A Reinforcement Learning Framework for Eliciting High Quality Information

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Abstract

Peer prediction is a class of mechanisms designed to elicit high-quality information from strategic human agents when there is no ground-truth for contribution verification. Despite its elegant design, peer prediction is often found to have two shortcomings: (1) agents' incentives for exerting effort are assumed to be known; (2) agents are modeled as fully rational. Both are too ideal in practice, leading to peer prediction's failure. In this paper, we propose the first reinforcement learning (RL) framework in this domain, *Reinforcement Peer Prediction*, to tackle these two limitations. In our framework, we develop a model-free RL algorithm for the data requester to dynamically adjust the incentive level to maximize his revenue, and to pay workers using peer prediction scoring functions. Experiments show significant improvement in data requestor's revenue under different agent models.

1 Introduction

Crowdsourcing rises as a promising inexpensive method to collect a large amount of training data quickly [14, 4]. Notwithstanding its high efficiency, one salient concern about crowdsourcing is the quality of the collected information, as it is often too costly to verify workers' contributions. This problem is called information elicitation without verification [15]. A class of incentive mechanisms, collectively called peer prediction, has been developed to solve this problem [10, 7, 18, 17, 11]. The core idea of peer prediction is quite simple and elegant. The mechanism designer financially incentivizes workers according to the scoring of their contributions in comparison with their peers', and the payment rules are designed so that each worker reporting truthfully or reporting a high-quality signal is a strict Bayesian Nash Equilibrium.

Many peer prediction mechanisms also adopt the effort-sensitive model to depict agents' trade-off reasoning in contributing high-quality information [16, 2, 12, 8]. In these mechanisms, workers are incentivized to exert high efforts to generate high-quality answers. All the aforementioned peer prediction mechanisms focus on a one-shot interaction with agents, and one critical assumption is an explicitly-known worker model which includes workers' incentives to exert effort. Further it is also assumed workers are fully rational and are able to compute the utility-maximizing strategy. Unfortunately, neither of above is true in practice. First of all, mostly likely workers' incentives, or cost, in exerting high effort can only be known after we, as the mechanism designers, interact with them. Secondly, there is strong evidence that human workers are not fully rational [13]. And they are often observed to be deviating from equilibrium strategies in practice [9, 6].

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To push peer prediction mechanisms towards a more practical end, we propose a reinforcement learning framework, *Reinforcement Peer Prediction*, to interact with workers, so we will be able to (1) incentive workers to converge to a high effort exertion state, and (2) learn the optimal payment based on workers' contributions at each step. Nevertheless, there are two main challenges. Firstly, classic reinforcement learning focuses on the interaction between a single agent and its environment. We, instead, effectively consider a multi-agent setting. Immediately, there forms a game among workers, due to the peer prediction nature of our incentive structure. Therefore, the evolution of workers' state is a outcome of collective actions from all workers, as well as our environment. Secondly, no ground-truth answers are available for evaluating the reward, as often referred to in the reinforcement learning framework. Hence, we need to find a proper way to evaluate workers' contributions so that model-free RL algorithms which learn based on the reward signal can be applied.

The main contributions of this paper are as follows. (1) We propose the first model-free reinforcement peer prediction mechanism. Our mechanism combines the traditional peer prediction mechanisms with reinforcement learning to jointly incentive workers, as well as to learn and adjust the incentive level to offer. (2) Due to the missing of ground-truth, we adopt Bayesian inference to evaluate workers' contributions, and to infer the reward following each action (offered incentive level). We derive the explicit posterior distribution of workers' contributions and employ Gibbs sampling for inference to eliminate its bias. (3) In our mechanism, the inferred contributions are corrupted by noise and we can only observe the last step worker state rather than the current one. We use the online Gaussian process regression to learn the Q-function and replace the unknown current state with the couple of the last step state and incentive level. (4) We conduct empirical evaluation, and the results show that our mechanism is robust, and is able to significantly increase data requester's revenue under different worker models, such as fully rational, bounded rational and learning agent models.

2 Problem Formulation

Our proposed mechanism mainly works in the setting where one data requester, at every step, assigns M binary tasks with answer space $\{1, 2\}$ to $N \geq 4$ candidate workers. At step t, worker i's labels for the task j is denoted as $L_i^t(j)$, and correspondingly the payment that the mechanism pays is denoted as $P_i^t(j)$. Note we use $L_i^t(j) = 0$ to denote task j is not assigned to worker i at step t, and naturally under this case $P_i^t(j) = 0$. After every step, the data requester collects labels and aggregates them through Bayesian inference [19]. Assuming the aggregate reaches an accuracy A_t, the revenue for the data requester can then be computed as $r_t = F(A_t) - \eta \sum_{i=1}^{N} \sum_{j=1}^{M} P_i^t j$, where $F(\cdot)$ is a non-decreasing monotone function mapping accuracy to revenue and η is a tunable parameter balancing label quality and costs. Intuitively, $F(\cdot)$ needs to be non-deceasing as higher accuracy is preferred and also labels are only useful when their aggregate accuracy reaches a certain requirement. Note our framework is robust to any formulation of $F(\cdot)$ though it is set as $F(A_t) = A_t^{10}$ in experiments. Our goal is to maximize the cumulative revenue $R = \sum_{t=1}^{T} \gamma^t r_t$, where γ is the discount rate and T is the ending time, by making wise choices of actions (i.e. deciding incentive levels) at each step.

3 Reinforcement Peer Prediction

We present *Reinforcement Peer Prediction* in Figure 1. Note at every step t, the payment to worker i for task j is factored as a function over two elements, namely $P_i^t(j) = I_t \cdot p_i^t(j)$, where I_t is the incentive level learned and computed by our RL algorithm, and $p_i^t(j)$ is the output of our peer prediction scoring function. Since the ground-truth is not available, we cannot directly compute the reward (i.e accuracy A_t), following each action (i.e. deciding incentive level). Thus, we introduce the expected accuracy $\mathbb{E}A_t$ as an unbiased estimator of the real accuracy A_t. It can be calculated as $\mathbb{E}A_t = \frac{1}{M} \sum_{j=1}^{M} \Pr(L^t(j) = y_j^t)$, where $L^t(j)$ and y_j^t are the aggregate and true labels at step t, respectively. Besides used to aggregate data, Bayesian inference is also used to generate confusion matrices of all workers and the distribution of task labels $[\Pr(l = 1), \Pr(l = 2)]$, with l denoting the ground-truth label. For worker i, his confusion matrix $C_i = [c_{ikg}]_{2\times 2}$ is a measurement of how much

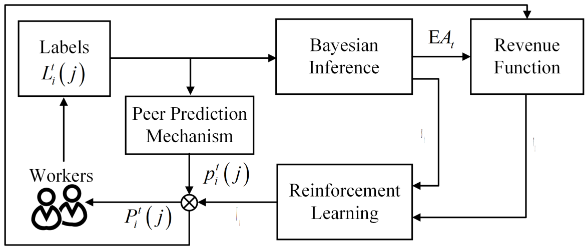


Figure 1: Illustration of our mechanism

efforts he exerts, where c_{ikg} denotes the probability that worker i labels a task in class k as class g. Since the accuracy of labels is determined by the overall efforts of workers, how well an individual worker performs is not a concern of our mechanism. Thus, we denote the state of the whole worker crowd s_t by workers' average probability of being correct, namely $s_t = \sum_{k\in\{1,2\}} \Pr(l = k) \cdot \frac{1}{N}\sum_{i=1}^{N} c_{ikk}$. After receiving the payment, workers may adjust their strategies in exerting efforts, which will lead to the change of s_t. However, when deciding the next-step incentive level I_{t+1}, we can only observe the last step state s_t. In other words, the state observation in our mechanism has one-step delay, which also makes our reinforcement learning problem different from traditional ones.

Peer Prediction Mechanism: We adopt the multi-task mechanism proposed by Dasgupta and Ghosh [2]. For each worker-task pair (i, j), it selects a reference worker k. Suppose workers i and k have been assigned d other distinct tasks $\{i_1, \ldots, i_d\}$ and $\{k_1, \ldots, k_d\}$, respectively. Then, the payment $p_i^t(j) = 1[L_i^t(j) = L_k^t(j)] - \xi_i^d \cdot \xi_k^d - \bar{\xi}_i^d \cdot \bar{\xi}_k^d$, where $\xi_i^d = \sum_{g=1}^{d} 1(L_k^t(i_g) = 1)/d$ and $\bar{\xi}_i^d = 1 - \xi_i^d$.

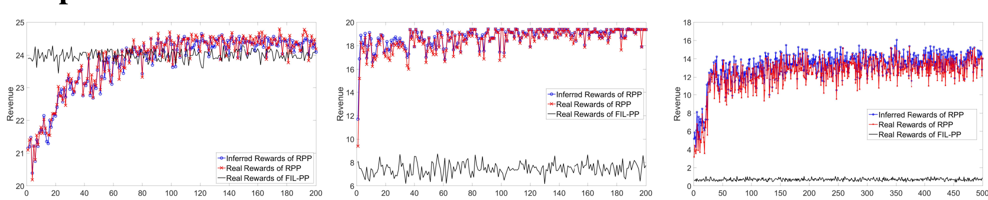
Bayesian Inference: Suppose the prior distributions that $c_{ik1} \sim \mathrm{Beta}(\alpha_{ik1}^p, \alpha_{ik2}^p)$ and $\Pr(l = 1) \sim \mathrm{Beta}(\beta_1^p, \beta_2^p)$. Then, we can explicitly derive the posterior distribution of true labels as

$$P(\boldsymbol{y}^t|\boldsymbol{L}^t) \propto B(\boldsymbol{\beta}^t)\prod_{i=1}^{N}\prod_{k=1}^{K} B(\boldsymbol{\alpha}_{ik}^t), \alpha_{ikg}^t = \sum_{j=1}^{M} \delta_{ijg}^t \xi_{jk}^t + \alpha_{ikg}^p, \beta_k^t = \sum_{j=1}^{M} \xi_{jk}^t + \beta_k^p \quad (1)$$

where $B(\cdot)$ denotes the beta function, $\delta_{ijg}^t = 1(L_i^t(j) = g)$ and $\xi_{jk}^t = 1(y_j^t = k)$. According to Gibbs sampling, we can generate posterior samples via iteratively sampling $P(y_j^t|\boldsymbol{L}, \boldsymbol{y}_{s\neq j}^t)$.

Reinforcement Learning: Recall that when computing the incentive level I_t for step t, the current state s_t cannot be observed. Because of it, we resort to the previous state and incentive level to define our policy $\pi(I_t|x_t)$, where $x_t = \langle s_{t-1}, I_{t-1}, t\rangle$. Then, the Q-function of our policy can be calculated as $Q(x_t, I_t) = \sum_{i=0}^{T-t} \gamma^i r_{t+i}$. Since both the state s_t and reward r_t can not be accurately observed, we have to approximate the temporal difference (TD) by assuming the residual follows a Gaussian process: $Q(x_t, I_t) - \gamma Q(x_{t+1}, I_{t+1}) = r_t + N(x_t, x_{t+1})$, where $N(\cdot)$ is the residual. With this assumption, the Q-function can be learned effectively using the online Gaussian process regression algorithm [5]. Furthermore, we use the classic ϵ-greedy policy to make decisions at every step.

4 Experiments



(a) Fully Rational Workers (b) Quantal Response Workers (c) MWUA Workers

The above figure shows our experiment results on three popular worker models. Suppose there are four incentive levels, namely $I_t \in \{0.1, 1.0, 5.0, 10.0\}$. In practice, traditional peer prediction mechanisms are often applied with a fixed incentive level. Here, we set the incentive level as 1.0 and denote the mechanism with a fixed incentive level by FIL-PP. By contrast, our reinforcement peer prediction (RPP) mechanism can dynamically learn and adjust the incentive level to maximize data requester's revenue. Besides, in our experiments, rational workers work with high efforts and report the true labels with probability 0.9 for any incentive level. Quantal response workers decide their strategy using the quantal response model, a classic bounded rationality model [9]. MWUA workers adapt their strategies via the MWUA model, a classic learning agent model [1]. From all the experiments, we can find that our mechanism is robust, and is able to significantly increase data requester's revenue, especially when workers are not fully rational.

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