REFORM: Reputation Based Fair and Temporal Reward Framework for Crowdsourcing

Extended Abstract

Samhita Kanaparthy
IIIT Hyderabad
Hyderabad, India
s.v.samhita@research.iiit.ac.in

Sankarshan Damle
IIIT Hyderabad
Hyderabad, India
sankarshan.damle@research.iiit.ac.in

Sujit Gujar
IIIT Hyderabad
Hyderabad, India
sujit.gujar@iiit.ac.in

ABSTRACT

Crowdsourcing is an effective method to collect data by employing distributed human population. Researchers introduce Peer-Based Mechanisms (PBMs) in crowdsourcing settings to incentivize agents to report accurately. We observe that with PBMs, crowdsourcing systems may not be fair. Unfair rewards for the agents may discourage participation. This work aims to build a general framework that assures fairness for PBMs in a temporal setting, i.e., where reports are time-sensitive. Towards this, we introduce two notions of fairness for PBMs, namely *γ-fairness* and *qualitative fairness*. To satisfy these notions, our framework provides trustworthy agents with additional chances of pairing. We introduce Temporal Reputation Model (TERM) to quantify agents' trustworthiness across tasks. Having TERM, we present our iterative framework, REFORM, that can adopt the reward scheme of any existing PBM. We demonstrate REFORM's significance by deploying the framework with RPTSC's reward scheme and prove that REFORM with RPTSC considerably improves fairness; while incentivizing truthful and early reports.

KEYWORDS

Crowdsourcing; Fairness; Reputation Scores; Nash Equilibrium

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1 INTRODUCTION

Crowdsourcing systems collect truthful information for vital tasks from multiple agents by *incentivizing* them [1, 2, 5]. Typically, these tasks do not have access to the *ground truth*. Hence, we cannot verify the correctness of the agents' reports. Towards this, researchers introduce *Peer Based Mechanisms* (PBMs). PBMs reward an agent based on its consistency with random agents referred to as "peers". We observe that PBMs are inherently *unfair* as the agent's reward depends on its consistency with peers and not primarily on its efforts. In such a case, *trustworthy* agent may not get the reward it deserves from unfair pairings. Thus, *fair* rewards are necessary to ensure the participation of trustworthy agents in crowdsourcing. Existing works ensure fairness in crowdsourcing through mechanism design [4, 9]. However, unfairness is still not addressed in PBMs without prior or ground truth access. Additionally, we consider *temporal setting* where the task's requester requires early reports. It is natural to assume that the reward should decrease with time to incentivize early reporting. However, this might encourage early random reports than exerting efforts, further aggravating the unfairness. Towards this, our goal is to devise a PBM that ensures fairness and truthful reporting in a temporal setting.

Crowdsourcing Model. The *requester* of the system assigns tasks $\mathcal{T}$ to agents $\mathcal{A}$, such that each task τ is assigned to at least two agents. An agent solves a task either by exerting high (e_H) or low (e_L) efforts in our setting. Once agent a_i solves the task, it obtains an evaluation x_i. Agents have choice among the following strategies (i) *Trustworthy*: Exert high effort and report true evaluation at earliest; (ii) *Deceiving*: Exert high efforts and may report false (iii) *Random*: Exert low effort and report the answer randomly. PBMs reward agent a_i if its report y_i matches that of peer's y_p and is penalised otherwise, based on the reward scheme, *peer-fac*(y_i). As we focus on temporal setting, we employ a decay factor $\beta(t)$ that decays with time to the reward scheme [3]. Thus, the reward agent a_i gets on reporting y_i for a task after time t_i is $R_i(y_i, t_i) = \textit{peer-fac}(y_i) \times \beta(t_i)$.

2 QUANTIFYING FAIRNESS IN PBMS

PBMs evaluate agents against a peer and reward if their reports match. Such evaluations may result in unfair rewards when a trustworthy agent is paired with random or deceiving agents. Towards this, we present two novel notions to quantify fairness in PBMs.

γ-Fairness. This depends on the difference in optimal and expected rewards of trustworthy agents in a PBM. For a given PBM, let M^* be the optimal reward a trustworthy agent gets when its report matches with a peer's report, and E^* be the expected reward. We say a PBM is γ-Fair if the expected difference in its optimal and the expected reward equals γ, i.e., $\mathbb{E}\left[\frac{M^*-E^*}{M^*}\right] = \gamma$.

Qualitative Fairness. This notion ensures that in PBMs with reputation scores, an agent with a higher reputation should have higher expected rewards than agents with the same report but a lower reputation. We capture this desired property formally as follows:

Definition 2.1 (Qualitative Fairness). Let agents $a_i, a_j \in \mathcal{A}$ submit their reports y_i, y_j at the same time t such that $y_i = y_j$. We say a PBM guarantees qualitative fairness if its rewards satisfy,

$$\mathbb{E}[R_i(y_i = y, t)|\Omega_i] \geq \mathbb{E}[R_j(y_j = y, t)|\Omega_j] \quad \forall \Omega_i \geq \Omega_j, \forall y \in \mathcal{X}, \forall i, j.$$

Here, $\mathbb{E}[R_i(y_i = y, t)|\Omega_i]$ is the expected reward of agent a_i with reputation score Ω_i for reporting y_i at time t.

Our Approach. To satisfy the above notions of fairness in PBMs, the ingenuity is to give trustworthy agents additional chances of

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pairing to evaluate their reports. These chances reduce the possibility of agents getting penalised for unfair pairings. The decrease in penalty leads to higher expected rewards, thereby improving fairness. To decide which agent will receive additional chances to pair, we use *reputation scores* as a metric. Towards this, we first introduce *TERM*, a novel reputation model to quantify trustworthiness in temporal setting. Later, having TERM as a critical component, we propose our iterative framework, REFORM.

3 TEMPORAL REPUTATION MODEL (TERM)

Crowdsourcing systems use reputation models to quantify the trust it can place towards an agent's report [6, 8]. Reputation scores of an agent must: (i) gradually build after several instances of trustworthy behaviour; (ii) reduce relatively quickly with adversarial behaviour; and (iii) saturate as it reaches the extremum. Additionally, the score's increase should be inversely proportional to the time taken to report in temporal setting. Towards this, we present TERM, which assigns scores to agents considering both the accuracy of the report and the time taken to submit it.

For TERM scores, we employ Gompertz function [11] since its growth is gradual and smooth. Algorithm 1 formally presents TERM. Here, we maintain every agent a_i's history $\mathcal{H}_{i,j}$ till round r_j and store the frequency $f(y_i)$ (from Framework 1). TERM calculates round-scores of agents from the reports submitted and time taken for reporting (Lines 5-6). The cumulative-score calculation uses round scores of all the rounds (Line 7). We take cumulative-score as input to Gompertz function, whose output is TERM score (Line 8).

Algorithm 1: TERM($y_i, t_i, \mathcal{H}_{i,j-1}$)

1 Agent a_i submits report y_i for a task τ in round r_j at time t_i.
2 **Input**: y_i, t_i, History $\mathcal{H}_{i,j-1} = (\Omega_{i,j-1}, |\phi|_{i,j-1}, \ldots, |\phi|_{i,1})$
3 Randomly choose a report y_p from the same task τ.
4 $\phi_{i,j} = \frac{\mathbb{I}_{y_i = y_p}}{f(y_i) t_i}$; ▷ round-scores calculation
5 $|\phi|_{i,j} \leftarrow$ normalised $\phi_{i,j}$ to [-1, 1];
6 $\psi_{i,j} = \sum_{k=1}^{j} \lambda^{(j-k)} |\phi|_{i,k}$; ▷ cumulative-scores calculation
7 **Output**: $\Omega_{i,j} = \exp(-\exp(\frac{-\psi_{i,j}}{2}))$; ▷ updated TERM score

We note that Gompertz function used in TERM gradually increases with early reporting but reduces relatively fast with random reporting when the reports do not match. We later show that trustworthy reporting is beneficial over other strategies.

4 REFORM: FRAMEWORK

We present REFORM a novel iterative framework for crowdsourcing (Framework 1). REFORM incentivises trustworthy behaviour by improving the expected reward of trustworthy agents. We achieve this increase in the expected reward by offering trustworthy agents additional chance(s) of pairing, $k \in \mathbb{Z}_+$. In Framework 1, the reward scheme *peer-fac*$(\cdot)$ can be adopted from any existing PBM. Based on the reward scheme, we evaluate an agent's report against a random peer's report from the same task and reward if the reports match. For temporal setting, we use TERM scores to decide whether to offer additional chance(s) of pairing to an agent. Specifically, if an agent's submitted report does not match its peer's report, and if the

Framework 1: REFORM

Agent a_i submits a report y_i for an assigned task τ at time $t_i \leq \delta_\tau$ in round r_j.
Input: *peer-fac*$(\cdot)$, $k > 1$, y_i, t_i, History $\mathcal{H}_{i,j-1}$
initialization: $l = 0$
while $l < k$ **do**
  Randomly choose peer report y_p from the same task τ.
  if $l = 1$ **then**
    $\Omega_{i,j} = \text{TERM}(y_i, t_i, \mathcal{H}_{i,j-1})$; ▷ update TERM score
  $l = l + 1$
  if $y_i = y_p$ **then**
    /* reports match, agent gets optimal reward */
    Return: $R_i(y_i, t_i) =$ *peer-fac*$(y_i | y_i = y_p) \times \beta(t_i)$
  else
    if $\Omega_{i,j} \leq \Omega_{p,j} \vee l = k$ **then**
      /* reputation score is less or maximum chances reached, no more pairing */
      Return:
      $R_i(y_i, t_i) =$ *peer-fac*$(y_i | y_i \neq y_p) \times \beta(t_i)$

agent has a TERM score *higher* than that of its peer without having reached the maximum number of chances k, we give it another chance to pair. Otherwise, we penalise according to the reward scheme adopted. Note that we can plug any relevant reputation model instead of TERM in REFORM, which still helps improve the fairness of a PBM. We next deploy the framework using the RPTSC reward scheme to demonstrate REFORM's significance [10].

REFORM with RPTSC. We focus on RPTSC [10] than other PBMs because of its practicality, as it (i) does not assume prior, (ii) incentivizes efforts and truthful reporting, and (iii) is resistant to single report strategy, i.e., where all agents collude to report the same.

Using similar assumptions to existing PBMs, we game-theoretically analyze REFORM with RPTSC. Specifically, we prove the following.

Lemma 4.1. *TERM incentivizes an agent to choose trustworthy strategy, given that all the other agents choose trustworthy strategy.*

Corollary 4.2. *In REFORM with RPTSC, the expected reward increases with an increase in additional chances, k.*

Theorem 4.3. *In REFORM with RPTSC, it is strict Nash equilibrium for agents to choose trustworthy strategy.*

Theorem 4.4. (Informal) *REFORM with RPTSC is fairer than RPTSC with respect to γ-fairness.*

Theorem 4.5. *REFORM with RPTSC satisfies qualitative fairness.*

Further, we empirically establish that REFORM with RPTSC achieves higher fairness with a marginal increase in the budget while preserving all the properties of RPTSC. For formal results and detailed discussion, we refer the reader to the full version [7].

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REFERENCES

[1] Arpit Agarwal, Debmalya Mandal, David C. Parkes, and Nisarg Shah. 2017. Peer Prediction with Heterogeneous Users. In *Proceedings of the 2017 ACM Conference on Economics and Computation* (Cambridge, Massachusetts, USA) *(EC '17)*. Association for Computing Machinery, New York, NY, USA, 81–98.

[2] Shani Alkoby, David Sarne, Erel Segal-Halevi, and Tomer Sharbaf. 2018. Eliciting Truthful Unverifiable Information. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems* (Stockholm, Sweden) *(AAMAS '18)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1850–1852.

[3] Sankarshan Damle, Moin Hussain Moti, Praphul Chandra, and Sujit Gujar. 2021. Designing Refund Bonus Schemes for Provision Point Mechanism in Civic Crowdfunding. In *PRICAI 2021: Trends in Artificial Intelligence*. Springer International Publishing, 18–32.

[4] Naman Goel and Boi Faltings. 2019. Deep Bayesian Trust: A Dominant and Fair Incentive Mechanism for Crowd. In *The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019*. AAAI Press, 1996–2003.

[5] Naman Goel and Boi Faltings. 2020. Personalized Peer Truth Serum for Eliciting Multi-Attribute Personal Data. In *Proceedings of The 35th Uncertainty in Artificial Intelligence Conference (Proceedings of Machine Learning Research, Vol. 115)*, Ryan P. Adams and Vibhav Gogate (Eds.). PMLR, 18–27. https://proceedings.mlr.press/v115/goel20a.html

[6] Hanieh JavadiKhasraghi and Shahriar Mohammadi. 2012. An Innovative Crowdsourcing Approach for Amazon Mechanical Turk. *International Journal of Computer Applications* 52 (08 2012), 20–13.

[7] Samhita Kanaparthy, Sankarshan Damle, and Sujit Gujar. 2021. REFORM: Reputation Based Fair and Temporal Reward Framework for Crowdsourcing. arXiv:2112.10659 [cs.GT]

[8] John Le, Andy Edmonds, Vaughn Hester, and Lukas Biewald. 2010. Ensuring quality in crowdsourced search relevance evaluation: The effects of training question distribution. In *SIGIR 2010 workshop on crowdsourcing for search evaluation*, Vol. 2126. 22–32.

[9] Moin Hussain Moti, Dimitris Chatzopoulos, Pan Hui, and Sujit Gujar. 2019. FaRM: Fair Reward Mechanism for Information Aggregation in Spontaneous Localized Settings. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*. International Joint Conferences on Artificial Intelligence Organization, 506–512.

[10] Goran Radanovic, Boi Faltings, and Radu Jurca. 2016. Incentives for Effort in Crowdsourcing Using the Peer Truth Serum. *ACM Trans. Intell. Syst. Technol.* 7, 4, Article 48 (March 2016), 28 pages.

[11] Yujian Tang, Samia Tasnim, Niki Pissinou, S.S. Iyengar, and Abdur Shahid. 2018. Reputation-Aware Data Fusion and Malicious Participant Detection in Mobile Crowdsensing. In *2018 IEEE International Conference on Big Data (Big Data)*. 4820–4828. https://doi.org/10.1109/BigData.2018.8622335