Infochain: A Decentralized System for Truthful Information Elicitation

Cyril van Schreven, Naman Goel and Boi Faltings
Artificial Intelligence Lab, École Polytechnique Fédérale de Lausanne, Switzerland
{cyril.vanschreven, naman.goel, boi.faltings}@epfl.ch

Abstract. Incentive mechanisms play a pivotal role in collecting correct and reliable information from self-interested agents. Peer-prediction mechanisms are game-theoretic mechanisms that incentivize agents for reporting the information truthfully, even when the information is unverifiable in nature. Traditionally, a trusted third party implements these mechanisms. We built Infochain, a decentralized system for information elicitation. Infochain ensures transparent, trustless and cost-efficient collection of information from self-interested agents without compromising the game-theoretical guarantees of the peer-prediction mechanisms. In this paper, we address various non-trivial challenges in implementing these mechanisms in Ethereum and provide experimental analysis.

Keywords: Truthful Information Elicitation, Incentive Mechanisms, Ethereum

1 Introduction

AI algorithms have witnessed huge success in the past decade in not only commercial but also various non-commercial applications that affect human life. Such widespread adoption of the algorithms requires a guarantee on their reliability and trustworthiness. It is a well known but often ignored fact that the algorithms are only as reliable and trustworthy as the data that is used to train them. Besides training AI, data is also used in various decision making processes. For e.g., reviews or ratings collected by e-commerce websites and other service providers influences customers’ buying decisions and crowdsourced outcome determination in decentralized prediction markets decides the payoffs of the market participants. Thus, it is necessary to develop transparent systems, which ensure that the collected information is reliable and trustworthy.

A crucial step in eliciting trustworthy information from self-interested agents is aligning their incentives with honest behavior. In the absence of an incentive mechanism, only agents with ulterior motives participate and the information is likely to be biased. This phenomenon is well-documented in the electronic commerce literature [5]. Unfortunately, a naive incentive mechanism (for e.g. a fixed payment for participation) invites free riders who submit random information. Designing truthful incentive mechanism is a hard problem when there is no way to verify the correctness of the information. This issue has been addressed by game theoretic peer-prediction mechanisms [3]. The broad idea in
these mechanisms is to reward the agents by “matching” the information provided by multiple agents, while discouraging any collusion.

However, for the mechanisms to be effective in practice, they also have to be implemented in a transparent and trustworthy manner. In most existing systems, either a trusted third party controls the entire system and also implements the incentive mechanisms (for e.g. reputation and fixed payment mechanisms implemented by Amazon MTurk) or the data requester independently implements the incentive mechanisms (for e.g. bonus payment mechanism on MTurk). Both the information requester and the information providers rely on the trustworthiness of the central authority to trust the information collected and the payments.

There also exist platforms where the information requester has complete control over the system (for e.g. those run by IARPA). In such systems, the information providers have to trust the information requester.

We implement a completely decentralized information collection system in Ethereum called Infochain. Information requesters post tasks, which can be selected by information providers. Once the information providers submit information for the selected tasks, their payments in Ether are processed by a smart contract that implements a peer-prediction mechanism. All the collected information and payments are stored on a public blockchain to ensure transparency and immutability. However, implementation of the peer-prediction mechanisms in Ethereum also faces several challenges, which we address in this paper. We list these challenges and our contributions as follows:

− One of the reasons for popularity of platforms like MTurk is their low cost. On the other hand, writing data and performing computation on Ethereum Virtual Machine (EVM) is very expansive. Information providers must be compensated for this cost, increasing the overall cost for information requesters. For the first time, we discuss several non-trivial ways of implementing three different peer-prediction mechanisms in Solidity and empirically compare the reduction in costs. This also leads to a novel finding that some peer-prediction mechanisms are costlier than others in this environment. The code for our implementation will be made public with the accepted paper.

− Transparency is a desired inherent feature of blockchain. But the peer-prediction mechanisms are compromised if an agent can access the information submitted by their “peers” before submitting own information. We implement a commit-reveal protocol to address this challenge.

− In order to reduce computation costs, most peer-prediction mechanisms use only one (or a few) randomly selected peer(s) for every agent. This doesn’t affect their game-theoretic properties since the rewards of the agents remain unchanged in expectation. However, if the random peer(s) can be predicted, the agents get an opportunity to collude and the mechanisms can be compromised. The transparency of blockchain increases this risk. We show that under some assumptions, it is possible to implement this safely in Solidity. We also observe that in some cases, the cost of this safe implementation may outweigh the reduction in cost expected from randomness.
In the incentive mechanisms literature, different mechanisms have always been compared in terms of their incentive properties and the technical assumptions that are required to ensure those properties. For the first time, we provide a new perspective for comparing different mechanisms. Thus, we hope that this paper will not only be of interest to the system development community but also of much help to the mechanism design community in developing new incentive mechanisms for decentralized settings.

2 Related Work

Peer-prediction Mechanisms Different information elicitation mechanisms exist in the literature for different settings. Proper scoring rules [4] and prediction markets [15] can be used to elicit truthful beliefs about events, if the ground truth about the events can be observed by the mechanism in future. However, in most interesting applications, the ground truth either doesn’t exist (e.g. subjective reviews) or is difficult to observe (e.g. ground truth labels of massive amount of training data for machine learning). The original peer-prediction method [9] and the Bayesian Truth Serum (BTS) [10] are two classic mechanisms that were proposed for such cases. Recently a lot of progress has been made in making these mechanisms suitable for practical use. In this paper, we will focus on three most important state-of-the-art peer-prediction mechanisms. We discuss these mechanisms briefly in a later section but a detailed discussion is beyond the scope of this paper. We encourage the readers to refer to [3] for more information.

Decentralized Systems for Crowdsourcing Many decentralized systems have been proposed for crowdsourcing and information trading [1,16,8,7] but none addresses the challenge of providing quality based incentives for information. [12] proposes a decentralized protocol for reputation systems on e-commerce websites, with focus on preserving the anonymity of the raters. In a recent and independent work, [6] also uses peer-prediction on trust-free data trading systems but the analysis in this theoretical paper focuses on a secure multi-party computation protocol for rewarding information that loses value if revealed.

3 Infochain

We give an overview of Infochain in Figure 1 and summarize only the main components of our implementation due to limited space. If accepted, the readers of the paper will have access to the full Solidity code to get all the details.

3.1 Baseline Reward Computation

In this section, we discuss the baseline computation involved in the peer-prediction mechanisms. We assume standard crowdsourcing settings: there exists a number of tasks on Infochain, each information provider (agent) solves some of the tasks, and each task is solved by multiple agents. Agents who solve some common tasks can act as peers for one another. We assume that the tasks have binary answers
but the mechanisms extend to multiple values under some assumptions. The rewards can be scaled with a constant to compensate for the costs and to balance the budget without affecting their incentive properties.

1. **The Output Agreement (OA) Mechanism** [14]: This is perhaps the simplest of all peer-prediction mechanisms. In the OA mechanism, an agent gets a reward of 1 unit only if her answer for a task matches the answer of her peer for the same task. The reward of the agent for a task is the average over the rewards earned by matching with all peers. The final reward of the agent is the average of her rewards from all the tasks solved by her.

2. **The Dasgupta and Ghosh (DG) Mechanism** [2]: In the DG mechanism, an agent gets a reward of 1 unit if her answer for a task matches the answer of her peer for the same task but also gets a penalty of 1 unit if her answers matches the answers of the peer on non-common tasks. The DG mechanism requires that two agents, who are peers of one another, must also have some non-common tasks that are solved by one of them but not by both. The final reward is calculated by averaging as described in the OA mechanism. The Correlated Agreement mechanism [13] is a generalization of the DG mechanism and involves similar computations.

3. **The Peer Truth Serum for Crowdsourcing (PTSC)** [11]: In PTSC, the reward of an agent $i$ for a task is calculated using the following formula:

$$
\begin{align*}
\alpha \cdot \left( \frac{\mathbb{1}_{y = y'}}{R_i(y)} - 1 \right) & \quad \text{if } R_i(y) \neq 0 \\
0 & \quad \text{if } R_i(y) = 0
\end{align*}
$$

where $y$ is the answer submitted by the agent and $y'$ is the answer submitted by her peer for the same task. $\alpha$ is a strictly positive scaling constant.

The mechanism uses $R_i(y) = \text{num}_i(y) / \sum_{\bar{y} \in \{0,1\}} \text{num}_i(\bar{y})$, where $\text{num}_i(y)$ is a function that counts occurrences of $y$ in the answers of all agents (except $i$) across all tasks. The final reward is calculated by averaging discussed earlier. Note that the DG mechanism and the PTSC allow negative rewards, which is implemented via making agents submit refundable deposits. Information requester also deposits the reward budget and an additional refundable deposit, which is returned after all the payments and computation costs are settled.
3.2 Commit-Reveal Protocol

Transparency is an inherent feature of blockchain. Thus, all the information submitted by an agent is visible to all others. The peer-prediction mechanisms guarantee their incentive compatibility assuming that an agent can only form a belief about what her peers are going to report but doesn’t know the actual report of peers. We ensure this in Infochain by making the agents follow a commit-reveal protocol to submit their answers:

1. **Commit**: An agent writes her commitment $\text{keccak256}(y, k)$ on the chain, where $y$ is the agent’s answer for a given task and $k$ is her secret key.

2. **Reveal**: Once all agents have finished submitting their commitments for a task or the commitment phase expires, they can reveal their respective secret keys and answers. If the commitment of an agent matches her revealed answer, the answer is written on the chain. If not, the answer is discarded.

3.3 Cost Optimizations

1. **Optimizing Writing Cost**: To minimize the costs of writing on the chain, agents on Infochain combine multiple answers in the form of a bit vector. This is motivated by two observations. First, the answers are revealed simultaneously and thus, they do not require separate commitments. Second, the Ethereum Virtual Machine operates on 256 bit words, thus a single bit vector is much cheaper to write than other formats. With this scheme, each 256-bit commitment can contain up to 42 answers (see a short online appendix for more details). This optimization helps both commit and reveal phases.

2. **Optimizing Computation Cost**: To reduce the cost of computing the rewards, a set of so-called intermediary values is introduced. These values naturally appear at intermediary states of reward computation. They will be precomputed and reused for each agent. What these intermediary values are, depends on the peer-prediction mechanism. This approach allows for the computation to traverse the data a minimum number of times. Since all rewards are computed at the same time, these intermediary values don’t need to be written on the blockchain and can be kept in memory instead.

3.4 Random Peer Selection

It is also possible to use only one or a few randomly selected peers for reward calculation. This is because, in expectation, the rewards of the agents remain unchanged and thus, the mechanisms with randomly selected peers also offer the same incentive compatibility (except that the variance in rewards increases). This is an interesting tradeoff between computation cost and variance in rewards. However, random peer selection on blockchain is subtle mainly due to the fact that nothing on the chain is a “secret”, including the seed for random number

\[1 \text{ Available at } \text{http://bit.ly/2PdDA1b}\]
If random peers can be known in advance, it may increase the risk of collusion between the agents compromising the incentive compatibility of the mechanisms. In Infochain, we use the block timestamps as well as the mining difficulty level as the seed. This avoids using any trusted third party for random peer selection. The approach works under the assumption that the miners will not try to cheat the smart-contract, which is a reasonable assumption given that the miners have no incentive to do so (they risk losing their mining rewards).

4 Experiments

We now discuss the results of some experiments performed on Infochain. The performance measure of interest in this discussion will be the total amount of gas used. Gas is a unit measuring the computational work of running transactions or smart contracts in the Ethereum network and is a good proxy for the cost in USD. Infochain has been deployed and tested on the Ropsten Test Network, one of the commonly used public testing framework for Ethereum smart contracts. To have no limitations in terms of gas, the results reported in this paper have been generated on a local instance of Ethereum.

Dataset Description

Imagine that an information requester is interested in using Infochain for collecting information about the quality of service offered by different web services. For this experiment, we used a dataset\textsuperscript{2} containing real-world quality of service evaluation from 339 trusted agents for 5,825 web services. The agents observe the response time (in seconds) of the web-services. The real valued observations were placed into two categories (“good” and “bad”), in order to fit them to our binary observation setting. We treated a response time of at most 1 second as “good” and the rest as “bad”. This dataset acts as the ground truth data that the information requester is interested in eliciting from self-interested agents. We simulated agent behavior as follows: 50% of the agents report truthfully, 25% report randomly (i.e. independent of the ground truth) and the rest report in an adversarial way (i.e. opposite of the ground truth).

Results

In Figure 2a, we show the reduction in writing cost due to the proposed optimization discussed in Section 3.3. As expected, the reduction becomes more significant as agents solve more number of tasks. In Figure 2b, shows the reduction in computation cost due to the proposed optimizations for the PTSC mechanism with varying number of agents and number of tasks per agent. We observed a similar trend for the OA and the DG mechanisms. We next compare the cost of the three mechanisms in Figure 2c. While the OA mechanism and the PTSC mechanism have similar cost, the DG mechanism is more costly. Finally, Figure 2d shows the effect of using randomly selected peers for reward computation in the DG mechanism. We note that there may be multiple ways to implement sampling without replacement; for e.g., 1) randomly select a peer,

\textsuperscript{2} Dataset is available at \url{http://wsdream.github.io}
Fig. 2: Experimental Results

check if it is already in the list of previously selected peers and repeat; and 2) sample from the list of not selected peers, update the list of not selected peers and repeat. The first method is not suitable as there is no upper bound on the number of necessary random selections. The results presented here correspond to the second method. As shown in Figure 2d, the cost is guaranteed to reduce if we randomly select only one peer per agent. But when multiple peers are to be selected (which is required to reduce variance in rewards), the cost may increase to a level higher than the cost of using all peers without any random selection.

5 Conclusions

AI is expected to increasingly make autonomous decisions based only on data. Implementing incentive mechanisms for truthful information elicitation is an
important component of transparent and trustworthy AI systems. In this paper, we have shown how this can be done on the blockchain for the first time.

References

1. An, B., Xiao, M., Liu, A., Gao, G., Zhao, H.: Truthful crowdsensed data trading based on reverse auction and blockchain. In: International Conference on Database Systems for Advanced Applications. pp. 292–309. Springer (2019)
2. Dasgupta, A., Ghosh, A.: Crowdsourced judgement elicitation with endogenous proficiency. In: Proceedings of the 22nd international conference on World Wide Web. pp. 319–330. ACM (2013)
3. Faltings, B., Radanovic, G.: Game theory for data science: Eliciting truthful information. Synthesis Lectures on Artificial Intelligence and Machine Learning 11(2), 1–151 (2017)
4. Gneiting, T., Raftery, A.E.: Strictly proper scoring rules, prediction, and estimation. Journal of the American Statistical Association 102(477), 359–378 (2007)
5. Hu, N., Pavlou, P.A., Zhang, J.: Can online reviews reveal a product’s true quality?: empirical findings and analytical modeling of online word-of-mouth communication. In: Proceedings of the 7th ACM conference on Electronic commerce. pp. 324–330. ACM (2006)
6. Kong, Y., Ma, Y., Wu, Y.: Securely trading unverifiable information without trust. arXiv preprint arXiv:1903.07379 (2019)
7. Li, M., Weng, J., Yang, A., Lu, W., Zhang, Y., Hou, L., Liu, J.N., Xiang, Y., Deng, R.H.: Crowdbc: A blockchain-based decentralized framework for crowdsourcing. IEEE Transactions on Parallel and Distributed Systems 30(6), 1251–1266 (2018)
8. Lu, Y., Tang, Q., Wang, G.: Zebralancer: Private and anonymous crowdsourcing system atop open blockchain. In: 2018 IEEE 38th International Conference on Distributed Computing Systems (ICDCS). pp. 853–865. IEEE (2018)
9. Miller, N., Resnick, P., Zeckhauser, R.: Eliciting informative feedback: The peer-prediction method. Management Science 51(9), 1359–1373 (2005)
10. Prelec, D.: A bayesian truth serum for subjective data. Science 306(5695), 462–466 (2004)
11. Radanovic, G., Faltings, B., Jurca, R.: Incentives for effort in crowdsourcing using the peer truth serum. ACM Transactions on Intelligent Systems and Technology (TIST) 7(4), 48 (2016)
12. Schaub, A., Bazin, R., Hasan, O., Brunie, L.: A trustless privacy-preserving reputation system. In: IFIP International Conference on ICT Systems Security and Privacy Protection. pp. 398–411. Springer (2016)
13. Shnayder, V., Agarwal, A., Frongillo, R., Parkes, D.C.: Informed truthfulness in multi-task peer prediction. In: Proceedings of the 2016 ACM Conference on Economics and Computation. pp. 179–196. ACM (2016)
14. Waggoner, B., Chen, Y.: Output agreement mechanisms and common knowledge. In: Second AAAI Conference on Human Computation and Crowdsourcing (2014)
15. Wolfers, J., Zitzewitz, E.: Prediction markets. Journal of economic perspectives 18(2), 107–126 (2004)
16. Xiong, W., Xiong, L.: Smart contract based data trading mode using blockchain and machine learning. IEEE Access (2019)
17. Zheng, Z., Zhang, Y., Lyu, M.R.: Investigating qos of real-world web services. IEEE transactions on services computing 7(1), 32–39 (2014)