A Quality Assuring Mechanism for Crowdsourcing with Strategic Agents

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Abstract

In this paper, we investigate a class of crowdsourcing problems that involve heterogeneous workers with varying quality levels. The problem we address is how to execute a set of similar tasks or services at high quality and minimum cost through crowdsourcing when only the costs but not the qualities of the workers are known. The problem belongs to a common value setting and standard mechanisms such as Vickrey-Clarke-Groves mechanisms cease to be applicable. However, many real-world crowdsourcing scenarios fall under the common value setting. We develop a novel mechanism, QUEST, and show that the mechanism satisfies three essential properties: ex-post incentive compatibility, individual rationality, and social utility maximization. While our theoretical work provides a single shot mechanism for the problem, the simulations show that this mechanism will work effectively under realistic dynamic crowdsourcing settings with boundedly rational workers. To our knowledge, this is the first effort in developing a reliable crowdsourcing mechanism under a common value setting with quality levels held private by the strategic agents.

1 Introduction

Organizations and institutions often face the problem of executing tasks for which they do not possess enough expertise or resources. Examples include classification of documents, labeling of images, developing efficient code for algorithmic problems, repetitive services such as event management, catering, etc. Outsourcing them to high quality experts at a cost is often an inexpensive solution for the organization than recruiting more people or acquiring more resources. Crowdsourcing is an efficient way of task execution for businesses [3]. With the proliferation of the Internet-based crowdsourcing platforms like Amazon Mechanical Turk, Innocentive, oDesk, Topcoder, etc., forwarding a task for a payment has become even easier. The goal of the outsourcer is to hire an optimal set of workers to maximize profit. In this paper, to simplify analysis, we consider tasks having only binary states, e.g., classifying a document into class 0 or 1, answering a 'true/false' question etc. We define the quality of a worker as the probability of correctly classifying the document or answering the question. Since the crowd workers originate from various demographics [12] and in addition could have a strategic intent, they form a heterogeneous group which could result in varying quality.

If the qualities of the workers were known to the designer, this problem reduces to a stochastic optimal control problem that can be solved using standard optimization techniques. However, the problem becomes non-trivial when the qualities are private information of the strategic workers and unknown to the designer. The workers can potentially misreport their qualities in order to maximize their payoff. This calls for a mechanism design approach. In this paper, we address the optimization problem with incomplete information from a game theoretic perspective, and provide a truthful, socially optimal mechanism, that encourages voluntary participation of the workers. We will use document labeling as an abstraction of the crowdsourcing task throughout the paper. Without loss of generality, in the sequel of the paper we use the following terminology: *labeling* in general corresponds to a *task* or *service*; *labeler* corresponds to a *crowd labeler*; and *center* refers to an intermediary or company interested in crowdsourcing the set of tasks.

1.1 Related Work

The literature on AI research has looked into crowdsourcing problems, and some of them use mechanism design as a tool. [2] look into the problem of online assignment in crowdsourcing markets and propose a two phase explore-exploit assignment algorithm. They first estimate the skill level and then exploit it to minimize the cost. Their approach is shown to be empirically better than some existing offline algorithms. However, they assume honest agents and also that costs are the same for all the agents. Our paper relaxes both these limitations and moreover offers a mechanism that is incentive compatible, individually rational, and social utility maximizing. [1] consider a model where they assume that every worker can improve her quality by exerting an extra effort. They consider a crowdsourcing contest where these competing workers win a reward by exerting the most extra effort. In this paper they design a contest to maximize the expected quality at the center while trading it off with the risk (or variance). [7] argue that the quality of an agent depends on the workflow of the task. They propose a graphical model to represent the multiple workflow scenario and provide algorithms to learn the parameters of the model. They empirically show the superiority of their approach to existing single workflow models.

A mechanism for determining near optimal prices for performing tasks in online labor markets that use crowdsourcing is presented by [13]. [4] develop incentive mechanisms for online question answer forums. [11] propose trust based mechanisms for procurement scenarios where there exists uncertainty about agents successfully completing their assigned tasks. The proposed mechanisms take into account the subjective measures of the probability of success of an agent and produce allocations that are efficient, incentive compatible, and individually rational.

[10] present a platform for crowdsourcing that assumes the worker abilities to be common knowledge and the costs are private. They solve a combinatorial optimization problem that finds an efficient allocation and they use the Clarke pivotal rule for payment. In real crowdsourcing applications it is often difficult to know the qualities of the participants. We, on the other hand, focus on a private quality and public cost, which leads us to a common-value model and VCG mechanisms are not applicable.

1.2 Contributions and Outline

In the problem studied in this paper, the center determines the payments to the labelers based on selection of labelers and their observed outputs. The qualities are independent across labelers, however, the allocation and payment decisions of the center are dependent upon the quality of all the selected labelers. The payment to the labelers will depend upon the actual label publicly observed in the end and hence our problem falls under the common value model (CVM). This immediately means that the class of VCG (Vickrey-Clarke-Groves) mechanisms cannot be used in this context (see, e.g., [8]).

Under this setting, one can think of a naïve mechanism that selects the labeler with least cost, treating the labeler's reports as truthful. This mechanism is susceptible to a high level of error if the least cost labeler has a low quality level. Another mechanism could be to ask the labelers to report the qualities and pay the labelers their costs if selected. It can be shown that this mechanism is not fair to the labelers and is truthful only in the weakest possible sense: net return to labelers is always 0 and not dependent on the reports. We omit the details due to space constraints.

The common value model of the crowdsourcing setting, therefore, poses a nontrivial challenge. Our main contributions to this problem are the following.

- We propose the mechanism QUEST (QUality Elicitation from STrategic agents) that allocates tasks to labelers and also determines payments in a way that high quality levels are achieved in a cost effective way.
- We show that QUEST satisfies three desirable properties, namely, ex-post incentive compatibility (Theorem 1), individual rationality (Theorem 2), social utility maximization (Theorem 3). The novelty of our mechanism is it achieves the above three properties in a common value setting. In contrast to the mechanism presented by [9], we exploit special model structure leading to a mechanism with a single reporting round that also satisfies a stronger notion of incentive compatibility.
- While our theoretical work offers a sound single shot mechanism for the problem, we conduct simulation experiments which demonstrate that the mechanism will work quite effectively under realistic dynamic crowdsourcing settings as well.

The QUEST mechanism could form the core of a deployable, interactive tool to design experiments with human participants.

2 The Model

We consider the center to be the mechanism designer. The set of labelers, whom the tasks are outsourced to, is represented by $N = \{1, \ldots, n\}$. The task is to identify the correct state of a random event, which has binary states, 0 or 1. We denote the true state of the event by y which is a Bernoulli random variable with parameter θ. Labelers make noisy observations of y. Agent i observes $\tilde{y}_i$ following $p(\tilde{y}_i = y|y) = q_i$, leading us to refer to q_i as the *quality* of agent i. The labelers privately observe their qualities. The effort to observe the true state comes at a cost c_i, which is a common knowledge.

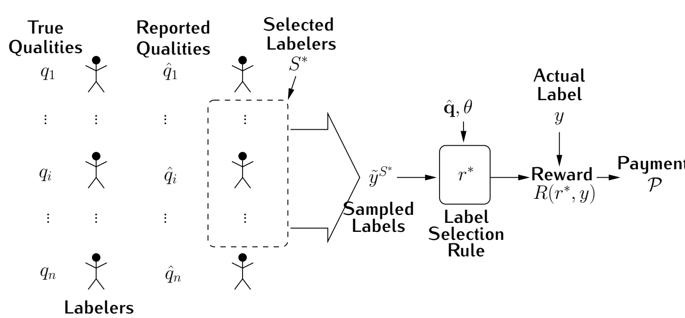

Figure 1: Illustration of the mechanism design problem

The goal of the designer (center) is to predict the right state (we will use state and label interchangeably in this paper) using the inputs from the labelers, and this results in the total reward the center earns. We model the reward using a function R, where $R(r, y)$ denotes the reward received when the true label is y and center predicts r. Since the qualities are private to the agents and we assume the labelers to be strategic, it induces a game between the labelers and the center. We adopt the design approach where the center asks the labelers to report their qualities. Let the reported

$N = \{1, \ldots, n\}$	set of labelers
q_i	quality of i, $\mathbb{P}(\tilde{y}^{(i)} = y \mid y)$
c_i	cost for labeler i to label
q	quality vector, $(q_1, \ldots, q_n)$
c	cost vector, $(c_1, \ldots, c_n)$
$y \in \{0, 1\}$	label of document
$\tilde{y}^{(i)} \in \{0, 1\}$	(noisy) observation of label y by i
$\mathbb{P}(y = 1 \mid \theta) = \theta$	Bernoulli data generation model
$r \in \{0, 1\}$	decision made by the center
$R(r, y)$	reward to the center after deciding r when true label is y
$S(\hat{q}, c, \theta)$	labeler selection rule
$r(\tilde{y}^S, \hat{q}, \theta)$	label selection rule
$\mathcal{P}(r, \hat{q}, \tilde{y}^S, y)$	payment rule
W	social utility of all agents
W_{-i}	expected social utility in absence of player i
$\mathbb{P}\left(\tilde{y}^S \mid q, \theta\right)$	probability of a noisy report vector from a labeler set S given q and θ

Table 1: Notation

qualities be denoted by $\hat{q}_i$'s. The mechanism will then select the set of labelers, $S(\hat{q}, c, \theta)$, to whom it will assign the task. The agents then perform the task and find the labels to be $\tilde{y}_i$'s, which is observed by the center. Depending on the reported qualities $\hat{q}_i$'s and the observed labels $\tilde{y}_i$'s, the center predicts the state r, before observing the true realization y. The payment is decided after the true state has been realized and the reward is obtained by the center. Our problem setting, therefore, follows the common value model, since the valuation of a labeler depends upon the amount they get paid which in turn depends upon the labels of the other selected labelers as well. Figure **??** graphically illustrates the dynamics. The notation is summarized in Table 1.

2.1 Reasons for a Two Stage Mechanism

Figure 1 shows that the game progresses in two stages: first, the agents report their qualities and the set of players are chosen, and second, after observing the true state, the payment is decided. One can question why we need a two stage mechanism. [5] showed that only constant functions are implementable in ex-post equilibria for multi-dimensional types using single stage mechanisms. [9] proposes a two-step mechanism to solve the problem under the private interdependent values setting. The second step of this mechanism is weak in the sense that agents can report anything they wish to without any impact on their rewards. Our setting differs in two ways: (a) it is a common value setting, (b) we are able to exploit a special structure in the problem and designed a novel mechanism that is EPIC in the first stage. The second stage in our case is truthful because the payment is linked to the reported labels. It is not possible for the agents to execute the task with higher than their inherent qualities. Likewise, a lower-than-true quality label will only harm an agent because it is indistinguishable from the case of an over-reported quality.

2.2 Design Desiderata

The problem of the center is to pick the right set of labelers to maximize the expected reward at the minimum cost. If center selects labelers S, it obtains the utility as follows. In the rest of the paper, for notational brevity, parameters of functions that are clear by context such as θ, c, q etc.

are omitted.

Definition 1 (Utility to the Center) *After a label has been reported by the center and the true label y is observed, the center obtains a reward R, pays selected labeler i an amount $\mathcal{P}_i$. Thus, the center obtains utility,*

$$u_c = R(r(\tilde{y}^S, q, \theta), y) - \textstyle\sum_{i \in S} \mathcal{P}_i(r, q, \tilde{y}^S, y) \tag{1}$$

The utility to labeler i is the payment i receives minus the cost she incurs, that is, $u_i = \mathcal{P}_i(r, q, \tilde{y}^S, y) - c_i$.

The total utility of all the agents including the center, which we call *s*ocial utility, is defined as follows:

Definition 2 (Social Utility) *After a label r has been decided by the center and the true label y is observed, the center obtains a reward $R(r, y)$ and pays $\mathcal{P}_i$'s to selected labelers. The social utility of all the agents is*

$$W(S, \tilde{y}^S, q, c, \theta, y) = R(r(\tilde{y}^S, q, \theta), y) - \textstyle\sum_{j \in S} c_j \tag{2}$$

Having chosen labeler set S, the center can evaluate the worth of an agent $i \in S$ by calculating the expected social utility in absence of i for the same observed y.

Definition 3 (Social Utility in Absence of i) *If S_{-i} is the labeler set chosen in the absence of i, the social utility in the absence of i is defined as,*

$$W_{-i}(q_{-i}, c_{-i}, \theta, y) = \mathbb{E}_X \left[R(r(\tilde{y}^{S_{-i}}, q_{-i}, \theta), y) - \sum_{j \in S_{-i}} c_j \right]$$

Where, $X = \tilde{y}^{S_{-i}(q_{-i}) \setminus S(q)} | y, q_{-i}, \theta$.

If the set S_{-i} contains labelers that are not present in the set S, and hence there are reported labelers "missing", we take the expectation (not conditioning on i's report) with respect to the missing labels from the set $S' = S_{-i} \setminus S$.

Since the actual qualities are private to the agents, we need to elicit them *truthfully* from the agents as we are interested in maximizing the true social utility realized. We use *Ex-Post Incentive Compatibility (EPIC)* as the notion of truthfulness.

Definition 4 (Ex-post Incentive Compatibility, EPIC) *A mechanism $(S, \mathcal{P})$ is ex-post incentive compatible, if for all realizations of q,*

$$\mathbb{E}_{X_1} u_i(q_i, q_{-i}, \tilde{y}^S) \geq \mathbb{E}_{X_2} u_i(\hat{q}_i, q_{-i}, \tilde{y}^{\hat{S}}), \quad \forall \hat{q}_i \tag{3}$$

where, $S = S(q_i, q_{-i})$, $\hat{S} = S(\hat{q}_i, q_{-i})$, and $X_1 = \tilde{y}^S, y | q, \theta$, $X_2 = \tilde{y}^{\hat{S}}, y | q, \theta$.

EPIC is a stronger notion of truthfulness than Bayesian Incentive Compatibility (BIC), but is weaker than Dominant Strategy Incentive Compatibility (DSIC) [8].

To ensure that the labelers participate voluntarily in this labeling exercise, the mechanism has to make sure that the ex-ante utility of every agent is non-negative. This desirable property is captured by the individual rationality, defined as follows.

Definition 5 (Ex-Ante Individual Rationality, EAIR) *The expected utility should be non-negative for all agents, i.e.,*

$$\mathbb{E}_{\tilde{y}^S, y | q, \theta} u_i(\tilde{y}^S, y, q, \theta) \geq 0, \ \forall i \in N \tag{4}$$

In summary, the design question, therefore, is to design an expected *social utility maximizing*, *truthful* mechanism in this setting where the agents *voluntarily participate*.

3 The QUEST Mechanism

We present our mechanism QUEST (QUality Elicitation from STrategic agents), that efficiently selects the set of high quality labelers to perform the task satisfying our design desiderata. The common knowledge includes the prior probability θ, reward matrix R, costs c. The individuals report their qualities q, and QUEST selects the labelers, selects the label, and decides the payment to the individuals as follows. Let us denote $Q(S, q, c, \theta)$ to be the expected social utility if S was the chosen labeler set. Formally,

$$Q\left(S, q, c, \theta\right) = \sum_{\tilde{y}^S \in \{0,1\}^N} K^*\left(\tilde{y}^S, q, \theta\right) \mathbb{P}\left(\tilde{y}^S | q, \theta\right) - c(S),$$

where,

$$K^*\left(\tilde{y}^S, q, \theta\right) = \max_r \sum_{y \in \{0,1\}} \mathbb{P}\left(y | \tilde{y}^S, q, \theta\right) R(r, y);$$

$$\mathbb{P}\left(\tilde{y}^S | q, \theta\right) = \sum_{y \in \{0,1\}} \mathbb{P}\left(\tilde{y}^S | y, q\right) \mathbb{P}(y|\theta);\ c(S) = \sum_{i \in S} c_i;$$

$\mathbb{P}\left(\tilde{y}^S | y, q\right) = \prod_i q_i^{\mathbb{I}(\tilde{y}^i - y)} (1 - q_i)^{1 - \mathbb{I}(\tilde{y}^i - y)}$, where $\mathbb{I}(x) = 1$, if $x = 0$, and 0 otherwise.

Definition 6 (Labeler selection rule) *We can write the labeler selection rule in terms of an* expected social utility function *as,*

$$S^*(q, c, \theta) = \arg\max_{S \subseteq N} Q(S, q, c, \theta), \tag{5}$$

The following rule selects the label that maximizes the center's reward. If S^* is selected, then the center selects a label that maximizes its reward based on the labels reported by the labelers in S^*.

Definition 7 (Label selection rule) *Given the quality vector q, intrinsic bias parameter θ, and the noisy observations of the labeler set S^*, the optimal label r^* is selected by,*

$$r^*(\tilde{y}^{S^*}, q, \theta) = \arg\max_r \sum_y \mathbb{P}\left(y | \tilde{y}^{S^*}, q, \theta\right) R(r, y)\ .$$

In a basic mechanism, every document would be labeled by exactly one labeler. Under QUEST, the optimal set can be zero, one, or more. Bayesian reasoning allows multiple reports to be combined to increase accuracy. QUEST optimally balances the costs of labeling, the importance of the task (represented in R), and the need for labeler's advice given prior knowledge (represented by θ).

The idea for designing the payment is to pay i her cost, and in addition a positive fraction $\alpha > 0$ of i's externality (which in this context is always positive). Let W be the realized social utility, as stated in Definition 2 (based on r^*, the report given, and the observed true label y), and W_{-i} be the social utility obtained under the report that would be given if i cannot participate, given by Definition 3.

Using the above setup, we define the payment rule as,

Definition 8 (Payment rule)

$$\mathcal{P}_i^{\text{QUEST}} = \begin{cases} \alpha\left[W - W_{-i}\right] + c_i & \text{if } i \in S^*, \text{ and} \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

Algorithm 1 QUEST

for agents $i = 1, \ldots, n$ **do**
  agent i observes q_i;
  agent i reports $\hat{q}_i$;
end for
select labelers $S^*(q, c, \theta)$ according to Def. 6;
for agents in $S^*(q, c, \theta)$ **do**
  agent i observes and reports $\tilde{y}_i$;
end for
center reports $r^*(\tilde{y}^{S^*}, q, \theta)$ as per Def. 7;
true state of the document y realizes;
center realizes social utility W
computes payment $\mathcal{P}_i^{\text{QUEST}}$ to agent i, as per Def. 8;

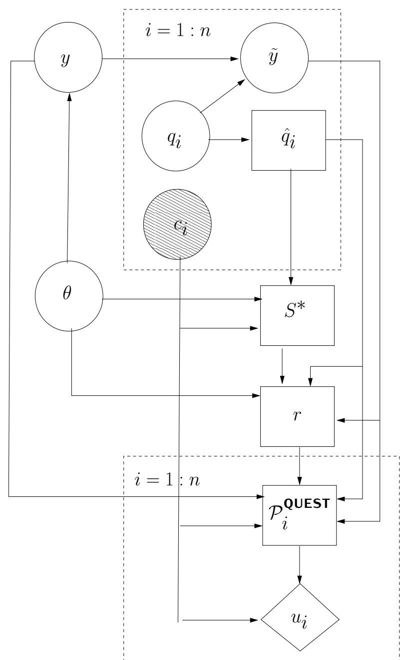

Figure 2: Multi-agent influence diagram for QUEST

This payment rule makes labelers partners in the center's venture. As we will see in the following section, an optimal selection rule can ensure non-negative payments in expectation, but it is possible that for a particular unfortunate realization of $\tilde{y}^S$ and y the return W_{-i} is higher than W and hence results in a negative term in (6).

Algorithm 1 shows the dynamics of QUEST in a subroutine format. Figure 2 shows the dependency of the different variables of this problem using a *multi-agent influence diagram* (MAID) [6].

4 Properties of QUEST

The proposed crowdsourcing mechanism has some important properties as follows. We denote $q = (q_i, q_{-i})$ to be the true quality of the agents.

First, we show that under QUEST, reporting truthfully is a best response for a labeler, if the other labelers respond truthfully.

Theorem 1 (Incentive Compatibility) QUEST *is EPIC.*

We prove this theorem with the aid of several lemmas.

Lemma 1 *Let* $S_1 = S^*(\hat{q}_i, q_{-i}), S_2 = S^*(q_i, q_{-i})$ *then,* $\mathbb{E}_{\tilde{y}^{S_1},y} W_{-i}(\hat{q}_i, q_{-i}) = \mathbb{E}_{\tilde{y}^{S_2},y} W_{-i}(q_i, q_{-i})$ *for all* $\hat{q}_i$.

This lemma shows that if i cannot participate in the labeler set, the expected social utility function is independent of i's reported quality.
Proof: Write $S_3 = S^*_{-i}(q_{-i}) \setminus S_1$ and $S_4 = S^*_{-i}(q_{-i}) \setminus S_2$, then we get,

$$\mathbb{E}_{\tilde{y}^{S_2},y} W_{-i}(q_i, q_{-i})$$

$$= \mathbb{E}_{\tilde{y}^{S_2},y} \mathbb{E}_{\tilde{y}^{S_4}|y,\theta} \left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \sum_{j \in S^*_{-i}} c_j \right]$$

Since $\tilde{y}^{S_2}$ is independent of $\tilde{y}^{S_4}$ given the true label y,

$$= \mathbb{E}_{\tilde{y}^{S_2},y} \mathbb{E}_{\tilde{y}^{S_4}|\tilde{y}^{S_2},y,\theta} \left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \sum_{j \in S^*_{-i}} c_j \right]$$

$$= \mathbb{E}_{\tilde{y}^{S_2},\tilde{y}^{S_4},y} \left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \sum_{j \in S^*_{-i}} c_j \right]$$

Observe that the term in expectation depends on $\tilde{y}^{S^*_{-i}}$and $S_2 \cup S_4 \supseteq S^*_{-i}(q_{-i})$. So, we have

$$= \mathbb{E}_{\tilde{y}^{S^*_{-i}(q_{-i})},y} \left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \sum_{j \in S^*_{-i}} c_j \right]$$

$$= \mathbb{E}_{\tilde{y}^{S_1},y} W_{-i}(\hat{q}_i, q_{-i}) \text{ (following similar steps).}$$

□

Lemma 2 *With* S_1, S_2 *as defined in Lemma 1. For any i,* $\mathbb{E}_{\tilde{y}^{S_2},y|q,\theta} W(q_i, q_{-i}) \geq \mathbb{E}_{\tilde{y}^{S_1},y|q,\theta} W(\hat{q}_i, q_{-i})$, *i.e., the expected social utility for the center is maximal when everyone reports truthfully.*

Proof: We have,

$$\mathbb{E}_{\tilde{y}^{S_2},y|q,\theta} W(q_i, q_{-i})$$

$$= \mathbb{E}_{\tilde{y}^{S_2}|q,\theta} \mathbb{E}_{y|\tilde{y}^{S_2},q,\theta} \left[R(r^*(\tilde{y}^{S_2}, q, \theta), y) - \sum_{j \in S_2} c_j \right]$$

The set $S_2 = S^*$ was chosen to maximize the term in the expectation hence $\forall S' \subseteq N$,

$$\geq \mathbb{E}_{\tilde{y}^{S'}|q,\theta} \mathbb{E}_{y|\tilde{y}^{S'},q,\theta} \left[R(r^*(\tilde{y}^{S'}, q, \theta), y) - \sum_{j \in S'} c_j \right].$$

In particular, the above is true for $S' = S_1$ which yields the desired inequality. $\square$

Proof of Theorem 1: The payment rule is ,

$$\mathcal{P}_i^{\text{QUEST}} = \begin{cases} \alpha(W - W_{-i}) + c_i & \text{if } i \in S^* \\ 0 & \text{otherwise} \end{cases}$$

The utility of agent i is $u_i = \mathcal{P}_i - c_i = \alpha(W - W_{-i})$.

To show that the mechanism is EPIC we need to show that

$$\begin{aligned} &\mathbb{E}_{\tilde{y}^{S_2}, y}\left[W(q_i, q_{-i}) - W_{-i}(q_i, q_{-i})\right] \\ &\geq \mathbb{E}_{\tilde{y}^{S_1}, y}\left[W(\hat{q}_i, q_{-i}) - W_{-i}(\hat{q}_i, q_{-i})\right] \end{aligned}$$

where $S_1 = S^*(\hat{q}_i, q_{-i}), S_2 = S^*(q_i, q_{-i})$ But the terms W_{-i} on either side of inequality cancel out due to Lemma 1, so to show EPIC we need to show

$$\mathbb{E}_{\tilde{y}^{S_2}, y} W(q_i, q_{-i}) \geq \mathbb{E}_{\tilde{y}^{S_1}, y} W(\hat{q}_i, q_{-i})$$

But this follows already from lemma 2. $\square$

Now we show that under QUEST, the expected utility of each agent is non-negative.

Theorem 2 (Individual Rationality) QUEST *is EAIR.*

Proof: If i is not selected in S^*, pay-off and cost are both 0 and IR holds. So we consider a q such that i is part of S^*, then,

$$\begin{aligned} &\frac{1}{\alpha}\mathbb{E}_{\tilde{y}^{S^*}, y|q,\theta} u_i(q_i, q_{-i}) \\ &= \mathbb{E}_{\tilde{y}^{S^*}, y|q,\theta}([W - W_{-i}]) + (c_i - c_i)/\alpha \\ &= \mathbb{E}_{\tilde{y}^{S^*}|q,\theta}\mathbb{E}_{y|\tilde{y}^{S^*}, q,\theta}\left[R(r^*(\tilde{y}^{S^*}, q, \theta), y) - \textstyle\sum_{j\in S_2} c_j\right] - \\ &\mathbb{E}_{\tilde{y}^{S^*}, y|q,\theta}\mathbb{E}_{\tilde{y}^{S^*_{-i}\setminus S^*}|y,q,\theta}\left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \textstyle\sum_{j\in S^*_{-i}} c_j\right] \end{aligned}$$

Writing $S_1 = S^*_{-i} \cap S^*$ and observing that $\tilde{y}^{S^*_{-i}\setminus S^*}$ is independent of $\tilde{y}^{S_1}$, we get,

$$\begin{aligned} &= \mathbb{E}_{\tilde{y}^{S^*}|q,\theta}\mathbb{E}_{y|\tilde{y}^{S^*}, q,\theta}\left[R(r^*(\tilde{y}^{S^*}, q, \theta), y) - \textstyle\sum_{j\in S_2} c_j\right] - \\ &\mathbb{E}_{\tilde{y}^{S^*}, y|q,\theta}\mathbb{E}_{\tilde{y}^{S^*_{-i}\setminus S^*}|y,\tilde{y}^{S_1},q,\theta}\left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \textstyle\sum_{j\in S^*_{-i}} c_j\right] \\ &= \mathbb{E}_{\tilde{y}^{S^*}|q,\theta}\mathbb{E}_{y|\tilde{y}^{S^*}, q,\theta}\left[R(r^*(\tilde{y}^{S^*}, q, \theta), y) - \textstyle\sum_{j\in S_2} c_j\right] - \\ &\mathbb{E}_{\tilde{y}^{S^*}, \tilde{y}^{S^*_{-i}\setminus S^*}, \tilde{y}^{S_1}, y|q,\theta}\left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \textstyle\sum_{j\in S^*_{-i}} c_j\right] \\ &= \mathbb{E}_{\tilde{y}^{S^*}|q,\theta}\mathbb{E}_{y|\tilde{y}^{S^*}, q,\theta}\left[R(r^*(\tilde{y}^{S^*}, q, \theta), y) - \textstyle\sum_{j\in S_2} c_j\right] - \\ &\mathbb{E}_{\tilde{y}^{S^*_{-i}}|q,\theta}\mathbb{E}_{y|\tilde{y}^{S^*_{-i}}, q,\theta}\left[R(r^*(\tilde{y}^{S^*_{-i}}, q_{-i}, \theta), y) - \textstyle\sum_{j\in S^*_{-i}} c_j\right] \end{aligned}$$

Now this difference is greater or equal to zero because the labeler selection rule chose S^* to maximize the term in expectation. $\square$

Even under the incomplete information setting, QUEST ensures that it maximizes the social utility (Equation (2)) in expectation. In other words, it does the same thing as an optimal controller would have done if he had access to the true qualities of the workers.

Theorem 3 (Social Utility Maximization) QUEST *controls the outsourcing work optimally in the sense that it maximizes the social utility (Equation (2)) in expectation over the true label* y *and the reported observed labels* $\tilde{y}^S$.

Proof: The proof follows directly from the fact that QUEST is ex post incentive compatible (Theorem 1), is individually rational (Theorem 2), and from the definition of the labeler selection rule (Definition 6) as QUEST chooses an allocation that maximize the expected social utility. □

Remark: QUEST is ex-post incentive compatible but not dominant strategy incentive compatible. This can be shown using a simple counter example which we skip due to lack of space.

5 Simulation Experiments and Empirical Robustness

We have shown that QUEST is an ex-post incentive compatible single shot mechanism. However, in a realistic crowdsourcing context, truth telling by strategic agents will happen over a period of time as the agents explore the outcomes of the mechanism during initial rounds and adjust their *bids* (we denote the report of a labeler's quality as her bid) according to (expected) utility obtained. In this section, we study the dynamic behavior of QUEST through simulations.

We consider all bids and true qualities to be in $[0.5, 1]$. If the quality is < 0.5, then one can flip the labels, and hence this interval is sufficient to consider.

We assume that the agents always start bidding above their true quality, as their primarily aim to get selected. They adjust their bids when they observe their utilities. However, they do not underbid, since it only reduces their chances of selection. We consider 250 discrete levels within $[0.5, 1]$ interval. In the simulations, we increase/decrease the bids of the agents only on these discrete levels. We fix the Bernoulli factor, $\theta = 0.75$, and the reward matrix R to be,

$$R = \begin{array}{c|cc} & r=0 & r=1 \\ \hline y=0 & 100 & -100 \\ y=1 & -100 & 200 \end{array}$$

The agents in our simulation could be *opportunistic*, *neutral*, *conservative* (explained below).

Conservative: An agent is conservative if she avoids risk. If she overbids and gets positive utility, she continues bidding in that level. If the overbid results in a negative utility, then she reduces the bid by 5 levels towards true quality. If the agent is not selected in spite of an overbid, she begins to bid in the true quality from the next round. After reaching the true quality level, she stays there forever.

Neutral: This type of agents are neutral about taking risks. Therefore, even if she overbids and gets positive utility, she continues with old bid w.p. 0.8 and begins to be truthful w.p. 0.2. If the overbid results in a negative utility, then she reduces the bid by 1 level. If the agent is not selected, she *resets* bid to the maximum quality (in this case, 1), and if selected, the previous subroutine continues. These *reset* attempts are limited to 2. If all attempts fail to get her selected, she continues with old bid. If she reaches true quality level, she continues bidding in that level.

Opportunistic: This refers to an agent that loves taking risk. Therefore, even if she overbids and gets positive utility, she reduces bid by 5 levels towards true quality. If the overbid results in a negative utility, then she reduces the bid by 1 level w.p. 0.4 and continue at the same level w.p. 0.6. If the agent is not selected, she *resets* bids to the maximum quality (in this case, 1), and if selected, the previous subroutine continues. These *reset* attempts are limited to 4. If all attempts fail to get her selected, she continues with old bid. If she reaches true quality level, she continues bidding at that level.

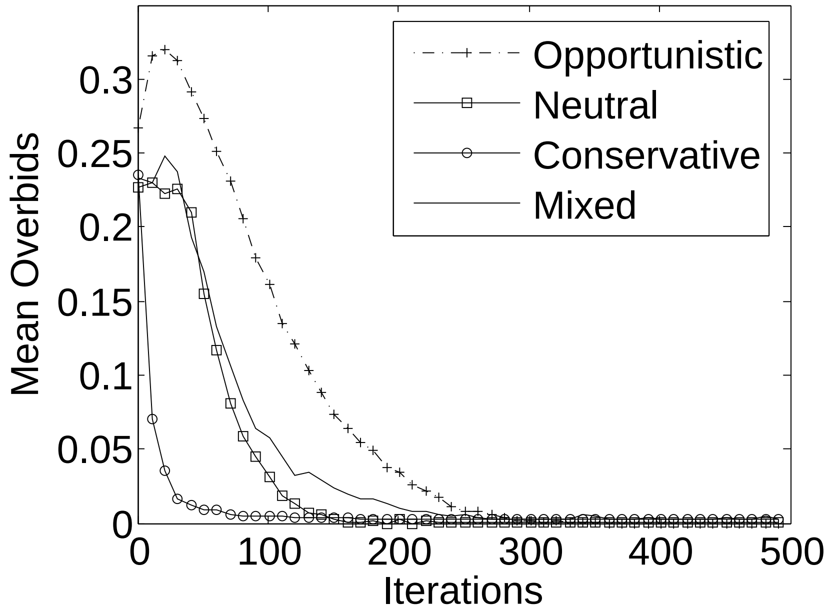

Figure 3: Average quality overbidding over iterations.

Considering that any kind of behavior can fit the labelers in the real world, we study four scenarios for a population consisting of five labelers: (1) *only* conservative agents, (2) *only* neutral agents, (3) *only* opportunistic agents, (4) a *mixed* population. For scenario 4, we consider 3 agents to be neutral, one to be conservative, and one to be opportunistic.

The costs and quality levels of the agents are chosen according to a uniform distribution over $[0.5, 1]$. In successive iterations of the game, we record the difference between the current bid and true quality, and plot its average for the *selected* agents on the y-axis of Figure 3 for all the four scenarios described above.

It shows that in all the cases, the bids of the agents converge to the true quality levels, however the rate of convergence increases as the population becomes more and more conservative. This phenomenon exhibits that even with a very realistic behavior of the population, the tendency to misreport the qualities eventually diminishes. While all the agents reach the truth-reporting state, it is not beneficial for them to unilaterally deviate since that it has been proved to be an ex-post Nash equilibrium of the quality reporting game.

6 Discussion

In this paper, we have investigated a class of crowdsourcing problems that belong to the common value model. We proposed a mechanism QUEST which guarantees ex-post incentive compatibility, individual rationality, and social utility maximization, which serves to perform as the first principled way of approaching this class of crowdsourcing problems.

This work is an excellent starting point for several important extensions. The exact assignment rule has a running time that is exponential in the crowd size, which limits it to modest sizes. It is of interest to try to find suitable approximations to the allocation rule that can, in combination with an adaptation to the payment rule, guarantee a suitable notion of IC and IR. Also adding document features and learning, and privately known costs would be of practical interest.

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