MELODY: A Long-term Dynamic Quality-Aware Incentive Mechanism for Crowdsourcing

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Abstract—Crowdsourcing allows requesters to allocate tasks to a group of workers on the Internet to make use of their collective intelligence. Quality control is a key design objective in incentive mechanisms for crowdsourcing as requesters aim at obtaining high-quality answers under a limited budget. However, when measuring workers' long-term quality, existing mechanisms either fail to utilize workers' historical information, or treat workers' quality as stable and ignore its temporal characteristics, hence performing poorly in a long run. In this paper we propose MELODY, a long-term dynamic quality-aware incentive mechanism for crowdsourcing. MELODY models interaction between requesters and workers as reverse auctions that run continuously. In each run of MELODY, we design a truthful, individual rational, budget feasible and quality-aware algorithm for task allocation with polynomial-time computation complexity and $O(1)$ performance ratio. Moreover, taking into consideration the long-term characteristics of workers' quality, we propose a novel framework in MELODY for quality inference and parameters learning based on Linear Dynamical Systems at the end of each run, which takes full advantage of workers' historical information and predicts their quality accurately. Through extensive simulations, we demonstrate that MELODY outperforms existing work in terms of both quality estimation (reducing estimation error by $17.6\% \sim 24.2\%$) and social performance (increasing requester's utility by $18.2\% \sim 46.6\%$) in long-term scenarios.

Index Terms—Crowdsourcing, incentive mechanism, quality control, approximation algorithm, inference and learning

1 INTRODUCTION

THE past decade has witnessed the proliferation of *crowdsourcing*, a new problem-solving platform which outsources small tasks to a large number of online labors and solves the tasks by harnessing their collective intelligence. In crowdsoucing markets such as Amazon Mechanical Turk (AMT)[1], requesters submit batches of small tasks whose solving is quite difficult or too expensive to automate but simple for humans, such as proofreading and image labeling, along with the amount of money they are willing to pay. Workers then choose to complete tasks and receive payment.

Most of the existing incentive mechanisms for crowdsoucing[2] use auction and pricing [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12] to provide workers with monetary rewards for their participation costs. In the proposed mechanisms [4], [5], [6], [7], [9], [10], [13], [14], [15], *quality control* is one of key considerations for platform designers, since requesters wish to maximize the quality of answers they obtained under a given budget. In general, requesters rely on redundancy (i.e., allocating a single task to multiple workers) to ensure quality and identify correct answers [16], [17]. Despite its seemingly simplicity, this method remains nontrivial due to the following two reasons. On the one hand, crowd workers are at different levels of problem-solving capability and may provide answers with varied quality [18], which should be timely detected and accurately measured by the crowdsourcing platform. On the other hand, given the estimated quality of users, it is still an open problem how to design an optimal task allocation scheme, while preserving several desirable scheme properties such as truthfulness and competitiveness (defined later). In this paper we try to solve the above two challenging issues.

It should be noted that, though many quality-aware incentive mechanisms for crowdsourcing have been proposed recently, they mainly focus on how to allocate a *single* set of tasks to a group of workers by running a particular task allocation algorithm, and how to measure workers' quality based on their performance in a *single run*. However, in reality, crowdsourcing platforms (e.g., AMT) need to outsource *multiple* sets of tasks continuously for a long time. To fit these *multi-run* scenarios, existing mechanisms [5], [6], [7], [9], [10], [14], [16] can only execute their algorithms for each set of tasks *independently*, without considering workers' quality of information gathered in previous runs. The independent repetition of the algorithm makes workers' quality overtuned to their current state and is vulnerable to workers' accidentally abnormal performance, which leads to a poor representation of workers' quality known as *over-fitting* [19]. On the contrary, a few existing mechanisms do utilize workers' historical information when measuring their quality [4], [13]. However, they consider it *stable* (i.e., it is drawn from a specific statistical distribution) and ignore its temporal characteristics (i.e., worker's prior information is treated as a set rather than a sequence). Such models lack sufficient fitting capability and fail to model real workers' long-term quality, which is known as *under-fitting* [19].

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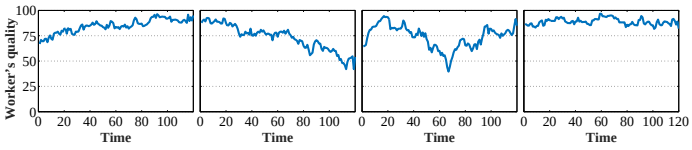
1. http://www.mturk.com

2. Some of the work is categorized as *crowdsensing* or *participatory sensing* rather than crowdsourcing. However, we do not distinguish these three paradigms since they make no essential difference in this paper.



(a) Rising (b) Declining (c) Fluctuating (d) Stable

Fig. 1: Four typical types of workers' long-term quality curves in reality. The data come from crowdsourcing tasks conducted on AMT for affective text analysis. We measure workers' quality as "maximum rating - average error", where the average error is the difference between ground truth and worker's average rating over 10 items.

To further illustrate these problems, we analyze a public data set[3] publicized by [20] and plot four typical types of worker's time-varying quality curves in Fig. 1, from which we learn two important properties of workers' long-term quality: 1) A worker's quality at a given point is much more related with his recent quality, because workers' latent quality is unlikely to change drastically in a few runs. 2) Except some rare cases (Fig. 1d) where quality exhibits stability in quite a long time[4], most workers' long-term quality curves present a notable rising, declining and fluctuating as shown in Fig. 1a, 1b, and 1c, respectively. Such trends usually result from worker's gradually accumulated change in the level of expertise, proficiency and effort rather than accidental error and cannot be characterized by a simple statistical distribution. However, existing mechanisms ignore these two properties of workers' long-term quality, thus fail in maintaining decent performance in a long run.

To address the above over-fitting and under-fitting problems, in this paper we propose MELODY, a truthful and budget feasible incentive MEchanism considering workers' LOng-term DYnamic quality for crowdsourcing markets. MELODY models the interaction between requesters and workers as continuously running reverse auctions. In each run, a requester posts a set of tasks with a budget and workers submit their bid information. MELODY then determines the task allocation scheme and payment scheme, such that the bid of each worker and quality requirement of each task are conformed, meanwhile the properties of truthfulness, individual rationality, competitiveness and computational efficiency are guaranteed. We compare properties of some popular incentive mechanisms for crowdsourcing with MELODY in Table 1.

To characterize the dynamicity of workers' long-term quality, in MELODY we also propose a novel framework for quality inference and parameters learning based on Linear Dynamical Systems (LDS) [19], [21], [22]. The LDS-based framework models worker's quality as latent time series which cannot be observed directly by the crowdsourcing platform but dominate worker's performance. At the end of each run, MELODY infers every worker's posterior quality after observing his performance in this run, and then makes prediction about his quality for the next run. In addition, MELODY re-estimates the hyper-parameters of every worker regularly to ensure accuracy of quality inference by using Expectation Maximization (EM) algorithm. Simulation results show that compared with prior work, MELODY increases requester's utility by $18.2\% \sim 46.6\%$ and reduce estimation error of workers' quality by $17.6\% \sim 24.2\%$.

3. http://sites.google.com/site/nlpannotations

4. A worker's quality is called *stable* in this case study if the slope of regression line of quality curve is within [-0.05, 0.05] and the variance of quality curve is below 100. The percentage of stable workers under the definition is 8.5%.

TABLE 1: Comparison of several popular incentive mechanisms for crowdsourcing with MELODY.

	[2]	[3]	[4]	[5]	[6]	[7]	MELODY
Truthfulness	✓	✓	✓	✓			✓
Individual rationality	✓	✓	✓	✓			✓
Competitiveness	✓	✓		✓			✓
Computational efficiency	✓	✓	✓	✓		✓	✓
Budget feasibility	✓	✓	✓			✓	✓
(short-term) Quality awareness			✓	✓	✓	✓	✓
Long-term quality awareness							✓

In summary, our contributions are as follows:

- To the best of our knowledge, we are the first to consider long-term characteristics of workers' quality that do matter to the performance of incentive mechanisms for crowdsourcing but have not been well addressed by existing work.
- We propose MELODY for crowdsourcing which models the interaction between requesters and workers as reverse auctions that run continuously. MELODY possesses most of the desired properties such as truthfulness and competitiveness. Meanwhile, we present a novel LDS-based inference and learning approach in MELODY to estimate workers' long-term dynamic quality.
- We conduct extensive simulations and the experimental results demonstrate the effectiveness and excellent performance of our mechanism compared with existing work.

2 Related Work

2.1 Incentive Mechanisms for Crowdsourcing

Except for a few non-monetary incentive mechanisms such as [23] and [24], most incentive mechanisms for crowdsourcing are based on auction and pricing, using monetary reward to incentivize workers [2], [3], [8], [9], [10], [11], [25], [26]. For example, Zhao *et al.* [2] propose a truthful mechanism based on online auction where users arrive in random order. Han *et al.* [3] take users' available time periods into consideration and design a truthful mechanism for mobile crowdsensing. Gao *et al.* [8] design a Lyapunov-based VCG auction policy for online worker selection while providing long-term participation. However, none of the above mechanisms takes the factor of workers' quality into consideration. Simply adding a random variable as the measurement of quality cannot well address the problem since the quality may be overfitted or underfitted in long-term scenarios, as mentioned in introduction.

Several prior work takes quality control into consideration when designing their task allocation schemes [4], [5], [6], [7], [12], [27], [28], [29]. For example, Zhang *et al.* [4] use Bayesian inference for task allocation and quality estimation. Jin *et al.* [5] model the task allocation problem as the

set cover problem and propose a quality-aware mechanism for mobile crowdsensing. Li *et al.* [7] take workers' reliability into consideration for crowdsoucing high quality labels. Ho *et al.* [27] study the problem of adjusting quality-contingent payments for tasks and establish a multi-armed bandit model. However, as mentioned before, these mechanisms do not consider long-term characteristics of workers' quality.

2.2 Quality Control for Crowdsourcing

Quality control is one of the biggest concern is crowdsourcing tasks. A large amount of work focuses on the research topic of how to aggregate crowd labels according to their different quality [30], [31], [32], [33], [34], [35]. Several approaches are proposed to select proper crowd workers to perform specific crowdsourcing tasks [36], [37], [38]. There is also some prior work investigating how to design the crowdsourcing questions or tasks better, for example, [39], [40], [41], [42]. Additionally, some work also studies the long-term incentive mechanism for user-generated content [43], [44]. These work are explicitly or implicitly related to quality control, as the requesters can obtain high-quality answers by designing better tasks or targeting a group of informative workers. However, none of these work considers budget constraint, which is the biggest difference between our mechanism and the above ones.

2.3 Quality Measurement for Crowdsourcing

How to measure quality of workers or answers in crowdsourcing is also attracting researchers' interest in recent years [10], [14], [17], [45]. For example, Liu *et al.* [14] propose a network management framework including quality of information (QoI) satisfaction index to tackle the challenges of supporting QoI requirements in participatory sensing. Yang *et al.* [10] measure data quality as its deviation from the cluster centroid in their quality-based surplus sharing method for participatory sensing. Mason *et al.* [45] introduce empirical analysis of quality assurance on AMT. Song *et al.* [17] propose a QoI satisfaction metric to describe the level that collected sensory data can satisfy the requirement of a task. The main difference between our paper and these work is that we focus more on estimation and update methods of workers' long-term quality rather than quality measurement metrics discussed in these work. Therefore, the above mentioned quality measurement metrics can be incorporated naturally into our work.

3 System Model and Problem Formulation

In this section we discuss the system model and formulate the task allocation problem. We first introduce our basic assumptions and system workflow, then present how to model workers and utility of workers and requesters. Finally, we define the design objectives of MELODY.

3.1 Basic Model and Assumptions

In our system we consider a single *platform*, upon which there are several *requesters* residing in the cloud and a universal set of *workers* $\mathcal{W}_U = \{1, 2, \ldots\}$. In each *run* $r \in \mathbb{N}^+$, one of the requesters publicizes a set of crowdsourcing *tasks* $\mathcal{T}^r = \{t_1^r, t_2^r, \ldots\}$ to a set of qualified workers $\mathcal{W}^r \subseteq \mathcal{W}_U$. We will explain why and how to choose qualified workers in Section 4. A crowdsourcing platform usually covers a wide variety of tasks. Without loss of generality, in this work we only consider tasks that are *homogeneous* in terms of the knowledge and effort needed to solve them, because the model proposed in this paper can be easily extended to the scenario with multiple types of tasks by designing the incentive mechanism for each individual type respectively [23].

TABLE 2: Lookup table for key notations.

Notation	Definition
$\mathcal{W}_U$	Universal set of workers
$\mathcal{W}^r$	Set of qualified workers in run r
i	The i-th worker in $\mathcal{W}_U$
$\mathcal{T}^r$	Set of tasks publicized by the requester in run r
t_j^r	The j-th task in $\mathcal{T}^r$
B^r	The budget set by the requester in run r
$x_{i,j}^r$	Indicator of whether t_j^r is allocated to i
$p_{i,j}^r$	Payment to i for completing t_j^r
$s_{i,j}^r$	Score for the answer of t_j^r from i
$\mathcal{S}_i^r$	Set of scores that i gets in run r
$\mathbf{S}_i^r$	Sequence $\{\mathcal{S}_i^1, ..., \mathcal{S}_i^r\}$
q_i^r	Latent quality of i in run r
$p(q_i^r \vert q_i^{r-1})$	Transition probability density of i
$p(S_i^r \vert q_i^r)$	Emission probability density of i
a_i	Transition coefficient of i
γ_i, η_i	Variance of transition and emission density of i
$\alpha(q_i^r)$, $\widehat{\alpha}(q_i^r)$	Prior and posterior probability of q_i^r
c_i^r, n_i^r	The cost and frequency that i bids in run r
$\overline{c}_i^r$, $\overline{n}_i^r$	The true cost and frequency of i in run r
$u_{i,j}^r$	The utility of i on t_j^r
u_i^r	The utility of i in run r
U^r	The utility of the requester in run r
Q_j^r	The quality threshold of t_j^r
μ_i^r	Mean of $\alpha(q_i^r)$ (estimated quality)
$\widehat{\mu}_i^r, \widehat{\sigma}_i^r$	Mean and variance of $\widehat{\alpha}(q_i^r)$
$[\Theta_m, \Theta_M]$	The acceptable interval of worker's quality
$[C_m, C_M]$	The acceptable interval of worker's bid of cost

We model the interaction between the requester and workers in a given run as a *reverse auction*. Game-theoretic workers sell their wisdom or effort to the requester and seek to make strategy to maximize their individual utility, and the requester decides whether and at what price to buy their services.

In our model we assume that a task can be allocated to multiple workers for quality guarantee, and a worker can be assigned multiple tasks in a run. We also assume that the requester holds a *budget* $B^r \in \mathbb{R}^+$ as the maximum amount of total payment he is willing to make in run *r*.

Table 2 summarizes the frequently used notations in this paper. Some will be introduced later.

3.2 System Workflow

Our auction-based system consists of multiple basic run units. In run r, the system workflow is described as follows:

1) Before auction starts, the platform receives a set of tasks $\mathcal{T}^r$ with a budget constraint B^r from one requester, and bids information from all workers. It then determines the set of qualified workers $\mathcal{W}^r \subseteq \mathcal{W}_U$.
2) The platform then determines allocation scheme $\mathcal{X}^r \triangleq \{x_{i,j}^r | i \in \mathcal{W}^r, t_j^r \in \mathcal{T}^r\}$, where the binary

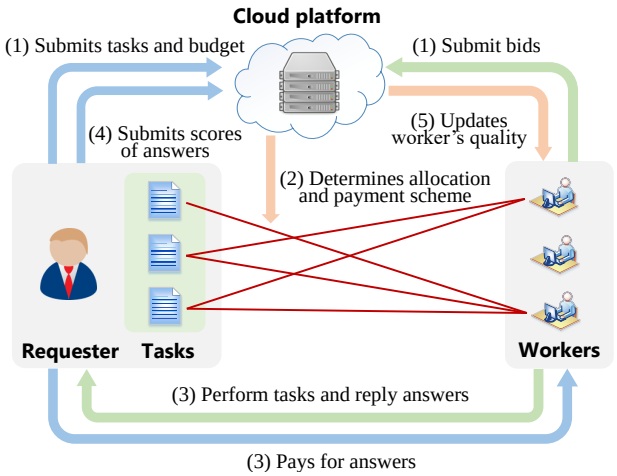


Fig. 2: System workflow in each run unit. The indices of arrows and captions in the figure are corresponding to those in Section 3.1.

variable $x_{i,j}^r \in \{0,1\}$ indicates whether t_j^r is allocated to worker i in run r.

3) Worker i completes every task t_j^r allocated to him, replies answer to the requester and gets payment $p_{i,j}^r \in \mathbb{R}^+$ for the task according to the payment scheme $\mathcal{P}^r \triangleq \{p_{i,j}^r | i \in \mathcal{W}^r, t_j^r \in \mathcal{T}^r\}$.
4) For the answer of task t_j^r from worker i, a *score* $s_{i,j}^r \in \mathbb{R}$ is given and submitted to the platform by the requester.[5] Denote $\mathcal{S}_i^r$ the set of scores worker i gets in run r and $\mathbf{S}_i^r$ the sequence of $\mathcal{S}_i^r$: $\{\mathcal{S}_i^1, ..., \mathcal{S}_i^r\}$.
5) After receiving all scores in this run, the platform then updates every worker's quality for the next run.

Fig. 2 illustrates the above system workflow in each run.

3.3 Worker Modeling

Consider the problem of modeling worker's performance $p(\mathbf{S}_i^r) = p(\mathcal{S}_i^1, ..., \mathcal{S}_i^r)$. The easiest way to handle this joint distribution for a sequence of observations would be simply to ignore the sequential aspects and treat all $\mathcal{S}_i^r$ as independent and identical distributions (i.i.d.), i.e., $p(\mathbf{S}_i^r) = \prod_{t=1}^r p(\mathcal{S}_i^t)$. However, such an approach would fail to exploit the correlations between observations that are close in the sequence which we have shown before. Therefore, it's natural to turn to the Markov model $p(\mathbf{S}_i^r) = \prod_{t=1}^r p(\mathcal{S}_i^t | \mathbf{S}_i^{t-1})$, in which worker's current performance is dependent on previous ones. But a new problem arises as the number of parameters will grow unlimitedly with the increase of length of the sequence. Certainly, we can reduce model complexity by making an assumption that $\mathcal{S}_i^r$ only depends on its most recent d predecessors, but any sort of hand-crafted d is hardly likely to be optimal. Besides, we lose correlations between two observations over d time units under the assumption.

To address the above shortcomings, instead of directly modeling worker's performance, we introduce a latent random variable $q_i^r \in \mathbb{R}$ to characterize the quality of worker i in run r, which dominates worker's immediate performance. Here "latent" means q_i^r cannot be observed directly and needs to be inferred by the platform. We allow the probability distribution of q_i^r to depend on the state of previous latent variable q_i^{r-1}, thus $p(q_i^r | q_i^{r-1})$ is known as the *transition probability density* from q_i^{r-1} to q_i^r. In addition, latent variable q_i^r and observed variable $\mathcal{S}_i^r$ are connected by the *emission probability density* $p(\mathcal{S}_i^r | q_i^r)$. It is worth noticing that such model is not limited by the Markov assumption to any order d (because there is always a path connecting any two observations via latent variables) and yet can be specified using a limited number of free parameters.

In practice, we concern two types of conditional probability of q_i^r. The first is the prior probability of q_i^r given all previous sets of observed scores:

$$\alpha(q_i^r) \triangleq p(q_i^r | \mathbf{S}_i^{r-1}), \tag{1}$$

and the second is the posterior probability of q_i^r given all sets of observed scores (including the set of scores from run r):

$$\widehat{\alpha}(q_i^r) \triangleq p(q_i^r | \mathbf{S}_i^r). \tag{2}$$

In our proposed model, $\alpha(q_i^r)$ is used to measure worker's quality in task allocation, while $\widehat{\alpha}(q_i^r)$ is used to infer worker's quality in the next run. The above prior and posterior probabilities are connected by transition density:

$$\alpha(q_i^r) = \widehat{\alpha}(q_i^{r-1}) p(q_i^r | q_i^{r-1}). \tag{3}$$

To formulate our problem, each worker $i \in \mathcal{W}_U$ in run r associates:

- a bid of *cost* for performing every single task: $c_i^r \in \mathbb{R}^+$;
- a bid of maximum number of tasks (also called *frequency*) he is willing to complete: $n_i^r \in \mathbb{N}^+$;
- the prior probability of q_i^r: $\alpha(q_i^r)$.

The above bid of cost and frequency constitute the *bid* $b_i^r = (c_i^r, n_i^r)$ of worker i. A worker may lie about his bid to maximize his utility, so we use $\overline{b}_i^r = (\overline{c}_i^r, \overline{n}_i^r)$ to denote worker i's true bid, which is private information and only known to himself.

Note that though the above model is similar to Hidden Markov Models (HMM), methods for solving HMM cannot be used here as the latent variables of workers' quality are continuous.

3.4 Utilities of Workers and Requesters

In run r, each worker strategically determines his bid to maximize his utility given his true bid. We formalize a worker's *utility* in Definition 1 as follows.

Definition 1 (A worker's utility). *The utility of worker i in run r is the difference between the total payment he receives and his total cost:*

$$u_i^r = \sum_{j=1}^{|\mathcal{T}^r|} u_{i,j}^r, \tag{4}$$

where

$$u_{i,j}^r = \begin{cases} p_{i,j}^r - \overline{c}_i^r, & if\ x_{i,j}^r = 1; \\ 0, & otherwise. \end{cases} \tag{5}$$

5. Scores can be given either by the requester manually after answer verification, or by unsupervised algorithms automatically such as majority voting. Readers could refer to Section 2.3 for more detailed discussion about quality (score) measurement.

To ensure quality of answers (e.g., confidence level of labeling) collected from workers, sufficient amount of collective intelligence and effort are necessary for each task. It is worth noticing that quantifying the *integrated crowd quality* remains a challenging problem in crowdsoucing, since types of answers are in varied forms (e.g., texts, photos, options), and there may exist correlation or interaction among answers. Therefore, existing mechanisms all make moderate simplification when measuring the integrated quality of a crowd of people, such as Bayesian assumption [4], additive assumption [5], and proportional assumption [7]. Based on our aforementioned model, we take the additive assumption [5] in this paper, in which the integrated quality that all workers generate on task t_j^r is defined as $\sum_{i\in\mathcal{W}^r} x_{i,j}^r \mathbb{E}[\alpha(q_i^r)]$, and a task t_j^r is *satisfied* if the integrated quality received by this task exceeds a threshold Q_j^r set by the requester. Therefore, we give the definition of satisfied tasks as follows.

Definition 2 (A satisfied task)**.** *Task t_j^r is satisfied if*

$$\sum_{i\in\mathcal{W}^r} x_{i,j}^r \mathbb{E}[\alpha(q_i^r)] \geq Q_j^r. \tag{6}$$

For simplicity, we denote $\mu_i^r = \mathbb{E}[\alpha(q_i^r)]$, and we call μ_i^r the *estimated quality* of worker i. Note that we are unable to use q_i^r to characterize worker i's quality since it is a hidden variable that cannot be observed directly by the platform (the platform is only aware of $\alpha(q_i^r)$, the prior probability of worker i's quality). Therefore, we use the estimated expected quality $\mathbb{E}[\alpha(q_i^r)]$ instead to define a satisfied task. We will empirically prove the efficacy of our proposed algorithm by measuring the number of truly satisfied tasks, i.e., task t_j^r satisfying $\sum_{i\in\mathcal{W}^r} x_{i,j}^r q_i^r \geq Q_j^r$, in the experiment part.

Based on above conceptions, we present the definition of requester's utility in Definition 3.

Definition 3 (A requester's utility)**.** *The utility of the requester in run r is the total number of satisfied tasks:*

$$U^r = \sum_{t_j^r\in\mathcal{T}^r} I\Big(\sum_{i\in\mathcal{W}^r} x_{i,j}^r \mu_i^r \geq Q_j^r\Big), \tag{7}$$

where $I(\cdot)$ is indicator function defined as $I(\mathrm{TRUE}) = 1$ and $I(\mathrm{FALSE}) = 0$.

It should be noted that, in the above definition we use binary values to measure the utility of the requester, that is, the utility of a task is 1 as long as its total received quality meets the threshold. The reason why we use the binary indicator rather than the amount of received quality as the requester's utility is that we aim to allocate workers to tasks evenly and maximize the number of completed tasks. Generally, the marginal utility of assigning a worker to a satisfied task is much less than that of assigning the worker to a new one. Therefore, as long as one task is satisfied, the allocating algorithm should be encouraged to avoid "wasting" and assign workers to new unsatisfied tasks, which can be achieved by Definition 3 since assigning the worker to satisfied tasks will no longer increase the requester's utility in this case. However, if we choose the amount of received quality as the requester's utility, the allocating algorithm will be in absence of such guidance and may end up with a scheme that assigns all workers to one task in extreme case.

3.5 Design Objectives of Platform

We formulate the *Single Run Auction* (SRA) problem as the following programming:

Definition 4 (The SRA problem)**.** *In run r, the platform wishes to maximize requester's utility under the constraints of requester's budget and workers' bids*[6]*:*

$$\max \quad U^r \tag{8}$$

$$\text{s.t.} \quad \sum_{i\in\mathcal{W}^r, t_j^r\in\mathcal{T}^r} p_{i,j}^r \leq B^r \tag{9}$$

$$\sum_{t_j^r\in\mathcal{T}^r} x_{i,j}^r \leq n_i^r, \qquad \forall i \in \mathcal{W}^r \tag{10}$$

$$x_{i,j}^r \in \{0,1\}, \qquad \forall i \in \mathcal{W}^r, \forall t_j^r \in \mathcal{T}^r \tag{11}$$

Due to the NP-hardness of the SRA problem (see Theorem 1) and to improve practicability of the platform, we aim to design MELODY satisfying the following desirable properties:

- **Short-term truthfulness:** A mechanism is *short-term truthful* if reporting the true bid is a *dominant strategy* for all workers in one particular run. Formally, a mechanism is short-term truthful if for every worker $i \in \mathcal{W}^r$ with true bid $\bar{b}_i^r$ and any set of bids $\mathcal{B}_{-i}^r$ posted by bidders in $\mathcal{W}^r\backslash\{i\}$, we have $u_i^r(\bar{b}_i^r, \mathcal{B}_{-i}^r) \geq u_i^r(b_i^r, \mathcal{B}_{-i}^r)$ for any bid b_i^r of worker i in run r.
- **Long-term truthfulness:** A mechanism is *long-term truthful* if a worker cannot increase his *expected* total utility by bidding untruthfully in the long term. Formally, let $V_i^T(\mu)$ and $V_i^U(\mu)$ be the expected total utility of worker i with an initial quality μ if he always bids truthfully or otherwise, respectively. Then we say a mechanism long-term truthful if $V_i^T(\mu) \geq V_i^U(\mu)$ for every worker i with any initial quality μ.
- **Individual rationality:** A mechanism is *individual rational* if each participating worker $i \in \mathcal{W}^r$ will have a non-negative utility: $u_i^r \geq 0$.
- **Competitiveness:** We use notation *OPT* to denote the *optimal solution* that can be computed in the case where the platform has full knowledge about workers' true bids, and *MEL* to denote the outcome of MELODY. A mechanism is *competitive* if the approximation factor $\frac{OPT}{MEL} = O(1)$.
- **Computational efficiency:** A mechanism is *computationally efficient* if both the allocation and the payment schemes run polynomial time.
- **Long-term quality awareness:** A mechanism is *long-term quality-aware* if it is able to utilize workers' historical information according to its long-term characteristics when estimating workers' quality.

6. Note that the SRA problem can be easily converted to its "dual" form where the platform wishes to minimize the requester's budget (i.e., to maximize the requester's profit) under the constraints of system-wide utility and workers' bids. Accordingly, the proposed algorithm in the following can be adapted to this dual case by modifying the terminating condition.

In the following sections, when our discussion is only on a fixed run (worker), the superscript r (subscript i) in all notations will be omitted for simplicity.

4 Mechanism Design for Single Run Auction

In this section, we present the mechanism design of MELODY for the SRA problem. We first prove the NP-hardness of the SRA problem. The superscript r in all notations is omitted in this section.

Theorem 1. *The SRA problem is NP-hard.*

Proof: It is sufficient to demonstrate that the classical NP-hard *dual bin packing* (DBP, also known as *bin covering*) problem introduced in [46], [47], [48] is polynomial-time reducible to the SRA problem. An instance of the DBP problem is, given a set $\mathcal{I} = \{a_1, a_2, \ldots, a_n\}$ of items, a size function $s(a) > 0$ for each item a, and a bin capacity C, how to pack the elements of $\mathcal{I}$ into a maximum number of bins so that the sum of sizes in any bin is at least C. We now construct a corresponding instance of the SRA problem specified in Definition 4. We first transform the item set $\mathcal{I}$ and size function $s(a)$ into workers' set $\mathcal{W}^r$ and the estimated quality μ_i^r, respectively. Next we set $p_{i,j}^r = 0$, $n_i^r = 1$, and $Q_j^r = C$ for all $i \in \mathcal{W}^r$ and $t_j^r \in \mathcal{T}^r$. Now it's easy to see that if there is a subroutine to solve the SRA problem, it could be used in polynomial time (excluding the time within the subroutine) to solve the DBP problem. Therefore, every instance of the DBP problem is polynomial-time reducible to an instance of the SRA problem. Since the DBP problem is NP-hard [48], we prove that the SRA problem is also NP-hard. □

Due to the NP-hardness of SRA problem, it is inadvisable for us to compute the precise optimal solution in real scenario because of its exponentially increasing execution time with input scale. Therefore, inspired by the basic idea proposed in [49], we design an approximated greedy algorithm to solve the SRA problem in run r, as shown in Algorithm 1.

Algorithm 1 takes workers' set $\mathcal{W}_U$, tasks' set $\mathcal{T}$ and budget B as input, and outputs allocation scheme $\mathcal{X}$ and payment scheme $\mathcal{P}$. Firstly algorithm 1 determines qualified workers' set $\mathcal{W}$ in this run according to an acceptable interval of quality $[\Theta_m, \Theta_M]$ and an acceptable interval of bid of cost $[C_m, C_M]$ (line 1). The reasons for setting such acceptable intervals lie in that: 1) Θ_m is used to ensure quality of selected workers; 2) Θ_M is implied by the maximum of scores generated by rating methods; 3) C_m and C_M are used to exclude malicious workers whose bids are too low for completing the tasks and to ensure budget feasibility, respectively. Algorithm 1 is subsequently divided into two stages: *pre-allocation* (lines 2-14) and *scheme determination* (lines 15-21).

In pre-allocation stage, the algorithm first sorts all workers in $\mathcal{W}$ in descending order of their *estimated quality per unit cost* μ_i/c_i and all tasks in ascending order of their quality requirement Q_j (lines 2-3). The sorted $\mathcal{W}$ is also referred to as *ranking queue*. For each task t_j, the algorithm uses P_j to denote total amount the requester needs to pay for this task if it is finally selected (line 4). In the main loop

Algorithm 1 MELODY Design for the SRA Problem

Input: $\mathcal{W}_U$, $\mathcal{T}$, B;
Output: $\mathcal{X}$, $\mathcal{P}$;
1: $\mathcal{W} \leftarrow \{i \in \mathcal{W}_U | \Theta_m \leq \mu_i \leq \Theta_M \ and \ C_m \leq c_i \leq C_M\}$
2: Sort all $i \in \mathcal{W}$ in descending order of μ_i/c_i;
3: Sort all $t_j \in \mathcal{T}$ in ascending order of Q_j;
4: $x_{i,j} \leftarrow 0$, $p_{i,j} \leftarrow 0$, $P_j \leftarrow 0$ **for each** $i \in \mathcal{W}$, $t_j \in \mathcal{T}$;
5: **for all** $t_j \in \mathcal{T}$ **do**
6: Find the smallest k such that $\sum_{i \leq k \ and \ n_i > 0} \mu_i \geq Q_j$;
7: **if** such k exists **then**
8: **for all** i s.t. $i \leq k \ and \ n_i > 0$ **do**
9: $x_{i,j} \leftarrow 1$;
10: $p_{i,j} \leftarrow \frac{c_{k+1}}{\mu_{k+1}} \mu_i$;
11: $n_i \leftarrow n_i - 1$, $P_j \leftarrow P_j + p_{i,j}$;
12: **end for**
13: **end if**
14: **end for**
15: $\mathcal{X} \leftarrow \emptyset$, $\mathcal{P} \leftarrow \emptyset$;
16: Remove all zero P_j and sort the remaining in ascending order;
17: **for all** P_j s.t. $P_j \leq B$ **do**
18: $\mathcal{X} \leftarrow \mathcal{X} \cup \{x_{i,j} \mid x_{i,j} = 1, i \in \mathcal{W}\}$;
19: $\mathcal{P} \leftarrow \mathcal{P} \cup \{p_{i,j} \mid p_{i,j} > 0, i \in \mathcal{W}\}$;
20: $B \leftarrow B - P_j$;
21: **end for**
22: **return** $\mathcal{X}$, $\mathcal{P}$;

(lines 5-14), the algorithm iterates among the tasks in sorted $\mathcal{T}$ and determines the scheme greedily based on the order of ranking queue. The algorithm, at the beginning of each iteration, finds top k available workers in ranking queue (if exist) whose total sum of estimated quality covers Q_j exactly (line 6). Then the algorithm chooses these workers as pre-allocation scheme for the task (line 9), determines their pre-payment (line 10), and updates their available frequency n_i and task t_j's P_j (line 11).

In scheme determination stage, the algorithm selects tasks as many as possible in ascending order of P_j until the sum of payment exceeds the given budget (lines 16-17). For each selected task, the algorithm adds its associated information to final allocation scheme $\mathcal{X}$ and payment scheme $\mathcal{P}$ (lines 18-19). Note that all $x_{i,j}$ and $p_{i,j}$ not included in final $\mathcal{X}$ and $\mathcal{P}$ equal 0.

It's easy to see that MELODY satisfies constraints (9), (10) and (11) in Definition 4. We will further prove truthfulness, individual rationality, competitiveness, and computational efficiency of the mechanism in Section 6.

5 Mechanism Design for Dynamic Quality Estimation

In this section we discuss the design of updating method for workers' quality between two consecutive runs in MELODY. The subscript i in all notations is omitted in this section.

According to our model, worker's quality in run r is represented as a latent random variable q^r with transition density $p(q^r|q^{r-1})$, and the observed set of scores $\mathcal{S}^r$ that the worker gets in run r follows emission density $p(\mathcal{S}^r|q^r)$. We propose a method of latent variables inference and parameters learning based on *Linear Dynamical Systems* (LDS)

framework [19], [21], [22]. LDS is widely used in inference and recognition of temporal hidden states in linear dynamical models. In this paper we choose Gaussian distribution as the form of density, but it is worth noticing that we do not impose a strong assumption on the model since any other distribution in exponential family, e.g., Gamma, Poisson, or Beta distribution, could also be used here to derive the solution [21].

The transition and emission density, in the form of Gaussian distribution, are

$$p(q^r|q^{r-1}) \sim \mathcal{N}(q^r; aq^{r-1}, \gamma), \tag{12}$$

$$p(\mathcal{S}^r|q^r) = \prod_j p(s_j^r|q^r) \sim \prod_j \mathcal{N}(s_j^r; q^r, \eta), \tag{13}$$

respectively[7], where $\mathcal{N}(x; \mu, \delta)$ denotes a Gaussian distribution with mean μ and variance δ for variable x, a is *transition coefficient*, γ and η are variance of transition and emission density, respectively. We do not set a corresponding *emission coefficient* in Eq. (13) (or in other words, the emission coefficient is set to 1), as quality and score are modeled in the same space scale. The posterior probability of q^r in run r, therefore, is also a Gaussian distribution

$$\widehat{\alpha}(q^r) \sim \mathcal{N}(q^r; \widehat{\mu}^r, \widehat{\sigma}^r). \tag{14}$$

In addition, we denote $\mathcal{N}(q^0; \widehat{\mu}^0, \widehat{\sigma}^0)$ the initial distribution of $\widehat{\alpha}(q^r)$ preset by the platform.

Given the above formalization, we now turn to two basic problems in our model: 1) The determination of worker's hyper-parameters $\boldsymbol{\theta} = \{a, \gamma, \eta\}$ given sequence of the worker's score set $\mathbf{S^r} = \{\mathcal{S}^1, ..., \mathcal{S}^r\}$; 2) The inference of the posterior distribution $\widehat{\alpha}(q^r)$ given $\widehat{\alpha}(q^{r-1})$, $\mathcal{S}^r$ and $\boldsymbol{\theta}$. We will discuss the two problems in the following subsections respectively.

5.1 Parameters Learning

The purpose of parameters learning is to determine the worker's hyper-parameters $\boldsymbol{\theta} = \{a, \gamma, \eta\}$ according to the sequence of worker's score set $\mathbf{S^r}$. Because the model has latent variables, this can be addressed using the Expectation Maximization (EM) algorithm [50]. The EM algorithm is an iterative method for finding the maximum likelihood estimation of parameters when the model contains unobserved data.

Consider the complete-data log likelihood function

$$\begin{aligned} &L(\mathbf{S^r}, \mathbf{Q^r}; \boldsymbol{\theta}) = \log p(\mathbf{S^r}, \mathbf{Q^r}; \boldsymbol{\theta}) \\ &= \sum_{t=1}^{r} \log p(q^t|q^{t-1}; a, \gamma) + \sum_{t=1}^{r} \log p(\mathcal{S}^t|q^t; \eta) + C, \end{aligned} \tag{15}$$

where $\mathbf{Q^r} = \{q^1, ..., q^r\}$ is sequence of worker's latent quality, and C consists of all terms independent of $\boldsymbol{\theta}$. We present the EM algorithm for parameters learning in Algorithm 2.

In iteration k of Algorithm 2, EM algorithm runs the following two steps: E-step computes the expected value of likelihood function with respect to the conditional distribution of $\mathbf{Q^r}$ given observation $\mathbf{S^r}$ under current estimation $\boldsymbol{\theta^k}$ (line 4), and M-step finds the new estimation that maximizes the expectation function (line 5). Algorithm 2 provide a feasible method to learn the parameters $\boldsymbol{\theta} = \{a, \gamma, \eta\}$ of any worker. We can run Algorithm 2 whenever we wish to re-estimate the worker's parameters.

7. We assume that all s_j^r are i.i.d. conditioned on q^r for the worker in run r.

Algorithm 2 EM Algorithm for Parameters Learning

Input: $\mathbf{S^r}$;
Output: $\boldsymbol{\theta}$;
1: Initialize $\boldsymbol{\theta^0}$;
2: $k \leftarrow 0$;
3: **while** $\boldsymbol{\theta}$ not converge **do**
4: Compute $Q(\boldsymbol{\theta}, \boldsymbol{\theta^k}) \triangleq \mathbb{E}_{\mathbf{Q^r} \sim p(\mathbf{Q^r}|\mathbf{S^r}; \boldsymbol{\theta^k})}[L(\mathbf{S^r}, \mathbf{Q^r}; \boldsymbol{\theta})]$;
5: $\boldsymbol{\theta^{k+1}} \leftarrow \arg\max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, \boldsymbol{\theta^k})$;
6: $k \leftarrow k + 1$;
7: **end while**
8: **return** $\boldsymbol{\theta^k}$;

5.2 Quality Inference

The posterior probability $\widehat{\alpha}(q^r)$ reflects our knowledge about q^r based on observation $\mathbf{S^r}$. Therefore, after a new observation $\mathcal{S}^r$, we wish to update $\widehat{\alpha}(q^r)$ from $\widehat{\alpha}(q^{r-1})$, for given parameters setting. We give the theorem of quality inference in general form as follows:

Theorem 2 (Quality inference in general form)**.** *The recursive equation of the posterior probability $\widehat{\alpha}(q^r)$ is*

$$p(\mathcal{S}^r|\mathbf{S^{r-1}})\widehat{\alpha}(q^r) = p(\mathcal{S}^r|q^r) \int \widehat{\alpha}(q^{r-1}) p(q^r|q^{r-1}) \mathrm{d}q^{r-1}. \tag{16}$$

The proof of Theorem 2 is given in Appendix A.

Theorem 2 provides a general formula for quality inference regardless of the choice of distribution for worker's quality. According to Theorem 2 and making use of Eq. (3), (12), (13), and (14), we give the following theorem for the inference of worker's latent quality in the Gaussian form.

Theorem 3 (Quality inference in the Gaussian form)**.** *For any worker, given $\boldsymbol{\theta} = \{a, \gamma, \eta\}$, observed set of scores $\mathcal{S}^r$ in run r, and posterior probability $\widehat{\alpha}(q^{r-1}) \sim \mathcal{N}(q^{r-1}; \widehat{\mu}^{r-1}, \widehat{\sigma}^{r-1})$ in run $r-1$, the mean and variance of the posterior probability $\widehat{\alpha}(q^r)$ in run r is*

$$\widehat{\mu}^r = \frac{a\eta}{NK + \eta} \widehat{\mu}^{r-1} + \frac{K}{NK + \eta} S, \tag{17}$$

$$\widehat{\sigma}^r = \frac{K\eta}{NK + \eta}, \tag{18}$$

where $K = a^2 \widehat{\sigma}^{r-1} + \gamma$ (here a^2 means a squared), $N = |\mathcal{S}^r|$ and $S = \sum_{s_j^r \in \mathcal{S}^r} s_j^r$. The mean of $\alpha(q_i^{r+1})$ (i.e., the estimated quality for the worker in run $r + 1$) is

$$\mu^{r+1} = a\widehat{\mu}^r. \tag{19}$$

The proof of Theorem 3 is given in Appendix B.

5.3 MELODY Design Between Two Runs

We propose the updating method for workers' quality between two consecutive runs by combining parameters learning and quality inference in MELODY, as shown in Algorithm 3.

Algorithm 3 MELODY Design for Quality Updating

Input: $\widehat{\mu}^{r-1}$, $\widehat{\sigma}^{r-1}$, $\mathbf{S^r}$;
Output: $\widehat{\mu}^{r}$, $\widehat{\sigma}^{r}$, μ^{r+1};
1: **if** i is a new comer **then**
2: $\quad\widehat{\mu}^{r} \leftarrow \widehat{\mu}^{0}$, $\widehat{\sigma}^{r} \leftarrow \widehat{\sigma}^{0}$, $\mu^{r+1} \leftarrow a\widehat{\mu}^{0}$;
3: **else**
4: $\quad$Update $\widehat{\mu}^{r}$, $\widehat{\sigma}^{r}$, and μ^{r+1} according to Eq. (17), (18), and (19) respectively;
5: **end if**
6: **if** $\boldsymbol{\theta}$ not updated for T runs **then**
7: $\quad\boldsymbol{\theta} \leftarrow$ Algorithm2($\mathbf{S^r}$);
8: **end if**
9: **return** $\widehat{\mu}^{r}$, $\widehat{\sigma}^{r}$, μ^{r+1};

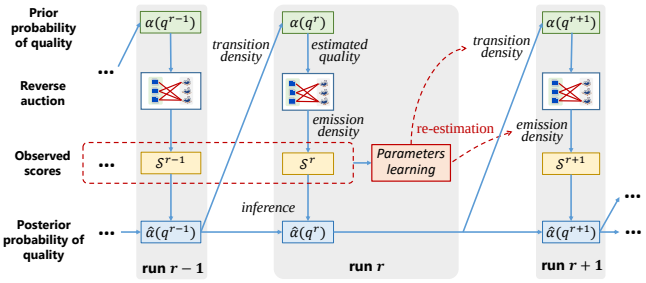


Fig. 3: The overall framework of MELODY. Arrows denote dependency relationship among random variables and algorithms. We assume that the platform decides to re-estimate parameters at the end of run r in this example.

In algorithm 3, we first update every worker's quality based on the updating rules in Theorem 3 (line 1-5). After that, if $\boldsymbol{\theta}$ of this worker is not updated for T runs (T is set by the platform), run Algorithm 2 to re-estimate the worker's parameters (line 6-8). Note that smaller T will bring higher accuracy of the model because we re-estimate $\boldsymbol{\theta}$ more frequently, but meanwhile will increase the time overhead of the algorithm.

Fig. 3 summarizes the overall framework of MELODY. We put more emphasis on quality inference and parameters learning in Fig. 3, while aforementioned mechanism for task allocation and payment determination is miniatured as "reverse auction" in the second row. After the reverse auction ends, the requester calculates a score for each of the answer from workers and submits all scores to the platform, as mentioned in Section 3.2. These observed scores (the third row of Fig. 3) are used to update the posterior probability of workers' quality and to re-estimate workers' parameters in every T runs.

6 MECHANISM ANALYSIS

In this section we prove that the MELODY design for the SRA problem is truthful, individual rational, competitive, and computational efficient. The superscript r in all notations is omitted in this section.

Theorem 4. *The* MELODY *algorithm is short-term truthful.*

Proof: Since a worker's bid consists of cost and frequency, we need to prove the algorithm both *cost-truthful* and *frequency-truthful*:

1) Cost-truthfulness: Given the set of bids $\mathcal{B}_{-i}$ by $\mathcal{W}\backslash\{i\}$, we prove that worker i cannot improve $u_{i,j}$ by reporting untruthful cost whatsoever. That is, $u_{i,j}(\overline{c}_i) \geq u_{i,j}(c_i)$ holds in all cases below.

Case 1 and 2: Worker i wins (or loses) task t_j with both truthful bid $\overline{c}_i$ and untruthful bid c_i. In these two cases, we have $u_{i,j}(\overline{c}_i) = u_{i,j}(c_i)$ according to our payment rule.

Case 3: Worker i wins task t_j with truthful bid $\overline{c}_i$, but loses task t_j with untruthful bid c_i. In this case, we have $u_{i,j}(c_i) = 0$ and $u_{i,j}(\overline{c}_i) = p_{i,j} - \overline{c}_i = \frac{c_{k+1}}{\mu_{k+1}}\mu_i - \overline{c}_i \geq 0$ (because worker i's winning with bid $\overline{c}_i$ implies $\frac{\mu_i}{\overline{c}_i} \geq \frac{\mu_{k+1}}{c_{k+1}}$ in the ranking queue). Thus we have $u_{i,j}(\overline{c}_i) \geq u_{i,j}(c_i)$.

Case 4: Worker i loses task t_j with truthful bid $\overline{c}_i$, but wins task t_j with untruthful bid c_i. In this case, we have $u_{i,j}(\overline{c}_i) = 0$ and $u_{i,j}(c_i) = p_{i,j} - \overline{c}_i = \frac{c_{k+1}}{\mu_{k+1}}\mu_i - \overline{c}_i \leq 0$ (because worker i's failure with bid $\overline{c}_i$ implies $\frac{\mu_i}{\overline{c}_i} \leq \frac{\mu_{k+1}}{c_{k+1}}$ in the ranking queue). Thus we have $u_{i,j}(\overline{c}_i) \geq u_{i,j}(c_i)$.

In summary, we have $u_{i,j}(\overline{c}_i) \geq u_{i,j}(c_i)$ for all task t_j. After summing up all the inequalities for j, we have $u_i(\overline{c}_i) \geq u_i(c_i)$.

2) Frequency-truthfulness: It is impossible for worker i to bid an untruthful frequency greater than $\overline{n}_i$ since $\overline{n}_i$ itself represents the maximum number of tasks he is willing to complete. On the other hand, worker i will not report an untruthful frequency less than $\overline{n}_i$ because it may reduce the number of tasks he may be assigned, as well as his utility. Hence, the mechanism is frequency-truthful. □

Theorem 5. *The* MELODY *algorithm is long-term truthful.*

Proof: As mentioned in the definition of long-term truthfulness, we use $V_i^T(\mu)$ to denote the expected total utility of worker i with quality μ under the circumstance that he always bids truthfully. In addition, we use $p_i^T(\mu)$ to denote the probability that worker i of quality μ is assigned task(s) under truthful bid, $P_i(\mu'|\mu)$ to denote the transition probability density that worker i's quality shifts from μ to μ' if he is assigned task(s), and $\overline{u}_i^r$ to denote the utility of worker i in run r if he is assigned task(s) with truthful bid. By the definition of $V_i^T(\mu)$, we have

$$
\begin{aligned}
&V_i^T(\mu) = \mathbb{E}\big[\sum_{r=1}^{\infty} u_i^r|\mu_i^1 = \mu\big] \\
=&\mathbb{E}[u_i^1|\mu_i^1 = \mu] + \mathbb{E}\big[\sum_{r=2}^{\infty} u_i^r|\mu_i^1 = \mu\big] \\
=&p_i^T(\mu)\overline{u}_i^1 + p_i^T(\mu)\int P_i(\mu'|\mu)\,\mathbb{E}\big[\sum_{r=2}^{\infty} u_i^r|\mu_i^2 = \mu'\big]\mathrm{d}\mu' \\
&+ \big(1 - p_i^T(\mu)\big)\mathbb{E}\big[\sum_{r=2}^{\infty} u_i^r|\mu_i^2 = \mu\big] \\
=&p_i^T(\mu)\overline{u}_i^1 + p_i^T(\mu)\int P_i(\mu'|\mu)V_i^T(\mu')\mathrm{d}\mu' + \big(1 - p_i^T(\mu)\big)V_i^T(\mu) \\
=&p_i^T(\mu)\big(\overline{u}_i^1 + \mathbb{E}_{\mu'}[V_i^T(\mu')]\big) + \big(1 - p_i^T(\mu)\big)V_i^T(\mu).
\end{aligned}
$$

Therefore, $V_i^T(\mu)$ can be written in the following recursive form:

$$
V_i^T(\mu) = p_i^T(\mu)\big(\overline{u}_i^1 + \mathbb{E}_{\mu'}[V_i^T(\mu')]\big) + \big(1 - p_i^T(\mu)\big)V_i^T(\mu). \tag{20}
$$

The intuitive understanding of Eq. (20) is that, if worker i is assigned task(s), then his expected long-term utility is the utility $\overline{u}_i^1$ plus the expected long-term utility in the next run with new quality μ'. Otherwise, his current utility is zero and his quality μ remains unchanged. Eq. (20) can be simplified as

$$V_i^T(\mu) = \overline{u}_i^1 + \mathbb{E}_{\mu'}[V_i^T(\mu')]. \tag{21}$$

Similarly, if the worker does not always bid truthfully in the long term, then his expected total utility can be derived as

$$V_i^U(\mu) = p_i^U(\mu)(\widetilde{u}_i^1 + \mathbb{E}_{\mu'}[V_i^U(\mu')]) + (1 - p_i^U(\mu))V_i^U(\mu), \tag{22}$$

where $p_i^U(\mu)$ and $\widetilde{u}_i^1$ is the probability that worker i of quality μ is assigned task(s) and the utility of worker i in run 1 if he is assigned task(s), respectively, after removing the truthful-bidding condition. Eq. (22) can be simplified as

$$V_i^U(\mu) = \widetilde{u}_i^1 + \mathbb{E}_{\mu'}[V_i^U(\mu')], \tag{23}$$

Note that the expectation terms in Eq. (21) and (23) are over the same distribution since the transition probability $P_i(\mu'|\mu)$ is irrelevant to worker i's bid, but only depends on worker i's latent quality and platform settings.

The recursive equation (21) or (23) is Bellman equation [51] and can be solved by dynamic programming technique. Specifically, the solution of V_i^T's or V_i^U's can be obtained by setting all V_i^T's or V_i^U's as zero initially and updating them iteratively according to Eq. (21) or (23) for given times. Therefore, we prove that $V_i^T(\mu) \geq V_i^U(\mu)$ for all μ by mathematical induction (the suffix $[k]$ in the following proof denotes the number of updating steps):

- When $k = 0$, we have $V_i^T(\mu)[0] \geq V_i^U(\mu)[0]$ for all μ since they are both initialized as 0.
- Suppose $V_i^T(\mu)[k-1] \geq V_i^U(\mu)[k-1]$ holds for all μ ($k \geq 1$). According to Theorem 4, a worker cannot increase his utility in any run by bidding untruthfully, so $\overline{u}_i^1 \geq \widetilde{u}_i^1$. Therefore, we have $V_i^T(\mu)[k] = \overline{u}_i^1 + \mathbb{E}_{\mu'}[V_i^T(\mu')[k-1]] \geq \widetilde{u}_i^1 + \mathbb{E}_{\mu'}[V_i^U(\mu')[k-1]] = V_i^U(\mu)[k]$.

By induction, when the updating completes, we can conclude that $V_i^T(\mu) \geq V_i^U(\mu)$ for all μ, i.e., worker i cannot increase his expected total utility by bidding untruthfully in the long term. □

Since c_i always equals $\bar{c}_i$ as proved, we do not differ c_i and $\bar{c}_i$ in rest of this paper. Neither do n_i and $\overline{n}_i$.

Theorem 6. *The* MELODY *algorithm is individual rational.*

Proof: From Theorem 4 we know that workers bid truthfully in MELODY. Therefore, if task t_j is finally allocated to worker i with bid c_i and n_i (which implies $\frac{\mu_i}{c_i} \geq \frac{\mu_{k+1}}{c_{k+1}}$), we have $u_{i,j} = p_{i,j} - c_i = \frac{c_{k+1}}{\mu_{k+1}}\mu_i - c_i \geq 0$; otherwise, $u_{i,j} = 0$. Above all, we have $u_{i,j} \geq 0$ for all i and t_j. Then we have $u_i \geq 0$ for all $i \in \mathcal{W}$. □

Before proving competitiveness, we first introduce several lemmas and notations: P_j is the total pre-payment for task t_j according to payment rule in Algorithm 1; P_j^{OPT} is the total payment of task t_j in optimum solution; $\mathcal{T}^{CAN}$ (candidate tasks set) is the set of tasks t_j with $P_j > 0$ by MELODY; $\mathcal{T}^{MEL}$ is the set of tasks finally chosen by MELODY (clearly $\mathcal{T}^{MEL} \subseteq \mathcal{T}^{CAN}$); $\mathcal{T}^{OPT}$ is the set of tasks chosen by optimum solution; $\mathcal{W}_j \triangleq \{i \in \mathcal{W} \mid x_{i,j} = 1\}$ is the set of workers pre-assigned with task t_j in Algorithm 1. We assume that $\mathcal{T}$ is sorted in ascending order of Q_j.

Lemma 1. *$P_j \leq \frac{C_M\Theta_M}{C_m\Theta_m}\sum_{i\in\mathcal{W}_j} c_i$ for all $t_j \in \mathcal{T}^{CAN}$.*

Proof: If task t_j is allocated to worker i then $p_{i,j} = \frac{c_{k+1}}{\mu_{k+1}}\mu_i$. Thus we have $\frac{p_{i,j}}{c_i} = \frac{c_{k+1}\mu_i}{c_i\mu_{k+1}} \leq \frac{C_M\Theta_M}{C_m\Theta_m}$. So the total payment for task t_j in the mechanism is $P_j = \sum_{i\in\mathcal{W}_j} p_{i,j} = \sum_{i\in\mathcal{W}_j} \frac{p_{i,j}}{c_i}c_i \leq \frac{C_M\Theta_M}{C_m\Theta_m}\sum_{i\in\mathcal{W}_j} c_i$. □

Lemma 2. *$\sum_{i\in\mathcal{W}_j} c_i \leq \frac{C_M(Q_j+\Theta_M)\Theta_M}{C_mQ_j\Theta_m}P_j^{OPT}$ for all $t_j \in \mathcal{T}^{OPT} \cap \mathcal{T}^{CAN}$.*

Proof: For each task $t_j \in \mathcal{T}^{CAN}$, the total quality that workers may cover is at most $(Q_j + \Theta_M)$ according to our allocation rule, and the "cost density" $\frac{c_i}{\mu_i}$ over all workers is at most $\frac{C_M}{\Theta_m}$. Hence, an upper bound of $\sum_{i\in\mathcal{W}_j} c_i$ can be given as $\sum_{i\in\mathcal{W}_j} c_i = \sum_{i\in\mathcal{W}_j} \mu_i\frac{c_i}{\mu_i} \leq \frac{C_M}{\Theta_m}\sum_{i\in\mathcal{W}_j}\mu_i \leq \frac{C_M(Q_j+\Theta_M)}{\Theta_m}$.

Similarly, for each task $t_j \in \mathcal{T}^{OPT}$, the total quality that workers must cover is at least Q_j, and $\frac{c_i}{\mu_i}$ over all workers is at least $\frac{C_m}{\Theta_M}$. Note that in optimum solution the requester pays worker i his cost c_i exactly to save payment since the requester knows all private information of workers. So P_j^{OPT} has an lower bound $P_j^{OPT} \geq Q_j\frac{C_m}{\Theta_M}$.

In summary, we can derive the inequality in Lemma 2. □

The final result can be obtained by combining the above two desired inequalities:

Lemma 3. *$P_j \leq \lambda P_j^{OPT}$ for all $t_j \in \mathcal{T}^{OPT} \cap \mathcal{T}^{CAN}$, where*

$$\lambda \triangleq \frac{C_M^2(\Theta_m + \Theta_M)\Theta_M^2}{C_m^2\Theta_m^3}. \tag{24}$$

Proof: After combining Lemma 1 and 2 for each task $t_j \in \mathcal{T}^{OPT} \cap \mathcal{T}^{CAN}$, we have $P_j \leq \frac{C_M\Theta_M}{C_m\Theta_m}\sum_{i\in\mathcal{W}_j} c_i \leq \frac{C_M\Theta_M}{C_m\Theta_m}\frac{C_M(Q_j+\Theta_M)\Theta_M}{C_mQ_j\Theta_m}P_j^{OPT} \leq \lambda P_j^{OPT}$. The last inequality holds because $Q_j \geq \Theta_m$ for all t_j. □

We use notations $CAN \triangleq |\mathcal{T}^{CAN}|$, $MEL \triangleq |\mathcal{T}^{MEL}|$, and $OPT \triangleq |\mathcal{T}^{OPT}|$ in the following lemma and theorem.

Lemma 4. *$CAN \geq \frac{1}{\beta}OPT$, where β is a constant greater than 1.*

Proof: Let OPT' be the optimum solution of the SRA problem without budget constraint. It is clear that $OPT' \geq OPT$, so we only need to prove $CAN \geq \frac{1}{\beta}OPT'$. Note that now this problem completely degrades into the classical dual bin packing problem, of which the proof can be found in [46]. □

Theorem 7. *The* MELODY *algorithm has an approximation factor of $\lambda\beta = O(1)$.*

Proof: It's easy to see that $\mathcal{T}^{OPT}$ contains first OPT tasks in $\mathcal{T}$, $\mathcal{T}^{CAN}$ contains first CAN tasks in $\mathcal{T}$, and $\mathcal{T}^{MEL}$ contains top MEL tasks t_j with smallest P_j in $\mathcal{T}^{CAN}$. We discuss in two following cases.

Case 1: $CAN \geq OPT$ (which implies $\mathcal{T}^{OPT} \subseteq \mathcal{T}^{CAN}$). In this case we aim to prove that $MEL \geq \frac{1}{\lambda}OPT$. To achieve this, we take $\lfloor\frac{OPT}{\lambda}\rfloor$ smallest P_j from $\mathcal{T}^{CAN}$ as set S, and it's sufficient to prove that $\sum_{P_j\in S} P_j \leq B$. We

further take out $\lfloor \frac{OPT}{\lambda} \rfloor$ smallest P_j from $\mathcal{T}^{OPT}$ as set S'. It is clear that $\sum_{P_j \in S} P_j \leq \sum_{P_j \in S'} P_j$ because $\mathcal{T}^{OPT} \subseteq \mathcal{T}^{CAN}$, so we only need to prove $\sum_{P_j \in S'} P_j \leq B$, which is achieved by contradiction. Suppose $\sum_{P_j \in S'} P_j > B$, then we have $\sum_{j=1}^{OPT} P_j \geq \lambda \sum_{P_j \in S'} P_j > \lambda B$. However, after listing and adding all inequalities in Lemma 3 for all $t_j \in \mathcal{T}^{OPT}$, we have $\sum_{j=1}^{OPT} P_j \leq \lambda \sum_{j=1}^{OPT} P_j^{OPT} \leq \lambda B$, which shows a contradiction.

Case 2: $CAN < OPT$ (which implies $\mathcal{T}^{CAN} \subset \mathcal{T}^{OPT}$). In this case we aim to prove that $MEL \geq \frac{1}{\lambda\beta} OPT$. Similar to the proof in Case 1, we take $\lfloor \frac{OPT}{\lambda\beta} \rfloor$ smallest P_j from $\mathcal{T}^{CAN}$ as set S, and it's sufficient to prove that $\sum_{P_j \in S} P_j \leq B$. Because $CAN \geq \frac{OPT}{\beta}$ according to Lemma 4, we have $\lfloor \frac{CAN}{\lambda} \rfloor \geq \lfloor \frac{OPT}{\lambda\beta} \rfloor$. So we further take $\lfloor \frac{CAN}{\lambda} \rfloor$ smallest P_j from $\mathcal{T}^{CAN}$ as set S'. Since we have $\sum_{P_j \in S} P_j \leq \sum_{P_j \in S'} P_j$, we only need to prove $\sum_{P_j \in S'} P_j \leq B$. This can be also achieved using the similar contradiction approach as in Case 1 expect that all $t_j \in \mathcal{T}^{OPT}$ are replaced by $t_j \in \mathcal{T}^{CAN}$.

Now we can conclude that $MEL \geq \frac{1}{\lambda\beta} OPT$, i.e., $\frac{OPT}{MEL} \leq \lambda\beta = O(1)$. □

We denote $N \triangleq |\mathcal{W}|$ and $M \triangleq |\mathcal{T}|$ for Theorem 8.

Theorem 8. *The time complexity of* MELODY *algorithm is* $O(NM)$.

Proof: The time complexity of line 2 is $O(N \log N)$, and the time complexity of lines 3-4 and 16 are all $O(M \log M)$. Consider the first loop in lines 5-14 for M iterations. During each iteration, the algorithm goes through every worker in lines 6 and 7-13 in the worst case. Therefore, the time complexity of this loop is $O(NM)$. Similar to the first loop, the time complexity of the second loop in lines 17-21 is also $O(NM)$. Thus we conclude that the time complexity is $O(N \log N + 3M \log M + 2NM) = O(NM)$. □

7 PERFORMANCE EVALUATION

In this section we evaluate the performance of MELODY. We first compare MELODY with benchmarks to prove its competitiveness. Then we verify the individual rationality, budget feasibility, truthfulness, and computational efficiency of MELODY. Finally, we conduct experiments in long-term scenarios to demonstrate the long-term quality awareness of MELODY against other baselines.

7.1 Competitiveness

To effectively evaluate the performance of our proposed mechanism, we implement MELODY against the following two benchmark mechanisms:

- OPT-UB is an estimated upper bound of the optimal solution of the SRA problem. Due to the fact that computing the optimal solution of the SRA problem is quite time consuming and cannot be computed in rational time as the scale of problem grows, we use an upper bound of optimum rather than optimum itself as the first benchmark. The detail of OPT-UB is given in Appendix C.
- RANDOM serves as a baseline solution for the SRA problem which selects tasks in random order. For each selected task t_j, RANDOM selects $k+1$ workers one by one randomly until the total quality of top k workers with higher $\frac{\mu_i}{c_i}$ just exceeds Q_j, i.e., $\sum_{i=1}^{k} \mu_i < Q_j$ and $\sum_{i=1}^{k+1} \mu_i \geq Q_j$ where all μ_i are sorted in descending order of $\frac{\mu_i}{c_i}$. Then these k workers win, each with payment $\mu_i \frac{c_{k+1}}{\mu_{k+1}}$, and the one with lowest $\frac{\mu_i}{c_i}$ is the only loser. The proof of truthfulness of RANDOM is given in Appendix D.

TABLE 3: Parameter settings for the SRA problem.

	μ_i	c_i	n_i	Q_j	M	N	B
I	[2, 4]	[1, 2]	[1, 5]	[6, 12]	500	10 to 700	600, 800
II	[2, 4]	[1, 2]	[1, 5]	[6, 12]	500	100, 250	10 to 2,310
III	[2, 4]	[1, 2]	[1, 5]	[6, 12]	10 to 700	100, 400	2,000

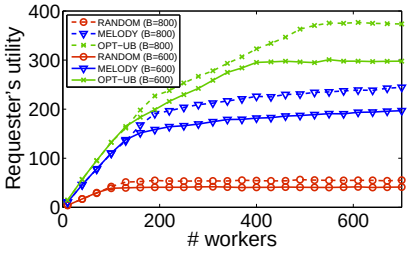
We consider the experiment settings shown in Table 3 for our simulation of the SRA problem. In the three settings, we vary the number of workers (N), budget (B), or the number of tasks (M), respectively, while keeping the other two parameters fixed. Values of μ_i, c_i, n_i, Q_j are drawn uniformly and randomly from the given ranges for each worker i and task t_j. Note that the parameter settings in Table 3 (as well as the following Table 4) are not deliberately selected, hence the experimental results are without loss of generosity.

The requester's utility of OPT-UB, MELODY and RANDOM is shown in Fig. 4. We observe from Fig. 4a that the requester's utility increases as the number of workers grows, until reaching a saturation level due to the limit of budget (rather than the number of tasks, as the requester's utility does not reach 500). Similar patterns are observed in Fig. 4b and Fig. 4c, too. We can also learn from Fig. 4 that MELODY is close to optimum and much better than the baseline. More specifically, our simulation result shows that MELODY outperforms RANDOM by 259.2% on average, and achieves an approximation factor of 1.337 at most (as OPT-UB is an upper bound of the optimum), which is much smaller than the theoretical approximation factor of 48β ($\beta > 1$) under the given experiment scenario according to Lemma 3 and Theorem 7. This important observation exhibits the high competitiveness of MELODY in reality.

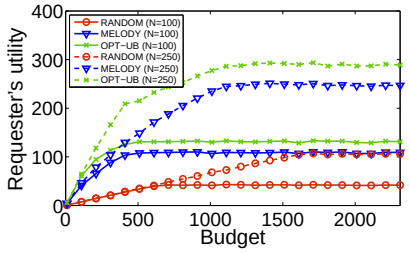
7.2 Individual Rationality

We verify the individual rationality of MELODY in this subsection. The experiment setting is the same as setting II in Table 3 except that N and B are fixed as 300 and 2000, respectively. For each worker i with non-zero payment, we plot his total cost ($c_i \cdot n_i$) and total payment he received ($\sum_j p_{i,j}$) in Fig. 5a. It is clear to see that a total payment is always greater than the corresponding total cost, which validates the individual rationality of MELODY.

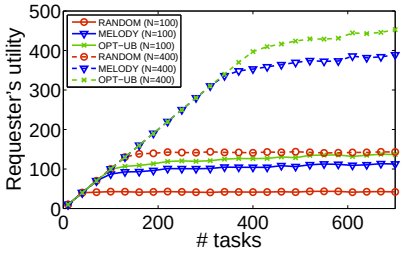
To get a further understanding of workers' utility distribution, we calculate the histogram and cumulative density function (CDF) of workers' utilities and show the results in Fig. 5b, from which we can conclude that: 1) The distribution of workers' utilities has a long tail with mean 0.059 and maximum 0.479. 2) Workers' utilities are all non-negative, which again validates the individual rationality of MELODY.



(a) Requester's utility changing with the number of workers

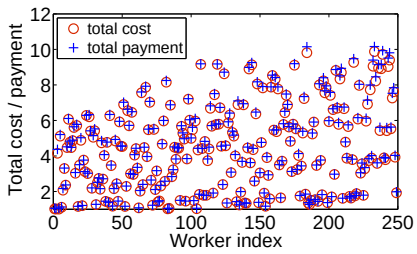


(b) Requester's utility changing with the value of budget

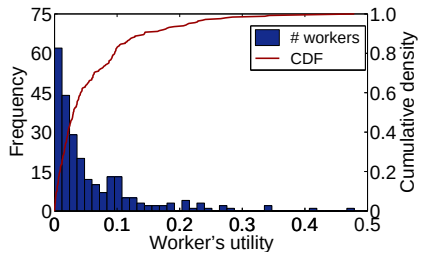


(c) Requester's utility changing with the number of tasks

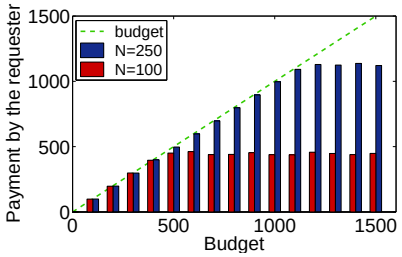
Fig. 4: Comparison of competitiveness of MELODY against benchmarks in the SRA problem.



(a) Individual rationality check



(b) Distribution of workers' utility



(c) Budget feasibility check

Fig. 5: Individual rationality check and budget feasibility check for MELODY in the SRA problem.

7.3 Budget Feasibility

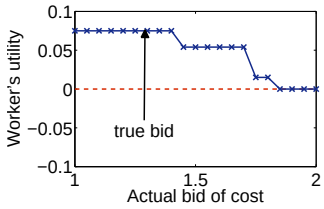
We verify the budget feasibility of MELODY in this subsection. The experiment setting is the same as setting II in Table 3 except that B is varied from 0 to 1,500 with step size 100. For each fixed budget, we calculate the actual total payment by the requester and show the result in Fig. 5c. From Fig. 5c we learn that, the total payment is close to the budget when budget is small, and reaches a saturation level when budget gets larger due to the limit of worker number. Apparently, total payment has never exceeded budget, which validates the budget feasibility of MELODY.

7.4 Short-term Truthfulness

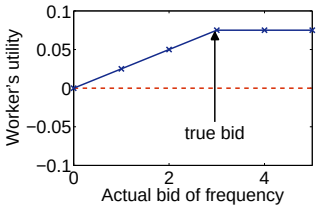
In this subsection we verify the short-term truthfulness of MELODY for two types of workers: winners (i.e., workers who is assigned task(s)) and losers (i.e., workers who is assigned no task). Given the parameter setting in Section 7.2, from the set of all workers we randomly pick a winner i whose true bid is $(\bar{c}_i = 1.292, \bar{n}_i = 3)$ and a loser j whose true bid is $(\bar{c}_j = 1.758, \bar{n}_j = 4)$, then vary their actual bid of cost and frequency to see how their utility changes. The check of cost-truthfulness and frequency-truthfulness with respect to winner i and loser j are plotted in Fig. 6. In each of the four cases we can observe that, a worker's utility is maximized when he bids his true value of cost or frequency. A user cannot increase his utility in one run by bidding untruthfully no matter he is a winner or loser, which validates the short-term truthfulness of MELODY.

7.5 Long-term Truthfulness

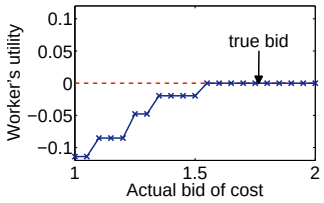
We investigate the long-term truthfulness of MELODY in this subsection. Similar to the experiments for short-term truthfulness, we demonstrate that MELODY is both cost-truthful and frequency-truthful in the long term. To this end, we randomly select one worker in the beginning, and



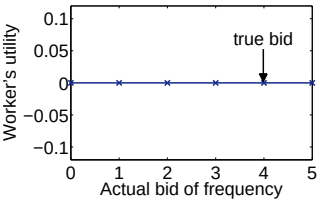
(a) Cost-truthfulness of a winner i



(b) Frequency-truthfulness of a winner i



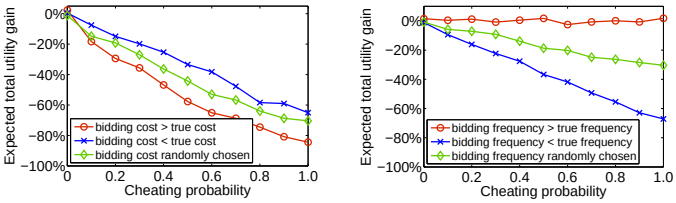
(c) Cost-truthfulness of a loser j



(d) Frequency-truthfulness of a loser j

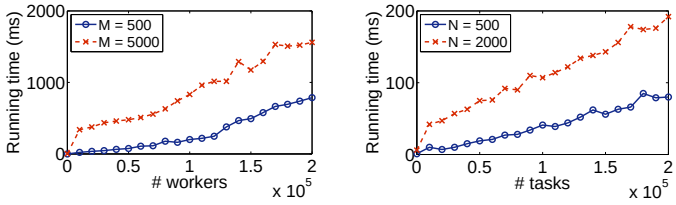
Fig. 6: Short-term truthfulness check for MELODY.

enable him to make untruthful bids of cost or frequency with certain probability in 100 runs. We repeat the process 1,000 times for the worker, and calculate his average total utility gain compared with the truthful case. To get further understanding of untruthful behaviors, we study the following three cases: the worker's bidding value is always higher/lower than his true value or the bidding value is chosen randomly. The results are plotted in Fig. 7. In Fig. 7a we can observe that a worker's expected total utility will decline with the increase of his cheating probability in all three cases, and the worker will probably suffer the most if his bidding cost is higher than his true value (the red curve), since a high bidding cost will bring down his rank and reduce the chance of being assigned tasks. In contrast,



(a) Cost-truthfulness (b) Frequency-truthfulness

Fig. 7: Long-term truthfulness check for MELODY.



(a) Running time changing with the number of workers (b) Running time changing with the number of tasks

Fig. 8: Running time of MELODY.

a lower bidding cost may bring the worker more chances (though his utility will be negative as proven in Theorem 4) to improve his quality parameters and alleviate the loss (the blue curve). Similarly, in Fig. 7b we can see that misreporting a high bidding frequency cannot increase the worker's expected total utility since the worker's true frequency value remains unchanged (the red curve), and misreporting a low bidding frequency will damage the worker's utility due to the loss of participating chance (the blue curve). In summary, a worker cannot improve his expected total utility by bidding untruthfully, which validates the long-term truthfulness of MELODY.

7.6 Computational Efficiency

In this subsection we study the computational efficiency of MELODY, i.e., whether the running time of MELODY grows linearly with the number of workers and tasks as proved in Theorem 8. Fig. 8a and 8b illustrate the running time changing with the number of worker and tasks, respectively. We set $M = 500$ or $5,000$, $B = 800$ for Fig. 8a, and $N = 500$ or $2,000$, $B = 800$ for Fig. 8b, while other parameter settings are the same as in Table 3. Fig. 8 clearly demonstrates the linear dependency of MELODY's running time on the number of workers and tasks. The experimental results prove that MELODY preserves desirable scalability in large-scale application scenarios.

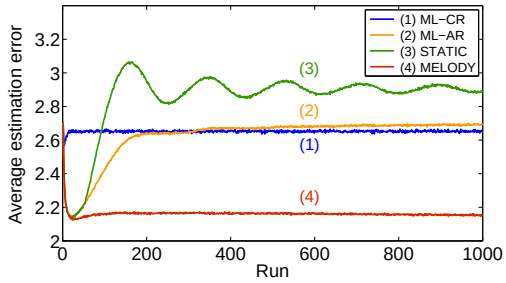
7.7 Long-term Quality Awareness

We implement the updating method for workers' quality of MELODY based on Algorithm 2 and 3 and compare MELODY with the following three benchmark methods:

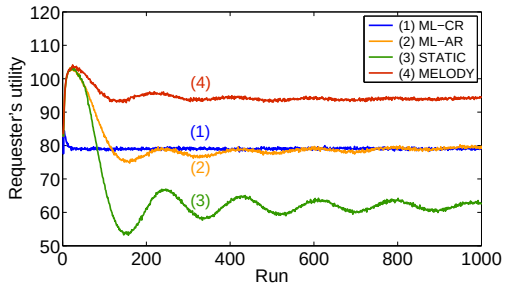
- STATIC is adopted in [7] which treats workers' quality as given values. In our simulation the STATIC mechanism calculates the value of workers' quality based on a few (50 in our simulation) runs at the beginning and keeps them unchanged during the remaining runs.

TABLE 4: Parameter settings for workers' long-term quality updating.

Parameters	$s^r_{i,j}$	c^r_i	n^r_i	Q^r_j	M^r	N
Value	[1, 10]	[1, 2]	[1, 5]	[20, 40]	500	300
Parameters	B^r	runs	σ_S	μ^0_i	σ^0_i	
Value	800	1000	3	5.5	2.25	



(a) Average estimation error of quality per run



(b) Requester's utility per run

Fig. 9: Average estimation error of quality and requester's utility per run of workers' long-term quality updating.

- ML-CR takes the Maximum Likelihood solution of Current Run as the estimated quality in next run (i.e., it is an over-fitting estimation). ML-CR is adopted in most existing crowdsourcing incentive mechanisms such as [5], [6], [9], [10], [14], [16].
- ML-AR takes the Maximum Likelihood solution of All Runs as the estimated quality in next run, which treats workers' historical scores with equal importance (i.e., it is an under-fitting estimation). ML-AR is used in [4], [13].

The performance metrics include average estimation error of quality per run and requester's utility per run. We first generate all latent quality q^r_i for each worker i in each run r, while the quality sequence of each worker follows a specific global pattern (rising, declining, fluctuating or stable) as shown in Fig. 1 with random noises. Based on each of the above four mechanisms, we perform the allocation and payment scheme in Algorithm 1 and update workers' quality in each run. We subsequently compute the average estimation error of quality as the average difference between workers' latent and estimated quality: $\frac{1}{|\mathcal{W}^r|}\sum_{i\in\mathcal{W}^r}|q^r_i - \mu^r_i|$, and requester's real utility as the number of tasks whose total received latent quality exceeds the threshold: $\sum_{t^r_j\in\mathcal{T}^r} I(\sum_{i\in\mathcal{W}^r} x^r_{i,j} q^r_i \geq Q^r_j)$.

Experiment settings of workers' long-term quality updating are described in Table 4. We perform our simulation

for 1,000 runs. All scores $s_{i,j}^r$ are generated according to Eq. (13) within range [1, 10]. Finally, we set $T = 10$ in Algorithm 3 for MELODY.

The average estimation error of quality and the requester's utility per run are plotted in Fig. 9a and Fig. 9b, respectively. We observe that the performance of the four mechanisms are roughly the same at the beginning due to the same initial settings, and differs significantly in the long term. Our proposed MELODY outperforms the other three in terms of both the average estimation error of quality and the requester's utility per run.

To further evaluate MELODY quantitatively, we compute the average estimation error of quality and requester's utility of all runs for STATIC, ML-CR, ML-AR and MELODY. According to the results shown in Fig. 9, MELODY achieves an average requester's utility at 94.6, which outperforms the other three mechanisms by 46.6%, 19.7%, and 18.2%, respectively. Meanwhile, the estimation error of workers' quality is reduced by 24.2%, 18.5%, and 17.6%, respectively. Experimental results show the significant improvement of performance brought by MELODY.

8 CONCLUSION

In this paper we propose MELODY, a truthful and long-term quality-aware incentive mechanism for crowdsourcing, where workers' quality changes dynamically over time. We design an approximation algorithm for task allocation and payment scheme within a single run, and propose a quality inference and parameters learning framework for workers' long-term quality between two consecutive runs based on Linear Dynamical Systems and EM algorithm. We prove that MELODY has strong theoretical guarantees such as truthfulness and competitiveness. Furthermore, simulation results show that MELODY outperforms baseline method and existing work significantly. For future work, we plan to test MELODY on real crowdsourcing platforms, such as Amazon Mechanical Turk.

ACKNOWLEDGMENTS

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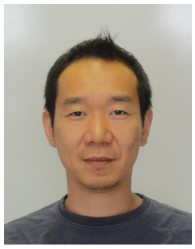

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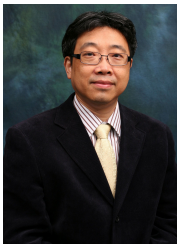

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