and necessary condition for answer truthfulness, we use reference answers, i.e., reported answers from each worker's peers. As a worker's true observation toward a task is only known to herself, workers have "incomplete information". For example, workers are unaware of the platform's payment and each other's best strategies, i.e., which answers everyone else could report in order to maximize their own benefits (payments). To take this characteristic into account, this paper resorts to the model of *Bayesian game* [31] instead of the standard game model. A worker's payment is evaluated in its expectation with respect to her entire (binary) observation space, as a function of the worker's payments given the various reference reports instances and her *posterior belief*. To be specific, the posterior belief is the probability of the worker having a particular observation, given the observations of other workers. Then, by setting a worker's expected payment while truth-telling no less than that while lying, the worker has little incentive to lie, which is so-called a *Bayesian Nash equilibrium* [31]. By applying Bayesian inference, the posterior belief can be converted into an expression of the ground truth's prior probability and the conditional probability of a worker's answer given the ground truth. Both probabilities are practically known to the platform (Section 3.1). The idea of utilizing reference answers to derive the condition for answer truthfulness was also used in the *peer prediction* approach [17], [18], [19]. However, in their work, only one reference answer is randomly picked from a worker's peers to evaluate the worker's truthfulness. Such a simplistic method will misjudge a worker when the selected peer reports incorrectly. Instead, our approach is more robust as answers from all peers are taken into account.

To derive the sufficient and necessary condition for profile truthfulness, we design a randomized worker selection and worker payment approach. We first formulate an optimization problem for worker selection, i.e., assigning suitable workers to each task. Since this problem is NP-hard, we first relax the integrality constraint of each variable to its fractional domain and optimally solve the relaxed problem. Given that the fractional optimal solution is inapplicable to practical worker selection, it is then decomposed into a weighted sum of a set of feasible integer solutions. All weights are real-valued and range from 0 to 1, with their sum equal to 1. Then, we come up with a randomized worker selection; each feasible integer solution is randomly picked at a probability equal to its associated weight. To ensure the randomized worker selection is feasible to apply, the factional optimal solution needs to scale up by a factor η. According to [32], given any α-approximate algorithm that proves an *integrality gap* of at most η for the "natural" linear relaxation, one can use η as the scaling factor. Thus, an α-approximate algorithm to the worker selection problem is further developed. Once the worker selection outcome is determined, we set a worker's payment as η times the fractional payment derived from fractional VCG (Vickrey-Clarke-Groves) [33]. We note that the fractional VCG was originally developed to achieve *bid truthfulness* in generic auctions via proper payment design. In this work, we tailor it to tackle profile misreporting. The joint randomized worker selection and worker payment ensure profile truthfulness.

The contribution of this work is summarized as follows.

- We develop an incentive mechanism that aims to achieve comprehensive joint answer and profile truthfulness in mobile crowdsourcing. The proposed mechanism ensures that truth-telling is a Bayesian Nash equilibrium.
- We propose a randomized worker selection algorithm and formally prove that the proposed algorithm produces an approximation ratio upper bounded by 2.
- To investigate the efficacy of our mechanism, a prototype consisting of a worker-side app and a platform-side program is implemented. We recruited 30 volunteers to conduct a series

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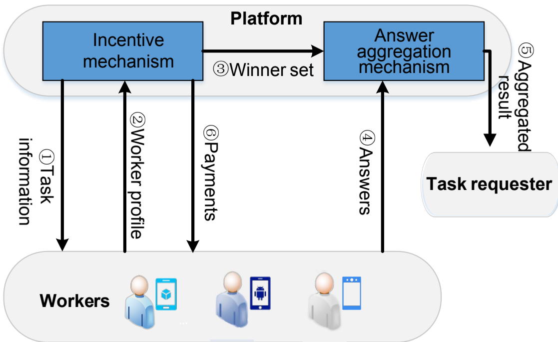

Fig. 1. A typical workflow of a mobile crowdsourcing system.

of in-field experiments. The full stack of code for the prototype implementation is open-sourced at https://sites.google.com/site/reportingtruthful/.

The rest of this paper is organized as follows. Section 2 presents the system model and problem statement. The proposed mechanism design is elaborated in Section 3. Its performance analysis is given in Section 4, followed by evaluation results in Section 5. Related work is discussed in Section 6. We conclude the paper in Section 7.

2 System Model and Problem Statement

2.1 System Model

We consider a mobile crowdsourcing system that consists of a set of mobile workers and a platform. The platform has a set of tasks to obtain answers from a crowd $\mathcal{W} = \{w_1, \cdots, w_i, \cdots, w_K\}$ of K candidate mobile workers. We consider binary-answer tasks and denote the answer space of each task as $\mathcal{A} = \{0, 1\}$. Besides, each task is associated with a ground truth $G \in \mathcal{A}$, which is unknown prior to the accomplishment of tasks. A typical workflow of the system is illustrated in Figure 1.

- Step ①: The platform publishes a task.
- Step ②: Each worker w_i submits her profile.
- Step ③: The platform selects the winner set $\mathcal{W}^*$ for this task.
- Step ④: Each winning worker $w_i \in \mathcal{W}^*$ submits her answer r_i.
- Step ⑤: The platform derives the task's final result by aggregating collected answers using methods such as *majority voting* [34] or *maximum a posterior probability estimate* (MAP) [35].
- Step ⑥: The platform determines payments to winning workers.

In order to select a proper set of workers for a task, conventional approaches formulate an optimization problem that aims to maximize or minimize a certain objective while satisfying a set of constraints [14], [26], [27], [28], [29]. In this paper, we consider a linear optimization problem in a generalized form, as follows.

$$\begin{aligned} \mathrm{P}_1: \quad \min \quad & \pi_1 = \sum_{w_i \in \mathcal{W}} f(\boldsymbol{b}_i) x_i \\ \text{s.t.} \quad & \sum_{w_i \in \mathcal{W}} d_i x_i \geq \gamma, \quad x_i \in \{0, 1\} \quad \forall w_i \in \mathcal{W}. \end{aligned}$$

The platform solves P_1 to choose a proper set of workers $\mathcal{W}^*$ for the task. In P_1, x_i is a binary variable: 1 if worker w_i is to be selected, and 0 otherwise. The self-reported profile from w_i, denoted $\boldsymbol{b}_i$, is a vector of task-dependent parameters. Take mobile crowdsourcing-based spectrum monitoring/sensing as an illustration. Each mobile device is associated with its specific sensing capabilities, such as the sensing range and operational frequency band. Besides, each mobile device is at a different distance away from the task location. $f(\cdot)$ can be any weighted aggregate function over all elements in $\boldsymbol{b}_i$. It is selected by the platform and unknown to the workers. For example, suppose a worker's profile $\boldsymbol{b}_i = \{s_i, t_i\}$ consists of her sensing capability t_i and its distance to the task location s_i, where s_i and t_i are normalized values. The function can be $f(\boldsymbol{b}_i) = 0.8 s_i + 0.2(1 - t_i)$. In this example, the worker's distance to the location of interest outweighs her sensing capability for being selected. Since $\boldsymbol{b}_i$ is both task-dependent and worker-dependent and thus *a prior* unknown to the platform, it is collected before the formulation of P_1. The scalar value of task-independent parameter d_i is available at the platform via long-term observation of w_i's performance, e.g., task accomplishment rate or average rating from task requesters. γ is a task-specific threshold value chosen by the platform.

2.2 Problem Statement and Design Objectives

Workers are modeled as rational and self-interested. They choose their strategies in a way to maximize their own benefits. Thus, workers may intentionally game the system. As discussed earlier, the platform collects data from workers for both worker selection and answer aggregation. Both procedures are thus vulnerable to manipulation. According to the formulation of P_1, w_i is more likely to be selected if she submits a fabricated profile $\boldsymbol{b}_i$ that produces a lower value of $f(\boldsymbol{b}_i)$. Workers are also interested in reporting falsified answers, if it generates higher gains than truth-telling. Therefore, the primal goal of this work is to elicit worker truthfulness in reporting both their profiles and answers.

We propose to leverage incentives to motivate workers to behave honestly. The idea is simple: a worker receives the highest payment for truth-telling. A winning worker w_i's payment is expressed as $p_i(r_i, \boldsymbol{r}_{-i}, \boldsymbol{b}_i, \boldsymbol{b}_{-i})$, where $\boldsymbol{b}_i$ and $\boldsymbol{b}_{-i}$ represent the worker profile reported by w_i and its peers, respectively, and r_i and $\boldsymbol{r}_{-i}$ are the answers reported by w_i and its peers, respectively. $\boldsymbol{b}_i$, $\boldsymbol{b}_{-i}$ and $\boldsymbol{r}_{-i}$ are vectors. $\boldsymbol{r}_{-i}$ is the *reference answers* from peers. Intuitively, payment p_i is dependent of r_i and $\boldsymbol{b}_i$. Besides, since the platform is unaware of a worker's true answer to the task, we propose to utilize reference answers to measure the worker's answer truthfulness. Hence, p_i also depends on $\boldsymbol{r}_{-i}$. Besides, to achieve profile truthfulness, p_i is also dependent of $\boldsymbol{b}_{-i}$. More details can be found in Section 3.2.

We now define truthfulness that is achieved by a proper incentive mechanism.

Definition 1. (Truthfulness.) *Given true reference answers $\boldsymbol{o}_{-i}$ and profiles $\boldsymbol{c}_{-i}$, the mechanism achieves truthfulness if and only if every worker's best strategy is truth-telling, i.e.,*

$$\begin{aligned} &\mathbb{E}_{\mathcal{A},\mathcal{I}}\left[p_i(r_i = o_i, \boldsymbol{b}_i = \boldsymbol{c}_i | \boldsymbol{o}_{-i}, \boldsymbol{c}_{-i})\right] \\ \geq &\mathbb{E}_{\mathcal{A},\mathcal{I}}\left[p_i(r_i = \bar{o}_i, \boldsymbol{b}_i = \bar{\boldsymbol{c}}_i | \boldsymbol{o}_{-i}, \boldsymbol{c}_{-i})\right] \end{aligned} \tag{1}$$

where o_i and $\boldsymbol{c}_i$ denotes w_i's true answer and profile, $\bar{o}_i \neq o_i$ and $\bar{\boldsymbol{c}}_i \neq \boldsymbol{c}_i$.

The above definition forms a *Bayesian Nash equilibrium*, where no individual can gain higher payment on average by lying when others behave honestly. Therefore, no worker has the incentive to alter her reported answer or profile unilaterally, because such a strategy would harm her interest. Since a worker's

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TABLE 1
Notation

$\mathcal{W}$	entire worker set	$\mathcal{W}^*$	winner set
G	ground truth	p_i	w_i's payment
$\boldsymbol{c}_i$	w_i's true profile	$\boldsymbol{b}_i$	w_i's reported profile
o_i	w_i's true answer	r_i	w_i's reported answer
$\mathcal{A}$	task answer set	x_i	recruitment variable
d_i	w_i's coefficient	γ	recruitment threshold
$\pi_1^*, \pi_2^*, \pi_3^*, \pi_4^*$	optimum result of $\mathrm{P}_1, \mathrm{P}_2, \mathrm{P}_3, \mathrm{P}_4$		
$\pi_1'^*$	optimum result of the linear relaxed P_1		
$\overline{o}_i$	opposite of true observation o_i		
$\boldsymbol{c}_{-i}$	true profile set from w_i's peers		
$\boldsymbol{b}_{-i}$	reported profile set from w_i's peers		
$\boldsymbol{o}_{-i}$	true answer set from w_i's peers		
$\boldsymbol{r}_{-i}$	reported answer set from w_i's peers		
$\mathcal{I}$	set of all possible task assignment outcomes		
θ	an instance of the true reference report		
$\boldsymbol{x}(I)$	a feasible solution to P_1 under index I		
$\beta(I)$	selection probability of $\boldsymbol{x}(I)$		
$\mathcal{I}$	the set of feasible solution to P_1		
$\boldsymbol{x}^F$	optimum solution to the linear relaxed P_1		
α	approximation ratio of Algorithm 1		
δ	truth-telling payment margin		
η	integrality gap between π_1^* and π_2^*; upper bound of the approximation ratio of our mechanism		

true observation toward a task is unknown to the platform, her payment is evaluated in the expectation with respect to $\mathcal{A}$ in (1). Besides, our proposed mechanism relies on a randomized worker selection, i.e., winning workers are selected in a probabilistic manner. Thus, the expected payment further takes into account all possible worker selection outcomes $\mathcal{I}$. The details of the randomized worker selection and $\mathcal{I}$ are discussed in Section 3.2.

Here we make a brief clarification why a Bayesian game is considered. Bayesian games are games with incomplete information, which are, informally, games where players may not know all aspects of the game, such as sequence, strategies, and payoffs of other players. In contrast, standard games refer to games of complete information. In our paper, each worker, i.e., player, is unaware of its payoff function because the platform's payment and other workers' submitted information (i.e., profiles and answers) are unknown. Hence, the interactions among workers in our case should be formulated as a Bayesian game.

3 Mechanism Design

Our design first derives the sufficient and necessary conditions for answer and profile truthfulness separately. In the framework of incentive design, such a condition is expressed in the form of worker payments. Specifically, for the condition of answer truthfulness, a worker's payment is set higher for reporting her true observation toward a task than lying. Given that workers' true observations are only known to themselves, we utilize reference answers to evaluate workers' answer truthfulness (Section 3.1). Motivated by the fractional VCG, the profile truthfulness is achieved via the design of a randomized worker selection and worker payments (Section 3.2). Since the proposed randomized worker selection requires a *scaling factor* to ensure its feasibility, we further develop an α-approximate algorithm to obtain this value (Section 3.3). All the derived conditions are finally incorporated into an incentive optimization problem as constraints. Its solution provides the payment for each worker that motivates truth-telling in two different kinds of submissions (Section 3.4).

3.1 Eliciting Truthful answers

This part derives a sufficient and necessary condition for answer truthfulness. For a given worker selection outcome $I \in \mathcal{I}$, (1) is then degenerated to $\mathbb{E}_{\mathcal{A}}\left[p_i(o_i|\boldsymbol{o}_{-i}=\theta)\right] \geq \mathbb{E}_{\mathcal{A}}\left[p_i(\overline{o}_i|\boldsymbol{o}_{-i}=\theta)\right]^2$. θ is an instance of the true reference answer, which is a vector.

A belief regarding the prior probability of task ground truth $\Pr[G=a_t]$ ($a_t \in \mathcal{A}$) is deemed available at the platform. It also knows the likelihood that a worker honestly reports its genuine answer given the ground truth, i.e., $\Pr[o_i=a_i|G=a_t]$ ($a_i \in \mathcal{A}$). This knowledge can be obtained by the platform via long-term observation. Specifically, if the proposed mechanism achieves truthfulness, then $r_i=o_i$ and thus $\Pr[o_i=a_i|G=a_t]=\Pr[r_i=a_i|G=a_t]$. Since r_i is observable at the platform and the ground truth G would be eventually derived, $\Pr[r_i=a_i|G=a_t]$ can be obtained.

We have

$$\mathbb{E}_{\mathcal{A}}\left[p_i(o_i|\boldsymbol{o}_{-i}=\theta)\right]=\sum_{a_i\in\mathcal{A}}\Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]\cdot p_i(a_i,\boldsymbol{o}_{-i}=\theta)$$

where $\Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]$ is the likelihood that given w_i's peers reporting honestly worker w_i does the same. We have

$$\Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]=\frac{\Pr[\boldsymbol{o}_{-i}=\theta|o_i=a_i]\Pr[o_i=a_i]}{\Pr[\boldsymbol{o}_{-i}=\theta]}. \tag{2}$$

Here, workers are assumed to report independently. Hence, $\Pr[\boldsymbol{o}_{-i}=\theta|o_i=a_i]$ can be expressed by

$$\Pr[\boldsymbol{o}_{-i}=\theta|o_i=a_i]=\prod_{w_k\in\mathcal{W}^*\backslash w_i}\Pr[o_k=a_k|o_i=a_i]$$

where

$$\begin{aligned}&\Pr[o_k=a_k|o_i=a_i]\\&=\sum_{a_t\in\mathcal{A}}\Pr[o_k=a_k|G=a_t]\Pr[G=a_t|o_i=a_i],\end{aligned} \tag{3}$$

and

$$\begin{aligned}\Pr[G=a_t|o_i=a_i]&=\frac{Pr[o_i=a_i|G=a_t]\Pr[G=a_t]}{\Pr[o_i=a_i]}\\=&\frac{Pr[o_i=a_i|G=a_t]\Pr[G=a_t]}{\sum_{a_{t'}\in\mathcal{A}}\Pr[o_i=a_i|G=a_{t'}]\Pr[G=a_{t'}]}.\end{aligned}$$

Recall that $\Pr[o_i=a_i|G=a_t]$ and $\Pr[G=a_t]$ are common knowledge at the platform. Thus $\Pr[o_k=a_k|o_i=a_i]$ (3) is derived. As $\Pr[o_i=a_i]=\sum_{a_t\in\mathcal{A}}\Pr[G=a_t]\cdot\Pr[o_i=a_i|G=a_t]$ and $\Pr[\boldsymbol{o}_{-i}=\theta]=\prod_{w_k\in\mathcal{W}^*\backslash w_i}\Pr[o_k=a_k]$, then $\Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]$ (2) is also derived. Finally, $\mathbb{E}_{\mathcal{A}}\left[p_i(o_i|\boldsymbol{o}_{-i}=\theta)\right]$ is obtained.

Similarly,

$$\mathbb{E}_{\mathcal{A}}\left[p_i(\overline{o}_i|\boldsymbol{o}_{-i}=\theta)\right]=\sum_{a_i\in\mathcal{A}}\Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]\cdot p_i(\overline{a}_i,\boldsymbol{o}_{-i}=\theta).$$

2. Since we focus on analyzing the relation between answer reporting and incentives, b_i and $\boldsymbol{c}_{-i}$ are temporarily dropped for expression simplicity. p_i is still dependent on them.

Therefore, the sufficient and necessary condition for answer truthfulness is

$$\begin{aligned}&\sum_{a_i\in\mathcal{A}}\Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]\cdot p_i(a_i,\boldsymbol{o}_{-i}=\theta)\\ \geq&\sum_{a_i\in\mathcal{A}}\Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]\cdot p_i(\overline{a}_i,\boldsymbol{o}_{-i}=\theta).\end{aligned}\tag{4}$$

Its instantiation is

$$\begin{aligned}&\Pr[o_i=1|\boldsymbol{o}_{-i}]\cdot p_i(1,\boldsymbol{o}_{-i})+\Pr[o_i=0|\boldsymbol{o}_{-i}]\cdot p_i(0,\boldsymbol{o}_{-i})\\ \geq&\Pr[o_i=1|\boldsymbol{o}_{-i}]\cdot p_i(0,\boldsymbol{o}_{-i})+\Pr[o_i=0|\boldsymbol{o}_{-i}]\cdot p_i(1,\boldsymbol{o}_{-i}).\end{aligned}$$

where $p_i(0,\boldsymbol{o}_{-i})$ and $p_i(1,\boldsymbol{o}_{-i})$ stand for w_i's payment when reporting "0" and "1", respectively, when $\boldsymbol{o}_{-i}$ is observed with an instance θ. If w_i's payment $p_i(0,\boldsymbol{o}_{-i})$ and $p_i(1,\boldsymbol{o}_{-i})$ satisfy the above constraint, a worker is more willing to report genuine observation for a higher payment in expectation. (5) will be integrated into the final mechanism design, which will be clear soon.

3.2 Eliciting Truthful Profiles

To elicit truthful profiles, inspired by a fractional version of the VCG mechanism [33], our design consists of randomized worker selection and worker payment.

Randomized worker selection. The objective of this part is to select a proper set of winning workers to carry out the task by solving P_1. Since P_1 is a *0-1 knapsack problem* [36], it is NP-hard to solve. We first consider its linear relaxed form by converting the binary variable $x_i\in\{0,1\}$ to $0\leq x_i\leq 1$. The relaxed problem transforms P_1 into a fractional domain and returns a fractional optimum solution, denoted by $\boldsymbol{x}^F$. Let $\pi_1'^*$ be the optimum result of the relaxed P_1. While $\boldsymbol{x}^F$ is inapplicable to task assignment, we are able to decompose it into a randomized format. Specifically, identify β_I and $\boldsymbol{x}(I)=\{x_i(I)|\forall i\}$ such that $\boldsymbol{x}^F=\sum_{I\in\mathcal{I}}\beta_I\boldsymbol{x}(I)$, where $\mathcal{I}=\{\boldsymbol{x}(I)|\forall I\in\mathcal{I}\}$ is the set of feasible integer solutions to P_1 and $\beta_I\geq 0$ ($\sum_{I\in\mathcal{I}}\beta_I=1$). Then a randomized task assignment chooses the I-th integer solution $\boldsymbol{x}(I)$ with probability β_I.

On the other hand, there does not exist a convex combination of integer solution $\sum_{I\in\mathcal{I}}\beta_I x_i(I)$ that equals x_i^F, because otherwise, the expected objective value generated by these integer solutions equals to that generated by the fractional solution, which is apparently a contradiction to the fact that the fractional solution achieves lower objective value than any possible integer solution. Therefore, to derive a feasible decomposition, we need to scale up the optimum fractional solution by a certain factor. According to [32], given any α-approximate algorithm that proves an *integrality gap* of at most η for the "natural" linear relaxation, one can use η as the scaling factor. We leave the job of finding such an approximation algorithm in Section 3.3.

The solution of β_I's is obtained via solving the following liner maximization problem

$$\begin{aligned}\max\quad&\sum_{I\in\mathcal{I}}\beta_I\\ \text{s.t.}\quad&\sum_{I\in\mathcal{I}}\beta_I x_i(I)\leq\eta x_i^F,\quad\forall i\\ &\sum_{I\in\mathcal{I}}\beta_I\leq 1,\ \beta_I\geq 0,\quad\forall I\in\mathcal{I}.\end{aligned}\tag{5}$$

Note that $\boldsymbol{x}(I)$ is obtained by enumeration. Since it has an exponential number of elements, the enumeration process is time-consuming. Motivated by the *ellipsoid method* [37], we resort to its dual problem and propose an algorithm that solves it within polynomial time. Note that the α-approximate algorithm providing the scaling factor η is also essential to solve (5). Details are given in Appendix. Besides, we are able to prove in Lemma 4 that the optimum value of (5) is 1.

A toy example. Here we provide a toy example to better illustrate how the proposed random worker selection works. Consider that there are two workers and one task. We further assume the result from the relaxed P_1 and the approximation ratio as $\boldsymbol{x}^F=(0.5,0.5)$ and $\eta=2$, respectively. Let $\mathcal{I}$, the set of feasible solution to P_1, as $\{(1,0),(1,1)\}$. We aim to find $\beta_{(1,0)}$ and $\beta_{(1,1)}$ such that $\beta_{(1,0)}\cdot 1+\beta_{(1,1)}\cdot 1=2\cdot 0.5$, $\beta_{(1,0)}\cdot 0+\beta_{(1,1)}\cdot 1=2\cdot 0.5$, and $\beta_{(1,0)}+\beta_{(1,1)}=1$. Through simple calculation, we derive $\beta_{(1,0)}=0$ and $\beta_{(1,1)}=1$, which means our randomized worker selection chooses $x_1=1,x_2=1$ (resp., $x_1=1,x_2=0$) with probability 1 (resp., 0).

Worker payment. Recall that $\pi_1'^*$ is the optimum result of the linear relaxed P_1. Consider a factional payment $p_i^F=\pi_{1,-i}'^*-(\pi_1'^*-f_i(\boldsymbol{b}_i)x_i^F)$, where $\pi_{1,-i}'^*$ stands for the optimum result of the linear relaxed P_1 when w_i is excluded from the formulation. The winner w_i's payment is then set to $p_i(I)=\eta p_i^F$. w_i is a winner if $x_i(I)=1$ given a randomly picked worker selection outcome $I\in\mathcal{I}$. The calculation of p_i^F quantifies the *externality* each winner causes to others under fractional worker selection. As we will show in Theorem 3, paying a winner with its externality and the scale-up factor η are essential to ensure profile truthfulness.

Justification of applying fractional VCG. The worker selection problem P_1 is NP-hard and thus computationally expensive to find its optimum solution. We thus propose a randomized worker selection to achieve a polynomial complexity. Here we give a definition of fractional VCG.

Definition 2. (Fractional VCG.) *In a fractional VCG, the allocation rule is given by $\boldsymbol{x}^F=\{x_i^F|\forall i\}$, the optimum allocation solution in the fractional domain; the pricing rule is given by $p_i=\pi_{1,-i}^*-(\pi_1^*-f_i(\boldsymbol{b}_i)x_i)$, where $\pi_1'^*$ is the optimum allocation result in the fractional domain, and $\pi_{1,-i}'^*$ stands for the optimum result when w_i is excluded from the auction.*

Compared with conventional VCG, the allocation and pricing are determined through solving LP problems in fractional VCG. Therefore, it is more efficient to execute at the crowdsourcing platform. Apparently, our computation efficiency is achieved by compromising allocation optimum. Fortunately, as we prove in Theorem 3 in the paper, the optimality gap, quantified in approximation ratio here, is upper bounded by 2. We would also like to mention some other existing approaches in tackling computation complexity of VCG auctions. They typically develop heuristic algorithms in allocation and pricing while achieving truthfulness and individual rationality simultaneously. Those approaches, however, are hard to bound the optimality gap especially when scenarios become complicated.

3.3 An α-Approximate Algorithm

This part develops an α-approximate algorithm that provides the scaling factor η for our randomized worker selection. It is also an indispensable component to the proposed algorithm to solve

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(5). We first transform P_1 into its equivalent form P_2.

$$\begin{aligned} \mathrm{P}_2: \quad & \min \quad \pi_2 = \sum_{w_i \in \mathcal{W}} f_i(\boldsymbol{b}_i) x_i \\ \text{s.t.} \quad & \sum_{w_i \in \mathcal{W} \backslash S} d_i(S) x_i \geq \gamma(S), \forall S \subseteq \mathcal{W} : \gamma(S) > 0, \qquad (6) \\ & x_i \in \{0, 1\}, \forall w_i \in \mathcal{W} \end{aligned}$$

where S is an arbitrary subset of workers, $\gamma(S) = \gamma - \sum_{w_i \in S} d_i$, and $d_i(S) = \min\{d_i, \gamma(S)\}$. (6) involves a series of constraints with respect to S satisfying $S \subseteq \mathcal{W}$ and $\gamma(S) > 0$. For a given S, its corresponding x_i's are set to 1's.

Lemma 1. *P_2 is equivalent to P_1.*

Proof. Denote by $\mathcal{S}_1$ and $\mathcal{S}_2$ the feasible solution sets of P_1 and P_2, respectively. Since P_1 and P_2 have the same objective function, it is equivalent to show $\mathcal{S}_1 = \mathcal{S}_2$.

First, we show $\mathcal{S}_1 \subseteq \mathcal{S}_2$. For an arbitrary feasible solution $\boldsymbol{x} \in \mathcal{S}_1$, denote its corresponding winner set as $\mathcal{W}^* = \{w_i | x_i = 1\}$. We have $\sum_{w_i \in \mathcal{W}^*} d_i \geq \gamma$, which can be transformed to

$$\sum_{w_i \in \mathcal{W}^* \backslash S} d_i \geq \gamma - \sum_{w_i \in S} d_i = \gamma(S), \qquad (7)$$

with $S \subset \mathcal{W}^*$. Then we discuss through the following two cases that $\boldsymbol{x} \in \mathcal{S}_1$ is also a feasible solution to P_2.

Case 1: There exist some workers $w_i \in \mathcal{W}^* \backslash S$ with $d_i \geq \gamma(S)$. Denote these workers as S'. Then $\sum_{w_i \in \mathcal{W} \backslash S} d_i(S) x_i = \sum_{w_i \in \mathcal{W}^* \backslash S} d_i(S) x_i = \sum_{w_i \in \mathcal{W}^* \backslash (S \cup S')} d_i + |S'| \gamma(S) \geq \gamma(S)$, which implies that (6) holds.

Case 2: No worker in $\mathcal{W}^* \backslash S$ has $d_i \geq \gamma(S)$. In another word, every worker in $\mathcal{W}^* \backslash S$ has $d_i < \gamma(S)$. We have $\sum_{w_i \in \mathcal{W} \backslash S} d_i(S) x_i = \sum_{w_i \in \mathcal{W}^* \backslash S} d_i(S) x_i = \sum_{w_i \in \mathcal{W}^* \backslash S} d_i \geq \gamma(S)$. The last inequality is due to (7). Therefore, (6) holds as well.

Second, we show $\mathcal{S}_2 \subseteq \mathcal{S}_1$. For an arbitrary feasible solution $\boldsymbol{x} \in \mathcal{S}_2$, we have $\sum_{w_i \in \mathcal{W} \backslash S} d_i(S) x_i \geq \gamma(S) = \gamma - \sum_{w_i \in S} d_i$. It can be written as $\sum_{w_i \in \mathcal{W} \backslash S} d_i(S) x_i + \sum_{w_i \in S} d_i x_i \geq \gamma$, because $x_i = 1 \; \forall w_i \in S$. Besides, $d_i \geq d_i(S)$ according to the definition of $d_i(S)$. Therefore, $\sum_{w_i \in \mathcal{W}} d_i x_i = \sum_{w_i \in \mathcal{W} \backslash S} d_i x_i + \sum_{w_i \in S} d_i x_i \geq \sum_{w_i \in \mathcal{W} \backslash S} d_i(S) x_i + \sum_{w_i \in S} d_i x_i \geq \gamma$, which implies that $\boldsymbol{x}$ is also a feasible solution to P_1.

From the discussion above, we have $\mathcal{S}_1 = \mathcal{S}_2$. Therefore, P_2 is equivalent to P_1. □

Since P_1 and P_2 are equivalent, if we can find an α-approximate algorithm for P_2, so it is for P_1.

Now consider a linear program P_3 by relaxing P_2's binary variable $x_i \in \{0, 1\}$ to $0 \leq x_i \leq 1$. We further formulate a dual problem of P_3 but with the dual variables associated with constraints $0 \leq x_i \leq 1 (\forall i)$ dropped

$$\begin{aligned} \mathrm{P}_4: \quad & \max \quad \pi_4 = \sum_{S \subseteq \mathcal{W} : \gamma(S) > 0} \gamma(S) y(S) \\ \text{s.t.} \quad & \sum_{S \subseteq \mathcal{W} : w_i \in \mathcal{W} \backslash S, \gamma(S) > 0} d_i(S) y(S) \leq f_i(\boldsymbol{b}_i), \forall w_i \in \mathcal{W} \qquad (8) \\ & y(S) \geq 0, \forall S \subseteq \mathcal{W} \end{aligned}$$

Algorithm 1 outlines the steps for the proposed α-approximate algorithm. It leverages the formulation of P_4 to derive a feasible solution to P_1. Its idea is to gradually grow the winning worker set $S^{(t)}$ by selecting the worker which produces the smallest $(f_i(\boldsymbol{b}_i) - q_i^{(t)})/d_i(S^{(t)})$ in each iteration (line 4). For each $S^{(t)}$, it then calculates the corresponding dual variable solution $y(S^{(t)})$. It continues until the termination condition $\gamma(S^{(t)}) > 0$ reaches.

Algorithm 1 The α-approximate algorithm

Input: $\{\boldsymbol{b}_i\}$, $\{d_i\}$, γ
Output: $\{x_i\}$, $\{y(S)\}$, π_1, $\mathcal{W}^*$

1: $x_i \leftarrow 0, q_i^{(0)} \leftarrow 0, \forall i, y(S) \leftarrow 0, \forall S, S^{(0)} \leftarrow \emptyset, \gamma(S^{(0)}) \leftarrow \gamma - \sum_{w_i \in S^{(0)}} d_i, \pi_1^{(0)} \leftarrow 0, t \leftarrow 0$;
2: **while** $\gamma(S^{(t)}) > 0$ **do**
3: $\quad d_i(S^{(t)}) \leftarrow \min\{d_i, \gamma(S^{(t)})\}, \forall i$;
4: $\quad i^{*(t)} \leftarrow \arg\min_{i \in \mathcal{W} \backslash S^{(t)}} (f_i(\boldsymbol{b}_i) - q_i^{(t)})/d_i(S^{(t)})$;
5: $\quad y(S^{(t)}) \leftarrow \left(f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}}) - q_{i^{*(t)}}^{(t)}\right)/d_{i^{*(t)}}(S^{(t)})$;
6: $\quad x_{i^{*(t)}} \leftarrow 1$;
7: $\quad \pi_1^{(t+1)} \leftarrow \pi_1^{(t)} + f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}})$;
8: $\quad S^{(t+1)} \leftarrow S^{(t)} \cup w_{i^{*(t)}}$;
9: $\quad q_i^{(t+1)} \leftarrow q_i^{(t)} + d_i(S^{(t)}) y(S^{(t)}), \forall i \in \mathcal{W} \backslash S^{(t)}$;
10: $\quad \gamma(S^{(t+1)}) = \gamma - \sum_{w_i \in S^{(t+1)}} d_i$;
11: $\quad t \leftarrow t + 1$;
12: **end while**
13: $\mathcal{W}^* \leftarrow S^{(t)}$, $\pi_1 \leftarrow \pi_1^{(t)}$.

Lemma 2. *Algorithm 1 provides a feasible solution to P_1 and P_4.*

Proof. We first examine if Algorithm 1 provides a feasible solution to P_1. According to the algorithm, x_i is either 0 or 1. Thus, the binary constraint is satisfied. Besides, the iteration of the algorithm stops when $\gamma(S) \leq 0$. Together with the definition of $\gamma(S)$, we have $\sum_{w_i \in \mathcal{W}} d_i \geq \sum_{w_i \in S} d_i \geq \gamma$. Then the other constraint of P_1 is also satisfied. Since the solution meets both constraints of P_1, it is feasible to P_1.

We next examine if Algorithm 1 provides a feasible solution to P_4. Suppose the while-loop consists of $T + 1$ iterations. We first verify if $y(S^{(t)})$ identified in an arbitrary iteration $t+1, \forall t \in [0, T]$ is non-negative. Particularly, when $t = 0$, $f_i(\boldsymbol{b}_i) \geq q_i^{(0)} = 0$, and thus $y(S^{(0)})$ is positive; when $t \in [1, T]$

$$\begin{aligned} q_i^{(t)} &= q_i^{(t-1)} + d_i(S^{(t-1)}) y(S^{(t-1)}) \\ &= q_i^{(t-1)} + d_i(S^{(t-1)}) \frac{f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}}) - q_{i^{*(t-1)}}^{(t-1)}}{d_{i^{*(t-1)}}(S^{(t-1)})} \\ &\leq q_i^{(t-1)} + d_i(S^{(t-1)}) \frac{f_i(\boldsymbol{b}_i) - q_i^{(t-1)}}{d_i(S^{(t-1)})} = f_i(\boldsymbol{b}_i). \end{aligned}$$

Thus, $q_{i^{*(t)}}^{(t)} \leq f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}})$. As $d_{i^{*(t)}}(S^{(t)}) > 0$, then we have $y(S^{(t)}) = (f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}}) - q_{i^{*(t)}}^{(t)})/d_{i^{*(t)}}(S^{(t)}) \geq 0$.

The remaining task is to verify if $\{y(S) : S \subseteq \mathcal{W}\}$ has the constraint (8) hold for all $w_i \in \mathcal{W}$. For this purpose, we divide $\mathcal{W}$ into two non-overlapping subsets: $\mathcal{W}^*$ and $\mathcal{W} \backslash \mathcal{W}^*$, i.e., the winning worker set and the losing worker set.

Case 1: $w_{i^{*(t)}} \in \mathcal{W}^*$, a worker selected in the arbitrary $(t+1)$-th ($t \in [0, T]$) iteration. We have

$$\begin{aligned} & \sum_{S \subseteq \mathcal{W} : w_{i^{*(t)}} \in \mathcal{W} \backslash S, \gamma(S) > 0} d_{i^{*(t)}}(S) y(S) = \sum_{\tau=0}^{t} d_{i^{*(t)}}(S^{(\tau)}) y(S^{(\tau)}) \\ = & \sum_{\tau=0}^{t-1} d_{i^{*(t)}}(S^{(\tau)}) y(S^{(\tau)}) + d_{i^{*(t)}}(S^{(t)}) \frac{(f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}}) - q_{i^{*(t)}}^{(t)})}{d_{i^{*(t)}}(S^{(t)})} \\ = & q_{i^{*(t)}}^{(t)} + f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}}) - q_{i^{*(t)}}^{(t)} = f_{i^{*(t)}}(\boldsymbol{b}_{i^{*(t)}}). \end{aligned}$$

Thus, (8) is satisfied for all winning workers.

Case 2: $w_i \in \mathcal{W}\backslash\mathcal{W}^*$, any losing worker. We have $(f_i(\boldsymbol{b}_i) - q_i^{(T)})/d_i(S^{(T)}) \geq (f_{i^*(T)}(\boldsymbol{b}_{i^*(T)}) - q_{i^*(T)}^{(T)})/d_{i^*(T)}(S^{(T)})$. Therefore,

$$\begin{aligned}
&\sum_{S\subseteq\mathcal{W}:i\in\mathcal{W}\backslash S,\gamma(S)>0} d_i(S)y(S) = \sum_{\tau=0}^{T} d_i(S^{(\tau)})y(S^{(\tau)})\\
=&\sum_{\tau=0}^{T-1} d_i(S^{(\tau)})y(S^{(\tau)}) + d_i(S^{(T)})\frac{(f_{i^*(T)}(\boldsymbol{b}_{i^*(T)}) - q_{i^*(T)}^{(T)})}{d_{i^*(T)}(S^{(T)})}\\
\leq& q_i^{(T)} + d_i(S^{(T)})\frac{(f_i(\boldsymbol{b}_i) - q_i^{(T)})}{d_i(S^{(T)})} = f_i(\boldsymbol{b}_i)
\end{aligned}$$

which implies that (8) holds for workers from $\mathcal{W}\backslash\mathcal{W}^*$ as well.

According to the analysis above, Algorithm 1 provides a feasible solution to P_4.

□

Proposition 1. *Algorithm 1 provides an α-approximation solution to P_1 where $\alpha = 2$, i.e., $\pi_1/\pi_1^* \leq 2$.*

Proof. Let w_{i^*} denote the worker selected in the last iteration by Algorithm 1. The while loop continues as long as $\gamma(S) > 0$. Then $\gamma(\mathcal{W}^*\backslash w_{i^*}) = \gamma - \sum_{w_i\in\mathcal{W}^*\backslash w_{i^*}} d_i > 0$ and thus

$$\sum_{w_i\in\mathcal{W}^*\backslash w_{i^*}} d_i < \gamma. \tag{9}$$

Besides,

$$\begin{aligned}
\pi_1 =& \sum_{w_i\in\mathcal{W}^*} f_i(\boldsymbol{b}_i) = \sum_{w_i\in\mathcal{W}^*}\ \sum_{S\subseteq\mathcal{W}:w_i\in\mathcal{W}\backslash S,\gamma(S)>0} d_i(S)y(S),\\
=& \sum_{S\subseteq\mathcal{W}:\gamma(S)>0}\ \sum_{w_i\in\mathcal{W}^*\backslash S} d_i(S)y(S).
\end{aligned}$$

The second equality can be easily inferred from the proof of Lemma 2. The third equality is obtained by switching the order of the two sum operations. Note that

$$\begin{aligned}
&\sum_{w_i\in\mathcal{W}^*\backslash S} d_i(S) \leq \sum_{w_i\in\mathcal{W}^*\backslash w_{i^*}} d_i - \sum_{w_i\in S} d_i + d_{i^*}(S)\\
\leq& \gamma - \sum_{w_i\in S} d_i + d_{i^*}(S) = \gamma(S) + d_{i^*}(S) \leq 2\gamma(S)
\end{aligned}$$

where the second inequality is due to (9). Let π_4^* be the optimum value of P_4. Due to the strong duality, $\pi_4^* \leq \pi_1^*$. Combining all the results above, we have

$$\pi_1 \leq \sum_{S\subseteq\mathcal{W}:\gamma(S)>0} 2\gamma(S)y(S) \leq 2\pi_4^* \leq 2\pi_1^*.$$

□

Based on Proposition 1 and its proof, we have

Corollary 1. *π_1 derived by Algorithm 1 and π_3^* have an integrality gap of at most η, i.e., $\pi_1/\pi_3^* \leq \eta$, where $\eta = 2$.*

Lemma 3. *The computation complexity of Algorithm 1 is $\mathcal{O}(K^2)$.*

The complexity of Algorithm 1 is dominated by the while-loop, which contains at most K iterations. Recall that K stands for the number of workers. In each iteration, the most time-consuming calculation is ranking (line 4), which is upper-bounded by K operations. Thus, the complexity is upper bounded by $\mathcal{O}(K^2)$.

While there have been some prior works [38] developing approximation algorithms to solve 0-1 knapsack problems, they all face a trade-off between iteration convergence and computation efficiency. Particularly, when updating the dual variable, i.e., line 5 in our algorithm, their solution does not specify the exact step size. As a result, if the step size is too small, then it takes excessively long rounds for the algorithm to stop; if the step size is too large, then the algorithm may fail to converge. Instead, Algorithm 1 identifies a proper step size, $\left(f_{i^*(t)}(\boldsymbol{b}_{i^*(t)}) - q_{i^*(t)}^{(t)}\right)/d_{i^*(t)}(S^{(t)})$, for each iteration that ensures the convergence within K iterations.

3.4 Piecing All Components Together

We are now ready to integrate all ingredients into a unified payment mechanism that elicit joint answer and profile truthfulness from strategic workers.

For the first objective, as discussed in Section 3.1, its sufficient and necessary condition is that each winning worker receives no less payment when reporting honestly than lying, as specified in (4). Practical mechanisms require certain margins for truth-telling [39]; honest reporting is better than lying by at least some margin δ, chosen by the platform to offset the external benefits a worker might obtain by lying. Thus, we twist a little bit over (4) and obtain (10) to account for the margin δ.

For the second objective, for a given worker selection outcome I, a winning worker w_i receives ηp_i^F. On the other hand, since w_i's true observation is unknown to the platform, we thus let w_i's expected payment with respect to $\mathcal{A}$ equal to ηp_i^F (11).

Combining all discussions above, we arrive at the following formulation in calculating winner w_i's payment, given a randomly picked worker selection outcome $I \in \mathcal{I}$

$$\begin{aligned}
P_5:\quad & \max\ \delta\\
\text{s.t.}\quad & \sum_{a_i\in\mathcal{A}} \Pr[o_i = a_i|\boldsymbol{o}_{-i}]p_i(a_i,\boldsymbol{o}_{-i}) -\\
& \sum_{a_i\in\mathcal{A}} \Pr[o_i = a_i|\boldsymbol{o}_{-i}]p_i(\overline{a}_i,\boldsymbol{o}_{-i}) \geq \delta \qquad (10)\\
& \sum_{a_i\in\mathcal{A}} \Pr[o_i = a_i|\boldsymbol{o}_{-i}]p_i(a_i,\boldsymbol{o}_{-i}) = \eta p_i^F \qquad (11)\\
& p_i(a_i,\boldsymbol{o}_{-i}) \geq 0 \quad \forall a_i \in \mathcal{A}.
\end{aligned}$$

The above optimization is a linear programming problem that can be efficiently solved via the conventional *simplex method* [40].

Algorithm 2 summarizes our final design.

Algorithm 2 The final design

Input: $\{\boldsymbol{b}_i\}$, $\{r_i\}$

Output: $\mathcal{W}^*$, $\{\beta_I\}$, $\{p_i\}$

1: Compute the optimal fractional worker selection $\boldsymbol{x}^F$ by solving the relaxed P_1;
2: Compute the scale-up factor η using Algorithm 1;
3: Derive β_I's by formulating and solving (5);
4: Select each integer solution $\boldsymbol{x}(I)$ of P_1 randomly with probability β_I, thus $\mathcal{W}^*$ is derived;
5: Calculate winner's payment $p_i(a_i,\boldsymbol{o}_{-i})$ ($a_i \in \mathcal{A}$) by solving P_5.

Theorem 1. *The computation complexity of Algorithm 2 is $\mathcal{O}(K^2)$.*

Proof. The computation of Algorithm 2 mainly consists of the following components, solving P_3 (line 1), obtaining η using Algorithm 1 (line 2), solving (5) (line 3), and solving P_5 (line 5).

In the following, we provide an analysis of these four components. We employ the simplex method to solve P_3, an LP problem. According to [41], the computation complexity of simplex method is $\mathcal{O}(nd)$, where n and d are the number of variables and constraints, respectively. Thus, the computation complexity for solving P_3 is $\mathcal{O}(K)$. Recall that K is the number of workers. Similarly, the complexity for solving P_5 is $\mathcal{O}(K)$. For Algorithm 1, its complexity is upper bounded by $\mathcal{O}(K^2)$. While (5) is an LP problem, it involves an exponential number of variables. Thus, we first convert it to its dual problem and then solve it via the ellipsoid method, whose complexity is at most $\mathcal{O}(n^2)$, where n is the number of variables. Thus, solving (5) causes $\mathcal{O}(K^2)$. To sum up, the computation complexity of the proposed mechanism is $\mathcal{O}(K^2)$. □

3.5 Extension to Multi-choice Tasks

When considering multiple-choice tasks, the change is applied to the instantiation of the sufficient and necessary condition for answer truthfulness, the form is still the same though

$$\begin{aligned}&\sum_{a_i\in\mathcal{A}} \Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]\cdot p_i(a_i,\boldsymbol{o}_{-i}=\theta)\\ \geq &\sum_{a_i\in\mathcal{A}} \Pr[o_i=a_i|\boldsymbol{o}_{-i}=\theta]\cdot p_i(\overline{a}_i,\boldsymbol{o}_{-i}=\theta),\end{aligned}$$

which denotes that truth-telling achieves higher payment than lying. Multiple-choice tasks introduces more choices of lying than binary-choice tasks. Specifically, for each $o_i = a_i$, there are $k-1$ lying cases. Thus, more cases are generated in its instantiation. All the instantiations will serve as constraints in P_5 to get final payments. Recall that P_5 is an LP problem, which can be efficiently solved by the simplex method with the computation complexity $\mathcal{O}(nd)$, where n and d are the number of variables and constraints, respectively. Hence, although multi-choice tasks would increase the number of constraints in P_5, it would not cause any change to our scheme design.

Theorem 2. *Given K workers and M k-choice tasks, the computation complexity of Algorithm 2 is $\mathcal{O}(MK^2+MKk(k-1)^k)$*

Proof. The proof follows the main idea of Theorem 1. Here we mainly highlight the changes due to multi-choice tasks. Under the k-choice setting, P_5 becomes the linear programming problem with $(k-1)^k$ constraints and k variables, where k is the number of choices in each task. Therefore, the complexity of P_5 for K workers is $\mathcal{O}(Kk(k-1)^k)$. Hence the computation complexity of the proposed mechanism for one k-choice task is $\mathcal{O}(K+K^2+K^2+Kk(k-1)^k)=\mathcal{O}(K^2+Kk(k-1)^k)$. For M tasks, its total computation complexity is $\mathcal{O}(MK^2+MKk(k-1)^k)$. □

Although Theorem 1 seems to indicate an exponential computation complexity, the exponential part k is typically a small value no larger than 6. Hence, the overall computation is still practical to implement on a regular server.

4 Performance Analysis

In this section, we analyze the properties achieved by our mechanism, including joint answer and profile truthfulness and its approximation ratio.

Theorem 3. *The proposed mechanism guarantees joint answer and profile truthfulness.*

Proof. According to Definition 1, we need to prove $\mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\boldsymbol{c}_i)] \geq \mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(\overline{o}_i,\overline{\boldsymbol{c}}_i)]$[3]. For this purpose, we first show $\mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\boldsymbol{c}_i)] \geq \mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\overline{\boldsymbol{c}}_i)]$ and then $\mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\overline{\boldsymbol{c}}_i)] \geq \mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(\overline{o}_i,\overline{\boldsymbol{c}}_i)]$.

Specifically,

$$\begin{aligned}&\mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\boldsymbol{c}_i)]=\sum_{I\in\mathcal{I}}\beta_I\mathbb{E}_{\mathcal{A}}[p_i(o_i,\boldsymbol{c}_i)]\\ =&\sum_{I\in\mathcal{I}}\beta_I\sum_{a_i\in\mathcal{A}}\Pr[o_i=a_i]p_i(a_i)=\sum_{I\in\mathcal{I}}\beta_I\eta p_i^F(\boldsymbol{c}_i)=\eta p_i^F(\boldsymbol{c}_i)\end{aligned}$$

which is exactly η times w_i's payment under the fractional VCG mechanism when reporting $\boldsymbol{c}_i$. Similarly, we have $\mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\overline{\boldsymbol{c}}_i)] = \eta p_i^F(\overline{\boldsymbol{c}}_i)$, i.e., η times w_i's payment under the fractional VCG mechanism when reporting untruthful $\overline{\boldsymbol{c}}_i$. On the other hand, as proved in [33], the fractional VCG guarantees $p_i^F(\boldsymbol{c}_i) \geq p_i^F(\overline{\boldsymbol{c}}_i)$, and thus $\mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\boldsymbol{c}_i)] \geq \mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\overline{\boldsymbol{c}}_i)]$.

When w_i submits $\overline{\boldsymbol{c}}_i$, under a specific feasible worker recruitment profile $I\in\mathcal{I}$, w_i either wins or loses. The following discussion is conducted for these two cases, separately.

For the first case, w_i loses with $\overline{\boldsymbol{c}}_i$. Then $\mathbb{E}_{\mathcal{A}}[p_i(o_i,\overline{\boldsymbol{c}}_i)] = \mathbb{E}_{\mathcal{A}}[p_i(r_i,\overline{\boldsymbol{c}}_i)]=0$. Since w_i loses, it will not be selected. Hence, its payment is 0.

For the second case, w_i wins with $\overline{\boldsymbol{c}}_i$

$$\begin{aligned}&\mathbb{E}_{\mathcal{A}}[p_i(o_i)]-\mathbb{E}_{\mathcal{A}}[p_i(\overline{o}_i)]\\ =&\sum_{a_i\in\mathcal{A}}\Pr[o_i=a_i]\cdot(p_i(a_i)-p_i(\overline{a}_i))\geq\delta.\end{aligned}$$

Combining these two cases, we have $\mathbb{E}_{\mathcal{A}}[p_i(o_i,\overline{\boldsymbol{c}}_i)] \geq \mathbb{E}_{\mathcal{A}}[p_i(\overline{o}_i,\overline{\boldsymbol{c}}_i)]$. Therefore, $\mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(o_i,\overline{\boldsymbol{c}}_i)] = \sum_{i\in\mathcal{I}}\beta_I\cdot\mathbb{E}_{\mathcal{A}}[p_i(o_i,\overline{\boldsymbol{c}}_i)] \geq \sum_{i\in\mathcal{I}}\beta_I\cdot\mathbb{E}_{\mathcal{A}}[p_i(\overline{o}_i,\overline{\boldsymbol{c}}_i)] = \mathbb{E}_{\mathcal{A},\mathcal{I}}[p_i(\overline{o}_i,\overline{\boldsymbol{c}}_i)]$. □

It is desirable to analyze the approximation ratio of the proposed mechanism to the optimum result of P_1, where truthfulness is not guaranteed. It evaluates the optimality tradeoff for truthfulness.

Theorem 4. *The proposed mechanism achieves the approximation ratio upper bounded by 2.*

Proof. The expected overall objective value achieved by the proposed mechanism is formulated by $\sum_{I\in\mathcal{I}}\beta_I\sum_{w_i\in\mathcal{W}}f_i(\boldsymbol{b}_i)x_i(I)$. Thus, the approximation ratio is calculated as

$$\begin{aligned}&\frac{\sum_{I\in\mathcal{I}}\beta_I\sum_{w_i\in\mathcal{W}}f_i(\boldsymbol{b}_i)x_i(I)}{\pi_1^*}=\frac{\sum_{w_i\in\mathcal{W}}f_i(\boldsymbol{b}_i)(\sum_{I\in\mathcal{I}}\beta_Ix_i(I))}{\pi_1^*}\\ =&\eta\frac{\sum_{w_i\in\mathcal{W}}f_i(\boldsymbol{b}_i)x_i^F}{\pi_1^*}=\eta\frac{\pi_3^*}{\pi_1^*}\leq\eta\end{aligned}$$

where $\eta=2$. □

5 Experimental Evaluation

5.1 Experimental Setup

As a proof-of-concept implementation, we develop a prototype of the proposed mechanism. The prototype mainly consists of the worker-side app and the platform-side program. Specifically, the app is developed in Android. The platform program runs

3. For expression simplicity, we omit $\boldsymbol{o}_{-i}$ and $\boldsymbol{c}_{-i}$ from p_i in the following discussion.

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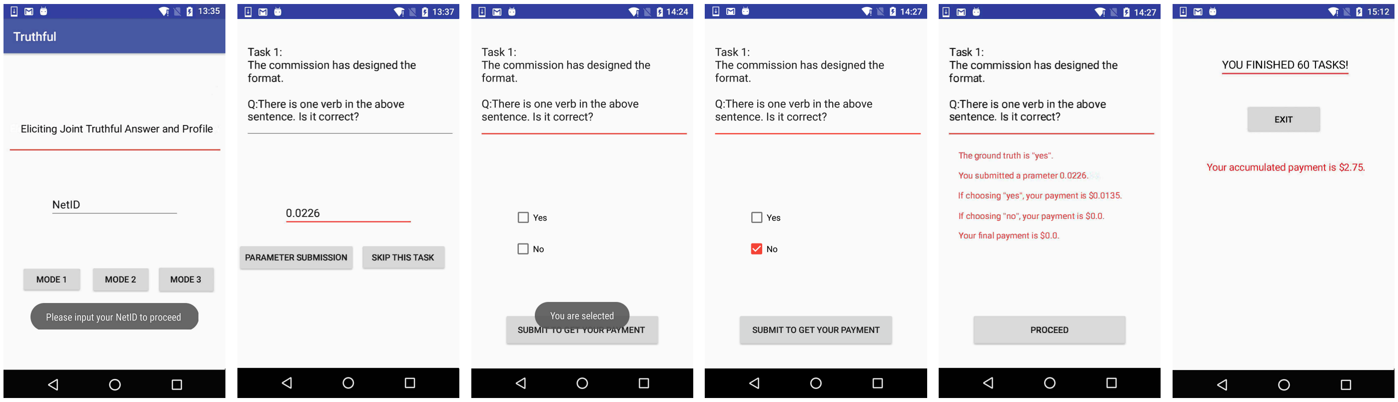


(a) Login page (b) Reporting profile (c) Selecting winners (d) Reporting answer (e) Payment for one task (f) Accumulated payment

Fig. 2. Screenshots of worker-side app.

on a Dell laptop with a 1.6GHz processor and 16GB RAM. facilitate the task publication and data reporting, the web serv named HTTP File Server (HFS) [42], is utilized. To investig the performance of our mechanism, in-field experiments involv 30 volunteers have been conducted. For each task, the work side app also generates a random number from $[0.005, 0.075]$ represent the volunteer's self-reported profile[4], which is unknown by the platform. There are 60 tasks in total. All of them are binary-answer English grammar questions from commonly used real-world crowdsourcing datasets [43]. An on-site training workshop on app usage was provided to volunteers before the experiment. The experiment procedure is briefly summarized as follows. Once the platform publishes a task, workers submit their reported profiles (Figure 2(b)). The volunteer decides if to submit the same profile as generated by the app or a different one. Then the platform determines which workers to recruit. The selected workers then solve the question and send back the answers, i.e., answers (Figure 2(c) and 2(d)). The platform determines payment to each worker for this task (Figure 2(e)). A worker's final payment is the accumulated amount it receives in all tasks (Figure 2(f)).

We developed our own prototype instead of using existing crowdsourcing platforms, such as Amazon Mechanical Turk or Flower Eight, due to the complex nature of our payment rule and the centralized worker selection. In these platforms, a worker's payment is predeclared and generally fixed. Thus, dynamic incentives cannot be implemented. All of our source codes are available online[5].

For comparison purposes, the experiment is also conducted with another two incentive mechanisms. The first one, called *random VCG*, employs the random VCG auction framework for worker selection and payment calculation so as to achieve profile truthfulness. The second one is called *truth serum* [16] that was designed for answer truthfulness. Specifically, truth serum extracts a worker's posterior belief from its reported answer and scores it using reference answers. The scoring rule is carefully designed such that truth-telling is a Bayesian Nash equilibrium.

5.2 Analysis of Answer Truthfulness

This section evaluates answer truthfulness. Since all tasks are relatively easy grammar questions for college students, we assume that their genuine answer to a task is the same as its ground truth.

4. In the experiments, there is only one parameter in a worker's profile for simplicity.

5. https://sites.google.com/site/reportingtruthful/

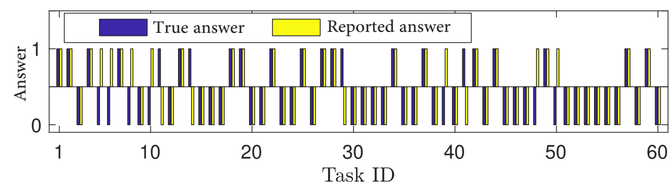
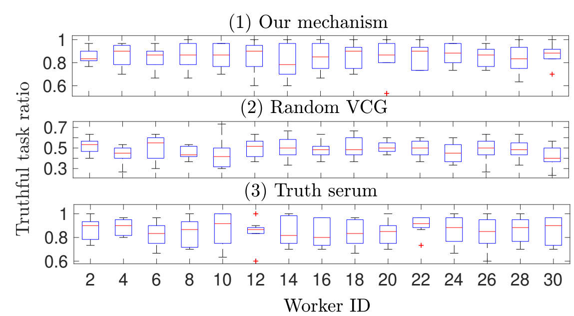
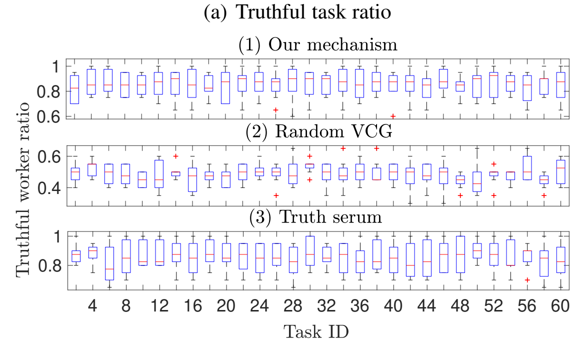


Fig. 3. A randomly selected worker's reported and true answer for 60 tasks in our mechanism.



(a) Truthful task ratio



(b) Truthful worker ratio

Fig. 4. Answer elicitation performance comparison among our mechanism, random VCG, and truth serum.

Figure 3 shows a randomly selected worker's reported answer and the ground truth across the entire 60 tasks. We use "1" and "0" to denote the answer "yes" and "no", respectively. This worker misreports more often at the beginning but tends to be honest later. Particularly, 7 tasks are misreported among the first half batch,

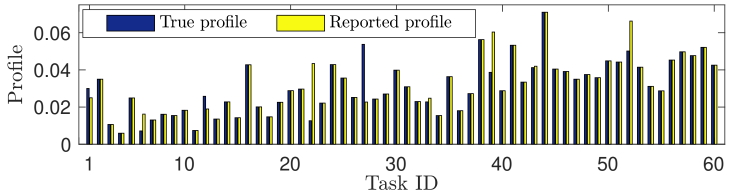
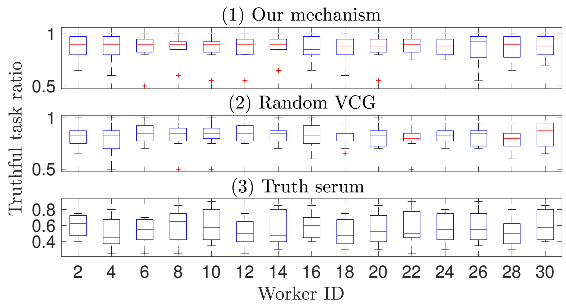
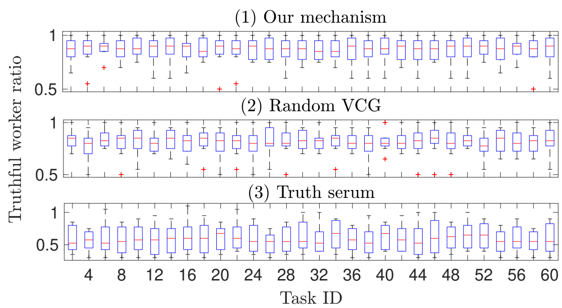


Fig. 5. A randomly selected worker's reported and true profile for 60 tasks in our mechanism.



(a) Truthful task ratio



(b) Truthful worker ratio

Fig. 6. Profile elicitation performance comparison among our mechanism, random VCG and truth serum.

while this number drops to 4 for the second half batch. Since the worker gets the best-expected payoff when behaving honestly, it gradually adjusts strategies to truth-telling.

Figure 4(a) examines the *truthful task ratio*, which is defined as the percentage of tasks that a worker honestly reports among all the tasks. We observe that the ratio achieved by our mechanism and truth serum is around 0.9, while that for the random VCG is as low as 0.5. Thus, workers demonstrate no preference in answer reporting when truth elicitation is not enforced. Our mechanism performs as good as truth serum in motivating truth-telling. However, the latter does not consider profile truthfulness, which will be discussed in the next section. In addition, we compare in Figure 4(b) the *truthful worker ratio*, which is defined as the percentage of honest-reporting workers for a given task, among the three mechanisms. Similarly, ours has a similar performance as truth serum. Both of them outperform the random VCG. It is worth mentioning that neither our mechanism nor truth serum can guarantee perfect truth-telling in real-world experiments. This is because workers are modeled as idealized "rational individuals" with perfect knowledge to act in the paper, which may not be reflective of their actual status in real-world scenarios.

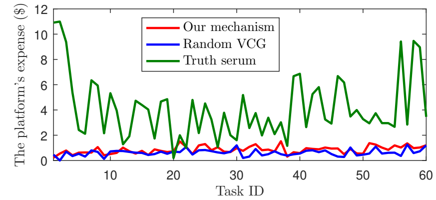


Fig. 7. The platform's expense for different tasks.

TABLE 2
Accuracy performance comparison.

	Accuracy	Error	Accuracy ratio
Our mechanism	55	5	91.7%
Truth serum	54	6	90.0%
Random VCG	32	28	53.3%

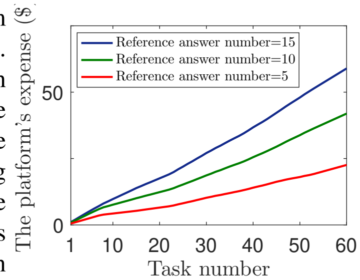
5.3 Analysis of Profile Truthfulness

Figure 5 depicts a randomly selected worker's reported profile and its genuine value for the 60 tasks. We observe a similar trend as in Figure 4: the worker is more likely to misreport at the beginning but tends to behave honestly after a few rounds of task executions. This is also because our mechanism effectively encourages workers to report true profiles. Figure 6(a) compares the truthful task ratio among the three mechanisms. We find that our mechanism and the random VCG have a similar performance in truthful profile elicitation, which outperforms truth serum. This is because the former two apply random VCG for worker selection where profile truthfulness is guaranteed while truth serum does not consider profile truthfulness but merely answer truthfulness. A similar observation is obtained in Figure 6(b).

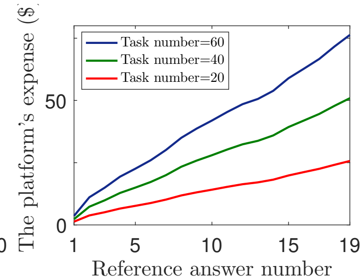
We further examine the platform's expense incurred by the three mechanisms for each task in Figure 7. The expense is the sum of all worker payments. Truth serum causes the highest expense among the three. Since it fails to consider profile truthfulness, workers can manipulate reported profiles and thus incur extra payment to the platform. We also observe that our mechanism brings a slightly higher expense than random VCG on average. This extra expense ensures the answer truthfulness that random VCG fails to achieve.

5.4 Accuracy Performance

Once the platform collects answers from workers, it aggregates them and derives the final result. We employ the majority voting as the aggregation method, i.e., if more than half answers are



(a)



(b)

Fig. 8. The platform's expense under different mobile crowdsourcing sizes.

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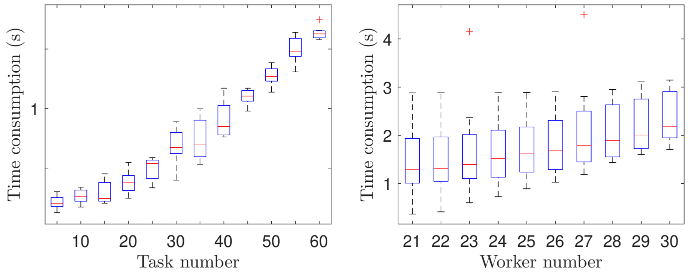

(a) Worker size=30 (b) Task size=60

Fig. 9. Time consumption of our mechanism under different system sizes.

"yes", then the final result of the task is deemed "yes"; otherwise, it is "no". Accuracy is different from answer truthfulness. The former denotes that the aggregated answer is the same as the ground truth, while the latter means a worker reports her true observation. Table 2 compares the accuracy performance among the three mechanisms. Our mechanism and truth serum have a similar performance. Specifically, we get correct answers in 55 and 54 tasks out of 60 via our mechanism and truth serum, respectively. The random VCG has the lowest accuracy ratio, 53.3%. Together with the answer truthfulness analysis Figure 4, we find that answer truthfulness and accuracy demonstrate a strong positive correlation in our mechanism. This property is useful, especially for the tasks whose ground truth is hard to derive.

5.5 Impact of System Size

We also analyze the impact of system size on the mechanism performance. Figure 8 shows the platform's expense under different system sizes. We find in Figure 8(a) that the expense increases linearly as the number of tasks grows. Specifically, the total amount is \$26.8 when there are 30 tasks and 15 reference answers. This value increases to \$60.5 when the task number becomes 60. The observation meets our expectation: more workers need to be recruited to execute more tasks, thus incurring higher expenses to the platform. Here, reference answers correspond to $\boldsymbol{r}_{-i}$ in the mechanism. Figure 8(b) shows that the platform's average expense also increases linearly with respect to the number of reference answers. Specifically, the platform's average payment is \$25.5 when there are 40 tasks and 10 reference answers. It increases to \$50.3 when the answer number becomes 15.

Figure 9 illustrates the time consumption of our mechanism under different settings. It mainly comes from three processes: winner selection, payment calculation, and the data communication between the platform program and the worker-side app. Notice that the task execution time, i.e., the duration for workers to conduct tasks and derive results, is not included, as this part depends on individual intelligence that varies from worker to worker. We observe from Figure 9(a) that the time slightly increases, from about 0.7s to 2.2s, when the task number changes from 5 to 60. The average time consumption for each task is as low as 0.05s. It is worth mentioning that tasks are conducted sequentially in the current experiment. The time consumption can be further reduced when they are processed in parallel, which we will implement and examine in our future work. A similar trend is observed in Figure 9(b). The time consumption slightly increases when more workers participate. Specifically, the value is 1.1s when there are 21 workers, and it becomes 2.1s when the worker size is 60.

To sum up, our mechanism can not only effectively elicit truthful answers and profiles, but is also feasible to implement for practical mobile crowdsourcing systems due to its moderate expense caused to the platform and high computation efficiency.

5.6 Analysis of Scalability

To evaluate the scalability of the proposed scheme, we further conduct a series of simulations. Besides, its performance is also compared with a baseline approach, i.e., the conventional VCG. To implement the baseline approach, we utilize CPLEX, a commercial optimization software package [44], to optimally solve the integer programming (IP) problem P_1 for task allocation and VCG for payment determination. For each task and worker, we randomly generate task-independent parameters d_i and workers' profile $\boldsymbol{b}_i$ from the normal distribution $N(0.5, 0.2)$. γ is set to 2 by default. The maximum worker size and task size is set to 1000 and 1600, respectively. All results are averaged over 100 trials. The evaluations run on a Dell laptop with a 1.6GHz processor and 16GB RAM.

Figure 10 compares the time consumption between our scheme and the baseline approach given different amounts of tasks. As a note, the baseline approach stands for the conventional VCG approach that directly applies CPLEX to find the optimum solution of task allocation and pricing. We observe in Figure 10 that our scheme spends much less time than the baseline approach given the same number of tasks. For example, when there are 400 tasks, it takes our scheme 2.3 s and 6.9 s to derive task allocation and pricing outcomes, respectively. However, the values become 62.5 s and 63.2 s for the baseline approach. This is because the latter solves computationally expensive IP problems, i.e., P_1, for both task allocation and payment determination; instead, our scheme follows the framework of fractional VCG that only involves solving LP problems with polynomial complexity.

Figure 11 compares the time consumption between our scheme and the baseline approach given different numbers of workers. We observe that our scheme's time for task allocation increases slower than that of the baseline approach as the worker number grows. This is because more variables introduce a lower time complexity to LP problems (or our scheme) than IP problems (or the baseline approach). We also notice in Figure 11(a) that our payment determination takes relatively stable time with the increase of worker numbers. Combining the results from Figure 10 and Figure 11, we conclude that our scheme is more practical for implementation than the conventional VCG in terms of computation efficiency, especially when the number of workers and/or tasks is large.

6 Related Work

Answer truthfulness. Mechanism design to elicit truthful answers/data, in binary-answer tasks, is an extensively studied topic [17], [18], [19], [20], [20], [21], [22], [23] The idea is to devise payment rules such that truth-telling is a Nash equilibrium. Since the ground truth for each task is unknown to the system, a natural solution is to reward workers based on other workers' reports, i.e., reference answers [17], [18], [19] Another solution is to utilize a truth detection technology that gives a signal indicating if a worker is truthful or lying based on factors, e.g., physiological measures (e.g., pupil dilation) [20], [21]. Realizing that workers' efforts also determine the accuracy of crowdsourcing services,

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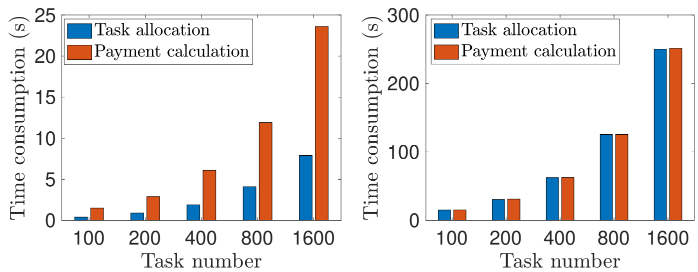
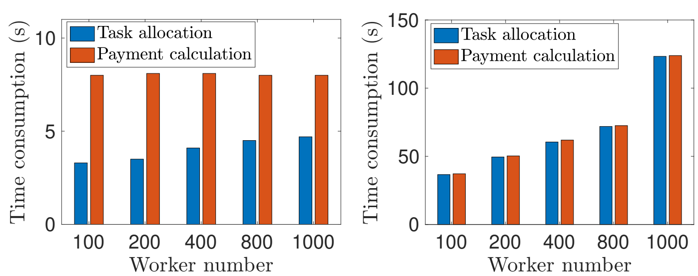


(a) Our scheme (b) The baseline approach

Fig. 10. Time consumption of our scheme and the baseline approach over different task numbers (Worker number=500).



(a) Our scheme (b) The baseline approach

Fig. 11. Time consumption of our scheme and the baseline approach over different worker numbers (Task number=500).

a couple of works [20], [22], [23] further utilize incentives to motivate workers to exert efforts in task execution. For example, Dasgupta et al. [22] incentivized maximum effort followed by truthful reports of answers in an equilibrium that achieves maximum payoffs for workers. Gong et al. [23] developed mechanisms to incentivize strategic workers to truthfully reveal their private quality and data, and make truthful efforts as desired by the crowdsourcing requester. The above two works assume that workers have the same cost of effort exertion and/or the same solution accuracy. In practice, for example, students with a better academic background are likely better at homework assessment. They may spend smaller costs (e.g., time) generating homework assessments with higher quality (i.e., higher solution accuracy). Huang et al. [20] then accommodated such worker heterogeneity in their incentive mechanism design. None of the above works considers profile truthfulness. As discussed, this property is of equal importance for the platform to deliver high-quality mobile crowdsourcing services.

Cost truthfulness. Minimizing the overall worker cost, in terms of energy consumption, travel distance, or computing resources, is a prevailing decision criterion to generate suitable worker-task pairs during task assignments. Since cost is private information and workers are strategic in reporting this value for favorable outcomes, the main challenge lies in how to stimulate workers to disclose their costs truthfully. Incentive mechanisms have attracted most attention for truthful cost elicitation due to their ability to deal with workers' strategic behaviors [1], [14], [25], [26], [27], [28], [29], [30] For example, Yang et al. [25] were among the first to discuss cost truthfulness during task assignment in crowdsourcing. Auction-based incentive mechanisms have been developed. Along this line of research, [1], [27], [29] then study the impact of budget constraints at the platform. Since the monetary provision is limited, the platform's strategy space is thus confined. Noticing that existing mechanisms assume the existence of only one task requester, [30] considers multiple requesters. The framework of double-auction is thus applied. Cost truthfulness is guaranteed at both requesters and workers. Since cost is merely one kind of self-reported profile, cost truthfulness is thus a special case of profile truthfulness that we aim to achieve. Aside from the cost, strategic workers are able to manipulate a much wider spectrum of self-reported profiles, which conventional cost truthfulness schemes cannot resist.

Summary. To our knowledge, this is the first study that protects two different stages, i.e., task assignment and answer aggregation, in crowdsourcing from workers' strategic misreporting simultaneously. In the task assignment stage, workers report their profiles, such as locations, expertise, and cost of task execution, to the platform, who then decides task assignment based on the collected profiles. Hence, strategic workers may manipulate their reports to gain benefit. This is the same case in the answer aggregation stage where workers lie about their reported answers. Prior works utilize incentive design to tackle either one of the above two kinds of misbehaviors. Instead, we aim to develop a unified framework to address them at the same time. It is infeasible to directly apply existing schemes in each stage, i.e., a worker is first paid for answer truthfulness and then paid for cost truthfulness. This is because the worker's total payment received from both stages, if not carefully calibrated jointly, would violate conditions for both profile truthfulness and answer truthfulness.

Another limitation of the prior works is that they mostly focus on cost truthfulness, i.e., motivating workers to reveal their genuine costs in task execution. In fact, in the stage of task assignment, workers are required to report many other information, such as location and expertise, in addition to the cost. We call them "profile" in this paper. Cost truthfulness cannot guarantee workers truth-telling over other information. To address this issue, our approach achieves profile truthfulness that covers a much wider spectrum of strategic behaviors.

7 Conclusion

In this paper, we develop an incentive mechanism to jointly elicit truthful answers and profiles from strategic workers in mobile crowdsourcing. Our design first derives the sufficient and necessary conditions for these two goals separately. Particularly, to achieve answer truthfulness, we leverage reference answers to evaluate the truthfulness of a given worker's answer. Under the model of *Bayesian game*, a worker's expected payment for truth-telling is set no less than that when lying, which leaves workers little incentive to lie. The condition of profile truthfulness is derived via the design of randomized worker selection and worker payment. We first formulate a worker selection optimization problem. Due to its NP-hardness, we resort to solving its relaxed version in a fractional domain. The factional optimal solution is then decomposed into a randomized format. An α-approximate algorithm is further developed. The upper bound of its integrality gap then serves as a scaling factor η, which is applied to the randomized worker selection to ensure its feasibility. As a final step, the conditions for answer and profile truthfulness are integrated as constraints of the payment optimization problem, whose solution is the incentive paid to each worker to motivate honest behaviors. As a proof-of-concept implementation, we prototype the proposed mechanism. A series of experiments that involve 30 volunteers have been conducted. Results show that our mechanism is effective and efficient for practical implementation.

REFERENCES

[1] Y. Hu and R. Zhang, "Differentially-private incentive mechanism for crowdsourced radio environment map construction," in *Proceedings of IEEE INFOCOM*, 2019.

[2] X. Li and Q. Zhu, "Social incentive mechanism based multi-user sensing time optimization in co-operative spectrum sensing with mobile crowd sensing," *Sensors*, vol. 18, no. 1, p. 250, Jan 2018.

[3] P. Smith, A. Luong, S. Sarkar, H. Singh, A. Singh, N. Patwari, S. K. Kasera, and K. Derr, "A novel software defined radio for practical, mobile crowd-sourced spectrum sensing," *IEEE Transactions on Mobile Computing*, 2021.

[4] Y. Hu and R. Zhang, "A spatiotemporal approach for secure crowdsourced radio environment map construction," *IEEE/ACM Transactions on Networking*, vol. 28, no. 4, pp. 1790–1803, Aug 2020.

[5] Y. Yang, Y. Ding, D. Yuan, G. Wang, X. Xie, Y. Liu, T. He, and D. Zhang, "Transloc: transparent indoor localization with uncertain human participation for instant delivery," in *Proceedings of MobiCom*, 2020.

[6] J. Purohit, X. Wang, S. Mao, X. Sun, and C. Yang, "Fingerprinting-based indoor and outdoor localization with lora and deep learning," in *Proceedings of IEEE GLOBECOM*, 2020.

[7] C.-L. Leca, I. Nicolaescu, and P. Ciotirnae, "Crowdsensing influences and error sources in urban outdoor wi-fi fingerprinting positioning," *Sensors*, vol. 20, no. 2, p. 427, Jan 2020.

[8] S. Li, Z. Qin, H. Song, C. Si, B. Sun, X. Yang, and R. Zhang, "A lightweight and aggregated system for indoor/outdoor detection using smart devices," *Future Generation Computer Systems*, vol. 107, pp. 988–997, June 2020.

[9] "Clickworker," https://www.clickworker.com.

[10] "Taskrabbit," https://www.taskrabbit.com/.

[11] G. Ye, Y. Zhao, X. Chen, and K. Zheng, "Task allocation with geographic partition in spatial crowdsourcing," in *Proceedings of ACM CIKM*, 2021, pp. 2404–2413.

[12] Y. Zhao, K. Zheng, Y. Cui, H. Su, F. Zhu, and X. Zhou, "Predictive task assignment in spatial crowdsourcing: a data-driven approach," in *Proceedings of IEEE ICDE*, 2020.

[13] H. Jin, L. Su, H. Xiao, and K. Nahrstedt, "Inception: Incentivizing privacy-preserving data aggregation for mobile crowd sensing systems," in *Proceedings of the ACM MobiHoc*, 2016.

[14] M. Xiao, M. Li, L. Guo, M. Pan, Z. Han, and P. Li, "Securing task allocation in mobile crowd sensing: An incentive design approach," in *Proceedings of IEEE CNS*, 2019.

[15] V. C. Raykar and S. Yu, "Eliminating spammers and ranking annotators for crowdsourced labeling tasks," *The Journal of Machine Learning Research*, vol. 13, no. Feb, pp. 491–518, Feb 2012.

[16] G. Radanovic, B. Faltings, and R. Jurca, "Incentives for effort in crowdsourcing using the peer truth serum," *ACM Transactions on Intelligent Systems and Technology*, vol. 7, no. 4, p. 48, July 2016.

[17] C. Huang, H. Yu, J. Huang, and R. Berry, "Eliciting information from heterogeneous mobile crowdsourced workers without verification," *IEEE Transactions on Mobile Computing*, Early Access, 2021.

[18] Y. Kong, "Dominantly truthful multi-task peer prediction with a constant number of tasks," in *Proceedings of the SODA*, 2020.

[19] Y. Kong, G. Schoenebeck, B. Tao, and F.-Y. Yu, "Information elicitation mechanisms for statistical estimation," in *Proceedings of AAAI*, 2020.

[20] C. Huang, H. Yu, R. A. Berry, and J. Huang, "Using truth detection to incentivize workers in mobile crowdsourcing," *IEEE Transactions on Mobile Computing*, Early Access, 2020.

[21] ——, "Using truth detection to incentivize workers in mobile crowdsourcing," *IEEE Transactions on Mobile Computing*, pp. 1–1, 2020.

[22] A. Dasgupta and A. Ghosh, "Crowdsourced judgement elicitation with endogenous proficiency," in *Proceedings of the WWW*, 2013.

[23] X. Gong and N. Shroff, "Incentivizing truthful data quality for quality-aware mobile data crowdsourcing," in *Proceedings of the ACM MobiHoc*, 2018.

[24] G. J. Mailath, "Do people play nash equilibrium? lessons from evolutionary game theory," *Journal of Economic Literature*, vol. 36, no. 3, pp. 1347–1374, Sep 1998.

[25] D. Yang, G. Xue, X. Fang, and J. Tang, "Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing," in *Proceedings of the ACM MobiCom*, 2012.

[26] W. Liu, Y. Yang, E. Wang, and J. Wu, "Dynamic user recruitment with truthful pricing for mobile crowdsensing," in *Proceedings of IEEE INFOCOM*, 2020.

[27] W. Jin, M. Xiao, L. Guo, L. Yang, and M. Li, "Ulpt: A user-centric location privacy trading framework for mobile crowd sensing," *IEEE Transactions on Mobile Computing*, 2021.

[28] M. Xiao, W. Jin, M. Li, L. Yang, A. Thapa, and P. Li, "Collusion-resistant worker recruitment in crowdsourcing systems," *IEEE Transactions on Mobile Computing*, 2021.

[29] W. Jin, M. Xiao, M. Li, and L. Guo, "If you do not care about it, sell it: Trading location privacy in mobile crowd sensing," in *Proceedings of IEEE INFOCOM*, 2019.

[30] Y. Wei, Y. Zhu, H. Zhu, Q. Zhang, and G. Xue, "Truthful online double auctions for dynamic mobile crowdsourcing," in *Proceedings of the IEEE INFOCOM*, 2015.

[31] V. Conitzer and T. Sandholm, "Complexity results about nash equilibria," in *Proceedings of the IJCAI*, 2002.

[32] R. Lavi and C. Swamy, "Truthful and near-optimal mechanism design via linear programming," *Journal of the ACM*, vol. 58, no. 6, p. 25, December 2011.

[33] R. Carr and S. Vempala, "Randomized metarounding," in *Proceedings of the ACM STOC*, 2000.

[34] Y. Zheng, G. Li, and R. Cheng, "Docs: a domain-aware crowdsourcing system using knowledge bases," *Proceedings of the VLDB*, vol. 10, no. 4, pp. 361–372, November 2016.

[35] X. Liu, M. Lu, B. C. Ooi, Y. Shen, S. Wu, and M. Zhang, "Cdas: a crowdsourcing data analytics system," *Proceedings of the VLDB Endowment*, vol. 5, no. 10, pp. 1040–1051, June 2012.

[36] H. Kellerer, U. Pferschy, and D. Pisinger, *Knapsack problems*, 2003.

[37] M. Grötschel, L. Lovász, and A. Schrijver, *Geometric algorithms and combinatorial optimization*, 1988.

[38] T. Carnes and D. Shmoys, "Primal-dual schema for capacitated covering problems," in *Proceedings of IPCO*, 2008.

[39] R. Jurca and B. Faltings, "Minimum payments that reward honest reputation feedback," in *Proceedings of the ACM EC*, 2006.

[40] W. Shi, L. Zhang, C. Wu, Z. Li, and F. C. Lau, "An online auction framework for dynamic resource provisioning in cloud computing," in *Proceedings of the ACM SIGMETRICS*, 2014.

[41] D. A. Spielman and S.-H. Teng, "Smoothed analysis of algorithms: Why the simplex algorithm usually takes polynomial time," *Journal of the ACM*, vol. 51, no. 3, pp. 385–463, May 2004.

[42] "Http file server," http://www.rejetto.com/hfs/.

[43] "Crowdsourcing datasets," http://dbgroup.cs.tsinghua.edu.cn/ligl/crowddata/.

[44] "Cplex," https://www.ibm.com/docs/en/icos/12.8.0.0?topic=programming-where-find-cplex-examples.

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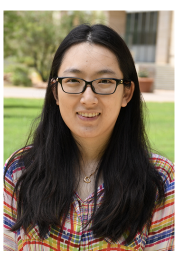

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