Incentivizing an Unknown Crowd

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Abstract
Motivated by the common strategic activities in crowd-sourcing labeling, we study the problem of sequential eliciting information without verification (EIWV) for workers with a heterogeneous and unknown crowd. We propose a reinforcement learning-based approach that is effective against a wide range of settings including potential irrationality and collusion among workers. With the aid of a costly oracle and the inference method, our approach dynamically decides the oracle calls and gains robustness even under the presence of frequent collusion activities. Extensive experiments show the advantage of our approach. Our results also present the first comprehensive experiments of EIWV on large-scale real datasets and the first thorough study of the effects of environmental variables.

1 Introduction
The increase in the model complexity of machine learning methods poses new challenges to data acquisition, as obtaining high-quality labeled data is often expensive and time-consuming. Crowdsourcing is proposed to use crowd’s wisdom to obtain a large volume of labeled data (Howe and others 2006; Simpson et al. 2015; 2015; Difallah et al. 2015). The crowdsourcing process can be depicted by a Stackelberg game consisting of two parties, the crowdsourcing workers and the platform (Cruz Jr 1975). The game proceeds in an iterative manner, where at each round the platform first posts a price for labeling and the workers then complete the labeling task in a way best to their interest. To obtain high-quality data, this group of workers has to be properly incentivized. With the presence of ground truth labels, it amounts to the incentive mechanism design and has been extensively investigated in the literature (Shah, Zhou, and Peres 2015; Shah and Zhou 2015; 2016). Yet in most scenarios, ground truth labels are not readily available. This leads to the problem of eliciting information without verification (EIWV), which is first formulated by (Witkowski and Parkes 2013) and later discussed from the perspectives across multiple domains, ranging from game theory, data inference, to machine learning (Dasgupta and Ghosh 2013; Liu and Chen 2016; 2017; Hu et al. 2018).

In this paper, we focus on the modeling and empirical performance of EIWV and propose a reinforcement learning approach to design an adaptive and effective incentive mechanism. Our study of EIWV is with dynamic and online interactions to corroborate real applications. We study the sequential EIWV problem, in which the crowd of workers strategically label assigned tasks (at some effort cost and payment) to maximize their overall utility. Stringent assumptions on the crowd of workers and the crowdsourcing tasks that are typical for mathematical tractability are removed. The adaptiveness of workers and arbitrariness of tasks then require the crowdsourcing platform to promote honest behavior via payment rule design. This arises the difficulty of inferring ground-truth labels among strategic responses.

Despite the community’s efforts on EIWV, relevant literature focus on theoretical guarantees of their approaches while imposing strong assumptions. Their approaches are thus under certain limitations in real applications. For example, assumptions like fixed and known cost and full rationality of workers are hard to satisfy in practice (Witkowski and Parkes 2012; Liu and Chen 2016; Hu et al. 2018). Without extensive empirical evaluation on real dataset, the robustness of the approach to violations of the assumptions are not verified. Moreover, existing approaches often focus on particular game-theoretic formulations, which are hard to be generalized to other settings and are difficult to scale. For mathematical tractability, previous theoretical analyses are often restricted to binary labeled tasks and binary effort labels, where both are relaxed in our setting. Meanwhile, workers are assumed to possess the ability to exactly optimize their utility, which does not hold in real settings (Witkowski et al. 2013; Shneyder et al. 2016a; Liu and Chen 2017). The above limitations indicate an immediate need in designing a practical mechanism that is robust in a variety of regimes regardless of worker ra-
3 Preliminaries

We model a crowdsourcing data acquisition task as a strategic game between workers and the crowdsourcing platform. Through a finite time horizon $T$, $N$ workers will label $m_t$ tasks at each time step $t$. The game pro-
ceeds as workers observe a posted payment for each task at each time step, then they modify their labeling and effort exertion strategy to maximize their utility. While the workers seek to maximize their utility, the crowdsourcing platform needs to balance between maximizing labels’ quality and minimizing payment spent.

We first give the definition of workers’ and the platform’s utility, which is general enough to be straightforwardly adapted to a variety of settings. Let worker $i$’s effort level at time $t$ be $e_{i,t}$, which is at least its base effort cost level. We do not impose assumptions on the workers’ background and thus they may possess diverse skills. This results in various base effort costs among workers, representing various capability of completing the tasks. Note that the true distribution of this base effort cost level remains unknown to the platform. Let total payment to worker $i$ at time $t$ be $P_{i,t}$, and the number of tasks completed by worker $i$ at $t$ be $m_{i,t}$. The utility $U_{w,i}$ of a worker is defined as

$$U_{w,i} = E\left[\sum_{t=0}^{T} (P_{i,t} - e_{i,t} \cdot m_{i,t})\right].$$ (1)

On the platform side, it needs to balance between accurate results and the payment spent through a variable parameter $\eta$ as the payment weight. Let the total number of tasks completed at time $t$ be $m_t$, which is the sum of all tasks completed by the workers ($m_t = \sum_{i \in N} m_{i,t}$). Denote the accuracy of a label $m_t$ as $A_t$. Then the platform’s utility, denoted by $U_p$, is defined as

$$U_p = E\left[\sum_{t=0}^{T} \left(A_t - \eta \cdot \sum_{i=1}^{N} P_{i,t}\right)\right].$$ (2)

Without the ground truth information about the labels, the platform only has limited access to the value of $A_t$ through an inference mechanism (e.g. an EM algorithm Zheng et al. 2017) that provides an estimation for label accuracy. Let $\hat{A}_t$ be the accuracy that the platform observes through the inference mechanism. The platform then aims to maximize $\hat{U}_p = E\left[\sum_{t=0}^{T} \hat{A}_t - \eta \cdot P_t\right]$.

With the utility definitions, we consider the interactions between the two parties by not only considering independent working strategies (Dasgupta and Ghosh 2013; Hu et al. 2018), but also collusion among workers. When collusion takes place, a subset of workers works together to modify their strategy according to the group interest. Formally, we define collusion for rational workers as follows.

**Definition 3.1 (Collusion for rational workers)**

Given a population $[N]$ of rational workers and a subset of workers $G \subseteq [N]$. For workers in $[N]$ and some assigned task, let $r_i$ be the honest response for worker $i \in [N]$ and $r = \{r_i, i \in G\}$ the honest response of the group of workers. If $G$ colludes, workers in $G$ will not submit $r_i$ if there exists an $r'$ such that $U_{w,i}(r) < U_{w,i}(r'), \forall i \in G$.

When workers are fully rational, existing works on peer prediction have effective ways to prevent collusion (Liu and Chen 2017). However, in sequential EIWV, it is hard in general for workers to exactly optimize towards the expected utility. Thus collusion becomes a much likely event and its occurrence brings catastrophic damage to the utility of the platform. Intuitively some payment rules can stop the collusion, for example, one that favors honest and non-collusion participants. Yet the crowdsourcing platform needs to identify collusion and properly incentivize workers with very limited information. It is immediate that without ground truth labels, collusion is impossible to detect. We thus propose an oracle-aided approach to this problem, where the definition of an oracle is formally given as follows.

**Definition 3.2 ($\alpha$-cost oracle)** For a given payment $P_t$, and when an $\alpha$-cost oracle is called, the crowdsourcing platform receives a signal $S_t$ which encodes the true effort level of workers at the cost of paying $P_t(1 + \alpha)$ instead.

Under our setting, the signal $S_t$ may be the true accuracy of the worker’s labeling service, which encodes information about the worker’s actual effort level. The oracle may be implemented in several ways in real settings. In the offline case it corresponds to a partially labeled dataset, where the fraction of tasks with ground truth labels can be utilized as the oracle. In an online case the $\alpha$-cost oracle can be intuitively understood as the option to resort to a trusted expert that is $\alpha$ more expensive than a normal worker. This costly oracle is realistic in general and is available in many real applications (Oleson et al. 2011; Shah and Zhou 2015; Yang, Cai, and Zheng 2018; Checco, Bates, and Demartini 2019).

![Figure 1: Flowchart of our framework](image)

With the described setting, we use reinforcement learning to derive an incentive payment policy. To cope with potentially adversarial or irrational behavior from workers, we let reinforcement learning to learn the
choice of calling a costly but accurate oracle, as a substitute for low-cost but potentially inaccurate inference mechanism (e.g. an EM algorithm). The interactions between workers and the underlying reinforcement learning can be captured by Figure 1.

4 Reinforcement Learning for EIWV

We first translate the setting of sequential EIWV into a Markov decision process (MDP) denoted by the tuple \( \mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma) \), where \( \mathcal{S} \) is the state space, \( \mathcal{A} \) is the action space, and \( \gamma \) is the discount factor. For an \((s, a, s')\) tuple where \( s, s' \in \mathcal{S}, a \in \mathcal{A}, \mathcal{R}(s, a) \) is the reward function and \( \mathcal{P}(s, a, s') \) describes the transition probability of the MDP. For our problem, let the accuracy of workers be the observation state \( s \) and let the payment to the workers be the action \( a \). Specifically, at time \( t \), the state is expressed as \( s_t = (s_{1,t}, \ldots, s_{N,t}) \), which is a vector representation for estimated accuracy of worker \( 1, \ldots, N \) based on the inference method of the platform’s choice. The action is also a vector representation of the payments for the next batch of tasks to worker \( 1, \ldots, N \), represented as \( a_t = (a_{1,t}, \ldots, a_{N,t}) \). The action space can be either discrete or continuous, where a continuous action space allows more flexible mechanism design but poses greater difficulty for RL algorithms. The state transition is governed by the workers’ adaptive labelling strategies and remains unknown to the RL algorithm. We define the reward function to be the running average of the platform utility (2) and the algorithm’s goal is to maximize the cumulative reward.

The objective of the RL algorithm is to learn a policy \( \pi : \mathcal{S} \rightarrow \mathcal{A} \) that maximizes the cumulative rewards over a finite horizon \( T \). The RL algorithm is provided with an \( \alpha \)-cost oracle as an optional alternative to the inference method. We augment this choice of calling oracle into the MDP action space with a simple trick. Specifically, when the RL algorithm decides to give the lowest possible payment to a larger portion than some threshold of the population, we regard that the RL algorithm is uncertain of its payment. An oracle will be called then at an extra cost and the overall effect of using the oracle is reflected on the received reward.

We adapt a popular RL algorithm, A2C, as our learning algorithm (Mnih et al. 2016). The A2C algorithm consists of an actor and a critic, where the actor aims to optimize the policy incorporating the information from the critic, and the critic evaluates the policy. When collusion is present and without an always available oracle, directly employing A2C with other popular inference methods (e.g. an EM algorithm) yields suboptimal performance caused by unstable training (see experiments). When the oracle is available as an option, we refer to this as partial oracle support. Under the existence of a partial oracle, we introduce an importance sampling-aided buffer to stabilize the training and further improve the performance.

4.1 Importance sampled experience replay

Collusion or irrational behavior may only appear for a limited fraction of timesteps but can cause catastrophic damage. Thus we desire the RL approach for EIWV to be robust to collusion and irrational workers with only limited experiences that are relevant to these situations. Without additional measure, due to the rarity of collusion and irrational activities, the RL agent has limited opportunity to learn its response during training. Intuitively, samples where collusion and irrational behavior happen should be emphasized and learned with high priority.

For existing popular off-policy RL algorithms, such as off-policy actor-critic (Konda and Tsitsiklis 2000; Haarnoja et al. 2018), experience replay plays an important role to help stabilize training and to improve sample complexity. Prioritized experience replay (PER), proposed by (Schaul et al. 2016), leverages the advantage of prioritizing sampling transitions based on their TD error to improve RL algorithm’s performance. Borrowing this idea, We re-weight the transitions by the likelihood of a collusion and irrational activities occur in and around it.

It is important to observe that when collusion and irrational activities occur, it usually comes with a sudden change in the observations received by the algorithm. Taking collusion as an example, in the case where a sufficiently large proportion of workers participate in the collusion and the inference method was mislead to the drastically different prediction, the RL algorithm may experience sudden changes of both the inferred true label and the inferred accuracy. In the extreme case where all workers coordinate their answers, the RL algorithm will receive a full accuracy for each entry in its observation state. Note that by describing the change being sudden, we are comparing it to observation state changed caused by the payment policy, which is more gradual.

We thus use this fact to prioritize importance transitions in the experience replay by importance sampling techniques. Denote the diameter in observation state by \( \Delta \), which is the maximum possible distance between two arbitrary states, and let \( \delta_t \) be the difference between the observation states \( s_t \) and \( s_{t+1} \). When transitions are sampled from the buffer during training, each transition is sampled with probability \( \delta_t / \Delta \).

5 Empirical Findings

We now give a description over the implementation details and the empirical results of our proposed framework for EIWV. We conduct our experiments over 4 datasets that contain a variety of tasks, including binary and multi-label tasks, with varying sizes. we defer the discussion of the flexibility of our algorithm under different environment configuration and a comprehensive list of dataset description to the appendix.
5.1 Framework for EIWV
To facilitate the empirical study of EIWV, we provide the first flexible framework for the task and will verify the flexibility and the performance in this section. Our framework can easily incorporate various peer predictions and inference methods, as well as different incentive mechanism including learning based ones. We highlight the following flexibility of our framework.

1. Dataset: We support both binary and multi-class, discrete and continuous labeled tasks. If the framework is used without oracle, then the dataset needs no ground truth labels.

2. Crowd: The framework is flexible with different crowd settings such as the cost distribution among crowd, the rationality, and the crowd labelling strategy.

3. Inference method and incentive mechanism: The framework works with any inference and peer prediction methods and various incentive mechanisms.

5.2 Experimental details
Effort cost distribution Previous works such as (Liu and Chen 2016) and (Liu and Chen 2017) require either known worker costs or the costs to be reported by the workers. In contrast, we consider incentivizing workers without the knowledge about their costs and regard such costs as private information of the workers. While previous empirical analysis which focuses on binary effort cost (e.g. either low or high) (Hu et al. 2018), we model the effort cost level to be in the range of $[h]$ (set as $h = 10$ through the experiments). To model the effort cost distribution, our framework takes an upper bound on the effort cost and uniformly randomly initiates an effort cost (without loss of generality, larger than 1) for each worker. This distribution remains unknown to the incentive mechanism throughout the interactions, though it remains stationary. This modeling allows the framework to cover a significantly more complicated worker crowd and thus represents a richer class of EIWV problems.

Task assignment A significant line of work (Ho and Vaughan 2012; Ho, Jabbari, and Vaughan 2013; Zhao et al. 2020) studies the optimal task assignment when tasks are heterogeneous. As optimal task assignment is out of the scope of this paper, during training and testing, our framework samples a specified amount of tasks uniformly randomly from all available tasks. The task is considered to be assigned to a worker if this worker has labeled the task in the dataset. Note that the number of tasks assigned to each worker can therefore be different. We should expect that with a more sophisticated task assignment strategy, the mechanism will perform better than under our framework.

Worker strategy Previous models such as (Liu and Chen 2017) and (Hu et al. 2018) assume that rational workers have the ability to exactly maximize their utility function. However, in real settings, rational workers may have limited information to achieve so. Thus we model the workers to be greedy and only optimize a one-step utility function $\mathbb{E}[P_i - e_{i,t} \cdot m_{i,t}]$ with an $\epsilon$ accuracy. Specifically, worker will exert effort $e_{i,t}$ such that $|\mathbb{E}[e_{i,t} - e_{i,t}^*]| \leq \epsilon$, where $e_{i,t}^* = \arg\max_{e} \mathbb{E}[P_i - e \cdot m_{i,t}]$.

Other experimental settings The performance of the mechanism is evaluated by the cumulative reward, where the reward is defined as a running average of utility over the timesteps. We employ the classic EM algorithm implemented by (Zheng et al. 2017) for our framework, but the framework can be easily adapted to other inference methods. The collusion activities is described by the collusion rate of $m$. The workers conduct a collusion every $m$ timesteps and can only be stopped by giving every participant the lowest possible payment. For each figure we present, we repeated with 5 different random seeds for better reproducibility.

5.3 Results
We first evaluate our importance sampled experience replay with A2C against the previous approach, its naive counterpart (without importance sampling), A2C with full oracle, and A2C without full oracles with different datasets. Due to the setting limitations of previous works, in which no collusion and multi-labeled tasks are considered, this result is obtained through interacting with a fully rational crowd with no possible collusion on the Bluebirds dataset. The previous approach is also only feasible for a discrete action space and a uniform payment rule for all workers (that is, every worker will receive the same amount of payment at each timestep), we thus discretize the continuous action space used for our approach for comparison. Among previous approaches, the closest to our setting is the Q-learning approach with Gibbs sampling (Gibbs with DQN) from (Hu et al. 2018). Compare with that, our approach gains effectiveness as is shown in Figure 2a. Intuitively, adopting an individualized payment rule with a continuous action space allows our mechanism to optimize much better towards the utility objective. Note that our algorithm outperforms the state-of-the-art method (Gibbs sampling with DQN) even without an oracle and the importance sampling.

With more tasks per timestep, such as 50 tasks per timestep with the Blubirds dataset, our method significantly outperforms the previous approach, Gibbs Sampling with DQN (Hu et al. 2018), as shown in Figure 3a. Moreover, the utility achieved by our methods (EM with A2C) is roughly five times (almost 1400) the utility it achieved with 10 tasks per timestep (around 270).
Figure 2: All figures are results of experiments conducted over 600 timesteps, collusion rate of 50, a maximum payment of 11, maximum effort cost of 10, and 10 tasks per time step. The reward is calculated by the rolling average of the utility in a window of the recent 200 timesteps. The environment configuration remains the same in other figures unless otherwise indicated. Figure 2a compares the performance of our mechanism with and without importance sampled buffer with the Gibbs sampling and Q-learning (Hu et al. 2018) on Bluebirds dataset without collusion. Figure 2b compares the performance with/without oracle on crowdsourced amazon dataset with a collusion rate of 150 and 100 tasks per timestep. Figure 2c compares the performance of A2C with and without an oracle with the Sentiment Popularity - AMT dataset. Figure 2d compares the performance of mechanism with A2C with the multi-label Weather Sentiment - AMT dataset.

(a) Comparison to Gibbs sampling with DQN (Hu et al. 2018) on Bluebirds with 50 tasks per timestep.

(b) Comparison to Gibbs sampling with DQN (Hu et al. 2018) on Crowdsourced Amazon Sentiment with 100 tasks per timestep.

Figure 3 showed in Figure 2a. In comparison, Gibbs sampling with DQN achieved only around 200 with 10 tasks per timestep and around 500-600 with 50 tasks per time step. This attests that our method is robust with various environments.

On larger datasets such as Crowdsourced Amazon Sentiment with 7, 803 answers from 284 workers, our method quickly learns an incentivizing payment strategy while our baseline, Gibbs sampling with DQN, fails to achieve a positive averaged utility.

Beyond this significant improvement in performance achieved by our approach in a benign environment, our approach is also shown to be effective in much complicated, potentially malicious environments, including ones with collusion. On larger datasets such as Crowdsourced Amazon Sentiment with 7, 803 answers, Figure 2b shows the effectiveness of our proposed approach (partial oracle) under collusion against baselines that are without an oracle or without IS. This result demonstrates the robustness of our approach gained through the availability of oracle under variants of worker strategies, regardless of the size of the datasets.

With the Sentiment Popularity - AMT dataset, our approach with partial oracle is not only shown to be robust under collusion, but also achieves similar performance as if the oracle is queried in every timestep (Figure 2c). When such availability is infeasible as is in most practical applications, our approach remains as effective, which allows the algorithms to be deployed onto a wider range of real-world crowdsourcing systems.

Lastly, our approach is flexible with multi-label datasets such as Weather Sentiment - AMT. Figure 2d shows that on this multi-label dataset, both importance sampled experience replay and partial oracle are essential for the performance under collusion. Moreover, without the constant availability of an oracle and consequently less burden on the payment, our approach is shown to be most effective when oracle is made available as an action.

5.4 Bridging theoretical and empirical metrics

In game theory and peer prediction literature, individual rationality (IR) and incentive compatibility (IC) are two important metrics to assess the mechanism. On a high level, a mechanism that achieves IR and IC should ensure that all participating workers are strictly better off when an honest response is submitted and have no incentive of dropping out of the framework. Notions extending from IC and IR, like strategyproof and group
strategyproof, are used to describe the mechanism’s capability to overcome potential collusion activities. Here we give formal definitions of IC, IR, strategyproof, and group strategyproof in the context of crowdsourcing and show how these notions are empirically satisfied in our experiments.

**Definition 5.1 (Individual rationality)** For all worker $i \in [N]$, the utility gained through participating in crowdsourcing labeling is non-negative.

In the context of crowdsourcing, let workers’ response be the generated labels. For response $r$ and $r'$, $r' < r$ means label $r$ is more accurate than $r'$. Then incentive compatibility is defined as follows.

**Definition 5.2 (Incentive compatibility)** For any worker $i \in [N]$ with response $r'$, the utility gained through submitting $r'$ is strictly less than the utility gain through submitting $r$.

In other words, a desired mechanism should ensure that honest workers receive better utility in expectation. Moreover, a desired mechanism should ensure that it is in the workers’ interests to participate in crowdsourcing. A stronger notion, strategyproof, is introduced to incentivize a worker to not participate in a collusion activity when it takes place.

**Definition 5.3 (Strategyproof)** Let $\mathbb{E}[U(e)]$ denote the expected utility when effort level $e$ is exerted. A mechanism is strategyproof if for any worker $i$ with the ability to exert effort level $e$, $e' < e$, $\mathbb{E}[U(e)] < \mathbb{E}[U(e')]$.

The above definition only helps to describe a mechanism that is resistant to individual non-rational workers. To define a mechanism that is resistant to group collusion, we need the following definition of group strategyproof.

**Definition 5.4 (Group strategyproof)** Let $\mathbb{E}[U(e)]$ denote the expected utility when effort level $e$ is exerted and $N$ be the population of workers. A mechanism is said to be strategyproof if for any worker subgroup $G \subseteq [N]$ with the ability to exert effort level $e$, $e' < e$, we have $\sum_{i \in G} \mathbb{E}[U(e')] < \sum_{i \in G} \mathbb{E}[U(e')]$ for any $t \in [T]$. Note that for strategyproof and group strategyproof, the definition is with respect to an adaptive adversarial strategy. With our sequential formulation of the problem and our learning approach, it is hard to ensure per step IR, IC, strategyproof, and group strategyproof. However, all of these metrics can be reflected through the fluctuation of the platform’s utility over the time horizon. Thus, we discuss the above-mentioned metrics in the long-term expected form over a finite time horizon.

**Long term expected IR and IC** When the long term expected utility of workers becomes negative (thus not IR) or the workers are rewarded better for fewer quality labels in expectation, it is reasonable to deduce that rational workers in the crowd are given no incentive to submit quality labels. According to our general definition of a platform’s utility, the platform should also receive a negative expected utility or have no significant improvement of utility over the time horizon (as the quality of labels now only depends on irrational workers). A negative utility is not observed in our approach but is observed in some baseline methods.

**Long term expected strategyproof and group strategyproof** Intuitively, any successful adversarial individual or group strategy would cause a significant decrease in the utility of the platform. Moreover, collusion may indeed be a deceptive enough move and should cause great harm to the platform utility without the existence of an external oracle.

**Bayesian Nash equilibrium** Previous related works such as (Liu and Chen 2016) characterize the Bayesian Nash equilibrium (BNE) and show that at equilibrium there is a unique strategy for positive effort exertion. With our deep reinforcement learning approach, though we cannot prove the uniqueness of our strategy at equilibrium, our results can be inferred that reinforcement learning does learn an incentive mechanism that approximately achieves Nash equilibrium. This is reflected through our increasing flat curve towards the end of the training, where the utility of the platform encounters very little changes as a result of little change in inferred label accuracy from workers.

6 Conclusion and future work

We propose a reinforcement learning based approach for the problem of sequential eliciting information without verification (EIWV) for an heterogeneous worker group of unknown cost distribution, potential irrationality and collusion. Our method is shown to be effective in a wide range of settings and robust to collusion with the aid of a costly oracle. We provide comprehensive experiments to validate our effectiveness on a variety of datasets. Our approach outperforms the baseline methods, with an especially large margin on large datasets.

An interesting direction of future work is to consider the fairness of the payment mechanism, which has a significant effect on the long-term prosperity of the crowdsourcing platform. Considering that the workers share some information among them, their willingness to exerting efforts and being truthful will be affected by comparing their utility with others. A fair distribution of payment will be the key to maintain the workers’ productivity in a long run.
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A Datasets

Bluebirds (Welinder et al. 2010) This dataset contains both individual answers from 108 workers and the ground truth labels for 38 tasks regarding whether there is a blue bird in the picture. The dataset only contains tasks with binary labels and includes 4,212 total answers from workers.

Crowdsourced Amazon Sentiment (Blitzer, Dredze, and Pereira 2007) The Crowdsourced Amazon Sentiment dataset includes 7,803 answers from 284 workers for 1,011 Amazon reviews to decide whether the review is about a book or not. The tasks are binary-labeled tasks and have ground truth labels.

Sentiment Popularity - AMT (Venanzi et al. 2015a) This is the largest binary labeled dataset we studied, with 10,000 answers from 143 workers and 500 tasks on deciding whether a movie review is positive or negative. Each task has a ground truth label provided by the review website. The crowdsourced labels are from Amazon Mechanical Turk.

Weather Sentiment - AMT (Venanzi et al. 2015b) This multi-labeled tasks dataset contains 6,000 answers from 110 workers on 330 tasks on classifying weathers into five categories by looking into a tweet: negative (0), neutral (1), positive (2), tweet not related to weather (3) and can’t tell (4). The labeled answers are data from Amazon Mechanical Turk and every task has a ground truth label.

B Flexibility of our framework

Figure 4: Figure 4b compares the performance with different levels of oracle cost from 5-40 percent more of the chosen payment. Figure 4c compares the performance with collusion rate of 50, 10, 150 (e.g. start colluding once every 50 timesteps). Figure 4d compares the performance with a different number of tasks per worker at each timestep, ranging from 20 to 80.

For the experimental setting, all experiments for the ablation study are conducted over 800 timesteps on the Bluebirds dataset. Figure 4a gives an overview of the performance of A2C with/without oracle and with/without importance sampled buffer with 20 percent oracle cost, collusion rate of 50, a maximum payment of 11, maximum effort cost of 10, and 10 tasks per time step. Unless otherwise indicated, all environment configuration remain the same in the following figures.

Before moving on to ablation results, we first perform a comparison between the effect of each components in our approach on the Bluebirds dataset (Figure 4a). This will showoff the flexibility of our environment under a variety of environment parameter combinations. The partial query of oracle and importance sampled experience replay are shown to be essential for better performance and stable training under complicated environment with possible collusion.

Figure 4b shows the effect of the $\alpha$-oracle cost on the performance of the algorithm. Regardless of the increased cost of the oracle, our approach’s performance decreases only in a moderate rate. The difference in cost of oracle is a realization of the availability of golden tasks or expert advice, thus proves the feasibility of our approach in a wide range of environments.

Figure 4c studies the effect of collusion rate to the performance. By collusion rate of $m$, the worker will conduct a collusion every $m$ timesteps and can only be stopped by giving every participant the lowest possible payment. The performance of an approach is likely to decrease when $m$ decreases. From the figure, A2C with important sampling performance can handle a collusion rate of 150 or larger. The algorithm will have limited performance for lower
collusion rates as the reinforcement learning algorithm has limited horizon between collusion points to balance the incentivizing payment strategy and the anti-collusion strategy.

Figure 4d shows the effect of a different number of tasks distributed at each time step. The utility is normalized to per task for a fair comparison. We observe that the number of tasks distributed at each time step does not have a significant impact on the performance.